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Performance Evaluation of Smart Decision Support Systems on Healthcare

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Tese para obtenção do Grau de Doutor em
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Dedication

To God, first and foremost.

For the Lord gives wisdom;
from his mouth come knowledge and understanding.
Proverbs 2:6

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Foreword

This thesis describes the research work performed in the scope of the 4-year doctoral research programme and presents its main contributions and achievements. This doctoral programme and inherent research activities were carried out at the Next Generation Networks and Applications Group (NetGNA) research group of the Departamento de Informática, Universidade da Beira Interior, Covilhã, Portugal and Instituto de Telecomunicações, Delegação da Covilhã, Portugal. The research work was supervised by Prof. Dr. Joel José Puga Coelho Rodrigues and financially supported by the National Council for Scientific and Technological Development (CNPq) through the grant contract 207706/2014-0.

List of Publications

Articles included in the thesis resulting from this 4-year doctoral research programme

1. **A Comprehensive Review on Smart Decision Support Systems for Healthcare**

   Mário W. L. Moreira, Joel J. P. C. Rodrigues, Valery Korotaev, Jalal Al-Muhtadi, and Neeraj Kumar

   IEEE Systems Journal, IEEE-Inst Electrical Electronics Engineers INC *(in press)*, 2019.

   DOI: dx.doi.org/10.1109/JSYST.2018.2890121

2. **Semantic Interoperability and Pattern Classification for a Service-oriented Architecture in Pregnancy Care**

   Mário W. L. Moreira, Joel J. P. C. Rodrigues, Arun K. Sangaiah, Jalal Al-Muhtadi, and Valery Korotaev

   Future Generation Computer Systems, Elsevier Science BV, Vol. 89, pp. 137–147, December 2018.

   DOI: dx.doi.org/10.1016/j.future.2018.04.031

3. **Biomedical Data Analytics in Mobile-health Environments for High-risk Pregnancy Outcome Prediction**

   Mário W. L. Moreira, Joel J. P. C. Rodrigues, Francisco H. C. Carvalho, Naveen Chilamkurti, and Victor Denisov

   Journal of Ambient Intelligence and Humanized Computing, Springer Heidelberg (in press), 2019.

   DOI: dx.doi.org/10.1007/s12652-019-01230-4

4. **Evolutionary Radial Basis Function Network for Gestational Diabetes Data Analytics**

   Mário W. L. Moreira, Joel J. P. C. Rodrigues, Neeraj Kumar, Jalal Al-Muhtadi, and Valery Korotaev

   Journal of Computational Science, Elsevier Science BV, Vol. 27, pp. 410–417, July 2018.

   DOI: dx.doi.org/10.1016/j.jocs.2017.07.015

5. **Neuro-fuzzy Model for HELLP Syndrome Prediction in Mobile Cloud Computing Environments**

   Mário W. L. Moreira, Joel J. P. C. Rodrigues, Jalal Al-Muhtadi, Valery V. Korotaev, and Victor Hugo C. de Albuquerque

   Concurrency and Computation: Practice and Experience, Wiley-Blackwell, Article 4651, July 2018.

   DOI: dx.doi.org/10.1002/cpe.4651

6. **Nature-inspired Algorithm for Training Multilayer Perceptron Networks in e-Health Environments for High-risk Pregnancy Care**

   Mário W. L. Moreira, Joel J. P. C. Rodrigues, Neeraj Kumar, Jalal Al-Muhtadi, and Valery Korotaev

Journal of Medical Systems, Springer, Vol. 42, Issue 3, Article 51, March 2018.

DOI: dx.doi.org/10.1007/s10916-017-0887-0

7. **Averaged One-dependence Estimators on Edge Devices for Smart Pregnancy Data Analysis**

   Mário W. L. Moreira, Joel J. P. C. Rodrigues, Vasco Furtado, Neeraj Kumar, and Valery V. Korotaev

   Computers & Electrical Engineering, Pergamon-Elsevier Science LTD *(in press)*, 2019.

   DOI: dx.doi.org/10.1016/j.compeleceng.2018.07.041

8. **Computational Learning Approaches for Personalized Pregnancy Care**

   Mário W. L. Moreira, Joel J. P. C. Rodrigues, Vasco Furtado, Kashif Saleem, and Valery V. Korotaev

   Paper submitted for publication in an international journal, 2018.

9. **Postpartum Depression Prediction through Pregnancy Data Analysis for Emotion-aware Smart Systems**

   Mário W. L. Moreira, Joel J. P. C. Rodrigues, Neeraj Kumar, Kashif Saleem, and Igor V. Illin

   Information Fusion, Elsevier Science BV, Vol. 47, pp. 23-31, May 2019.

   DOI: dx.doi.org/10.1016/j.inffus.2018.07.001

Other publications resulting from this doctoral research programme not included in the thesis

10. **A Preeclampsia Diagnosis Approach using Bayesian Networks**

    Mário W. L. Moreira, Joel J. P. C. Rodrigues, Antonio M. B. Oliveira, Ronaldo F. Ramos, and Kashif Saleem

    IEEE International Conference on Communications (ICC), Kuala Lumpur, Malaysia, May 22–27, 2016, pp. 1-5.

    DOI: dx.doi.org/10.1109/ICC.2016.7510893

11. **Smart Mobile System for Pregnancy Care Using Body Sensors**

    Mário W. L. Moreira, Joel J. P. C. Rodrigues, Antonio M. B. Oliveira, and Kashif Saleem

    International Conference on Selected Topics in Mobile & Wireless Networking (MoWNeT), Cairo, Egypt, April 11–13, 2016, pp. 1-4.

    DOI: dx.doi.org/10.1109/MoWNet.2016.7496609

12. **Performance Evaluation of Predictive Classifiers for Pregnancy Care**

    Mário W. L. Moreira, Joel J. P. C. Rodrigues, Antonio M. B. Oliveira, Kashif Saleem, and Augusto Neto

    IEEE Global Communications Conference (GLOBECOM), Washington, DC, USA, December 4-8, 2016, pp. 1-5.

    DOI: dx.doi.org/10.1109/GLOCOM.2016.7842136

13. **An Inference Mechanism Using Bayes-based Classifiers in Pregnancy Care**

    Mário W. L. Moreira, Joel J. P. C. Rodrigues, Antonio M. B. Oliveira, Kashif Saleem, and Augusto V. Neto

    IEEE 18th International Conference one-Health Networking, Applications and Services (Healthcom), Munich, Germany, September 14–16, 2016, pp. 1-5.

    DOI: dx.doi.org/10.1109/HealthCom.2016.7749475

14. **Predicting Hypertensive Disorders in High-risk Pregnancy Using the Random Forest Approach**

    Mário W. L. Moreira, Joel J. P. C. Rodrigues, Antonio M. B. Oliveira, Kashif Saleem, and Augusto J. Venâncio Neto

    IEEE International Conference on Communications (ICC), Paris, France, May 21–25, 2017, pp. 1-5.

    DOI: dx.doi.org/10.1109/ICC.2017.7996964

15. **A Mobile Health Solution for Diseases Control Transmitted by *Aedes Aegypti* Mosquito using Predictive Classifiers**

    Oton C. Braga, Olimária C. Fonsêca, Mário W. L. Moreira, Joel J. P. C. Rodrigues, Francisca R. V. Silveira, Antônio M. B. Oliveira, and Augusto J. V. Neto

    I Workshop de Computação Urbana (CoUrb) in conjuction with the XXXV Simpósio Brasileiro de Redes de Computadores e Sistemas Distribuídos (SBRC), Belém, PA, Brazil, May 15-19, 2017, pp. 144-156.

    URL: portaldeconteudo.sbc.org.br/index.php/courb/article/view/2570

16. **Performance Evaluation of the Tree Augmented Naïve Bayes Classifier for Knowledge Discovery in Healthcare Databases**

    Mário W. L. Moreira, Joel J. P. C. Rodrigues, Antonio M. B. Oliveira, Kashif Saleem, and Augusto J. Venâncio Neto

    17º Workshop de Informática Médica (WIM) in conjunction with the XXXVII Congresso da Sociedade Brasileira de Computação (CSBC), São Paulo, SP, Brazil, July 02-06, 2017, pp. 1835-1844.

    URL: www2.sbc.org.br/csbc2017/public/files/17-wim/6.pdf

17. **Performance Assessment of Decision Tree-based Predictive Classifiers for Risk Pregnancy Care**

    Mário W. L. Moreira, Joel J. P. C. Rodrigues, Neeraj Kumar, Jianwei Niu, and Isaac Woungang

    IEEE Global Communications Conference (GLOBECOM 2017), Singapore, Singapore, December 4–8, 2017, pp. 1-5.

    DOI: dx.doi.org/10.1109/GLOCOM.2017.8254451

18. **Using Predictive Classifiers to Prevent Infant Mortality in the Brazilian Northeast**

    Ronaldo Ramos, Cristiano Silva, Mário W. L. Moreira, Joel J. P. C. Rodrigues, Mauro Oliveira, and Odorico Monteiro

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19. **Multilayer Perceptron Application for Diabetes Mellitus Prediction in Pregnancy Care**

    Mário W. L. Moreira, Joel J. P. C. Rodrigues, Neeraj Kumar, Jianwei Niu, and Arun Kumar Sangaiah

    In: Hung J., Yen N., Hui L. (eds) Frontier Computing (FC 2017), Lecture Notes in Electrical Engineering, Vol. 464, Springer, Singapore, 2018, pp. 200–209.

    DOI: dx.doi.org/10.1007/978-981-10-7398-4_22

20. **A Preterm Birth Risk Prediction System for Mobile Health Applications Based on the Support Vector Machine Algorithm**

    Mário W. L. Moreira, Joel J. P. C. Rodrigues, Guilherme A. B. Marcondes, Augusto J. Venâncio Neto, Neeraj Kumar, and Isabel de la Torre Díez

    IEEE International Conference on Communications (ICC), Kansas City, MO, USA, May 20–24, 2018, pp. 1-5.

    DOI: dx.doi.org/10.1109/ICC.2018.8422616

21. **Predicting Neonatal Condition at Birth through Ensemble Learning Methods in Pregnancy Care**

    Mário W. L. Moreira, Joel J. P. C. Rodrigues, Guilherme A. B. Marcondes, Augusto J. Venâncio Neto, and Vasco Furtado

    18º Simpósio Brasileiro de Computação Aplicada à Saúde (SBCAS) in conjunction with the XXXVIII Congresso da Sociedade Brasileira de Computação, Natal, RN, Brazil, July 22–26, 2018, pp. 1-11.

    URL: portaldeconteudo.sbc.org.br/index.php/sbcas/article/view/3671

Resumo

A atividade médica requer responsabilidade não apenas com base no conhecimento e na habilidade clínica, mas também no gerenciamento de uma enorme quantidade de informações relacionadas ao atendimento ao paciente. É através do tratamento adequado das informações que os especialistas podem consistentemente construir uma política saudável de bem-estar. O principal objetivo para o desenvolvimento de sistemas de apoio à decisão (SAD) é fornecer informações aos especialistas onde e quando são necessários. Esses sistemas fornecem informações, modelos e ferramentas de manipulação de dados para ajudar os especialistas a tomar melhores decisões em diversas situações.

A maioria dos desafios que os SAD inteligentes enfrentam advêm da grande dificuldade de lidar com grandes volumes de informação, que é gerada constantemente pelos mais diversos tipos de dispositivos e equipamentos, exigindo elevados recursos computacionais. Essa situação torna este tipo de sistema suscetível a não recuperar a informação rapidamente para a tomada de decisão. Como resultado dessa adversidade, a qualidade da informação e a provisão de uma infraestrutura capaz de promover a integração e a articulação entre diferentes sistemas de informação em saúde (SIS) tornam-se promissores tópicos de pesquisa no campo da saúde eletrônica (e-saúde) e que, por essa mesma razão, são abordadas nesta pesquisa. O trabalho descrito nesta tese é motivado pela necessidade de propor novas abordagens para lidar com os problemas inerentes à aquisição, limpeza, integração e agregação de dados obtidos de diferentes fontes em ambientes de e-saúde, bem como sua análise.

Para garantir o sucesso da integração e análise de dados em ambientes e-saúde é importante que os algoritmos baseados em aprendizado de máquina (AM) garantam a confiabilidade do sistema. No entanto, neste tipo de ambiente, não é possível garantir um cenário totalmente confiável. Esse cenário torna os SAD inteligentes suscetíveis à presença de falhas de predição, que comprometem seriamente o desempenho geral do sistema. Por outro lado, os sistemas podem ter seu desempenho comprometido devido à sobrecarga de informações que podem suportar.

Para tentar resolver alguns destes problemas, esta tese apresenta várias propostas e estudos sobre o impacto de algoritmos de AM no monitoramento e gestão de transtornos hipertensivos relacionados com a gravidez (gestação) de risco. O objetivo das propostas apresentadas nesta tese é melhorar o desempenho global de sistemas de informação em saúde. Em particular, os métodos baseados em AM são explorados para melhorar a precisão da predição e otimizar o uso dos recursos dos dispositivos de monitorização. Ficou demonstrado que o uso deste tipo de estratégia e metodologia contribui para um aumento significativo do desempenho dos SAD inteligentes, não só em termos de precisão, mas também na diminuição do custo computacional utilizado no processo de classificação.

Os resultados observados buscam contribuir para o avanço do estado da arte em métodos e estratégias baseadas em inteligência artificial que visam ultrapassar alguns desafios que advêm da integração e performance dos SAD inteligentes. Como o uso de algoritmos baseados em inteligência artificial é possível analisar de forma rápida e automática um volume maior de dados complexos e focar em resultados mais precisos, fornecendo previsões de alto valor para uma melhor tomada de decisão em tempo real e sem intervenção humana.

Palavras-chave

Sistemas Inteligentes de Apoio à Decisão, Arquitetura Orientada a Serviços, Sistemas Eletrônicos de Saúde, Sistemas de Informação da Saúde, Saúde Móvel, Saúde Eletrônica, Computação em Nuvem, Computação de Borda, Internet das Coisas, Interoperabilidade Semântica, Ontologia, Análise de Big Data, Inteligência Computacional, Computação Inspirada pela Natureza, Computação Cognitiva, Mineração de Dados, Aprendizagem de Máquina, Redes Neurais Artificiais, Cuidados da Saúde Materna, Distúrbios Hipertensivos da Gravidez.

Extended Abstract in Portuguese

Introdução

Esta seção resume, de forma alargada, os 4 anos de trabalho de investigação no âmbito da tese de doutoramento intitulada "Performance Evaluation of Smart Decision Support Systems on Healthcare". Esta tese foca-se no estudo e proposta de estratégias e metodologias de análise de dados para a monitorização e gestão dos transtornos hipertensivos da gravidez em ambientes de e-saúde. Na primeira etapa é descrito o enquadramento da tese, definido o problema abordado e os principais objetivos do estudo. Em seguida, a hipótese de investigação é descrita e são apresentadas as principais contribuições deste trabalho para o avanço do estado da arte.

Foco e Escopo

Na última década, os sistemas de apoio à decisão (SAD) têm apresentado inúmeros serviços confiáveis de saúde. Esses serviços ofereceram às pessoas soluções de saúde acessíveis em qualquer momento e em qualquer lugar. Atualmente, os usuários podem utilizar as tecnologias de informação e comunicação (TIC), que favorecem a interação entre os pacientes e seus médicos, para melhorar a proximidade e a sua qualidade de vida. Os médicos podem facilmente ter acesso aos registros clínicos do paciente, resultados de laboratório, imagens e informações sobre medicamentos de forma rápida e acessível. Da mesma forma, os pacientes podem ter acesso à sua situação de diagnóstico, bem como informações sobre como ter uma vida saudável [1, 2].

Segundo [3], o acompanhamento em saúde é bastante complexo e muitas habilidades são necessárias para as tarefas que estão envolvidas no processo de tratamento do paciente. Este acompanhamento representa a maior parte do trabalho da rotina diária da equipe médica. Em [4], os autores mencionam que os SAD fornecem assistência diagnóstica aos profissionais de saúde e aconselham pacientes sugerindo padrões e estilos de vida apropriados. Segundo [5], nos sistemas de saúde, a tomada de decisão é conduzida com o clínico para identificar as melhores opções de tratamento em momentos de incerteza. Em [6], os autores mencionam que esses sistemas podem melhorar o atendimento ao paciente, produzindo informações valiosas para o diagnóstico, prognóstico e tratamento.

Kurzyński *et al.* enfatizam que o diagnóstico médico é um dos tópicos de pesquisa mais importantes em tecnologia da informação e informática médica [7]. Para Kozlowski e Worthington, esses sistemas também podem ajudar a melhorar o tempo de espera nos hospitais devido ao recurso insuficiente e à grande quantidade de serviço [8]. Os sistemas inteligentes apresentam vários problemas e limitações desafiadores. Nesse sentido, abordagens baseadas em computador são propostas para solucionar tais limitações, com foco no aumento da qualidade de vida das pessoas.

Apesar dos inúmeros cenários em que podem ser aplicados em saúde, os SAD têm ainda de ultrapassar alguns desafios/problemas de características tecnológicas. Alguns destes desafios são partilhados pelas redes de última geração baseadas nos paradigmas da Internet das Coisas

(IoT), enquanto outros advêm das propriedades únicas da análise de Big Data.

Existem, pelo menos, cinco tendências significativas de pesquisa sobre a IoT, sendo este um dos principais tópicos atuais de pesquisa, juntamente com o monitoramento e tratamento remotos do paciente [9, 10, 11]. O aumento de registros de pacientes traz uma nova complexidade para o tratamento de dados pelo prestador de cuidados e especialistas em saúde. O desenvolvimento de plataformas de IoT ajuda a extrair insights de grandes conjuntos de dados, resolvendo vários problemas desses moldes. A análise centrada no paciente se concentra no emprego de ferramentas avançadas de análise, visualização e suporte à decisão para melhorar a precisão do diagnóstico [12]. Pesquisas sobre esse tema poderiam melhorar os tratamentos, tornando-os mais precisos, eficientes e personalizados [13]. A interoperabilidade semântica dos sistemas de saúde permitem o gerenciamento do registros eletrônicos de saúde (RES) de pacientes distribuídos em vários sistemas heterogêneos. Esta abordagem tem um papel importante na descrição de fatores essenciais para melhorar a qualidade do atendimento ao paciente, serviços de saúde pública e investigação médica. Tendo em vista que os usuários estão a cada dia assumindo mais responsabilidade por sua saúde, pesquisas sobre esse tópico podem resultar em melhor acesso aos dados e melhores soluções de tecnologia em saúde. Além disso, também pode permitir que os consumidores gerenciem seus próprios serviços de saúde. Outra tendência importante está relacionada ao estabelecimento de um novo conjunto de políticas de proteção voltadas para a IoT, principalmente para tecnologias vestíveis e implantáveis [14].

A análise de Big Data tem grande potencial para modificar a maneira como os profissionais de saúde usam tecnologias modernas para obter conhecimento de seus repositórios médicos e outros repositórios de dados [15]. As aplicações de análise de Big Data na área da saúde estão no estágio inicial de desenvolvimento, mas avanços rápidos em plataformas e ferramentas estão acelerando seu processo de desenvolvimento [16]. Analisando padrões de doenças, rastreamento de surtos e transmissão de dados para melhorar a vigilância e dar uma resposta mais rápida em emergências, precisam de mais melhorias. Transformar grandes quantidades de evidências em informações significativas é bastante útil para identificar necessidades na prestação de serviços. Da mesma forma, essa informação pode ajudar a prever e prevenir situações de risco.

Apesar dos avanços já alcançados nos últimos anos através dos estudos realizados nos tópicos de pesquisa acima apresentados, os SAD ainda enfrentam alguns desafios que têm de ser superados. Estes desafios incluem soluções para a interoperabilidade semântica entre os diferentes registros de eletrônicos de saúde (codificação, transmissão e uso da informação relativa a serviços de saúde entre os diversos intervenientes) e soluções para a interoperabilidade técnica (integração dos diferentes sistemas ao nível técnico, de infraestruturas, meios de comunicação, transporte, armazenamento e representação de dados). Estes campos de investigação são importantes e desafiantes dada a sua complexidade de implementação. Por esta razão, a investigação realizada no âmbito deste programa de doutoramento foca-se nos problemas inerentes à interoperabilidade semântica e metodologias de classificação para a predição de problemas complexos relativos à gravidez. Estes problemas serão estudados através da implementação e avaliação de desempenho de algoritmos baseados em aprendizagem de máquina para a gestão e monitorização de transtornos hipertensivos da gravidez, considerando ambientes de e-saúde.

Definição do Problema

Esta tese aborda não só a problemática da interoperabilidade entre RES, mas também como algoritmos de inteligência artificial podem ajudar ao especialista em saúde na monitorização da gestação de alto risco, com o intuito de melhorar a qualidade de vida da grávida. A importância destes dois tópicos advém da exigência que o aumento da complexidade dos dados coletados de dispositivos e equipamentos trouxe, exigindo que sejam desenvolvidas novas ferramentas e estratégias mais sofisticadas. Nos SAD, a tomada de decisão deve ultrapassar a barreira física das diversas organizações de saúde, a integração dos dados provenientes de diversas fontes e sua partilha de forma segura e privativa entre estas organizações, ajudando o especialista a tomar melhores decisões a qualquer momento e em qualquer lugar, reduzindo problemas que podem levar ambos gestante e feto a desenvolverem graves problemas de saúde. Por sua vez, a gestão e monitorização da saúde da grávida procura manter uma visão clara do estado de saúde da paciente, abordando e corrigindo situações à medida que estas vão surgindo.

No que diz respeito ao cuidado com a gravidez, segundo a Organização Mundial da Saúde (OMS), os distúrbios hipertensivos da gravidez atingem cerca de 10% de todas as gestações em todo o mundo. Estes distúrbios são as principais causas de morbidade, incapacidade e morte entre mães e recém-nascidos [17]. Essas complicações durante a gravidez foram uma importante causa de mortalidade na América Latina e no Caribe, contribuindo para 22,1% de todas as mortes maternas nessa região [18]. Ao fornecer atendimento oportuno e eficiente, a maioria das mortes relacionadas a essas complicações poderia ser evitada. Assim, a otimização dos cuidados de saúde para as mulheres grávidas para prevenir e tratar distúrbios hipertensivos é necessário. Neste sentido, as TIC desempenham um papel fundamental para melhorar a qualidade de vida das mulheres grávidas. Com o desenvolvimento de sistemas inteligentes para o monitoramento da gravidez de risco, especialistas em saúde podem identificar sérios problemas causados pelos distúrbios hipertensivos da gestação em seus estágios iniciais, salvando vidas de mães e recém-nascidos. Várias soluções tecnológicas já estão sendo implantadas para combater a pré-eclâmpsia em sua condição mais crítica [19, 20]. Muitas abordagens conseguiram uma avaliação adequada, mas ainda são incapazes de reduzir a situação crítica das mortes maternas e fetais por si próprias, principalmente nos países em desenvolvimento. Os SAD inteligentes são considerados uma boa ferramenta capaz de contribuir para esse objetivo.

Objetivos de Investigação

Neste contexto, objetivo principal deste trabalho é a construção e a avaliação de um modelo de apoio à tomada de decisão baseado em técnicas de aprendizado de máquina para serviços e aplicações para saúde. Esta proposta baseada em inteligência artificial incentiva os especialistas em saúde a monitorar o estado de saúde da gestante através da predição de futuras complicações, causadas pelos distúrbios hipertensivos em uma gravidez de risco, através dos fatores de risco, sintomas e dados de exames clínicos apresentados pela gestante.

Para alcançar este objetivo, foram definidos os seguintes objectivos parciais:

- Revisão do estado da arte sobre tecnologias, serviços e aplicações relacionadas aos SAD inteligentes existentes em saúde e sobre os algoritmos de inferência para a análise de dados em ambientes de e-saúde.

- Proposta e avaliação de uma arquitetura de serviços suficiente para atender aos requisitos de interoperabilidade semântica em sistemas de informação de saúde através da adoção de modelagem ontologica.
- Implementação e avaliação do desempenho de algoritmos baseados em aprendizado de máquina para aplicações móveis em saúde que serão usados para avaliar e validar possíveis resultados do parto em uma gestação de alto risco.
- Proposta e implementação de uma nova estratégia de partição e agrupamento de dados para o treinamento de modelos de inferência em serviços e aplicações de saúde em ambientes de computação em nuvem.
- A avaliação do desempenho de algoritmos de aprendizado de máquina, através da análise do custo computacional, aplicados em dispositivos IoT em redes de borda.
- Proposta e avaliação de um modelo híbrido de aplicação generalizada e interoperável para o cuidado da gravidez baseada em classificadores de aprendizagem em conjunto para sistemas inteligentes conscientes da emoção.

Hipótese de Investigação

Esta tese propõe um conjunto de novas abordagens focadas em aprendizagem de máquina para a monitorização da condição clinica da grávida com o intuito de prever situações que podem levar ambos mãe e recém-nascido a sérios problemas de saúde. O argumento apresentado nesta tese é o seguinte:

O desempenho de um SAD depende da aquisição semântica dos dados de diferentes RES, da identificação correta dos padrões presentes em diversas complicações da gravidez, bem como das relações entre os atributos pertencentes a determinado distúrbio hipertensivo, e da quantidade de recurso computacional que a análise desta grande quantidade de informação consome. Os arquétipos desenvolvidos para a integração de fontes de dados de saúde baseados em ontologias apresentam características diversas, porém acredita-se não ter sido produzida ainda uma análise abrangente destes modelos para a integração semântica de dados voltados para o cuidado com a gravidez. A predição para cada situação de risco pode ser medida através de porcentagem, ganho de informação ou soma de pesos, dependendo do algoritmo de aprendizagem de máquina utilizado. É possível a implementação de um algoritmo que una diversas características mantendo sua robustez e precisão. O consumo de recursos computacionais para a tarefa de predição e análise de grande quantidade de dados pode ainda ser atenuado através de técnicas de otimização para o treinamento de algoritmos mais robustos, como uma rede neural multicamadas por exemplo.

De forma a sustentar este argumento, foi utilizada a seguinte abordagem:

Em primeiro lugar foi estudado o progresso dos algoritmos de aprendizado de máquina e sua aplicação em serviços de saúde. Através deste estudo os principais métodos foram identificados, bem como as suas principais limitações e desafios. A seguir, foram revistas e estudadas de forma mais profunda as principais estratégias de otimização para os modelos já existentes, identificando as suas limitações, desafios, e pontos de investigação ainda em aberto.

Relativamente ao tópico da classificação, a tese começa por propor e estudar algoritmos baseados do Teorema de Bayes. Os classificadores Bayesianos convencionais supõem como hipótese que o efeito do valor de um atributo não-classe é independente dos valores dos outros atributos, *i.e.*, o valor de um atributo não influencia o valor dos outros. Esta hipótese tem como objetivo reduzir o custo computacional envolvido na tarefa de classificação. Quando a hipótese da independência entre os atributos se verifica, então o classificador Bayesiano ingênuo apresenta a melhor performance em termos de acurácia, com relação a outros classificadores. Entretanto, em saúde, é comum existir dependência entre os atributos. Neste caso, utilizamos uma Rede Bayesiana de crença como método classificador. Este método é estruturado por duas componentes. Primeiro, um grafo dirigido acíclico onde cada vértice representa um atributo e os arcos ligando os vértices representam uma dependência entre estes atributos. A segunda estrutura consiste de uma tabela de probabilidade condicional para cada atributo. Contudo, não é possível assumir a existência de um cenário totalmente condicional, pelo que são propomos diferentes tipos de RNAs (*e.g.*, função de base radial, máquina de vetores suporte e perceptron multicamadas) que lidam melhor com a presença de atributos condicionalmente relacionados. Todos estes algoritmos preditivos usam uma estratégia diferente para relacionar os diversos atributos e classificar os diversos distúrbios hipertensivos da gravidez quanto a sua gravidade. Enquanto os modelos probabilísticos usam a modelagem matemática para a classificação, os modelos baseados em RNAs procuram ajustar os pesos da primeira para à última camada para, ao final, produzir uma saída. Foram realizados diversos estudos para avaliação de desempenho destes algoritmos. Os resultados obtidos são usados para demonstrar a viabilidade e vantagens das novas modelos de classificação.

Principais Contribuições

A primeira contribuição desta tese é a revisão aprofundada do estado da arte sobre sistemas inteligentes de apoio à decisão e aplicações para a saúde. Esta revisão analisa a fundo as arquiteturas e cenários em que aplicações e serviços para a saúde são aplicados, bem como os seus desafios e problemas associados. Este estudo está descrito com detalhe no Capítulo 2, que consiste em um artigo aceito para publicação no IEEE Systems Journal [21].

A segunda contribuição é a proposta de desenvolver um SAD baseado em conhecimento que utiliza ontologias para integrar dados relacionados a distúrbios hipertensivos na gravidez. Esse modelo permite, ao lidar com casos novos, inferir a partir de uma base de conhecimento e prever situações de alto risco que podem levar a sérios problemas durante a gestação tanto para gestantes quanto para fetos. Esta proposta veio resolver o problema da interoperabilidade semântica entre diferentes RES. O cenário de testes envolveu 133 prontuários eletrônicos de gestantes que desenvolveram algum tipo de distúrbio hipertensivo durante a gestação. Concluiu-se que que o uso de ontologias para abordar padrões semanticamente adquiridos a partir de diferentes RES tem o potencial de influenciar significativamente uma implementação de arquitetura orientada a serviços para SAD clínica. Esta contribuição está descrita com detalhe no Capítulo 3, que consiste em um artigo publicado na revista Future Generation Computer Systems da Elsevier [22].

A terceira contribuição inclui o desenvolvimento, avaliação de desempenho e comparação de algoritmos de aprendizagem de máquina baseados em redes Bayesianas capazes de identificar gestações de risco com base nos sintomas e fatores de risco apresentados pelas pacientes. Esta contribuição apresenta uma comparação de desempenho de vários algoritmos de aprendizagem de máquina baseados no Teorema de Bayes para determinar o algoritmo mais adequado para a previsão, identificação e acompanhamento de distúrbios hipertensivos durante a gravidez. Esta solução construída a partir de estimadores de uma dependência em média apresenta melhores resultados em média do que as outras abordagens estudadas. Essas descobertas são fundamentais para melhorar o monitoramento da saúde de mulheres que apresentam gravidez de alto risco. Assim, este estudo contribui para a redução de óbitos maternos e fetais. Esta proposta é apresentada no Capítulo 4, que consiste num artigo aceito para publicação no Journal of Ambient Intelligence and Humanized Computing num número especial intitulado "Bio-medical Signal Processing for Smarter Mobile Healthcare using Big Data Analytics" [23].

A quarta contribuição desta tese propõe a modelagem, avaliação de desempenho e análise comparativa de uma técnica de redes neurais artificiais (RNAs) conhecida como rede de função de base radial para identificar possíveis casos de diabetes gestacional que podem levar a múltiplos riscos tanto para a gestante quanto para o feto. Este estudo foi realizado através do uso de um banco de dados envolvendo 394 mulheres. Os testes mostraram que este método alcançou resultados promissores em relação a indicadores de precisão, medida F, área ROC e estatística Kappa. Esses indicadores mostram que essa abordagem baseada em uma RNA é um excelente em predizer o diabetes mellitus gestacional. Este estudo é apresentado em detalhe no Capítulo 5, em um artigo publicado no Journal of Computational Science [24].

A quinta contribuição desta tese, é a proposta do uso de uma técnica de aprendizado de máquina neuro-difusa para predição do transtorno hipertensivo mais complexo da gravidez conhecido como síndrome de HELLP. Esse classificador serve como um mecanismo de inferência para aplicativos móveis baseados em nuvem, para um monitoramento efetivo através da análise dos sintomas apresentados por mulheres grávidas. Esta proposta foi construída, demonstrada e avaliada com uma aplicação móvel envolvendo 205 participantes. O estudo concluiu que o modelo proposto alcança excelentes resultados em relação a vários indicadores. Assim, essa técnica pode prever com precisão as situações que podem levar à morte da mãe e do feto, em qualquer local e horário. Esta contribuição é descrita com detalhe no Capítulo 6 em artigo publicado na revista Concurrency and Computation: Practice and Experience da editora John Wiley & Sons [25].

A sexta contribuição foi publicada em uma edição especial intitulada "Convergence of Deep Machine Learning and Nature Inspired Computing Paradigms for Medical Informatics" do Journal of Medical Systems da Springer [26], e é descrita com detalhe no Capítulo 7. Essa contribuição apresenta a proposta da utilização de uma técnica de inspiração biológica, conhecida como otimização de enxame de partículas, para reduzir o custo computacional do método baseado em RNA, denominado perceptron multicamadas, sem reduzir sua taxa de precisão. Esta técnica é capaz de melhorar o desempenho do modelo computacional, apresentando menores taxas de erro de validação do que a abordagem convencional através da seleção dos melhores parâmetros, fornecendo uma solução eficiente para o treinamento do algoritmo perceptron multicamadas.

A sétima contribuição, descrita no Capítulo 8, analisa o uso de estimadores de dependência única para a análise de dados de gravidez em tempo real a partir de dispositivos e gateways da IoT. Essa técnica estatística é útil para o pré-processamento descentralizado de dados e seu armazenamento intermediário, reduzindo a quantidade de dados a serem transferidos para a nuvem e garantindo a operabilidade, mesmo em caso de falha de rede. Este estudo foi aceito para publicação na revista Computers & Electrical Engineering da Elsevier [27].

A oitava contribuição é descrita e analisada em detalhe no Capítulo 9. Esta contribuição consiste a proposta do uso de técnicas de aprendizado de máquina para a avaliação de dados reais referentes a distúrbios hipertensivos na gravidez. O algoritmo de aprendizagem computacional melhor avaliado melhora o desempenho dos SIS através de seu diagnóstico preciso e baixo custo computacional. Esse método pode ser aplicado em ambientes de e-saúde como uma ferramenta útil para lidar com a incerteza no processo de tomada de decisão relacionado à gravidez de alto risco. Esta contribuição foi submetida para pulicação em um periódico internacional [28].

Por fim, a última contribuição desta tese, é a criação de um algoritmo aperfeiçoado para sistemas inteligentes, capaz de prever o risco de depressão pós-parto em mulheres que desenvolveram distúrbios hipertensivos durante a gravidez por meio de análise de dados biomédicos e sociodemográficos. Esta contribuição foi publicada na revista Information Fusion da Elsevier [29].

Principais Conclusões

Ao longo da presente tese foi estudado e avaliado o desempenho de vários algoritmos baseados em aprendizagem de máquina através da aplicação de estratégias de partição de dados, otimização de algoritmos e classificação através de aprendizagem conjunta. Este ponto apresenta um resumo do trabalho realizado e aponta algumas sugestões que podem ser seguidas como linhas de orientação para futuras investigações neste tópico.

A primeira parte deste trabalho é descrita de forma detalhada no Capítulo 2 do presente documento. Foi realizado o estudo aprofundado do tema de pesquisa da tese com o objetivo de compreender e analisar detalhadamente o estado da arte. Em seguida, os principais objetivos foram definidos e descritos, bem como o enfoque deste trabalho de investigação foi delimitado. O Capítulo 2 apresenta um estudo abrangente sobre a evolução dos SAD para a saúde, sobretudo, na área do diagnóstico médico. Através deste estudo foi possível identificar as principais limitações e problemas em aberto nestes tipos de sistemas. Foram igualmente identificados algoritmos de classificação baseados em aprendizado de máquina que apoiaram a proposta de uma solução viável para os problemas analisados. Depois de analisar e identificar as principais limitações das soluções existentes forma identificadas e discutidas algumas questões em aberto.

A segunda parte deste trabalho é apresentada no Capítulo 3 e diz respeito a um dos principais objetivos desta tese, a proposta de uma nova metodologia para a interoperabilidade semântica em arquiteturas orientada a serviços de saúde. Esta proposta integra dados semanticamente adquiridos de diferentes RES usando diferentes arquétipos e infere sobre esta base de conhecimento através de regras de ontologia prevendo situações de alto risco que podem levar a sérios problemas durante a gestação. Esta metodologia serve de base para uma arquitetura orientada a serviços que integra e classifica novos casos a partir de uma base de conhecimento.

A avaliação do desempenho da proposta foi realizada através de validação cruzada que requer a partição do banco de dados em dez subconjuntos de tamanhos semelhantes envolvendo 133 dados de gestantes. As métricas utilizadas para a avaliação do desempenho das regras de ontologias foram a precisão, o recall, a medida F e a área sobre a curva ROC. Os principais tipos de distúrbios hipertensivos da gestação foram analisados durante as experimentações, assumindo como pior caso uma precisão de 0,714 para a predição de eclampsia. Os resultados foram bastante animadores. Como resultado observou-se que o uso de ontologias para abordar padrões semanticamente adquiridos a partir de diferentes RES tem o potencial de influenciar significativamente uma implementação de arquitetura orientada a serviços para SAD clínica. Para o pior caso, a probabilidade média para a predição da eclampsia foi de 71,4% e a área sobre a curva ROC foi de 0,976. De realçar que algoritmos que apresentam uma área sobre a curva ROC próxima de 1 são considerados ideais para tarefas de classificação. Estes valores são todos influenciados pela complexidade de prever alguns tipos de situações de risco, como a eclampsia por exemplo, onde, apesar de extensa linha de pesquisa na área, sua causa permanece desconhecida [30].

A terceira parte deste trabalho é descrita de forma detalhada nos Capítulos 4-9 e diz respeito à construção e avaliação do desempenho de uma solução utilizando inteligência artificial para aplicações em a saúde em diversos tipos de ambiente. Os capítulo 4 e 9 apresentam a proposta utilizando estimadores de dependência única que faz uso de algoritmos Bayesianos para garantir a acurácia, precisão, e uma baixa taxa de falsos positivos da classificação dos dados de gestantes que desenvolveram algum tipo de distúrbio hipertensivo durante a gestação. Os capítulos 5-8 apresentam a avaliação do desempenho das soluções baseadas em RNAs. Esta avaliação envolveu de 100 a 400 participantes que disponibilizaram seus prontuários para o desenvolvimento das propostas baseadas em aprendizado de máquina para RNAs. A avaliação do desempenho concluiu que o algoritmo perceptron multicamadas, otimizado pelo algoritmo exame de partículas, apresentou a melhor performance em termos de precisão, no entanto, este método também apresenta um alto custo computacional por se tratar de um modelo que usa um algoritmo de retro propagação para alimentar a RNA. A otimização do algoritmo perceptron multicamadas por uma técnica inspirada na natureza superou, em média, outras abordagens em 26,4% em termos de precisão e 14,9% em termos da taxa de verdadeiros positivos, e apresentou uma redução de 35,4% na taxa de falsos positivos. Além disso, esse método foi superior ao algoritmo perceptron multicamadas clássico em termos de precisão e área sob a curva ROC em 2,3 e 10,2%, respectivamente, quando aplicado ao desfecho de parto para gestantes.

A quarta e última parte dos trabalhos desta tese é apresentada no Capítulo 10 e diz respeito a uma proposta de um algoritmo baseado em aprendizado conjunto para sistemas conscientes da emoção com o objetivo de prever situações de risco antes, durante e após o parto. Esta proposta tem como principal objetivo oferecer um modelo híbrido baseado em árvore de decisão e nos algoritmos *bootstrapping aggregating* e *adaptive boosting* para identificar qualquer situação de risco e para que médicos obstetras/ginecologistas possam facilmente acompanhar o desenvolvimento do estado de saúde da gestante, bem como da gestação. Para a avaliação do desempenho desta proposta foram utilizadas as mesmas métricas em um banco de dados real envolvendo 205 gestantes. Os resultados foram muito positivos, com o algoritmo proposto a apresentar 94.5% de acurácia para a predição da admissão em unidades de tratamento intensivo (UTI) no resultado do parto para a gestante e 86,8% de acurácia para a predição da admissão em UTI para o resultado de parto para o feto.

O objetivo principal desta tese e todos os objetivos parciais foram totalmente cumpridos. A proposta de um modelo para serviços e aplicações para a saúde possibilita aos médicos especialistas avaliarem com precisão o estado de saúde de gestantes que desenvolveram algum distúrbio hipertensivo durante a gestação. Através de um algoritmo de predição híbrido é possível tomar decisões em momentos de incerteza em qualquer momento e em qualquer lugar. Dada a complexidade dos dados e informação médica utilizadas neste trabalho, a solução proposta foi avaliada com sucesso. Como extensão do trabalho realizado foi proposto um modelo de aplicações generalizadas para qualquer situação relacionada a problemas na gravidez, que apresentou excelente desempenho em diversos indicadores.

Perspectivas de Trabalho Futuro

Para concluir este trabalho de investigação, resta sugerir futuros tópicos de estudo resultantes do trabalho de investigação desenvolvido:

- Estender este estudo a universos de dados maiores e geograficamente distintos, assim como aplicar outras técnicas de aprendizagem em conjunto baseadas em aprendizagem estatística relacional.
- Para resolver problemas que envolvam o tratamento de grandes volumes de dados, apresentar uma solução ideal envolvendo o uso de um modelo de processamento paralelo e distribuído que se adapte a qualquer volume e grau de complexidade [31].
- Utilizar técnicas baseadas em *deep learning* para contribuir para a solução de novos desafios referentes ao cuidado com a gestação, *e.g.*, o vírus *Zika* que representa uma causa em potencial para o nascimento de crianças com microcefalia, principalmente em países subdesenvolvidos e em desenvolvimento [32].
- Desenvolver um sensor único para medir a hipertensão arterial, bem como a eliminação de proteína na urina para o monitoramento da gestação de risco [33].
- Implementar e avaliar os resultados das propostas apresentadas nesta tese em um ambiente hospitalar real, para sua validação e comparação com os resultados obtidos pelos modelos propostos.

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Abstract

Medical activity requires responsibility not only from clinical knowledge and skill but also on the management of an enormous amount of information related to patient care. It is through proper treatment of information that experts can consistently build a healthy wellness policy. The primary objective for the development of decision support systems (DSSs) is to provide information to specialists when and where they are needed. These systems provide information, models, and data manipulation tools to help experts make better decisions in a variety of situations.

Most of the challenges that smart DSSs face come from the great difficulty of dealing with large volumes of information, which is continuously generated by the most diverse types of devices and equipment, requiring high computational resources. This situation makes this type of system susceptible to not recovering information quickly for the decision making. As a result of this adversity, the information quality and the provision of an infrastructure capable of promoting the integration and articulation among different health information systems (HIS) become promising research topics in the field of electronic health (e-health) and that, for this same reason, are addressed in this research. The work described in this thesis is motivated by the need to propose novel approaches to deal with problems inherent to the acquisition, cleaning, integration, and aggregation of data obtained from different sources in e-health environments, as well as their analysis.

To ensure the success of data integration and analysis in e-health environments, it is essential that machine-learning (ML) algorithms ensure system reliability. However, in this type of environment, it is not possible to guarantee a reliable scenario. This scenario makes intelligent SAD susceptible to predictive failures, which severely compromise overall system performance. On the other hand, systems can have their performance compromised due to the overload of information they can support.

To solve some of these problems, this thesis presents several proposals and studies on the impact of ML algorithms in the monitoring and management of hypertensive disorders related to pregnancy of risk. The primary goals of the proposals presented in this thesis are to improve the overall performance of health information systems. In particular, ML-based methods are exploited to improve the prediction accuracy and optimize the use of monitoring device resources. It was demonstrated that the use of this type of strategy and methodology contributes to a significant increase in the performance of smart DSSs, not only concerning precision but also in the computational cost reduction used in the classification process.

The observed results seek to contribute to the advance of state of the art in methods and strategies based on AI that aim to surpass some challenges that emerge from the integration and performance of the smart DSSs. With the use of algorithms based on AI, it is possible to quickly and automatically analyze a larger volume of complex data and focus on more accurate results, providing high-value predictions for a better decision making in real time and without human intervention.

Keywords

Smart Decision Support Systems, Service-oriented Architecture, Electronic Health Systems, Health Information Systems, Mobile Health, Electronic Health, Cloud Computing, Edge Computing, Internet of Things, Semantic Interoperability, Ontology, Big Data Analytics, Computational Intelligence, Nature Inspired Computing, Cognitive Computing, Data Mining, Machine Learning, Artificial Neural Networks, Maternal Healthcare, Hypertensive Disorders in Pregnancy.

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Acronyms

5G	Fifth-generation
ACO	Ant Colony Optimization
AdaBoost	Adaptive Boosting
ADL	Archetype Definition Language
AI	Artificial Intelligence
AIS	Artificial Immunology System
ANFIS	Adaptive Network-based Inference System
ANN	Artificial Neural Network
AODE	Averaged One-dependence Estimators
API	Application Programming Interface
AST	Aspartate Aminotransferase
AUC	Area Under the Curve
BI	Business Intelligence
BMI	Body Mass Index
BN	Bayesian Network
CDA	Clinical Document Architecture
CDSS	Clinical Decision Support System
CI	Computational Intelligence
CKM	Clinical Knowledge Manager
DBMS	Database Management System
DM	Data Mining
DSS	Decision Support System
DT	Decision Tree
ECG	Electrocardiogram
EHR	Electronic Health Records
EIS	Executive Information System
EPR	Electronic Patient Record
ESS	Executive Support System
ETL	Extract, Transform, and Load
FN	False Negative
FP	False Positive
FPR	False Positive Rate
GA	Genetic Algorithm
GIS	Geographic Information System
GLM	Generalized Linear Model
HIS	Health Information System
HL7	Health Level Seven
ICD-10	International Statistical Classification of Diseases and Related Health Problems-10th Revision
ICT	Information and Communication Technology
ICU	Intensive Care Unit
IEEE	Institute of Electrical and Electronics Engineers

IoT	Internet of Things
ISPP	International Scientific Partnership Program
IT	Information Technology
KDD	Knowledge Discovery in Databases
LDH	Lactate Dehydrogenase
MCC	Matthews Correlation Coefficient
MCC	Mobile Cloud Computing
MDG	Millennium Development Goals
ML	Machine Learning
MLP	Multilayer Perceptron
NB	Naive Bayes
NetGNA	Next Generation Networks and Applications Group
NHS	National Health Service
NIDKK	National Institute of Diabetes and Digestive and Kidney Diseases
NN	Nearest Neighbors
OLAP	On-line Analytical Processing
OWL	Web Language Ontology
P2P	Peer-to-peer
PPD	Postpartum Depression
PRC	Precision-recall Curve
PSO	Particle Swarm Optimization
QoE	Quality of Experience
QoS	Quality of Service
RBF	Radial Basis Function
RF	Random Forest
RIM	Reference Information Model
ROC	Receiver Operating Characteristic
SaaS	Software as a Service
SDN	Software-defined Network
SGA	Small for the Gestational Age
SNOMED-CT	Systematized Nomenclature of Medicine-Clinical Terms
SOA	Service-oriented Architecture
SSD	Solid-state Drive
SVM	Support Vector Machine
TAN	Tree Augmented Naive Bayes
TN	True Negative
TNR	True Negative Rate
TP	True Positive
TPR	True Positive Rate
UN	United Nations
vMR	Virtual Medical Record
WHO	World Health Organization
XML	Extensible Markup Language

Chapter 1

Introduction

This section summarizes, in a comprehensive way, the 4 years of research work under the Ph.D. thesis titled "Performance Evaluation of Smart Decision Support Systems on Healthcare." This thesis focuses on the study and proposal of analysis strategies and methodologies of data for the monitoring and management of hypertensive disorders of pregnancy in e-health environments. The first stage describes the structure of the thesis as well as it defines the problem addressed and the primary objectives of the study. The main contributions of this work for the advance of state of the art are also presented.

1.1 Focus and Scope

In the last decade, decision support systems (DSSs) have presented many reliable health services. These services have provided people with affordable health solutions anytime and anywhere. Nowadays, users can use information and communication technologies (ICTs), which foster interaction between patients and their physicians, to improve their proximity and quality of life. Doctors can easily access patient records, lab results, images, and drug information quickly and easily. Similarly, patients may have access to their diagnostic situation as well as information on how to live a healthy life [1, 2].

According to [3], health monitoring is quite complicated, and many skills are needed for the tasks that are involved in the patient care process. This monitoring represents most of the day-to-day work of the medical staff. In [4], the authors mention that DSSs provide diagnostic assistance to health professionals and advise patients suggesting appropriate standards and lifestyles. According to [5], in health systems, decision-making is conducted with the clinician to identify the best treatment options in uncertainty moments. In [6], the authors mention that such systems can improve patient care, yielding valuable information for diagnosis, prognosis, and treatment.

Kurzyński *et al.* emphasize that medical diagnosis is one of the most important research topics in information technology and medical informatics [7]. For Kozlowski and Worthington, these systems can also help improve hospital waiting time due to insufficient recourse and the vast service quantity [8]. Intelligent systems present many challenging problems and limitations. In this sense, computer-based approaches are proposed to solve such limitations, focusing on increasing the people's quality of life of people.

Despite the numerous scenarios in which they can be applied in health, DSSs still have to overcome some challenges/problems of technological characteristics. Some of these challenges are due to the last generation of networks based on the Internet of Things (IoT) paradigms, while others come from the unique properties of the Big Data analytics.

There are at least five significant research trends on IoT, this being one of the top current research topics along with remote patient monitoring and treatment [9, 10, 11]. Increasing patient records brings a new complexity to the treatment of data by the caregiver and health experts. The development of IoT platforms helps to extract insights from large datasets, solving various problems of these molds. The patient-centered analysis focuses on the use of advanced analysis, visualization, and decision support tools to improve diagnostic accuracy [12]. Research on this topic could improve treatments by making them more accurate, efficient and personalized [13]. The semantic interoperability of health systems allows the management of electronic health records (EHRs) of patients distributed in several heterogeneous systems. This approach has an essential role in describing key factors to improve the quality of patient care, public health services, and medical research. Given that users are increasingly assuming more responsibility for their health, research on this topic can result in better data access and better health technology solutions. Besides, it can also allow consumers to manage their health services. Another significant trend is related to the establishment of a new set of protection policies aimed at IoT, mainly for wearable and implantable technologies [14].

The Big Data analytics has excellent potential to modify the way that health professionals use modern technologies to gain insight into their medical repositories and other data repositories. [15]. Big Data health analysis applications are in the early stages of development; however, rapid advances in platforms and tools are accelerating their development process [16]. By analyzing disease patterns, outbreak tracking, and data transmission to improve surveillance and respond faster to emergencies, they need further improvement. Turning large amounts of evidence into meaningful information is very useful for identifying needs in delivering services. In the same way, this information can help to predict and prevent risk situations.

Despite the advances already made in recent years through the studies conducted in the research topics presented above, DSSs still face some challenges that have to be overcome. These challenges include solutions for semantic interoperability among different EHRs (coding, transmission, and use of healthcare information among the various stakeholders) and solutions for technical interoperability (integration of different systems at the technical, infrastructures, means of communication, transport, storage and representation of data). These fields of research are relevant and challenging given their complexity of implementation. For this reason, the research conducted in this Ph.D. program focuses on the inherent problems of semantic interoperability and classification methodologies for the prediction of complex problems related to pregnancy. These problems will be studied through the implementation and performance evaluation of algorithms based on ML for the management and monitoring of hypertensive disorders of pregnancy, considering e-health environments.

1.2 Problem Definition

This thesis addresses not only the problem of the interoperability among EHRs however also as AI algorithms can help the health specialist in monitoring high-risk pregnancy to improve the pregnant woman's quality of life. The importance of these two topics comes from the requirement that the increased complexity of data collected from devices and equipment has brought about, requiring that more sophisticated tools and strategies be developed. In DSSs, decision-making need go exceeding the physical barrier of various health organizations, integration of data from various sources and their sharing in a secure and private way among these organizations, helping the expert to make better decisions at any time and in reducing problems that can lead both pregnant and fetus to develop serious health problems. In turn, the management and monitoring of the health of the pregnant woman seek to maintain a clear vision of the patient's health status, approaching and correcting situations as they appear.

Regarding pregnancy care, according to the World Health Organization (WHO), hypertensive disorders of pregnancy account for about 10% of all pregnancies around the world. These disorders are the leading causes of morbidity, disability, and death among mothers and newborns [17]. These complications during pregnancy were a major cause of mortality in Latin America and the Caribbean, accounting for 22.1% of all maternal deaths in that region. [18]. By providing timely and efficient care, most deaths related to these complications could be avoided. Thus, the optimization of health care for pregnant women to prevent and treat hypertensive disorders is necessary. In this regard, ICTs play a key role in improving the pregnant women's quality of life. By developing intelligent systems for monitoring pregnancy at risk, health experts can identify serious problems caused by the hypertensive disorders of pregnancy in its early stages, saving the lives of mothers and newborns. Several technological solutions are already being deployed to combat the preeclampsia in its most critical condition [19, 20]. Many approaches have achieved adequate evaluation, but are still unable to reduce the critical situation of maternal and fetal deaths on their own, especially in developing countries. Smart DSSs are considered an excellent tool capable of contributing to this goal.

1.3 Research Objectives

In this context, the primary objective of this work is the construction and evaluation of a decision support model based on ML techniques for health services and applications. This proposal based on AI encourages health experts to monitor the state of health of the pregnant woman through the prediction of future complications caused by hypertensive disorders in a risky pregnancy, through the risk factors, symptoms, and clinical examination data presented by the pregnant woman.

To achieve this objective, the following partial objectives have been defined:

- Review of the state-of-the-art technologies, services, and applications related to existing smart DSSs and about inference algorithms for data analysis in e-health environments.
- Proposal and evaluation of a service architecture sufficient to meet the requirements of semantic interoperability in HISs through the ontological modeling adoption.
- Implementation and performance evaluation of algorithms based on ML for m-health applications that will be used to evaluate and validate possible outcomes of labor in a high-risk pregnancy.
- Proposal and implementation of a novel partitioning and data grouping strategy for the training of inference models in health services and applications in cloud computing environments.
- The performance evaluation of ML algorithms through computational cost analysis, applied to IoT devices in edge networks.

- Proposal and evaluation of a hybrid model of a generalized and interoperable application for pregnancy care based on ensemble learning classifiers for context-aware smart systems.

1.4 Research Hypothesis

This thesis proposes a set of novel approaches focused on ML to monitoring the clinical condition of the pregnant woman to predict situations that can lead both mother and newborn to serious health problems. The argument presented in this thesis is as follows:

The performance of a DSS depends on the semantic acquisition of the data of different EHRs, the correct identification of the patterns present in several pregnancy complications, as well as the relationships among the attributes belonging to a specific hypertensive disorder, and the amount of computational resource that the analysis of this massive amount of information consumes. The archetypes developed for the integration of health data sources based on ontologies have different characteristics, but it is believed that a comprehensive analysis of these models for the semantic integration of data on care with pregnancy has not yet been produced. Probabilistic methods can measure the prediction for each risk situation, as well as the information gain or a sum of weights, depending on the ML algorithm used. It is possible to implement an algorithm that unites several characteristics while maintaining its robustness and accuracy. The consumption of computational resources for the task of predicting and analyzing massive amounts of data can also be attenuated through optimization techniques for the training of more robust algorithms, a multilayer neural network for example.

To support this argument, the following approach was used:

First, the progress of ML algorithms and their application in health services were studied. Through this study, the primary methods were identified, as well as their main limitations and challenges. Next, the leading optimization strategies for existing models have been reviewed and studied in depth, identifying their limitations, challenges, and research topics still open.

Regarding the topic of classification, the thesis begins by proposing and studying algorithms based on the Bayes' Theorem. Conventional Bayesian classifiers hypothesize that the effect of the value of a non-class attribute is independent of the values of the other attributes, *i.e.*, The value of one attribute does not influence the value of the other attributes. This hypothesis aims to reduce the computational cost involved in the classification task. When the hypothesis of the independence among the attributes is verified, then the naive Bayesian classifier presents the best performance regarding accuracy, compared with other classifiers. However, in health, there is a common dependency among attributes. In this case, this research used a Bayesian belief network as a classification method. Two components structure this method. First, an acyclic directed graph where each vertex represents an attribute and the arcs connecting the vertices represent a dependency among these attributes. The second structure consists of a conditional probability table for each attribute. However, it is not possible to assume the existence of an entirely conditional scenario, so this study proposed different types of ANNs (*e.g.*, radial base function, SVM, and MLP) that best deal with the presence of attributes conditionally related. All of these predictive algorithms use a different strategy to associate various attributes and to classify the various hypertensive disorders of pregnancy as to their severity. While probabilistic models use mathematical modeling for classification, ANN-based models seek to adjust weights from the first to the last layer to ultimately produce an output. Several studies were conducted to evaluate the performance of these algorithms. The results obtained are used to demonstrate the feasibility and advantages of the novel classification models.

1.5 Main Contributions

The first contribution of this thesis is the in-depth state-of-the-art review of smart DSSs and health applications. This review thoroughly analyzes the architectures and scenarios in which health applications and services are applied, as well as their associated challenges and problems. This study is described in detail in Chapter 2, which consists of a paper accepted for publication in the IEEE Systems Journal [21].

The second contribution is the proposal to develop a knowledge-based DSS that uses ontologies to integrate data related to hypertensive disorders in pregnancy. This model allows when dealing with new cases, inferring from a knowledge base and predicting high-risk situations that can lead to severe problems during pregnancy for both pregnant women and fetus. This proposal solved the problem of semantic interoperability among different EHRs. The testing scenario involved 133 electronic records of pregnant women who developed some hypertensive disorder during pregnancy. It was concluded that the use of ontologies to address semantically acquired patterns from different EHRs has the potential to influence an SOA implementation for CDSSs significantly. This contribution is described in detail in Chapter 3, which consists of a paper published in the journal Future Generation Computer Systems of Elsevier [22].

The third contribution includes the development, performance evaluation and comparison of ML algorithms based on Bayesian networks capable of identifying risk pregnancies based on the symptoms and risk factors presented by the patients. This contribution presents a performance comparison of several ML algorithms based on the Bayes' Theorem to determine the most appropriate algorithm for the prediction, identification, and monitoring of hypertensive disorders during pregnancy. This solution constructed from averaged one-dependence estimators presents better results on average than other approaches studied. These findings are critical to improving the health monitoring of women with high-risk pregnancies. Thus, this study contributes to the reduction of maternal and fetal deaths. This proposal is presented in Chapter 4, which consists of a paper accepted for publication in the Journal of Ambient Intelligence and Humanized Computing in a special issue entitled "Bio-medical Signal Processing for Smarter Mobile Healthcare using Big Data Analytics" [23].

The fourth contribution of this thesis proposes the modeling, performance evaluation, and comparative analysis of an ANN technique known as a radial basis function network to identify possible cases of gestational diabetes that may lead to multiple risks for both pregnant women as for the fetus. This study was conducted through the use of a database involving 394 women. The tests showed that this method achieved promising results concerning precision, F-measure, AUC, and Kappa statistics indicators. These indicators show that this ANN-based approach is an excellent predictor of gestational diabetes mellitus. This study is presented in detail in Chapter 5, in a paper published in the Journal of Computational Science [24].

The fifth contribution of this thesis is the proposal of the use of a neuro-diffuse ML technique to predict the more complex hypertensive disorder of pregnancy known as HELLP syndrome. This classifier serves as an inference mechanism for cloud-based mobile applications for effective monitoring by analyzing the symptoms presented by pregnant women. This proposal was built, demonstrated and evaluated with a mobile application involving 205 participants. The study concluded that the proposed model achieves excellent results concerning several indicators. Thus, this technique can accurately predict situations that can lead to the death of the mother and fetus, anywhere and anytime. This contribution is described in detail in Chapter 6 in a paper published in the journal Concurrency and Computation: Practice and Experience of John Wiley & Sons [25].

The sixth contribution was published in a special issue entitled “Convergence of Deep Machine Learning and Nature Inspired Computing Paradigms for Medical Informatics” from the Journal of Medical Systems of Springer [26], and is described in detail in Chapter 7. This contribution presents a proposal of the use of a nature-inspired technique, known as PSO, to reduce the computational cost of the ANN-based method, called MLP, without reducing its accuracy rate. This technique is capable of improving the computational model performance, presenting lower validation error rates than the conventional approach through the selection of the best parameters, providing an efficient solution for the training of the MLP algorithm.

The seventh contribution, described in Chapter 8, analyzes the use of one-dependence estimators for analyzing real-time pregnancy data from IoT devices and gateways. This statistical technique is useful for decentralized pre-processing of data and its intermediate storage, reducing the amount of data to be transferred to the cloud and ensuring operability even in the event of a network failure. This study was accepted for publication in the journal Computers & Electrical Engineering of Elsevier [27].

The eighth contribution is described and analyzed in detail in Chapter 9. This contribution consists of the proposal of the use of ML techniques for the evaluation of real data regarding hypertensive disorders during pregnancy. The best evaluated computational learning algorithm improves the performance of HISs through its precise diagnosis and low computational cost. This method can be applied in e-health environments as a useful tool to deal with uncertainty in the decision-making process related to high-risk pregnancies. This contribution was submitted for publication in an international journal [28].

Finally, the last contribution of this thesis is the development of an improved algorithm for smart systems capable of predicting the risk of postpartum depression in women who developed hypertensive disorders during pregnancy through the analysis of biomedical and sociodemographic data. This contribution was published in the journal Information Fusion of Elsevier [29].

1.6 Thesis Statement

This Thesis proposes several machine learning classifiers for prevention of risk situations on pregnancy using ensemble learning classifiers, mainly the proposed algorithm called bagged trees, which is the more powerful model for pattern recognition in complex pregnancy data in comparison with conventional ANN-based models. Despite the complexity and the difficulty of learning in traditional meta-heuristic models, such as the AdaBoost and bagging algorithms, this study demonstrates that the classification can be precise using ensemble learning methods. Furthermore, this study claims that this model leads to competitive algorithms for various problems in pregnancy caused by hypertensive disorders like eclampsia, HELLP syndrome, and fetal weight estimation.

1.7 Document Organization

This thesis consists of eleven Chapters, which are organized as follows. The first chapter presents the scope of the thesis, focusing the topics under study, the definition of the problem and primary objectives. The research hypothesis, the main contributions, and the document's organization are also included in this chapter. Except this and the conclusions chapter, all the others are based on a paper published in or submitted to an international journal.

Chapter 2 presents a survey focusing on smart DSSs, entitled "A Comprehensive Review on Smart Decision Support Systems for Healthcare". It also identifies several open issues that may be used as a starting point to propose novel and better approaches to deal with problems related to pregnancy.

Chapter 3, entitled "Semantic Interoperability and Pattern Classification for a Service-oriented Architecture in Pregnancy Care", studies and proposes a knowledge-based DSS that uses ontologies for integrating data related to hypertensive disorders in pregnancy. It also demonstrates the role of interoperability as one of the key factors to improve and optimize HISs.

In Chapter 4 ("Biomedical data analytics in mobile-health environments for high-risk pregnancy outcome prediction"), three different algorithms to classify identifying at-risk pregnancies based on the symptoms and risk factors presented by the patients are proposed and their performance is analyzed by applying the most popular evaluation metrics.

Chapter 5 presents a study addressing the applicability of an evolutionary computational intelligence technique to analyze a significant amount of data as an essential strategy to solve several problems in healthcare management, entitled "Evolutionary radial basis function network for gestational diabetes data analytics". In this context, several other studies are conducted to improve the classification precision.

Chapter 6 ("Neuro-fuzzy model for HELLP syndrome prediction in mobile cloud computing environments") describes a neuro-fuzzy ML technique for predicting the most complex hypertensive disorder in pregnancy called HELLP syndrome.

Chapter 7, entitled "Nature-Inspired Algorithm for Training Multilayer Perceptron Networks in e-health Environments for High-Risk Pregnancy Care”, proposes the use of a biologically inspired technique, known as PSO, for reducing the computational cost of the ANN-based method referred to as MLP, without reducing its precision rate.

Chapter 8 presents a detailed study regarding one-dependence estimators, entitled “Averaged One-dependence Estimators on Edge Devices for Smart Pregnancy Data Analysis”. It also presents an architecture for decentralized pre-processing of data and its intermediate storage, reducing the amount of data to be transferred to the cloud and ensuring operability, even in an event of network failure.

Chapter 9 (“Computational Learning Approaches for Personalized Pregnancy Care”) presents the performance evaluation of the best ML-based algorithms using the 10-fold cross-validation method.

Chapter 10 describes the proposal and performance evaluation of improved algorithms for emotion-aware smart systems, capable of predicting the risk of postpartum depression in women suffering from hypertensive disorders during pregnancy through biomedical and sociodemographic data analysis. This strategy consists of an ensemble learning model, based on decision trees for emotion-aware applications. Its primary goal is to be a basis for developing several applications so that medical experts can efficiently use it for pregnancy care.

Finally, chapter eleven summarizes the main conclusions of the thesis drawn throughout the document and proposes several insights and suggestions for future work.

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Chapter 2

A Comprehensive Review on Smart Decision Support Systems for Healthcare

This chapter consists of the following article:

A Comprehensive Review on Smart Decision Support Systems for Healthcare

Mário W. L. Moreira, Joel J. P. C. Rodrigues, Valery Korotaev, Jalal Al-Muhtadi, and Neeraj Kumar.

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A Comprehensive Review on Smart Decision Support Systems for Health Care

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***Abstract*— Medical activity requires responsibility not only based on knowledge and clinical skills, but also in managing a vast amount of information related to patient care. It is through the appropriate treatment of information that experts can consistently build a strong policy of welfare. The primary goal of decision support systems (DSSs) is to give information to the experts where and when it is needed. These systems provide knowledge, models, and data processing tools to help the experts make better decisions in several situations. They aim to resolve several problems in health services to help patients and their families manage their health care by providing better access to these services. This paper presents a deep review of the state of the art of smart DSSs. It also elaborates on the latest developments in intelligent systems to support decision-makers in health care. The most promising findings brought in literature are analyzed and summarized according to their taxonomy, application area, year of publication, and the approaches and technologies used. Smart systems can assist decision-makers to improve the effectiveness of their decisions using the integration of data mining techniques and model-based systems. It significantly improves the current approaches, enabling the combination of knowledge from experts and knowledge extracted from data.**

***Index Terms*—Applications, data mining (DM), decision-making, health care, smart decision support systems (DSSs) technologies.**

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I. Introduction

In the last decade, decision support systems (DSSs) have presented numerous reliable health services. These services have offered affordable health care solutions. Nowadays, people can use information and communication technologies that favor the interaction between patients and their physicians, improving the patient's quality of life. Physicians can have easy access to patients' medical records, lab results, images, and information about medication, anytime and anywhere [1]. In the same way, patients can have access to their diagnostic situation as well as information about how to have a healthy life. Medical diagnosis is one of the most important research topics in information technology and medical informatics. Smart systems present several challenging issues and limitations. In this sense, computer-based techniques are proposed as a solution to overcome such barriers, concentrating on enhancing the patients' quality of life.

Schummers *et al.* discuss risk prediction models in development by evaluating their performance under various predictive characteristics [2]. This study shows that the state of the art on such systems offers little insight for researchers looking to assess whether a predictive model works well for a particular research question. Thus, Yoo *et al.* present data mining (DM) techniques as an essential solution that has been growing in recent decades [3]. These inference mechanisms for intelligent systems can help decision-makers obtain meaningful information, facilitating the understanding of large health datasets. Besides this, there are several approaches to the validation of DM solutions, giving support to all phases of DM testing. These assessment techniques provide objective measures that can be used to evaluate the computer-assisted method's reliability for predictive analysis. Feinleib suggests that DM methods are an excellent way to transform health care through decision-making assistive instruments [4]. Health-care experts make several decisions during a day. These can have important effects on their patients' health and their well-being. Although medical care is improving, the escalating amount of data and consequently, the way in which that data can relate to patients, is making these decisions more and more complicated. Rubiano and Garcia analyze the results obtained at each iteration in a DM process [5]. Each obtained result is evaluated as to the expected results, the characterization of the data input and output, and the model pertinence achieved regarding its prediction accuracy. The results show that, depending on the strategies implemented during the DM process, a careful preprocessing could have a significant impact on the mining results. Decisions such as the elimination

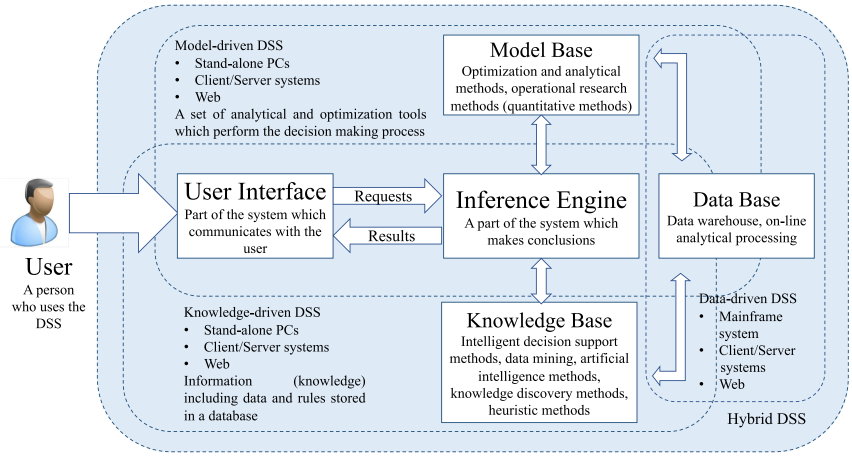

Fig. 1. Overall architecture scheme of a DSS. Source: Authors' elaboration.

of attributes or the discretization of data should not be taken without due consideration. Besides, a careful evaluation of the removal of ignored and misclassified instances can substantially improve accuracy rates in the predictive model development.

The main contributions of this research include the review of the state of the art, analysis, discussion, and identification of open issues in each type of DSS for health care. Related technologies, approaches, and applications will be described to provide insights into the primary trends, implications, and future research directions for novel theoretical developments. The results of this research will show the potential of further studies, showing that this topic is a hot topic for the research community and will have a significant impact on most readers. This study will enable a more precise mapping of the advances in health care research, implying the development of its primary activity sectors. In this perspective, this research seeks to improve the entire health care field through an appropriate research development, indicating trends, recurrences, and gaps.

The layout of the paper is organized as follows. Section II overviews the works related to smart DSSs for health care. Then, the third section provides an analysis of the novel smart systems solutions for health care. In Section IV, the open issues are illustrated, and the suggested further research is presented. Finally, the main conclusions will be presented in Section V.

II. Smart DSSs in Health Care

The previous section addressed the applications of DSSs in several areas of knowledge. This section will discuss the use of three primary types of smart DSSs in health care. It categorizes these systems by their leading dimensions as well as three secondary aspects (the users, degree of generality, and technology). The main differences among these three categories within the taxonomy proposed by Power [6] are as follows, while model-based intelligent systems provide decision support with the use of analytical tools such as algebraic analysis and simulation, data-based systems enable the management, retrieval, and manipulation of unstructured information in various storage formats. Knowledge-based systems, however, provide a set of solutions or suggestions of the problem through knowledge stored as a form of facts, rules, procedures or similar structures. Fig. 1 presents an overall framework illustrating the main categories of DSSs.

A. Data-Driven DSSs

A data-driven DSS allows the "access and manipulation of time series of internal, external, and real-time data" [7]. In more recent years, data-driven DSSs with on-line analytical processing, data warehouse systems, executive information systems, also referred to as executive support systems, and geographic information systems are considered the main approaches to decision support.

In the last decade, research has been conducted in systems designed to support people's daily activities. The use of smart systems is needed to support emergency medical services. Xu *et al.* discuss "a semantic data model to store and interpret Internet of Things (IoT) data" [8]. This approach is designed to collect and treat ubiquitous data to enhance the feasibility of data storage. It can access universal data in real time on a cloud, using a mobile platform. This IoT-based system for emergency medical services provides support for emergency medical services. The results of the research show that this process is efficient in a diversified and distributed data environment. Sunyaev and Chornyi create a prototype of a system of self-management in health that assists patients with diabetes to track their blood glucose levels [9]. The results show that this system is an important instrument in an integrated diabetes treatment that encompasses hospital care, rehabilitation, and self-care.

Recently, health care organizations have adopted electronic health records (EHRs) as a reference on medical registries, and this suggests a high potential for clinical DSSs (CDSSs) that directly use data collected by such an organization [10]. Cheng *et al.* have developed a CDSS for intensive care units to improve outcomes for critically ill patients [11]. That system provides real-time decision support, decreasing the errors in medical decisions. An interactive and easy-to-use user interface was developed that enables decision-makers to use the DM for decision-making in real time. To help people with Parkinson's disease who suffer from mobility problems, Blake and Kerr investigate environments in which physicians diagnose patients with sleep disorders [12]. The study develops an online support system that gathers patients' historical data. It improves the effectiveness of the consultations, medical diagnosis, and patient treatment plans. Puppala *et al.* propose the design of an analytics platform for the health care industry [13]. The research develops an integrated clinical informatics environment for improving research. This framework considers an enterprise data warehouse and intelligent and analytical software for enabling a broad range of CDSS to facilitate data access. The results show that this system could aid significant research in clinical informatics, providing a means for data synthesis and adequate access in promoting medical research. Goldberg *et al.* test the effectiveness of performing brain trauma prognostication rules for children with minor blunt head injury [14]. The study integrates EHRs and a web-based CDSS for emergency departments to assess the performance features of the combined model and the source of the recommendations generated by experts. The results show that a remote clinical decision support system decreases time-to-trial in the decision support to clinical interventions.

The increasing number of wearable systems for collecting data provides a better opportunity for an early diagnosis. Mazilu *et al.* present a wearable system designed for independent use [15]. This system uses a smartphone application to allow careful and long-term monitoring of the patient's medical condition by sending sensing data and statistical information to an e-health service. The statistical results show a positive effect on participants' mobility when using the wearable support system [16].

Data-driven systems can be crafted to enable diagnostics and prognostics even without system-specific knowledge. Data-driven approaches that use pattern recognition and statistical techniques to detect changes in the system can be suitable for diagnostic purposes. There are some limitations to data-driven systems. Their approaches depend on historical data to determine correspondences, establish patterns, and assess data. In most cases, there will not be sufficient data to achieve health evaluations. Therefore, this requirement of historical data to make decisions is one of the restrictions of data-driven methods.

B. *Knowledge-Driven DSSs*

In the 1990s, the DSSs began to use artificial intelligence (AI) techniques. Expert systems are modeled using reasoning to solve problems on a machine by way of inference engines. The knowledge domain may be classified in three levels—contextual, content, and structured or unstructured knowledge. Moreover, there are two types of technologies for knowledge modeling—clustering and ontology. Clustering techniques classify the knowledge into different classes whereas ontology captures the consensual experience.

Ontologies are commonly used for the integration of knowledge, as well as for performing inferences about this knowledge. This approach promotes the representation of information through terms, real-world concept definitions, and the description of semantic relations. Thus, this approach does more than describing the syntactic relationships among data. The clustering analysis, which is present in the domain ontology, corresponds to the unsupervised learning most used in data analysis and mining, focused on the discovery and interpretation of groups of objects presenting similar properties and/or behaviors.

Tawfik *et al.* review clinical applications in three different geographical regions. This research reveals that ontological practices play a fundamental purpose in adapting information for decision support [17]. It proposes an advanced web-based framework for effective clinical practices in decision support. The conceptual design of this system uses a comprehensive-based analysis of health care into ontological methods. Khan *et al.* present a medical DSS that uses an approach based on the probabilistic reasoning for time-critical decision scenarios [18]. This hybrid system uses an ontology to support decision-making about patient treatment. This research combines semantic, ontology, and probabilistic reasoning to give decision-makers an effective treatment to offer to the patients. This approach can be applied in other decision-making situations where several restrictions limit the application of conventional processes. Zhang *et al.* present a semantic-based method for the combined description of health care field knowledge and patient data for decision-making in clinical employment [19]. The study performs a learning engineering sequence to generate a semantic base, including an ontology to represent the information and the patient data. An expression repository is used to codify clinical decision-making standards and consultations. A case study was performed using inpatient management data of diabetes mellitus patients to assess this approach. The proposed method provides a high accuracy rate.

Dong *et al.* propose the use of a CDSS "to improve the accuracy of the diagnosis of headache disorders" [20]. The methodology applied in this proposal for the construction of an ontology makes use of a computerized clinical model for guidelines and a medical knowledge base. The results show that this knowledge-based model had "high diagnostic precision for most of the primary headaches and some categories of secondary headaches." It could help experts at first attendance hospitals "improve the diagnostic accuracy and reduce headache disorders."

Basilakis *et al.* describe a telehealth system that uses a combination of obtained clinical measurement parameters of a DSS [21]. This model combines "a rules mechanism and statistical analysis instruments to analyze the collected data searching for trends and patterns in parameter values". It influences the changes in targeting clinical resources to patients with the most need. This research shows the potential benefits of integrating telehealth and decision-making support in the management of chronic diseases. Bi and Abraham introduce a web-based CDSS "that integrates intelligent technology, complex guidelines, and knowledge to improve decision-making in asthma care" [22]. The system uses a model-view-controller approach. It uses three tiers—"a web-server, reasoning algorithms, and a database."

The recent development of technologies and application domains of knowledge-based DSSs, such as ontology engineering, and contextual knowledge in medical systems, has elicited a strong link showing a broader picture and provided a synergistic view of these systems. Future research will focus on the development of these systems in general and, in particular, clinical systems to support decision-making groups.

C. *Model-Driven DSSs*

The model-driven DSS optimizes or simulates the outcomes of decisions based on provided data. In these systems, the decision-maker manipulates the model to analyze a situation. The mathematical model is a plausible representation of the real process. In these systems, the statistical data input is limited, and the computational methods and evaluation of uncertainty are essential. Nowadays, there are three techniques used to create a model-driven system—decision analysis, mathematical programming, and simulation. This section focuses on the recent applications of these technologies in the construction of a model-driven system.

Zarkogianni *et al.* present the latest studies in sensors for glucose and lifestyle monitoring [23]. This study discusses a CDSS that facilitates the self-management of diseases and gives support to health care professionals in the decision-making process. The results show that the integration of sensor data and EHR combined with intelligent data analytics methods and user-based approaches enable necessary changes in diabetes care. Nair *et al.* have developed a smart system for managing anesthesia that works in conjunction with an information management system to provide clinical decision support [24]. This system uses logical rules and notification strategies. This real-time approach can be extended to identify medical problems and inform the health care providers in other fields [25], [26]. Such systems can also interact with various data systems and tools to improve the range of decision support.

Laskowski *et al.* present an agent-based modeling system to simulate the propagation of influenza virus contamination [27]. This research uses mathematical modeling techniques for disease spread. It uses ordinary least squares regression to analyze data. The results suggest that this DSS could assess the impact of infection control strategies. Hudson and Cohen describe a DSS that combines several methodologies for trend analysis in cardiology [28]. This system uses a general algorithm that uses a variety of techniques. This system needs "changes in the structure of the EHR to form a comprehensive record" of the patient lifetime. Emanet *et al.* develop predictive models that use machine learning (ML) methods to diagnose an asthma patient [29]. These models use sounds obtained from the thorax of the patient in a clinical laboratory. The performance evaluation of these models compares the accuracy of ensemble models, such as random forest (RF) and artificial neural network (ANN) models. The results show that this approach could help health practitioners make faster and reliable diagnostic decisions in conditions constrained by limited resources. Temko *et al.* present different approaches for visualizing the output information in a neonatal convulsion detection system [30]. This method is based on a binary output, probabilistic evidence, and a spatiotemporal map. This research evaluates the accuracy of a support vector machine (SVM) classifier, comparing its results with clinical expert knowledge using conventional metrics. This study also establishes an association among information visualization and the different techniques to determine these evaluation metrics. The results show that the aggregation of binary output and a probabilistic evidence method is a better technique to visualize the output in neonatal illness prediction systems.

Tekin *et al.* propose an expert system that learns online and suggests to the patient the best health expert, depending on the context [31]. A novel class of algorithms, aimed at discovering the most relevant patient circumstances, as well as the best clinics and specialists, is developed. The performance evaluation uses a real breast cancer dataset. The results show that this model-based approach could be applied in other environments. Champaign *et al.* present a framework for the care of children with autism [32]. The main focus of this system is for patients selecting objects from a web repository giving the caregivers the children's condition. This approach uses a method of simulated learning through a user survey. The results show its effectiveness at acquiring knowledge.

Bashir *et al.* propose a "multi-layer classifier ensemble model based on the association of different classifiers" [33]. A performance evaluation of several well-known classifiers uses datasets of heart, breast cancer, diabetes, liver disease, Parkinson's disease, and hepatitis, acquired from public repositories. This comparison shows that the proposed framework has achieved high diagnostic accuracy.

Model-based DSSs integrate different kinds of mathematical and analytical models for simulation and prediction of trends [34]. Therefore, the problem resolution capability of these simulation models contributes to avoiding the limitations of the approximations often used for optimization. The critical issue is the choice of the proper models and software, and the definition of the data format.

III. Classification Based on Power's Taxonomy

This section presents the critical aspects and objectives of the most vital smart DSSs for healthcare. Table I provides a summary and offers a comparative analysis of the most meaningful solutions for intelligent systems on health care. Moreover, this table highlights the classification of each solution into specific categories and approaches. The first column presents the references for the leading works in current literature. The second column (Power's taxonomy [6]/approach) considers the technologies for each type of approach, for example, the techniques for reasoning and inference. The third column discusses the contribution of each research as well as the methodologies used to reach these objectives. The critical aspects of each approach are presented in the fourth column. This point of view is essential for identifying future research directions. In the last column, future research suggestions are considered. This analysis is important for understanding the different types of approaches used in recent studies that will support and justify

TABLE I
COMPARISON ANALYSIS BETWEEN THE MOST VITAL SMART DSSS ON HEALTH CARE

Authors' name	Proposal approach	Main goals	Main technical aspects	Future work
Chalmers *et al.* [36]	Model-driven	· Specify a system that constitutes a prediction model.	· Use a conditional fuzzy c-means clustering with a custom distance to identify patterns in patient's data. · Need several simulations and tests.	· Improve the indicators of treatment outcomes.
Yao and Azam [37]	Model-driven (Web-based)	· Extend the game-theoretic rough set mode.	· Use a three-way decision-making strategy as well as the Markovian approach. · There is the occurrence possibility of inconsistencies among predictions performed by different classifiers.	· Analyze diverse decision-making perspectives.
Valenza *et al.* [38]	Model-driven	· Use a wearable system able to monitoring physiological parameters.	· Use a stochastic process based on the Markov chain to mood recognition. · Present a low storage and processing capacity. Need for a bridge device for data collection of the embedded devices.	· Develop a monitoring system for health care.
Kothari *et al.* [39]	Hybrid (computer-aided)	· Develop an image-based prediction model.	· Use a multiclass SVM algorithm. · High computational complexity and processing time.	· Increase the expanse of data repositories.
Taati *et al.* [40]	Model-driven	· Compare several DM techniques to recognize patients with the best survival chances.	· Use binary classifiers, such as logistic regression, SVM, and RF to achieve excellent classification results. · Lack of capacity of traditional tools to handle a large volume of data.	· Improvement in algorithms based on binary matrix operations.
Maggio *et al.* [41]	Hybrid (computer-aided)	· Describe an efficient approach to perform a computer-aided detection scheme.	· Use a nonlinear multi-characteristic algorithm for the classification task. · The unequal distribution of examples in the classes remains an issue to be addressed.	· Improvements regarding Performance evaluation related to prediction significance of the proposed technique.
Niaf *et al.* [42]	Hybrid (computer-aided)	· Address the pattern classification problem that is resulting from uncertainty caused by lack of information.	· Use a hybrid approach based on the classic SVM algorithm and fuzzy logic. · There is no precise mathematical definition.	· Investigate other multitask approaches.
Sukor *et al.* [43]	Data-driven	· Performance assessment of algorithms for measuring the quality of acquired signals.	· Use a novel noise detection algorithm based on waveform morphology analysis to identify noise artifacts in contaminated waveforms. · Necessity more investigation regarding the impact of data quality on model precision.	· Investigate the impact of data quality on system precision.
Mattila *et al.* [44]	Data-driven	· Classification assessment and computational performance using medical datasets.	· Use probability density functions for determining the resulting fitness function and the optimal classification threshold. · The implementations considered use more computational resources than other recent models.	· Algorithm precision enhancements to reach better performance results.
Mougiakakou *et al.* [45]	Data-driven	· Present a platform to assist the monitoring, administration, and treatment of patients with chronic diseases.	· Use a hybrid algorithm based on the combination of a compartmental model and a real-time ANN. · Issues related to standardization and interoperability need to be addressed to universalize the access to telemedicine.	· Investigate the quality of the service and the experience of telemonitoring systems.

the best technology for the development of further research on the topic. The use of DM appears in most of these research. This concept has been increasingly used in information management to reveal important knowledge structures for decision-making [35].

IV. OPEN ISSUES AND SUGGESTIONS FOR FURTHER DSS APPLICATIONS RESEARCH

After a detailed analysis of the above-presented approaches used in DSSs (in several areas of knowledge), the design of a smart system to give support to decision-makers still presents

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TABLE I
(CONTINUED.)

Authors' name	Proposal approach	Main goals	Main technical aspects	Future work
Billis *et al.* [46]	Knowledge-driven	· Propose a decision support framework that can accurately evaluate the progression of the depression symptoms.	· Use Hebbian learning for fuzzy cognitive map-based algorithms for data classification. · Algorithms based on logic fuzzy do not learn quickly. · Difficulty setting rules correctly.	· Development of applications for monitoring daily living activities and identification of diseases.
Zięba [47]	Hybrid (service-oriented)	· Proposes a service-oriented DSS for diagnostic problems. · Applies several ML solutions in different distributed Web services.	· An ensemble SVM algorithm together with the repeated incremental pruning to produce error reduction algorithm presents the best performance. · Needs large volumes of clinical data to learn and reach high accuracy.	· Use ensemble learning classifiers for decision-making in diagnostic problems.
Exarchos *et al.* [48]	Hybrid	· Propose a DSS for integrate heterogeneous data.	· The best performing classification method involves a Bayesian network joint with a correlation-based feature subset selection algorithm. · Ensure shared information remains with the same context and meaning for all actors involved.	· Further evaluation to enhance the generalization capability of the proposed approach.
Guidi *et al.* [49]	Knowledge-driven	· Present a CDSS for the examination of heart failure cases. · Adopts classifiers based on decision trees to reach satisfactory results.	· The classification and regression tree algorithm is the most adequate to provide reliable outputs regarding the severity and type of heart failure. · Decision Trees do not extract patterns from the examples, only memorize observations. Thus, it is not expected that their capability can extrapolate to unforeseen cases.	· Generalize the findings to other approaches to improve the classification performance.
Soguero-Ruiz *et al.* [50]	Knowledge-driven	· Propose ontologies for cardiovascular risk recognition.	· Use ontologies for developing a cardiovascular risk stratification standardization framework. · Requires the presence of domain specialists for the construction of ontologies.	· Integrate several techniques to provide evidence-based decision support.
Lee and Wang [51]	Knowledge-driven	· Integrate new tools based on DM techniques with evidence-based decision support.	· Present a fuzzy ontology generation for semantic decision-making. · New assertion additions alter possible interpretations, which is improper for some domains.	· Refine the fuzzy ontology for a better complex illness prediction.

several challenges. A plethora of approaches and technologies have been identified in this survey. These technologies have influenced the development of novel systems significantly [52]. Moreover, it is possible to guarantee that these systems can support health professionals to cope with problems of uncertainty and complexity, increasing the efficiency and reliability of their decisions [53]. Based on the contributions collected from related literature, the most significant open issues can be classified into three main groups: 1) big data analytics; 2) DM; and 3) IoT. These issues are discussed and analyzed in the following sections.

A. *Big Data Analytics*

Big data analytics has great potentiality to modify the manner that health care professionals use modern technologies to gain knowledge from their medical and other data repositories [54]. "Big Data Analytics applications in healthcare are at the beginning stage of development, but fast advances in platforms and tools" are accelerating its development process [55]. Analyzing disease patterns, outbreak tracking, and data transmission to improve surveillance and give a more rapid response in emergencies, need more improvement. Transforming large amounts of evidence into significant information is very useful to identify needs in providing services. In the same way, this information can help predict and prevent risk situations. The next points address the major research fields on big data in health care.

- Hardware improvements. Development of necessary hardware components in the big data analytics in the health care field. For example, the development of cheaper solid-state drive technology with faster reading/recording time.
- Development of big data platforms and languages. Conventional tools are inefficient at handling big data. Big data-based platforms are very useful because most of the standard platforms have datasets that are too large for database management applications. Research on this trend could better the execution of enormous datasets to reduce costs and processing time.
- Development of role-specific database solutions. A significant problem in this research topic is predicting the

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potential relationships between the existent nodes in the graph network. The composition of this network is frequently changing and continuously morphs with the inclusion, removal, and modification of existing nodes or borders. Comprehending the network organization might permit a better prediction of the dynamics or development of the network [56].

- Improvements in data visualization. To visualize essential information from a poorly understood and complex data, the development of complex algorithms is decisive for an accurate result. The accelerated development of knowledge visualization, visual analytics, and health informatics has produced substantial benefits in personal health monitoring [57], [58], medical treatment decisions, and general welfare policy [59]. These three domains have benefited from new relevant trends in several health application areas. The extraordinary affluence of the potential for knowledge visualization methods to improve health care will induce profound changes in many of these fields.

B. Data Mining

Knowledge discovery, as one of the DM techniques, affords a new way to extract valuable data information. It consists of the extraction of potentially useful information from data using ML [60], statistical [61], and "visualization techniques to discover and to present knowledge" that is easily comprehensible [62]. This method allows finding useful correlations, patterns, and trends, by filtering vast amounts of data using statistical and mathematical techniques. The directions of research in DM can be presented in terms of three main topics.

- Classical statistics. Conventional statistics adopt such concepts as "regression analysis, standard distribution, deviation and variance, cluster analysis" [63], and confidence intervals, used essentially to study data and data relationships [64]. Health care practitioners and researchers have been encouraged to investigate together further medical and public health applications using classical statistics. These have the opportunity to make some significant additional contributions to the theory using conventional statistical methods for the improvement of clinical diagnosis.
- AI. The primary objective of the development of AI is to understand the human intelligence at all levels. In another way, it represents a valuable technological development based on knowledge. AI has been used to create novel paths in addressing and solving very complex and math-based problems. Nowadays, the health care field is facing new challenges. These could be solved with the use of AI techniques. For example, the treatment of new diseases, cost reductions, and quick decisions during moments of emergency [65]. In the collection, treatment, processing, and presentation of patients' data, these techniques perform a significant role in decision making [66]. AI could be useful to test and simulate novel treatments, scenarios, and devices [67].
- ML. The new trends of DM are the ML techniques, more accurately described as the union of statistics and AI. First, AI methods were used as research tools. Then, ML adopted these methods. This technique is an evolution from AI because it blends AI heuristics with statistical analysis. For the health care field, an important research topic is the development of algorithms that learn to recognize complex patterns using a large amount of data to make smart decisions. The primary focus is on developing techniques for an array of different challenging problems, such as clinical analysis [68], planning CDSS, and real world review evidence.

C. Internet of Things

There are, at least, five significant research trends on IoT.

- Extracting insights from remote monitoring data. IoT is one of the actual major research topics alongside patient remote monitoring and treatment [69]–[71]. The increase of patient records brings a new complexity for data treatment by the care provider and health experts. The development of IoT platforms helps extract insights from large datasets, solving several issues of these molds.
- Patient-centered analytics. This trend focuses on employing advanced analytics, visualizations, and decision support tools to improve diagnostic accuracy [72]. Research on this topic could improve treatments, making it more accurate, efficient, and personalized [73].
- Semantic interoperability and data integration. The semantic interoperability of health systems will allow managing the EHR of patients distributed on several heterogeneous systems. It has an important role in describing essential factors to improve patient care quality, public health services, and medical investigation.
- IoT solutions for health management. Each day, users are taking more responsibility for their health. Research on this topic could yield better access to data and improved health technology solutions. Besides, it could also allow consumers to manage their health care.
- Sharing of patient data with security and privacy. It is important to establish a novel set of protection policies focused on the IoT, mainly for wearable and implantable technologies [74].

V. Conclusion

Smart systems are intended to support experts in identifying and solving problems of decision-making. Systems that combine both statistical models and data are projected to assist the decision-makers better. The primary goal of intelligent systems is to improve the effectiveness of decision-making. This work stresses that DM integration approaches can significantly improve the available approaches, enabling the union of knowledge from experts with information obtained from data. This research is based on a deep analysis of the state of the art and identifies the approaches and technologies employed in DSSs in several areas of knowledge. The objective of this chronological survey contributes in making a comprehensive analysis of the state of the art, identifying open research issues in smart DSSs in health care. For this purpose, this paper presented a broad discussion, identifying the open topics of several research studies, discussing the primary challenges, qualities, and weaknesses in the development of smart solutions for decision support. The limitations of this research are related to the difficulty in enclosing the recent studies in a given category, considering that the development of new approaches is dynamic and discusses several aspects found in each of these categories. Another limitation is the rapid development of methods and technologies, which precludes a complete view of the whole state of the art.

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Chapter 3

Semantic Interoperability and Pattern Classification for a Service-oriented Architecture in Pregnancy Care

This chapter consists of the following article:

Semantic Interoperability and Pattern Classification for a Service-oriented Architecture in Pregnancy Care

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Semantic interoperability and pattern classification for a service-oriented architecture in pregnancy care

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HIGHLIGHTS

- A comparative analysis of standards used as pattern reference model for CDSSs.
- OpenEHR Performance and its compatibility keeping semantics interoperability of HISs.
- Archetypes to support the identification of high-risk situations in pregnancy.
- Proposed semantic model performance of a SOA for gestation related chronic diseases.

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ABSTRACT

Semantic interoperability represents one of the main challenges in health information systems. The development of novel interoperability models should promote the integration of heterogeneous information in the acquisition and semantic analysis of complex data patterns, which are typically used in clinical information. The purpose of this study is to develop a knowledge-based decision support system that uses ontologies for integrating data related to hypertensive disorders in pregnancy. This model allows, when dealing with new cases, inferring from a knowledge base and predicting high-risk situations that could lead to serious problems during gestation in both pregnant women and fetuses. Results demonstrate that the use of ontologies to address semantically acquired patterns from different electronic health records has the potential to significantly influence a service-oriented architecture implementation for clinical decision support systems.

1. Introduction

The integration of distributed and heterogeneous health data has become an essential requirement for health institutions. This integration represents the challenge of reducing the high costs and increasing the quality of the services provided. The development of different database architectures has increased the necessity for data integration significantly. With the advent of the Web, novel proposals have been developed to solve complex interoperability issues [1]. The main challenges for interoperability among different knowledge sources must be resolved at both the technical and information levels. Thus, distributed data must not only be accessed but also integrated and processed by other systems. The restrictions that occur due to the heterogeneity of these data are mainly related to the heterogeneity among database management systems (DBMSs) and structural, syntactic, and semantic heterogeneity [2,3]. Recently, the use of ontologies has emerged as a potential solution to solve the complex problem of semantic data heterogeneity. The reason is that an ontology can provide a shared common understanding of an application field, in a consensual manner, with the meaning of the terms and their relationships

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to the modeled domain. That is, this methodology provides interoperability among health information systems (HISs) in such a fashion that users have no preoccupation regarding the data source or its storage method [4]. For heterogeneous data sources, the use of ontologies can make distributed processing understandable for a computer by describing entities and relationships among these data sources, as well as integrity rules for the domain. In this sense, an ontology can be used to define an overall system, serving as a fundamental basis for the data integration process.

The merging of clinical information is one of the most significant challenges in health informatics [5]. Once a patient receives additional or new care at a different healthcare institution in his lifetime, his information is distributed in different HISs, which typically execute on different hardware and software platforms. The difficulty of integrating heterogeneous databases for knowledge sharing does not only occur in healthcare systems [6]. This primary issue has been the subject of study for many years [7,8]. One of the most implemented techniques to address this problem is the development of ontologies to represent the knowledge domain [9]. An ontology is a description of concepts and relationships that can exist among these concepts in a given domain. For there to be knowledge sharing, there must be a standardized method to represent this knowledge. Novel patterns have been developed for this representation, making the possibility of semantic information sharing a reality [10,11].

Maternal mortality is an indicator of the status of women, their access to healthcare systems, and the adequacy of these systems to respond to their requirements [12]. The leading causes of maternal deaths are related to complications during and after pregnancy and childbirth. The principal complications are severe hemorrhage (27.1%), infections (10.7%), hypertension during pregnancy (14.0%), childbirth complications, and unsafe abortion (7.9%) [13]. High blood pressure accounts for 14% of the total number of deaths. To improve maternal health, according to the United Nations (UN) Millennium Development Goals (MDGs), difficulties that limit access to maternal health services must be identified and addressed at all levels of HISs [14]. In this context, efforts have been undertaken to provide health units with information and communication technologies (ICTs) that can contribute to improved access to information and adequate care. The development of intelligent solutions aimed at supporting health professionals in prenatal care is of fundamental importance to assist them in the search for better conditions for both pregnant women and fetuses [15]. The data generated during antenatal care constitute a significant information volume, being of fundamental importance for the identification of gestational risk factors. Thus, these data can provide an improved control throughout the gestation, contributing to the early diagnosis of possible complications. The development of methods for predicting risk situations through the use of knowledge-based decision support systems (DSSs) is essential to mitigate the difficulties inherent in gestational monitoring [16]. These models, when used with semantic integration, can cooperate to obtain excellent results in the prediction of risks related to pregnancy. This work presents the development of an intelligent system, based on ontologies, to predict pregnancy diagnosis risk levels. This model is integrated into a semantic platform supporting health professionals in prenatal care monitoring. The use of intelligent approaches to gestation monitoring allows that the data generated during the prenatal period can be processed automatically and, thus, can infer a pre-diagnosis autonomously, generating alerts for risk situations and providing valuable information for health professionals, anytime and anywhere. The contribution of this study to the literature is twofold. First, this work presents a knowledge-based model that links semantic interoperability to data analytics capabilities in real-time. Concerning other approaches, the proposed model offers a novel perspective to complement the data semantic acquisition, providing a comprehensive understanding of how data analytics in real-time can facilitate the decision-making process for the monitoring of chronic diseases. Secondly, the elements of a smart DSS are extracted from a real-world context and applied in different health care scenarios, providing new perspectives for healthcare practitioners. Thus, the main contributions of this paper are as follows:

- A comparative analysis of the leading standards used as information models and their compatibility in maintaining semantics in electronic health (e-health) environments;
- Development of archetypes based on the openEHR standard to recognize high-risk situations during pregnancy;
- Performance assessment of the proposed semantic model, which can serve as the basis for the development of a service-oriented architecture (SOA) for healthcare.

The remainder of this paper is organized as follows. Section 2 elaborates on the related work regarding this topic, focusing on semantic interoperability and its application in healthcare. Section 3 describes the use of ontology for pattern recognition in predicting hypertensive disorders in pregnancy. A performance evaluation, comparison of different methods, and analysis of the results of the proposed approach are presented in Section 4. Finally, Section 5 concludes the paper and suggests further works.

2. Related work

The increasing incorporation of informatics in health services has favored agility in the production, organization, and sharing of information. With the interoperability among HISs, information exchange among electronic health records (EHRs) has facilitated longitudinal patient monitoring, enabling improvements in their care, reducing errors and duplications, and minimizing the high costs of unnecessary diagnostic investigations [17]. The most important characteristic of EHRs is the sharing of information among systems. However, this requires the resolution of several problems related to functional interoperability [18], which represents the ability of systems to share information with each other. An archetype set involves complex tools for storing, indexing, and sharing information among HISs. Its vast diversity and scope represent one of its primary characteristics, for example, in epidemiological studies, the notification of diseases and reimbursement of health service providers [19,20].

The development of an EHR must consider health criteria because it contains complex information and the requirement of strict confidentiality. These records must also consider the recent reference models. Among the current models most used in the literature, the clinical document architecture (CDA) [21] and virtual medical record (vMR) [22], both developed by Health Level Seven, Inc. (HL7), and the model based on archetypes proposed by the openEHR foundation [23] are noteworthy.

2.1. HL7 CDA: an XML-based electronic pattern for clinical document exchange

The HL7 CDA is an extensible markup language (XML)-based standard that specifies the structure and semantics of clinical documents for information exchange. CDA aims to provide a model for clinical documents such as hospital discharge, clinical history, and transfers, advancing the healthcare industry closer to an EHR accepted by all. The use of XML by the HL7 reference information model (RIM) allows the use of clinical codes such as the systematized nomenclature of medicine — clinical terms (SNOMED CT) and the International Classification of Diseases, Tenth Revision (ICD-10) [24]. Thus, the CDA standard provides documents readable by both computers and users because of the ease of analyzing the content and process the contained information represented by codes. CDA documents can be used by the majority of common Web browsers and wireless devices [25] such as mobile phones.

In [26], for precise information exchange, Khan et al. suggested a data interoperability mediation system for collaboration among HISs compliant with different healthcare patterns. This model stores the semantic information of the different standards using ontology. This work also presented a performance comparison related to the transformation process of medical records between CDA and vMR standards. The conversion process achieved an excellent degree of accuracy between the CDA and vMR standards, improving the global communication process among HISs. Lee et al. discussed issues related to the deployment costs and adoption of interoperable HISs in health organizations [27]. These problems involve mainly difficulties of managing scattered CDA format documents. The authors proposed an open application programming interface (API) service for CDA document generation and integration using cloud computing concepts. This solution represents a low-cost service for hospitals that provides interoperability among HISs and improved information management. Similarly, Wu et al. presented a cloud-based EHR exchange approach using the HL7 CDA standard [28]. This study discussed four scenarios to determine the feasibility and effectiveness of the suggested model. The results demonstrated that the EHR exchange was satisfactory under the studied scenarios. A performance comparison among the proposed EHR-exchanging mechanisms and conventional electronic medical record exchange systems was also conducted. The proposed model presented the best results related to response time.

A model based on the HL7 CDA standard can assist the process of clinical information transfer among different HISs, from the department or place where the first delivery of medical care occurs to the patient's discharge. This characteristic is the main difference from other standards and systems that are more centralized.

2.2. HL7 vMR: a standardized EHR data model designed to support interfaces compatible with SOA for CDSSs

HL7 vMR is an object-oriented data model where there is no dependency on specific classes or tables. This standard enables an abstract representation of the inputs and outputs of clinical information that can be exchanged among the clinical decision support system (CDSS) mechanism and HISs. This reference model represents a standardized interface for heterogeneous EHR systems, allowing access to data structures of different formats with the same code.

Hussain et al. presented an intelligent CDSS that receives data from several sources including health experts, to generate pattern-based personalized recommendations [29]. This work included an interface based on the HL7 vMR standards for submitting data to the clinical system for generating the recommendations. The performance assessment used data from diabetic patients to evaluate the proposal. The system performed the set of syntax rules using a cloud infrastructure, achieving a reasonable performance regarding computational time. Similarly, González-Ferrez and Peleg performed a comparison of several data standards to solve the issue regarding interoperability in knowledge-based DSSs through the integration of several data sources in an EHR [30]. This study identified important criteria to this evaluation using a case-study methodology. The results indicated the main advantages/disadvantages of each approach, concluding that the HL7 vMR standard demonstrated the best conceptual model in an evaluation curve. Among the key characteristics identified in this specification were the ease of use of its query mechanisms and significant support in clinical vocabulary integration. Zhang et al. suggested a framework based on ontology to integrate clinical data, medical knowledge, and rules for patient evaluation regarding diabetes mellitus [31]. This CDSS used automatic selection and adaptation of standard evaluation protocols to assess the patient's clinical conditions. For this research, the authors adopted the SNOMED CT standard for terminology regarding semantic interoperability. As standard schema for syntactic interoperability, this work used the HL7 vMR standard. The results demonstrated that this approach could contribute to an improvement in the integration of medical decision support services related to chronic diseases classification.

2.3. OpenEHR: Integration of heterogeneous HISs using the openEHR reference model and its archetype-based methodology

The changes provided by the openEHR standard have the potential to expedite the information technology (IT) development in healthcare [32]. Its impact affects the rapid evolution and updating of novel EHRs, as well as the development of CDSSs adapted to different clinical guidelines. openEHR represents a set of specifications and open tools. This combination facilitates the development of clinical records in modules according to the necessity and, therefore, is capable of performing operations among them. The primary objective of this open standard is to expand interoperability and computability in e-health systems [33]. The main focus is on enabling the construction of EHR systems that can communicate with each other without content meaning loss, *i.e.*, semantically interoperable systems.

In [34], Pahl et al. discussed the adequacy of the openEHR reference model, its archetypes, and templates for digital representation of obstetric clinical data. Furthermore, this work elaborated a modeling for HISs using the openEHR standard based on a regional level of hospital management into a major logical infrastructure. Results indicate that the openEHR standard represents a suitable tool for complex data processing in healthcare. Demski et al. suggested a model-driven DSS, using standardized clinical information, for the development of interoperable EHR systems [35]. This system considered several schemes for data exchange, automated generation of input forms, and platforms for executing the models directly, based on the openEHR standard usage. The results confirmed that the use of the openEHR standard could assist the development of innovative smart health applications for interoperable SOAs. Ulriksen et al. discussed the developing process of the archetypes as an infrastructure for interoperable EHR systems based on the openEHR standard [36]. This work also presented the main gaps in the infrastructure of a large-scale user-driven standardization focused on healthcare. The results indicated that the development of archetypes represents the backbone for novel EHR implementations.

OpenEHR archetypes provide a significant advantage over HL7 standards because data can be specified understandably for both healthcare and IT professionals. This approach represents an efficient manner of managing data specifications to be shared among HISs. Table 1 presents a comparison between the HL7 and openEHR standards.

3. Use of ontologies for the representation of archetypes in pregnancy care

The approach of this study is based on the dual model architecture. This architecture is based on the ontological separation between the information model, developed by IT professionals, and the knowledge model, built by health experts. The ontology provides the basis for the reference model classes. The reference

Table 1
Comparative analysis of HL7 standards and openEHR archetypes.

Advantages	Disadvantages
HL7 CDA	
· Supports the XML format; · Presents a well-defined reference model e.g., the HL7 RIM; · Uses a coded vocabulary and has a standardized and straightforward structure; · Is sufficiently flexible to be read on any platform and by any application.	· Implies a thorough understanding of RIM for the schematization of the structure; · Overly flexible; · In certain situations can be overly complex; · Information can be encoded in fields other than those that would be expected; · Occurrence of the same information in several fields and/or segments.
HL7 vMR	
· Reduces data and terminology divergencies in CDSSs; · Identifies restrictions that can be made to existing HL7 data models to simplify · CDSSs development; · Allows clinical decision support through a consistent set of standardized data inputs and outputs; · Encourages clinical decision support at the point of care, reducing costs and response time.	· Presents difficulties in representing, abstractions or high-level concepts.
OpenEHR	
· Clinical information can be created and modified at any time; · Allows defining a common knowledge shared by all actors involved in the service process; · Access to data can be controlled; · Allows the use of a knowledge base for automatic processing, such as DSSs; · Allows the definition and control of knowledge in healthcare at the level of concepts.	· Data structures may not have sufficient information to be well represented in an entity; · Challenges in the construction of the graphical interface; · Requirement for a terminology service that does not lose its semantic portability; · Costs for the technical team in the development of templates because there are no free editors.

model is generic and allows raw information registry, without the semantic specification of the particular clinical concepts, which are dynamic to be modeled a priori. The knowledge model is based on archetypes and specifies constraints on the constituent elements of the reference model, i.e., this model represents particular clinical concepts. Archetypes are external, as opposed to the reference model, which is part of the software. The former is expressed as constraints imposed on the information model. The information model is characterized by its stability, containing the semantic base that remains unchanged. Conversely, the knowledge model is susceptible to changes that occur in the application domain. The separation of these models allows future modifications in the HISs, without the requirement for changes in the software code because their construction is based on the information model, resulting in higher interoperability. The openEHR standard is object-oriented and incorporates types of robust data to represent health information and is based on an ontology of concepts represented by archetypes.

Archetypes are key specifications of shareable clinical information necessary for the provision of quality healthcare. These specifications have been formally accepted as standard. Each archetype represents a complete, discrete, and most inclusive specification, always regarding the openEHR reference model. Fig. 1 displays an example of the `openEHR-EHR-EVALUATION.pregnancy_summary.v0` archetype for pregnancy evaluation. The application of several concepts inherent to knowledge organization systems is found in this architecture. Archetypes are classified into several categories such as observation, evaluation, instruction, and action; at the same time, they are hierarchically structured into sections, namely, data, protocol, state, events, and description, forming a clinical information ontology. This archetype includes all the data and information inherent to the clinical pregnancy concept, such as data regarding pregnancy outcome, childbirth onset, and induction method, as well as the pregnant woman's clinical condition. The occurrence of events is registered in this section. The protocol section presents the methods, equipment, and medication. Finally, the description section provides a complete description of the archetype, such as author, date, and function.

Templates are used to group archetypes, defining a clinical or demographic form. From these models, it is possible to develop an input interface for data that can be customized according to the specialty and/or necessity. Fig. 2 presents a detailed clinical model that uses templates for the grouping of archetypes.

Archetypes use ontologies, which are sets of concepts belonging to a specific field of knowledge. Ontologies describe complex information structures that indicate how information is to be expressed, what is mandatory or optional, and what are the sensitive values for each data, while defining usage rules that must be expressed. This work sought the entry archetype development called `CEN-EN13606-ENTRY.HypertensiveDisorders.v1` and its modeling, which contain a cluster object called "List of hypertensive disorder" and another named "Illness". This second object includes two elements, "Hypertensive disorders classification" and "Observations". For this model presentation, this archetype is divided into three sections, namely, header (identification and description), definition, and ontology. Next, the details of the archetype definition language (ADL) code referring to each of these mentioned sections is presented.

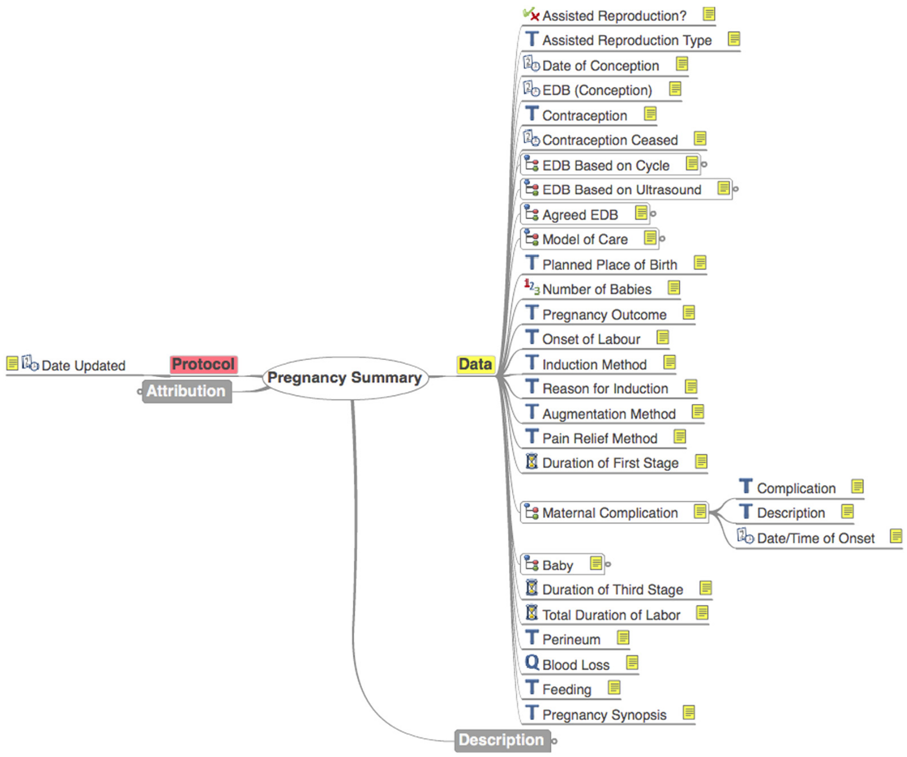

Fig. 1. Mind map representation of pregnancy evaluation archetype.

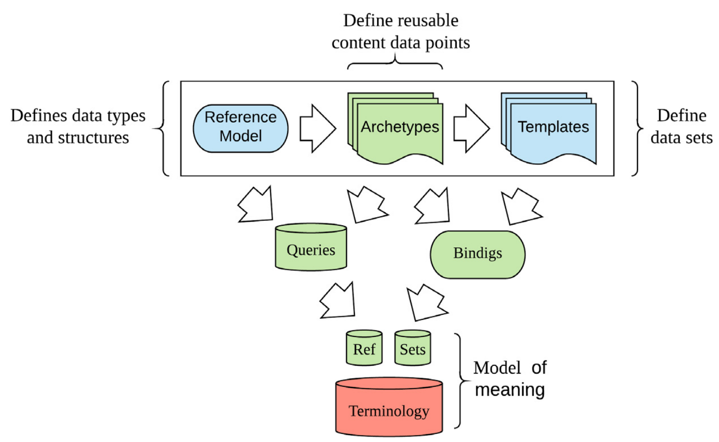

Fig. 2. Structured grouping of archetype sets through templates to originate to a clinical record.

3.1. Header: archetype, concept, language, and description sections

The ADL part of the header refers to the archetype, concept, language, and description sections. This section includes the identification of the archetype, if this archetype was based on another archetype, its original language, authorship information, life cycle, purpose, and intended use. Fig. 3 displays the ADL code corresponding to this part of the code. This structure indicates the subsections of the header. The archetype subsection consists of the code defined in use. The concept defines the central idea represented by the archetype, *i.e.*, every archetype represents a real-world conception. The language indicates the original language and all translations that have occurred in the archetype. This subsection must be written in the ADL data (dADL) language. The description subsection presents information regarding the archetype and what can be used to retrieve it from a repository. This subsection includes author data, archetype status, purpose, and intended use, among other information.

```
Archetype (adl_version=1.4)
    CEN-EN13606-ENTRY.HypertensiveDisorders.v1
concept
    [at0000]
language
    original_language = <[ISO_639-1::en]>
description
    original_author = <
        ["date"] = <"20170927">
        ["name"] = <"Mário W. L. Moreira">
        ["organization"] = <"University of Beira Interior ">
    >
    lifecycle_state = <"Draft">
    details =
        ["en"] = <
            language = <[ISO_639-1::en]>
            purpose = <"This archetype defines the semantics of the data
elements of entry Illness.">
            keywords = <"Hypertension">
            copyright = <"Maternity School Assis Chateaubriand">
            use = <"Descriptive archetypes of the central repository -
UFC/CE - version 1.0">
        >
    >
```

Fig. 3. First part of ADL code sample.

3.2. Definition: formal constraints of the archetype

In the definition section, this paper presents the main formal constraints of the archetype, written in the ADL constraints (cADL) language. Fig. 4 displays part of the ADL code for this section, explaining the restrictions in cADL code necessary for the formation of the tree structure of the "Illness" archetype, as displayed in Fig. 1.

Each code entry identifies an object. The `ENTRY` object, for example, is identified by `at0000`, at line 25. The assertions `occurrence matches` {1..1} restrict its structure such that it is necessarily present in the generated instances. The `Items` attribute, line 26, represents an association between the `ENTRY` and `ITEM` classes. This is an attribute of the container type. The assertion `existence matches` {0..1} indicates that the `items` attribute, in this case, is optional. The empty case could indicate, in conjunction with other attributes of the reference model, an `ENTRY` exclusion transaction. The assertion `cardinality matches` {1..1} indicates that although the attribute is a container, it cannot receive more than one instance of the `CLUSTER` object. The `ELEMENT` object is defined in line 31 and receives the `at0011` code. At line 33, the `CV` object (`datatype`) is defined as mandatory. At line 34, the `codevalue` attribute is related to the constraint code `ac0001`. This code is defined in the ontology/`constraint_binding` section. The `codingscheme` attribute, line 35, defines the ICD-10 code of the terminology in use. The `codingschemename` attribute, line 36, defines the name of the terminology (in this case, an internal reference to the archetype).

3.3. Ontology section

This section describes, in dADL, the object codes present in the archetype, translations, constraints on terms, and references to terminologies. The ADL language separates the descriptions and terminologies (dADL) from the constraint code (cADL) to facilitate the maintenance of the archetype. Fig. 5 displays part of the ADL code for this section.

The assertive `terminologies_available` defines the terminologies used in the archetype. The assertive `term_definitions` describes all term codes employed in the archetype. The codes are indexed considering the language, in this case `["en"]`, which allows a multilingual archetype. The assertive `constraint_definitions` allows the detailing of all the constraint codes used in the archetype. Although empty in this example, the `term_binding` part is used to define the descriptive terminologies that explain the semantics of the subjective terms utilized in the archetype. Finally, the `constraint_binding` part defines the external terminologies related to each constraint code and the location where they are available.

Addressing the security issue, this study considered the ISO 13606 standard, which presents a basic set of rules that can be used as a minimum access policy specification for an EHR system [37]. This standard presents information structures to exchange an access policy as objects of the `EHR_EXTRACT` class, describing a methodology to specify the level of privilege required to access data from an EHR system, in alignment with the information model. The `EHR_EXTRACT` class is used to represent part or all the information extracted, share data with another system (or repository), and certify the faithful transmission of the data.

The next section describes the performance assessment of the ontological rules used for classification of the data integrated semantically.

4. Performance evaluation and results analysis

This study considered 133 participants diagnosed with a hypertensive disorder during pregnancy. The data were collected during May and September of 2017, after approval of the project by the research ethics committee at the Maternity School Assis Chateaubriand (from the Federal University of Ceará, Fortaleza, CE, Brazil) under the certificate of presentation for ethical appreciation, number 66929317.0.0000.5050, and receiving assent with protocol number 2.036.062.

This work also considered the clinical knowledge manager (CKM) and national health service (NHS) eLearning repositories for the modeling process. Table 2 provides a list of archetypes that

```
Definition
  ENTRY[at0000] occurrences matches {1..1} matches { -- Illness
    items existence matches {0..1} cardinality matches {1..1; unordered; unique} matches {
      CLUSTER[at0001] occurrences matches {1..1} matches { -- List of Hypertensive Disorders
        parts existence matches {0..1} cardinality matches {1..*; unordered; unique} matches {
          CLUSTER[at0004] occurrences matches {1..1} matches { -- Illness
            parts existence matches {0..1} cardinality matches {1..2; ordered; unique} matches {
              ELEMENT[at0011] occurrences matches {0..1} matches { -- Hypertensive disorders classification
                value matches {
                  CV[at0023] occurrences matches {1..1} matches { -- CV
                    codeValue matches {[ac0001]}
                    codingscheme matches {"2.16.840.1.113883.13.88"}
                    codingSchemeName matches ["Illness"]
                  }
                }
              }
              ELEMENT[at0014] occurrences matches {0..1} matches { -- Observations
                value matches {
                  SIMPLE_TEXT[at0024] occurrences matches {1..1} matches { -- SIMPLE_TEXT
```

Fig. 4. Second part of ADL code sample.

```
Ontology
  terminologies_available = <"ILLNESS", ...>
  term_definitions = <
    ["en "] = <
      items = <
        ["at0000"] = <
          text = <"Illness">
          description = <"Illness">
…
    constraint_definitions = <
      ["en"] = <
        items = <
          ["ac0001"] = <
            text = <"Hypertensive disorders classification of UFC/CE">
            description = <"Hypertensive disorders classification referring to version 1.0 of the B-EHR. September 2017">
          >
        >
      >
    >
    term_binding = <
    >
    constraint_binding = <
      ["Illness"] = <
        items = <
      ["ac0001"] = <http://termiologies.EBSERH.ufc.br/hypertdisordersMSBRA.xml>
        >
```

Fig. 5. Third part of ADL code sample.

specify the medical concepts involved in the hypertensive disorders expertise. These archetypes are divided into four classes, Composition, Section, Entry.Evaluation, and Entry.Observation. Some of these archetypes were reused directly, with minimal or no change; others were extended or specialized. Thus, the development of archetypes was required to complete the diagnosis process of

Table 2
List of archetypes used to specify hypertensive disorder concepts.

Classes	Archetypes	Type of use
Composition	Encounter	Reuse
	Problem_list	Reuse
	Report	Extension
	History	Specialization
Section	Conclusion	Reuse
	Diagnostic_report	Extension
	Simple_object_access_protocol	Extension
	Physical_exam	Specialization
	Family_history	Extension
Entry.Evaluation	Pregnancy	Extension
	Problem_diagnosis	Extension
	Checklist_condition_history	Specialization
Entry.Observation	Body_weight	Reuse
	Global_assessment	Extension
	Notification	Extension
	Patient_record_notes	Specialization
	Blood_pressure	Reuse
	Urine_protein_loss	Specialization
	Hemolysis	Extension
	Elevation_of_liver_enzymes	Specialization
	Thrombocytopenia	Specialization
	Edema	Specialization
	Hyperreflexia	Specialization
	Headache	Extension
	Epigastric_pain	Specialization
	Nausea_vomiting	Specialization
	Vision_blurring	Specialization
	Dizziness	Specialization
	Oliguria	Specialization

hypertensive disorder in pregnancy. The achieved result presented a high degree of EHR interoperability.

The ontology used in this model was created under the open-source ontology editor and framework Protégé. This ontology is a formulation in the Web language ontology (OWL) of the well-known international classification of diseases, ICD-10. Table 3 presents the main hypertensive disorders in pregnancy and their description according to the ICD-10 medical coding reference.

Table 4
Evaluation results of the proposed method, using the performance indicators obtained through the confusion matrix, for the classes related to hypertensive disorders in pregnancy according to the ICD-10 codes.

Precision	Recall	F-measure	Class
1.000	0.600	0.750	O10
0.880	0.846	0.863	O11
0.000	0.000	0.000	O12
0.739	0.944	0.829	O13
1.000	0.375	0.545	O14.0
0.844	0.982	0.908	O14.1
1.000	0.714	0.833	O14.2
0.714	0.714	0.714	O15
0.000	0.000	0.000	O16
0.847	**0.842**	**0.827**	**Weighted Avg.**

The performance evaluation employed a confusion matrix, which is widely used in the assessment of classification models [38,39]. The confusion matrix of a hypothesis provides an effective measure of the classification model by proving the number of correct classifications versus the classifications predicted for each class over a set of examples. The elements that form this matrix are true positives (TP), *i.e.*, the pregnant woman has a certain hypertensive disorder, and the model correctly classifies it; and true negatives (TN), where the pregnant woman does not present a certain hypertensive disorder and the model classifies it correctly as negative. In false positives (FP), also known as false alarms, the patient does not present a certain hypertensive disorder; however, the ontological model classifies it as positive for this gestational complication. In false negatives (FN), the input case is positive, that is, the pregnant woman suffers from a certain disease; however, the system incorrectly classifies this condition. Table 4 presents the result for the confusion matrix of the model proposed in this work.

Precision represents the number of cases classified as belonging to a determining class, which truly are of that class (TP), divided by the sum of this number and the number of examples classified in this class, yet belonging to others (FP). Recall represents the number of cases classified as belonging to a determining class,

Table 3
Hypertensive disorders related to pregnancy, childbirth, and puerperium, according to the international statistical classification of diseases and related health problems (ICD-10).

Code	Hypertensive disease related to pregnancy, childbirth, and puerperium	Observations
O10	Pre-existing hypertension complicating pregnancy, childbirth, and puerperium	Incl.: the listed conditions with pre-existing proteinuria Excl.: those with increased or superimposed proteinuria (O11)
O11	Pre-existing hypertensive disorder with superimposed proteinuria	Incl.: Conditions in O10 - complicated by increased proteinuria Superimposed pre-eclampsia
O12	Gestational [pregnancy-induced] edema and proteinuria without hypertension	
O13	Gestational [pregnancy-induced] hypertension without significant proteinuria	Incl.: Gestational hypertension Mild pre-eclampsia
O14	Gestational [pregnancy-induced] hypertension with significant proteinuria	Excl.: superimposed pre-eclampsia (O11) O14.0 Moderate pre-eclampsia O14.1 Severe pre-eclampsia O14.2 HELLP syndrome O14.9 Preeclampsia, unspecified
O15	Eclampsia	Incl.: convulsions following conditions in O10-O14 and O16 eclampsia with pregnancy-induced or pre-existing hypertension
O16	Unspecified maternal hypertension	

Table 5
ROC area for classes related to hypertensive disorders in pregnancy according to the ICD-10 codes.

TP rate	FP rate	ROC area	Class
0.600	0.000	0.960	O10
0.846	0.028	0.863	O11
0.000	0.000	–	O12
0.944	0.052	0.973	O13
0.375	0.000	0.948	O14.0
0.982	0.128	0.966	O14.1
0.714	0.016	0.976	O15
0.714	0.000	0.992	O14.2
0.000	0.000	0.931	O16
0.847	**0.066**	**0.968**	**Weighted Avg.**

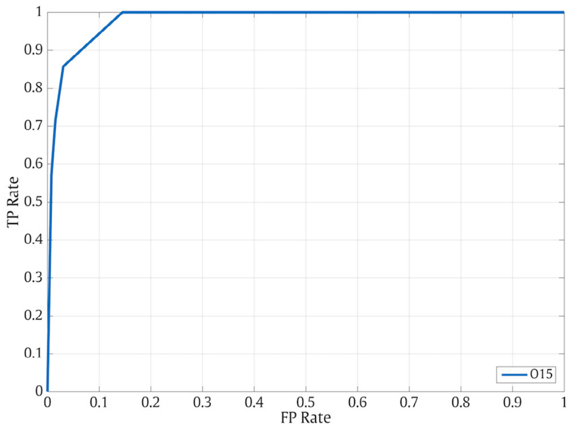

Fig. 6. ROC curve for O15 class, which is related to the hypertensive disease in pregnancy that causes the majority of deaths worldwide, *i.e.*, the eclampsia.

which truly belong to that class, divided by the total number of cases belonging to this class, even if they are classified into another class, *i.e.*, TP divided by total positives. The *F*-measure is a harmonic average between precision and recall. Eqs. (1), (2), and (3) present the mathematical model for these metrics.

$$Precision = \frac{TP}{TP + FP} \quad (1)$$

$$Recall = \frac{TP}{TP + FN} \quad (2)$$

$$F\text{-}Measure = 2 \times \frac{Recall \times Precision}{Recall + Precision} \quad (3)$$

The area under the receiver operating characteristic (ROC) curve is an interesting metric for tasks with disproportionate classes. In this indicator, the area under a curve (AUC) formed by the graph is calculated between the TP rate and the FP rate. The main advantage concerning the *F*-measure indicator is that the ROC curve measures the model performance at different cut-off points, not necessarily assigning examples with probability greater than 50% for the positive class, and lower for the negative class. Table 5 presents the results for this indicator.

Fig. 6 displays the ROC curve for the O15 class, *i.e.*, eclampsia, which is responsible for the majority of maternal deaths worldwide. The ROC curve permits evaluation of classification models for which there is more significant optimization of sensitivity (TP rate) as a function of the specificity (TN rate), that corresponds to the point where it is closest to the diagram upper left corner because the TP rate is one and the FP rate is zero.

Table 6
Performance comparison among recent similar works related to pregnancy care.

	Method	TPR	FPR	Prec.
Moreira et al.	Ontology	0.842	0.066	0.847
Paydar et al. [40]	RBF	0.533	0.206	0.714
	MLP	0.800	**0.059**	**0.909**
Pereira et al. [41]	GLM	**0.890**	0.709	0.586
	SVM	0.856	0.721	0.621
	DT	0.883	0.200	0.839
	NB	0.843	0.370	0.747

To demonstrate the feasibility of the proposed semantic model, Table 6 compares similar approaches, used recently in the literature for pregnancy care, using the metrics of the confusion matrix.

The performance evaluation indicates that, concerning classification, the proposed ontology-based model is equivalent to algorithms based on artificial neural networks (ANNs), *e.g.*, radial basis function (RBF) network, multilayer perceptron (MLP), and support vector machine (SVM). The approach proposed in this work also presented accuracy close to decision tree-based algorithms, *e.g.*, decision tree (DT) and statistically based models, *e.g.*, the naïve Bayes (NB) classifier. Thus, regarding the use of rules and constraints, using the OWL language in the Protégé framework, it is possible to classify the hypertensive disorders of pregnancy correctly through information clustering.

5. Conclusion and future work

An SOA is based on a conjunction of services that communicate with each other, transmitting valuable information. This architecture can be involved in the cooperation of several activities, anywhere and anytime. However, an SOA implementation can consist of a combination of different technologies including resources, applications, and platforms. This combination presents a series of challenges to be solved, with the interoperability, at the technical level and the semantic and syntactic levels, representing the main issue.

Interoperability represents innovation and progress in healthcare, and its users increasingly perceive its benefits; these are essential to attain excellence in the use of this technology, to offer the best possible services to the patient, generating lower costs for institutions. Several standards for reference models of health information and for the exchange of information among EHR systems have been established in the international scenario. Among these, the openEHR standard is noteworthy. The use of standards to ensure the semantic interoperability of EHRs is not a trivial issue. The challenge that remains is to broaden the research community to build a library of archetypes capable of identifying patterns to improve the medical care. Today, knowledge combined to define patterns at the ideal level of granularity, specificity, quality, and to classify these for broad adoption, represents the leading challenge.

In this regard, this work sought a solution based on the development and integration of archetypes necessary to solve the problems related to semantic interoperability among EHRs. The second contribution of this research was to use rules based on ontology for pattern classification from data acquired in the previous stage. The results confirmed that the proposed semantic model was efficient for the acquisition and classification of data on hypertensive disorders of pregnancy. As a proof-of-concept, this research strongly suggested that recent state-of-the-art approaches based on openEHR data representation are not sufficient for representing all pregnancy-related data. Therefore, this paper extended the openEHR through new gestational related data and also complemented those previously developed. Moreover, this novel study developed different archetypes, which represents a contrasting view to studies published by other research groups related to pregnancy care [34]. Thus, the conventional archetypes were adequate for this study through domain-specific modifications.

Obstetric/gynecologist physicians from the health unit of the Maternity School Assis Chateaubriand and information-modeling experts assessed the content of the archetypes used to represent the information contained in the forms provided by this health unit. The CKM collaborative system provided some of the archetypes to represent part of specific data. All archetypes and templates presented the requirements for the pregnancy data modeling. Regarding technical semantic and syntactic interoperability requirements, this study used the ADL Workbench and CKM application through multiple iterations of the review process. This study used the LinkEHR-Ed Archetype Editor for modification of the archetypes. This graphical application developed the syntactically correct ADL code automatically. This study also developed technical approaches to associate archetypes using the International Classification of Diseases and health-related problems, ICD-10. The second part of this study resulted in a single template, equivalent to a single broad archetype, built through the semantic data capture, presenting an associated generic XML schema. The semantic rules were developed in OWL language as part of the ontology where they were created. Regarding classification, the rules and their parts were represented internally by the Protégé framework as individuals belonging to one or more classes and having properties that relate them to each other.

Further work would involve using other types of standards to acquire data semantically. This work strongly supports the development of more archetypes aimed at the care of pregnant women. Developing an SOA that can be accessible in remote locations is also a challenge to be addressed. Other approaches to classifying and clustering data also require further study.

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Chapter 4

Biomedical Data Analytics in Mobile-health Environments for High-risk Pregnancy Outcome Prediction

This chapter consists of the following article:

Biomedical Data Analytics in Mobile-health Environments for High-risk Pregnancy Outcome Prediction

Mário W. L. Moreira, Joel J. P. C. Rodrigues, Francisco H. C. Carvalho, Naveen Chilamkurti, Jalal Al-Muhtadi, and Victor Denisov.

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ORIGINAL RESEARCH

Biomedical data analytics in mobile-health environments for high-risk pregnancy outcome prediction

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Abstract
According to the World Health Organization (WHO), a significant reduction in mortality and maternal morbidity has occurred in developed countries over the past decades. In contrast, these rates remain high in developing countries. Smart mobile-health (m-health) applications that use machine learning (ML) approaches are necessary tools for pregnancy monitoring in an accessible, reliable, and cost-efficient manner, making the prediction of high-risk situations possible during gestation. This paper, therefore, proposes the development, performance evaluation, and comparison of ML algorithms based on Bayesian networks capable of identifying at-risk pregnancies based on the symptoms and risk factors presented by the patients. A performance comparison of several Bayes-based ML algorithms determined the best-suited algorithm for the prediction, identification, and accompaniment of hypertensive disorders during pregnancy. The contribution of this study focuses on finding a smart classifier for the development of novel mobile devices, which presents reliable results in the identification of problems related to pregnancy. Through the well-known cross-validation method, this proposal is evaluated and compared with other recent approaches. The averaged one-dependence estimators presented better results on average than the other approaches. These findings are key to improving the health monitoring of women suffering from high-risk pregnancies around the world. Thus, this study can contribute to a reduction of both maternal and fetal deaths.

Keywords Mobile health · Data analytics · Machine learning · Bayesian inference · Hypertensive disorders · Pregnancy

1 Introduction

There are significant differences in social, economic, and political formations between developed and developing countries, but unfortunately, the populations in developing countries have to face much worse health conditions, their life expectancy is much lower, and they are in extreme need of novel medical solutions. Innovative m-health technologies have significant potential to save millions of lives around the world. It is significant that, in today's world, the speed of

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change and the availability of information are growing both exponentially and globally. Increased access to the Internet has enabled more and more people to access medical information. According to Dieleman et al., even with health financing in developing countries facing a crisis resulting from both low domestic investment and the stagnation of international aid, achieving universal health coverage and its financial sustainability remains feasible for most countries, although the challenge is enormous (Dieleman et al 2016). Faced with this, innovative m-health technologies are enabling people to self-monitor their health, anywhere and anytime, without having to go to a clinic or hospital (Mushcab et al 2017). This revolution in health care has also reached pregnant women with the emergence of novel health (Dunsmuir et al 2014) and wearable (Penders et al 2015; Zuckerwar et al 1993) devices. To improve the assistance to pregnant women in developing countries, it is important to find low-cost forms of intervention that allow families to create strategies to respond to health expenditures that are less penalizing to their own development. In particular, such strategies should be developed to avoid family spending required to meet these costs. In this way, smart m-health applications are low-cost solutions capable of extracting valuable information from various operational applications of health organizations (Ferradji and Zidani 2016; Raffaeli et al 2016), helping the various actors involved in the process of pregnancy monitoring, particularly in underserved areas. These intelligent solutions are designed to make it easier and more flexible to obtain reliable information and a quick understanding, providing health experts a multi-dimensional analysis tool and immediate feedback regarding the clinical condition of their patient (Manirabona et al 2017; Tambe and Gajre 2018).

Health organizations, in general, accumulate a large amount of biomedical data and information, in different formats and structures, which are in constant demand. Among the most frequently used strategies for such data are information and knowledge extraction. It is worth mentioning that these two forms complement each other, depending on the context situation of the problem in question. Occasionally, an information analysis generated from a set of data can require significant amounts of time and resources. In such cases, data mining (DM) techniques can be considered to expedite this process. DM and ML techniques are used to make decision support more efficient (Veloso et al 2017). Numerous DM and ML applications are used in health care. In Bâra and Lungu (2012), the authors discuss DM techniques in m-health applications for improving the decision-making process through pattern finding and hidden (but necessary) relations, which might lead to a better understanding of the information. Mertz debated how DM applications can help researchers extract rare-disease data from several different sources, including databases designed to select and choose relevant information from electronic health records (EHR), as well as information coming directly from the patients themselves (Mertz 2017). Based on this information, it is possible to understand the moment at which worsening clinical conditions occur during high-risk pregnancy caused by certain hypertensive disorders, and in what way this infirmity contributes to the health status of pregnant woman. Among the different DM approaches, probabilistic methods are widely used in several knowledge areas (Misirli and Bener 2014). Recent researches in health care have used Bayes' Theorem based approaches for classifying attributes, including symptoms and risk factors, that can lead health experts to a disease diagnosis (Ceccon et al 2014; Orphanou et al 2016). Bayesian networks (BNs) represent a powerful probabilistic modeling method for identifying patterns. This approach allows the identification of significant parameters and the relationships between them (Chakraborty et al 2016), which may be complicated, as in the case of hypertensive disorders during pregnancy. An advantage of a BN is that it allows accurate results to be obtained even when dealing with vast amounts of data. In this context, this research proposes the use and performance comparison of probabilistic DM techniques based on Bayesian networks to make inferences from the data of pregnant women suffering from hypertensive disturbances. Based on a probabilistic inference of the data, it is possible to predict a worsening of the clinical condition of a new patient. Thus, with reliable information, it is possible to predict for new cases the outcome of high-risk pregnancy, helping health experts identify, accompany, and avoid possible situations that can lead to death. Similar approaches are commonly used to predict heart-related diseases, turning the cardiovascular monitoring less invasive (Saxena et al 2016; Verma et al 2016).

This study contributes to filling gaps in reliable technologies for complex diseases that occur during pregnancy, principally the hypertensive disorders and their risk factors. Taking into account that developing countries have become more dependent on developed countries for access to novel remote monitoring devices due to their technology lag and health policy in vulnerable situations. This study has a vital role in the development and support to actions that contribute to the strengthening of the innovation system to reverse this situation through a reliable and accessible model for evaluating the health situation of pregnant women at risk, promoting the enhancement and modernization of existing devices. Thus, the main contributions of this paper are as follows:

- an extensive review of the state-of-the-art classification of hypertensive disorders occurring during pregnancy;
- a study of Bayes-based ML algorithms in terms of their identification of pregnancy-related diseases for predicting maternal and fetal childbirth outcomes;

- a performance assessment of these different techniques using a cross-validation method and its related indicators; and
- a comparison between the proposed model and similar studies to demonstrate the efficiency of the proposed approach.

The rest of this article is organized as follows. Section 2 presents the general principles in identifying a high-risk pregnancy. Section 3 describes the classification of hypertensive syndromes during pregnancy based on symptoms presented by the pregnant woman. Section 4 discusses the use of Bayes-based ML classifiers for childbirth outcome prediction. Performance evaluations of the proposed ML methods and the analysis results are discussed in Sect. 5. Finally, Sect. 6 concludes this study and suggests further works.

2 General principles for identifying a high-risk pregnancy

According to estimates by the World Health Organization (WHO), owing to complications during pregnancy and childbirth, hypertensive disorders caused about 216 deaths per 100,000 live births in 2015. These disorders are a leading cause of maternal mortality worldwide. For each death, ten other women survived their disorder with several recurrences (Alkema et al 2016). Although the number of deaths from complications during pregnancy and childbirth has decreased by around 43% over the past 25 years, the annual rate of decline has been less than half that expected by the Millennium Development Goal (MDG), which aimed at reducing the maternal mortality rate by 75%. Despite the fact that the maternal death rate has decreased, particularly in developed countries, the number of deaths in developing countries remains considerably high (Ghulmiyyah and Sibai 2012). This mortality has declined over the past decades, but avoidable cases continue to occur. Most maternal deaths take place in developing countries at a rate of approximately 600,000 annually, whereas in developed countries, such situations are frequently prevented. Overall, preeclampsia and eclampsia are responsible for 10–15% of maternal deaths in low and moderate-income countries. Ninety-nine percent of such deaths occur in these countries (Duley 2009). Hypertension is the most common medical complication during pregnancy, occurring in about 5–10% of women. Significant incidence occurs with black women, women over 45 years in age, and women with diabetes. Medical research has associated this disorder with the increased risks of intracerebral hemorrhaging, placental abruption, intrauterine growth retardation, prematurity, and intrauterine death (Vest and Cho 2014). There are four different classifications of hypertensive disorders during pregnancy. Preeclampsia occurs in 2–5% of pregnancies, and eclampsia occurs in approximately 0.0003%. Chronic or pre-existing hypertension occurs in 1–5% of all pregnancies. Preeclampsia along with chronic hypertension occurs in 20–25% of chronic hypertension cases, whereas gestational hypertension, also known as transient hypertension of gestation, or chronic hypertension, identified in the latter half of the pregnancy period occurs in 6–7% of pregnancies. Identifying the threshold between low-risk pregnancies and women at highest risk, with such pregnancy complications, it is essential to reduce the number of maternal and fetal deaths. Thus, the main factor for this reduction is not only disease diagnosis, but also identifying increased risk markers, and careful monitoring indicators in the mother and baby (Lei et al 2017; Malasinghe et al 2017; Ni et al 2018).

Gestation is a physiological phenomenon and must be seen as part of a healthy life experience involving dynamic changes from physical, social, and emotional points of view. However, it can involve several risks for both the mother and the fetus. There are large numbers of pregnant women who, based on their particular characteristics, are more likely to develop complications during pregnancy; that is, they are part of a high-risk group. Despite difficulties in differentiating high-risk pregnant women from low-risk women in accurately predicting their pregnancy problems, there are known risk factors that should be identified that can alert the health staff regarding the possible emergence of complications (Lawn et al 2016). Gestational risk factors can be readily identified during prenatal care as long as the health care providers are alert during all stages including anamnesis, general physicals, and obstetrical and gynaecological examinations; such risks can also be identified during home visitations. Markers and gestational risk factors present prior to pregnancy can be divided into (1) individual characteristics and unfavorable sociodemographic conditions, (2) previous reproductive history, and (3) preexisting clinical conditions (Ferrari et al 2015). Figure 1 shows all of these markers and risk factors categories.

Other risk factor groups refer to conditions or complications that may appear during gestation and result in a high-risk pregnancy. The first group is made up of those with excessive or accidental exposure to teratogenic factors. The second group relates to obstetric diseases during the current pregnancy, such as preeclampsia or eclampsia, gestational diabetes, or gestational hemorrhaging, among others. Finally, the third group is related to clinical occurrences, with an emphasis on infect-contagious diseases experienced during the present gestation and their initially diagnosed clinical conditions. The routine use of resources and procedures dedicated to high-risk factors for a low-risk pregnancy does not improve the quality of care or the results, and can delay access to pregnant woman who genuinely need them.

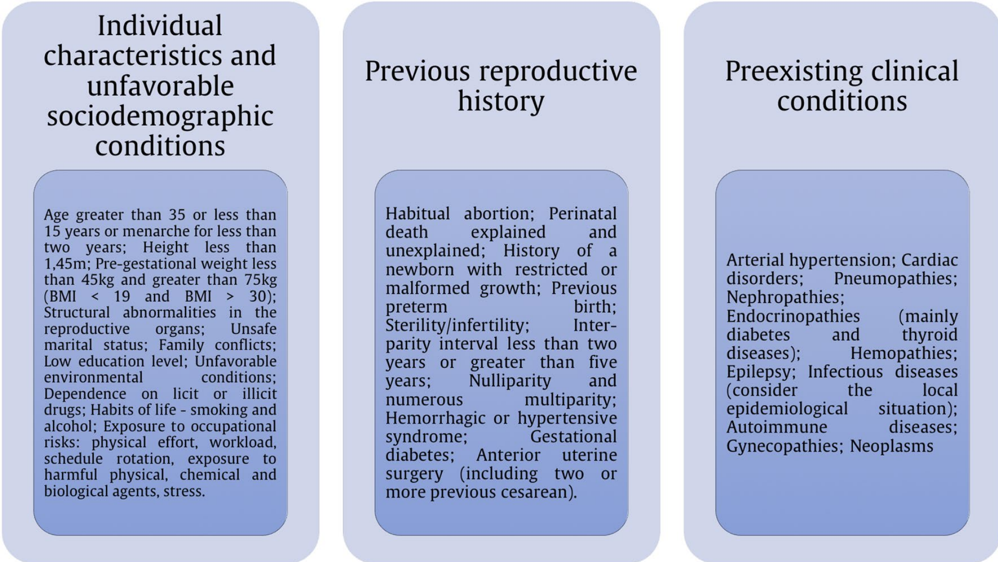

Fig. 1 Markers and gestational risk factors present before gestation

Hence, adequate risk classification is important for a proper referral.

3 Hypertensive syndrome classification based on biomedical indicators presented during pregnancy

The differential diagnosis of pregnancy hypertensive syndromes is based on its classification (Magee et al 2014). Chronic hypertension is observed before pregnancy or before 20 weeks of gestation, or is diagnosed for the first time during pregnancy and does not resolve until 12 weeks after childbirth.

Preeclampsia and eclampsia identification is based on the occurrence of hypertension after 20 weeks of gestation accompanied by proteinuria, with disappearance at up to 12 weeks postpartum. In the absence of proteinuria, the suspicion is strengthened when the pressure increase accompanied by a headache, visual disturbances, abdominal pain, thrombocytopenia, and/or an increase in liver enzymes. Preeclampsia is classified as mild or severe, according to the degree of impairment. It is considered severe under one or more of the following criteria: the diastolic blood pressure is equal to or greater than 110 mmHg; proteinuria is equal to or greater than 2.0 g in 24 h, or 2 + in reagent strips during a urine chemical examination; oliguria (less than 500 ml/day, or 25 ml/h) occurs; the serum creatinine levels are greater than 1.2 mg/dL; there are signs of headache and/or visual disturbances; epigastric or right hypochondrium pain occurs; clinical and/or laboratory evidence of coagulopathy can be seen; thrombocytopenia ($< 100{,}000/\text{mm}^3$) is evident, liver enzymes and bilirubin increase; and/or schizocytes are present in a peripheral blood smear. Other signs that may suggest such diagnosis include a stroke, heart failure, or cyanosis, and the presence of an intrauterine growth restriction and/or oligohydramnios. Eclampsia is characterized by the presence of generalized tonic-clonic seizures or coma in women with any hypertensive conditions, and is not caused by epilepsy or any other seizure disorder. It can occur during pregnancy, childbirth, or immediate puerperium.

Preeclampsia superimposed with chronic hypertension is characterized by the appearance of preeclampsia in women with chronic hypertension or renal disease. In these expectant women, the condition worsens, and the proteinuria appears (or aggravates) after the 20*th* week of pregnancy. Thrombocytopenia (platelets $< 100{,}000/\text{mm}^3$) and increased liver enzymes can occur.

A gestational hypertension diagnosis (without proteinuria) should be retrospective because the proteinuria can appear later, and it is necessary to differentiate this disorder from preeclampsia. The recommended clinical and obstetrical procedures for preeclampsia should be followed. For transient hypertension during pregnancy, the blood pressure returns to normal until 12 weeks postpartum (retrospective diagnosis), or for chronic hypertension, elevation of the blood pressure persists beyond 12 weeks postpartum.

With this information, the nodes used in the Bayesian classifier modeling presented in this work were defined. Figure 2 summarizes and divides these nodes into risk factors,

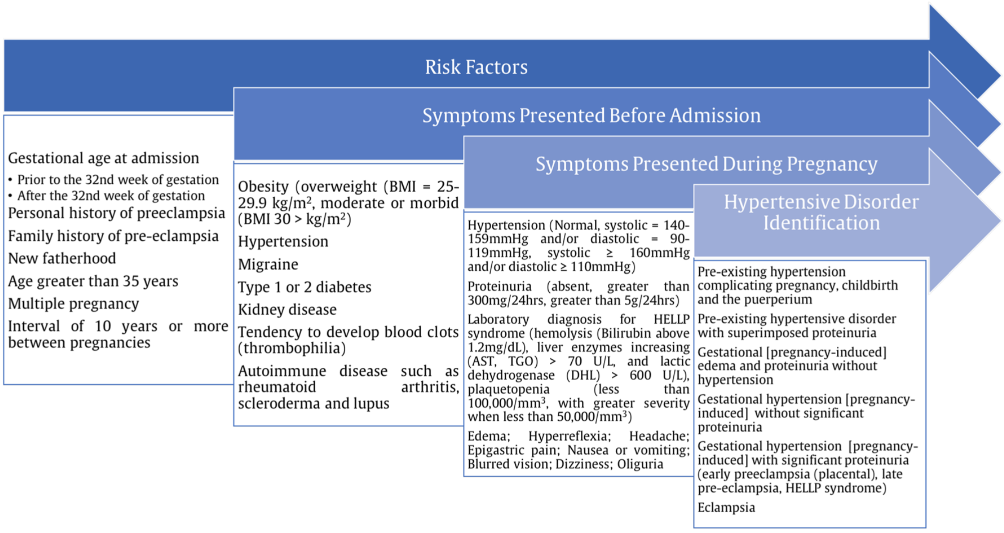

Fig. 2 Main information used to define the nodes applied to the modeling of the Bayesian classifiers described in this study

symptoms, and hypertensive disorder identification. Based on this, the delivery outcome for a high-risk pregnancy can be predicted, helping decision-makers identify which pregnant women need more intensive care with regard to their high-risk pregnancy.

Based on a risk factor analysis, the symptoms, and a hypertensive disorder occurring during pregnancy, it is possible to predict the childbirth outcome using DM-based inference machines, thereby determining its severity. In addition to the previous illustration, Fig. 3 shows the relevant information and possible outcomes for an at-risk pregnancy, which permit, together with the experience of the specialist physician, early identification of cases that can lead to the death of the pregnant woman and/or fetus.

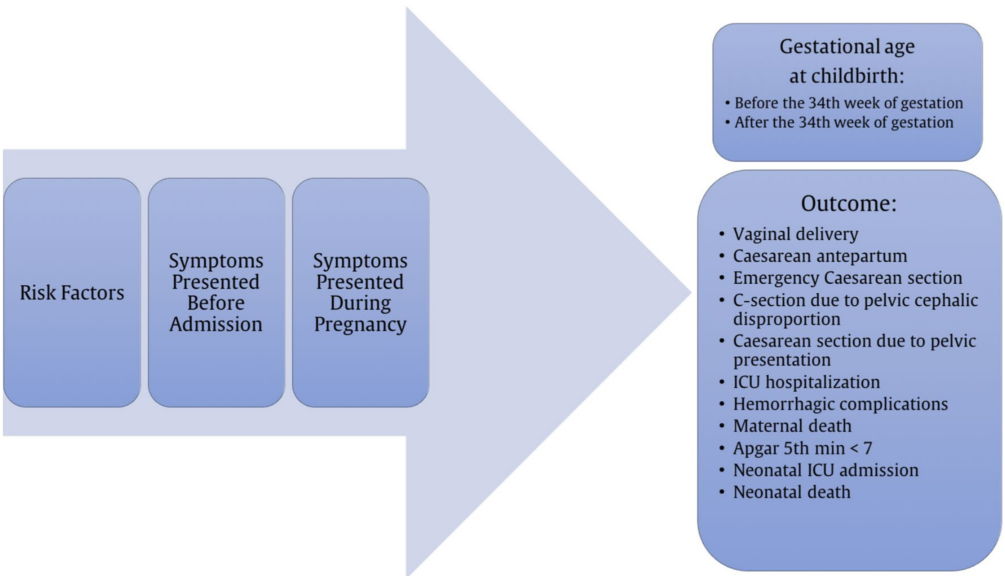

Fig. 3 Main information used to identify possible outcomes for an at-risk pregnancy

The next section presents the modeling of the leading Bayesian approaches for the possible outcome identification of an at-risk pregnancy.

4 Use of Bayesian classifiers for high-risk pregnancy identification

Bayesian classifiers are inference mechanisms that use statistics to classify a given element into a given class based on the probability of it belonging to that class. This is a type of supervised learning that relies on the Bayes Theorem. Such techniques have the characteristics of statistical learning, that is, each training example increases/decreases the probability of an individual hypothesis being correct. This method also provides a statistical prediction. The classification allows the prediction of multiple theories according to their probabilities. These classifiers can be used in classifying texts (De Campos and Romero 2009), spam filtering (Guo et al 2014), and recommendation systems (Adomavicius and Tuzhilin 2015).

4.1 Naïve Bayes classifier

In the naïve Bayes (NB) classifier, the attributes are conditionally independent, that is, the value of one attribute does not influence the values of the other attributes. The algorithm uses an initial dataset that classifies into clusters, and from the input data, seeks to infer this new information. This is particularly recommended when the entrance dimensionality is large. Because of its simplicity, computing and training are facilitated.

The primary purpose of this study is to classify a new case of hypertensive disorder during pregnancy according to its most probable outcome, given the set of symptoms and risk factors $\langle a_1, a_2, \ldots, a_n \rangle$ presented by the pregnant woman. Equation 1 shows the use of the Bayes' Theorem:

$$v_{MAP} = \underset{v_j \epsilon V}{argmax} \frac{P(a_1, a_2, \ldots, a_n | v_j) P(v_j)}{P(a_1, a_2, \ldots, a_n)} \tag{1}$$

The NB classifier simplifies the probabilistic induction, assuming that the symptoms and risk factors are all independent in estimating the pregnancy outcome. It is essential that each probability estimate of the training set be reliable. Therefore, this method classifies a given set of data through the following expression 2.

$$\underset{c_i}{argmax} \left(P\left(c_i\right) \prod_{j=1}^{n} P(a_j | c_i) \right) \tag{2}$$

This approach is simpler and computationally more efficient than other Bayesian classifiers owing to the attribute independence, and is widely used in medicine (Alanazi et al 2017; Hashi et al 2017).

4.2 Tree augmented naïve Bayes classifier

Although the NB classifier usually shows good results in prediction tasks, the attribute independence (given a determined class) represents a disadvantage of this method because this independence rarely occurs in the health field. In this way, it is necessary to propose a classifier that has the advantage of modeling dependencies between attributes (de Campos et al 2014). The tree augmented naïve Bayes (TAN) classifier presents this characteristic (Chang et al 2014). This approach models the attribute dependency in a tree structure. In the TAN classifier structure, the class (childbirth outcome) is the parent of all attributes (symptoms, risk factors, and type of hypertensive disease). Each attribute has at most one other attribute, resulting in a tree structure. Figure 4 shows the structural difference of both classifiers.

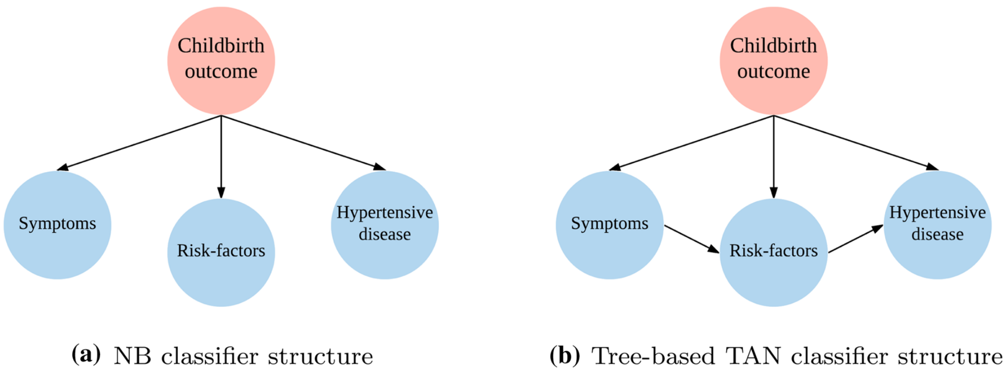

Fig. 4 Comparison between dependence structures of naïve Bayes and tree augmented naïve Bayes classifiers

In the TAN classifier, the parent of each attribute A_i is indicated as $\pi(A_i)$. Hence, this method classifies a determining class through the following expression 3.

$$\underset{c_i}{argmax}\left(P(c_i) \prod_{j=1}^{n} P(a_j|c_i, \pi(a_j)) \right) \tag{3}$$

The dependency tree construction differentiates the TAN from the NB approach. This structure determines the performance of the TAN classifier. Theoretically, this is due to the dependence between the attributes in that the method improves the performance with regard to the NB technique.

4.3 Averaged one-dependence estimators classifier

The averaged one-dependence estimators (AODE) classifier adopts a strategy to minimize the attributes dependence (Wang et al 2016). This method extends the NB classifier structure, including the unique dependence of each attribute of the TAN classifier. However, the AODE approach relates each node to all remaining attributes. That is, the AODE algorithm calculates the level of dependency n times. Figure 5 illustrates this model. How each attribute influences the other attributes is shown.

In the TAN classifier, each attribute depends on class c_i and another single attribute. Equation 4 shows the formula for calculating the probability P for class c_i given a set of attributes a_j.

$$P(c_i, I) = P(c_i, a_j)P(I|c_i, a_j) \tag{4}$$

Equation 4 holds for every a_j. Therefore,

$$P(c_i, I) = \frac{\sum_{j:1\le j\le n \wedge F(a_j)\ge m} P(c_i, a_j)P(I|c_i, a_j)}{|j : 1 \le j \le n \wedge F(a_j) \ge m|} \tag{5}$$

where $F(a_j)$ represents the frequency of a_j in the training set. Expression 6 shows the AODE approach formula for classifying the hypertensive disorders during pregnancy.

$$\underset{c_i}{argmax}\left(\sum_{j:1\le j\le n \wedge F(a_j)\ge m} P(c_i, a_j) \prod_{h=1}^{n} P(a_h|c_i, a_j) \right) \tag{6}$$

In the field of health care, the AODE classifier is commonly used in image processing (Bantan 2016) as well as the association between environmental issues and health problems (Karatzas et al 2017).

5 Performance evaluation of the machine learning proposed methods and analysis results

This study considers 205 parturients diagnosed with a hypertensive disorder during pregnancy. The data were collected between May and September 2017, after approval of the project by the research ethics committee at the Maternity School Assis Chateaubriand (from the Federal University of Ceará, Brazil) under the certificate of presentation for ethical appreciation, number 66929317.0.0000.5050, and receiving assent with protocol number 2.036.062. Table 1 summarizes the baseline characteristics, as well as the physical and biochemical parameters, collected from pregnant women diagnosed with a hypertensive disorder during pregnancy.

Table 2 below summarizes the diagnosis of pregnancy-specific hypertensive disease for the 205 cases analyzed.

The HELLP syndrome is a laboratory condition defined by three signs, namely, Hemolytic anemia, Elevated Liver enzymes, and Low Platelet count. This disease represents a

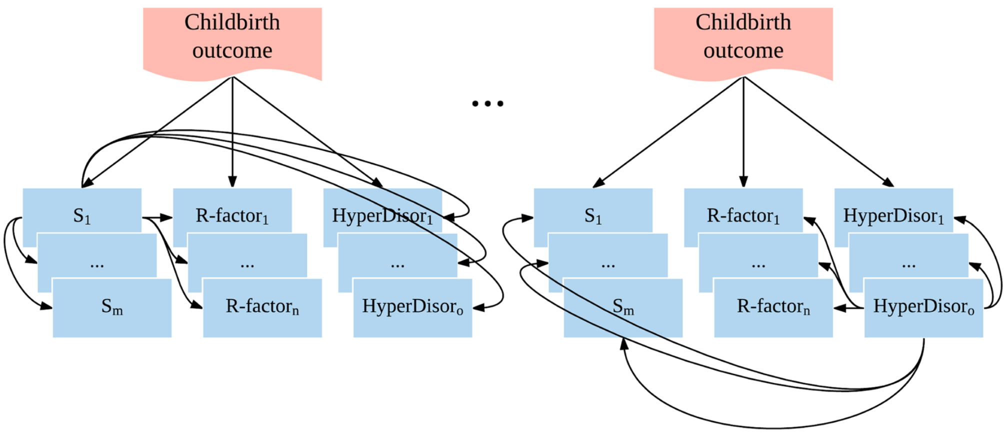

Fig. 5 Illustration of the averaged one-dependence estimators classifier structure

Table 1 Summarization of main characteristics and parameters from parturients with diagnosis of hypertensive disorder during pregnancy

	(n = 205)
Maternal age (years), mean (SD)	26.6
No. of pregnancies, mean (SD)	2.2
No. of normal labors, n (%)	32 (15.6)
No. of cesareans, n (%)	173 (84.4)
No. of live births, n (%)	195 (95.1)
No. of abortions, n (%)	10 (4.9)
Gestational age at delivery (weeks), mean (SD)	37.0
Body mass index (BMI) (kg/m^2), n (%)	29.0
< 25 (healthy)	128 (62.4)
25–30 (overweight)	34 (16.6)
> 30 (obese)	43 (21.0)
Blood pressure (mmHg)	
Normal	0 (0)
High (syst. = 140–159 and/or diast. = 90–119)	78 (38.0)
Very high (syst. ≥ 160 and/or diast. ≥ 110)	127 (62.0)
Loss of protein in the urine	
Absent	40 (19.5)
Traces (close to 300 mg/24 h)	145 (70.7)
Severe (greater than 5 g/24 h)	20 (9.8)

life-threatening condition that can potentially complicate a pregnancy. From the identification of the potential hypertensive disorder during pregnancy through the risk factors and symptoms presented by the pregnant woman, the next step for the model is to predict the possible outcomes for both the pregnant woman and the fetus. Regarding the outcome for the fetus, the model is also able to predict whether the newborn will be small for the gestational age (SGA), in which the probability for the Apgar scale at the fifth minute is less than 7. The following are the main problems requiring careful monitoring to avoid metabolic alterations in the newborn, which can hinder development.

This work uses a *k*-fold cross validation technique to evaluate the predictive model based on ML and DM (Link and Sauer 2016; Vehtari et al 2016). The method splits the dataset into a number *k* of subsets (or folds) (Braga-Neto et al 2014). The Bayesian models are then trained one time, excluding cases from each subset. The first step is based on all cases, except those in the first subset fold. The second phase relies on all cases, except those in the second sample fold, and so on. For each step, the errors are estimated by testing the removed subsamples when training the models. The best predictive model achieves the smallest error among the others. Cross validation with $k = 10$ is most commonly used to determine the best predictive model.

With the information gathered during the first stage of evaluation (cross-validation), it is possible to construct a confusion matrix. This approach is a widely used tool for a statistical model evaluation, such as for those models based on the Bayes' theorem (Deng et al 2016; Ohsaki et al 2017). This assessment method classifies all model cases into categories, determining whether the predicted condition for a particular delivery outcome corresponds to a real situation. The rows of the matrix represent the predicted values for the model, whereas the columns express the current values. The categories used in the analysis are false positives (FP), true positives (TP), false negatives (FN), and true negatives (TN). Tables 3 and 4 show the performance evaluation for the proposed ML classifiers suitable for predicting the outcome of both the pregnant woman and fetus at childbirth.

The precision is an indicator for classifier accuracy. Its maximum value is equal to 1. This measure indicates the percentage of cases classified as belonging to a particular childbirth outcome class that truly belongs to the class, i.e., there are no FPs. The recall is a completeness measure, with a maximum value equal to 1. This measure means that all cases belonging to a particular class are classified as belonging to that class, i.e., there are no FNs. These two measures provide additional information and are therefore commonly used together in a classifier evaluation. Equations 7 and 8 show the formulas for precision and recall calculations.

$$Precision = \frac{TP}{TP + FP} \tag{7}$$

Table 2 Classification of 205 cases through clinical diagnostics of the hypertensive syndromes

Hypertensive disorder	n = 205	%
Pre-existing hypertension complicating pregnancy, childbirth, and the puerperium	14	6.8
Pre-existing hypertensive disorder with superimposed proteinuria	34	16.6
Gestational edema and proteinuria [induced by pregnancy] without hypertension	1	0.5
[Pregnancy-induced] gestational hypertension without significant proteinuria	21	10.2
[Pregnancy-induced] gestational hypertension with significant proteinuria	105	51.2
Early-onset preeclampsia (placental)	13	6.3
Late-onset preeclampsia	92	44.9
Eclampsia	12	5.9
HELLP syndrome	15	7.3
Unspecified maternal hypertension	3	1.5

Table 3 Performance evaluation of all Bayes-based machine learning techniques for the prediction of the delivery outcome for the pregnant woman

	TPR	FPR	Prec.	Rec.	F-measure	MCC	ROC area	PRC area	Class
NB	0.929	0.652	0.918	0.929	0.923	0.288	0.853	0.978	Normal
	0.333	0.047	0.357	0.333	0.345	0.295	0.888	0.389	ICU hospitalization
	0.000	0.025	0.000	0.000	0.000	-0.027	0.611	0.057	Hemorrhagic complications
	0.500	0.005	0.500	0.500	0.500	0.495	0.998	0.833	Maternal death
Weighted avg.	0.854	0.583	0.846	0.854	0.850	0.281	0.850	0.907	
TAN	0.984	0.696	0.918	0.984	0.950	0.422	0.791	0.959	Normal
	0.333	0.016	0.625	0.333	0.435	0.427	0.858	0.452	ICU hospitalization
	0.000	0.000	0.000	0.000	0.000	0.000	0.580	0.200	Hemorrhagic complications
	1.000	0.000	1.000	1.000	1.000	1.000	1.000	1.000	Maternal death
Weighted avg.	0.907	0.619	0.870	0.907	0.885	0.415	0.792	0.901	
AODE	0.967	0.652	0.921	0.967	0.944	0.394	0.864	0.981	Normal
	0.400	0.021	0.600	0.400	0.480	0.458	0.888	0.474	ICU hospitalization
	0.000	0.010	0.000	0.000	0.000	-0.017	0.686	0.062	Hemorrhagic complications
	1.000	0.000	1.000	1.000	1.000	1.000	1.000	1.000	Maternal death
Weighted avg.	0.898	0.581	0.872	0.898	0.883	0.393	0.862	0.917	

Table 4 Performance evaluation of all Bayes-based machine learning techniques for the prediction of the delivery outcome for the fetus

	TPR	FPR	Prec.	Rec.	F-measure	MCC	ROC area	PRC area	Class
NB	0.947	0.321	0.894	0.947	0.920	0.668	0.867	0.929	Normal
	0.581	0.093	0.625	0.581	0.602	0.502	0.803	0.578	ICU hospitalization
	0.300	0.005	0.750	0.300	0.429	0.459	0.949	0.590	Neonatal death
Weighted avg.	0.839	0.257	0.831	0.839	0.830	0.623	0.858	0.839	
TAN	0.928	0.377	0.876	0.928	0.901	0.587	0.846	0.929	Normal
	0.442	0.111	0.514	0.442	0.475	0.350	0.763	0.422	ICU hospitalization
	0.300	0.021	0.429	0.300	0.353	0.332	0.926	0.451	Neonatal death
Weighted avg.	0.795	0.304	0.778	0.795	0.785	0.525	0.832	0.799	
AODE	0.961	0.358	0.885	0.961	0.921	0.665	0.857	0.926	Normal
	0.488	0.074	0.636	0.488	0.553	0.459	0.787	0.551	ICU hospitalization
	0.400	0.015	0.571	0.400	0.471	0.456	0.949	0.511	Neonatal death
Weighted avg.	0.834	0.282	0.817	0.834	0.822	0.612	0.847	0.827	

$$Recall = \frac{TP}{TP + FN} \tag{8}$$

The AODE classifier presents the best results in terms of precision (0.872) and the TAN classifier in terms of recall (0.907) for the maternal outcome, whereas the TAN classifier presents the best results for the outcome of the fetus, (0.831) and (0.830), respectively. All classifiers show excellent TP rates. However, the "normal" class for the pregnant woman outcome shows particularly high FP rates. This high probability occurs because the different disorders present the same risk factors and/or symptoms, and the diagnostic hypotheses are occasionally not fully formulated. Precision and recall provide additional information regarding the classifier performance. By combining the information from these two measurements using a harmonic means, it is possible to determine another important indicator, namely, the F-measure. For the F-measure, the TAN classifier shows better results for the outcome of the pregnant woman (0.885), as well as for the outcome of the fetus (0.830). That is, these ML techniques indicate a better relationship between precision and recall. Equation 9 is the formula used for this indicator.

$$F\text{-}measure = \frac{2}{\frac{1}{precision} + \frac{1}{recall}} \tag{9}$$

The Matthews correlation coefficient (MCC) represents a quality measurement that returns a value between − 1 and + 1, where a coefficient of + 1 accounts for a great prediction, 0 accounts for a mean random prediction, and − 1 denotes a disagreement between the prediction and observation. This indicator summarizes the quality (and efficiency) of the confusion matrix in a single numerical value to be compared among the different approaches. For this coefficient, the TAN classifier shows better results for the outcome of the pregnant woman (+ 0.415), as well as for the outcome of the fetus (+ 0.623). All proposed classifiers have an MCC between 0 and + 1, which indicates that these techniques are excellent predictors. However, the TAN classifier represents a unique approach showing excellent results for both classes. Equation 10 shows the formula for calculating the MCC.

$$MCC = \frac{TP \times TN - FP \times FN}{\sqrt{(TP + FP)(TP + FN)(TN + FP)(TN + FN)}} \tag{10}$$

An efficient way to demonstrate the relationship between the FP and TP rates, which is usually antagonistic, of the classifiers with continuous results are the receiver operating characteristic (ROC) curves (Bradley 1997). This method represents a powerful mechanism to measure and specify problems in the performance of a health diagnostics model. It allows studying the variations in the PF and TP rates for different cut-off values. An algorithm entirely incapable of predicting the normality or severity of parturition result would present an area under the ROC curve near to 0.50, whereas an algorithm with an area under the curve above 0.70 is considered as a model with reliable performance.

Figures 6 and 7 show the ROC curve for the normal class regarding the childbirth outcomes for the pregnant woman and fetus. For this important indicator, the AODE classifier shows a better relationship on average between the FP and TP rates than the other classifiers regarding the outcome for the pregnant woman (ROC area = 0.862). The NB classifier shows better results for the fetus outcome (ROC area = 0.858). The best values for the area under the ROC curve are the closest to 1. In this case, all of the proposed classifiers show excellent results, i.e., a remarkable relation between the FP (best values close to 0) and TP (best values close to 1) rates.

The precision-recall curves (PRCs) indicate the relationship between precision and recall. The main difference between this approach and the method involving the ROC curves is that the graphics of this second method will always be the same. PRCs are most useful for problems where predictive successes are more interesting than prediction errors. The machine learning approach resulting in the best performance for this indicator is the AODE classifier for the maternal outcome class (PRC area = 0.917), whereas for the fetal outcome class, on average, the NB classifier shows the best results (PRC area = 0.839).

The Kappa coefficient (k) represents a statistical measure of agreement, categorized at a nominal scale, and provides information regarding how distant the predictions are from the real values, thus indicating the reliability of

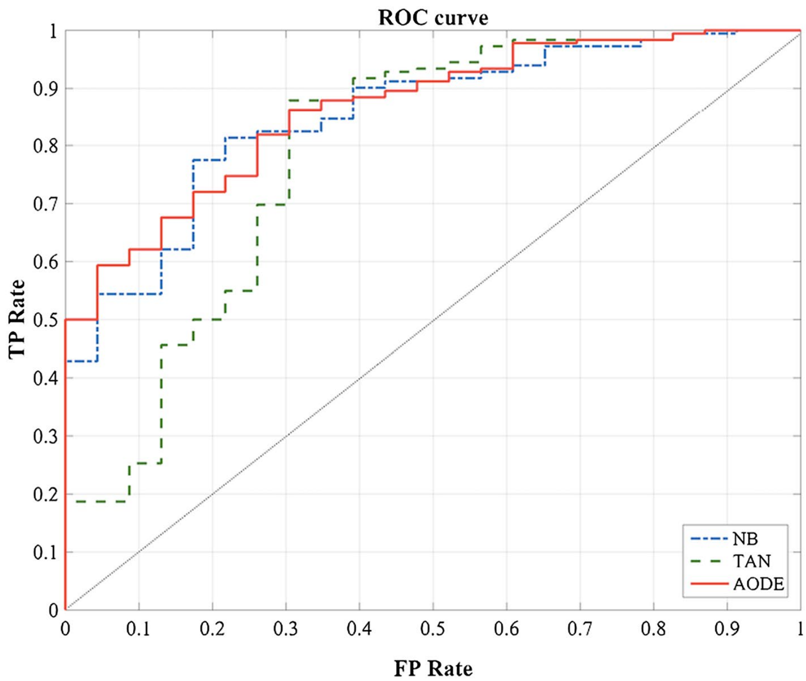

Fig. 6 Receiver operating characteristic curve for the “normal” class regarding the childbirth outcome for the pregnant woman

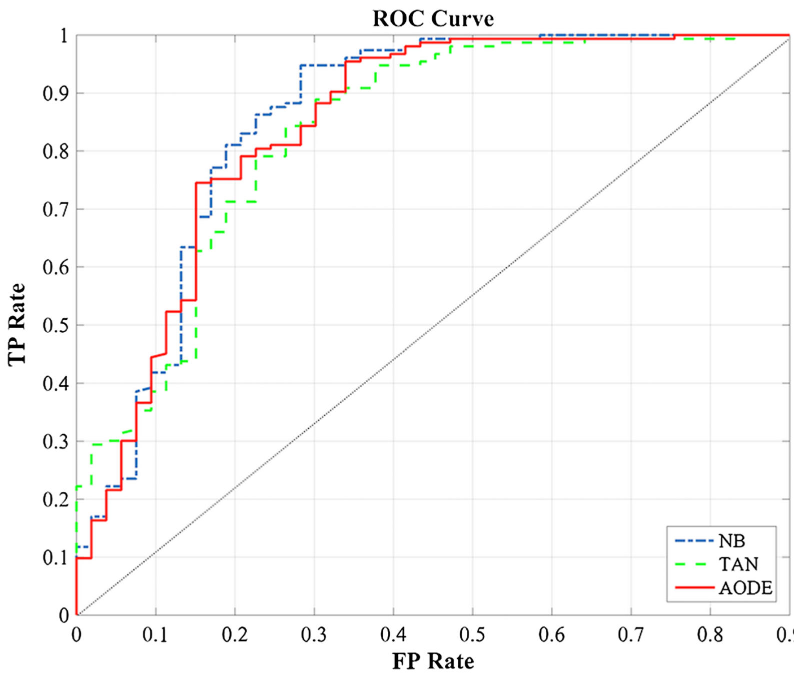

Fig. 7 Receiver operating characteristic curve for the "normal" class regarding the childbirth outcome for the fetus

the predictive method. Table 5 shows the nominal interpretation for this coefficient.

The results for this indicator show that the AODE classifier represents a unique approach that satisfies an excellent reliability condition for both predictive classes.

To demonstrate the model efficiency, Table 6 shows a performance comparison between the best model proposed in this work, namely the AODE classifier, and the results of recent similar studies.

After a detailed analysis of the classification results, obtained from the confusion matrix and several related indicators, all proposed approaches achieved excellent results for the childbirth outcome prediction of both the pregnant woman and fetus. In turn, this work concludes that the AODE classifier achieves the best performance results, and shows, on average, the best values for both classes.

6 Conclusion

Hypertensive disorders during pregnancy, particularly preeclampsia, account for the largest number of deaths of pregnant women worldwide. In developing countries, the rates of maternal and fetal deaths remain high despite UN efforts. The hospital conditions, a lack of equipment, and difficulties in achieving access to adequate medical care are the main factors composing these numbers. Through the MDG, health experts, along with the WHO, are spearheading innovative campaigns to provide technologies for the early diagnosis of such disorders. However, the difficulty of obtaining access to information is leading many women to suffer during pregnancy owing to a lack of adequate assistance. Among the recent advances in the paradigms of artificial intelligence (AI), approaches based on ML are highlighted as smart mechanisms capable of predicting risk situations that can

Table 5 Kappa coefficient (k) interpretation

k value	Concordance	Method	k	Class	Reliability
< 0.00	Poor	NB	0.2584	Maternal outcome	Regular
0.00–0.20	Low	TAN	0.3925		Regular
0.21–0.40	Regular	AODE	0.3934		Regular
0.41–0.60	Moderate	NB	0.5716	Fetal outcome	Moderate
0.61–0.80	Substantial	TAN	0.4582		Moderate
0.81–1.00	Almost perfect	AODE	0.5490		Moderate

Table 6 Performance comparison among the averaged one-dependence estimators classifier and other machine learning based approaches found in the literature

Authors	Model	Data	# of attr.	Prec.	TPR	1 − FPR
Moreira et al.	AODE	205	35	0.872	**0.898**	0.419
Pereira et al (2015)	DT	4236	26	0.839	0.883	0.801
	GLM			0.774	0.843	0.676
	SVM			0.621	0.856	0.279
	NB			0.747	0.843	0.630
Paydar et al (2017)	RBF	149	16	0.714	0.533	0.794
	MLP			0.909	0.800	**0.941**
Fergus et al (2018)	FLDA	552	12	0.910	0.530	0.700
	RF			0.930	0.590	0.570
	SVM			**0.950**	0.660	0.410

Best values are in bold

lead to serious problems in gestation. In this context, this paper presented several statistical techniques based on ML and DM that are capable of identifying arterial hypertension during pregnancy, as well as predicting different situations for the childbirth outcome, both for the pregnant woman and the fetus. These models, based on Bayes' theorem, are also able to alert physicians regarding the prediction of the possible health conditions for the newborn, both reliably and at an early stage. The AODE classifier showed very close results in comparison with other ML techniques and other recent studies. This approach achieved a precision of 0.872, F-measure of 0.883, ROC area of 0.862, and a regular classification in the Kappa coefficient for the outcome prediction of the pregnant woman. This method also presented a precision of 0.817, F-measure of 0.822, ROC area of 0.847, and a moderate classification in the Kappa coefficient for the outcome prediction for the fetus.

The importance of this proposal is related to the rapid access to information through mobile devices, allowing a constant observation of the pregnant woman's health status. This study presents a probabilistic model that provides real-time data analysis, resulting in greater agility in the decision-making process. This advantage is even more significant at critical moments that involve uncertainty since it is possible to predict how the decisions taken can influence the delivery outcome. The analysis of real-time data by mobile devices also allows efficient and continuous monitoring of high-risk pregnancies, since these situations can be identified at the moment they occur, avoiding further complications.

6.1 Future scope and limitations

Further work will focus on other techniques based on ML for the modeling of predictive mechanisms of complex diseases. Decision-tree based techniques, as well as techniques based on artificial neural networks, can be a major path toward increasing the model reliability, making it possible to assist health experts in reducing sequelae related to gestational diseases.

The limitation of the use of algorithms that use probability as part of their logic is directly related to the fact that, in health, the intrinsic dependence among specific attributes of a particular disease is challenging to be reached.

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Compliance with ethical standards

Conflict of interest The authors declare that they have no conflict of interest.

Ethical approval The ethics board approval was obtained by the Research Ethics Committee of the Maternity School Assis Chateaubriand of the Federal University of Ceará, Fortaleza, CE, Brazil under the certificate of presentation for ethical appreciation, number 66929317.0.0000.5050, and receiving assent with protocol number 2.036.062.

Informed consent Informed consent was obtained from all individual participants included in the study.

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Chapter 5

Evolutionary Radial Basis Function Network for Gestational Diabetes Data Analytics

This chapter consists of the following article:

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Evolutionary radial basis function network for gestational diabetes data analytics

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ABSTRACT

The development of smart decision support systems (DSSs) that seek to simulate human behavioral aspects is a major challenge for computational intelligence (CI). Artificial neural network (ANN) approaches have the ability to solve complex decision-making problems that involve uncertainty and a large amount of information in a fast and reliable way. The application of this evolutionary CI technique to analyze a large amount of data is an important strategy to solve several problems in healthcare management. This paper proposes the modeling, performance evaluation, and comparison analysis of an ANN technique known as the radial basis function network (RBFNetwork) to identify possible cases of gestational diabetes that can lead to multiple risks for both the pregnant women and the fetus. This method achieved promising results with a precision of 0.785, *F*-measure of 0.786, ROC area of 0.839, and Kappa statistic of 0.5092. These indicators show that this ANN-based approach is an excellent predictor for gestational diabetes mellitus. This research provides a comprehensive decision-making model capable of improving the care provided to women who are at a risk of developing gestational diabetes, which is the most common metabolic problem in gestation with a prevalence of 3–18%. Thus, this work can contribute to the reduction of maternal and fetal mortality and morbidity rates.

1. Introduction

The business intelligence (BI) concept that is applied to health includes a set of strategies, processes, methodologies, technologies, and tools focused on the management and creation of knowledge by collecting, organizing, analyzing, sharing, and monitoring data in order to support the management of hospitals [1]. That is, all the relevant information from a hospital is properly stored and classified by computational devices that use data mining (DM) and artificial intelligence (AI) methodologies to generate indicators that support the decision-making process. ANNs represent a paradigm of CI that brings together several approaches and techniques that seek to model information through the numerical representation of knowledge. Several knowledge areas apply ANN-based techniques in pattern recognition and learning of non-linear functions, *e.g.*, image processing [2–4], robotic vision [5,6], voice recognition [7,8], control [9], text categorization [10,11], and data mining [12,13], among others. In health management, it is possible to develop applications using ANNs that identify individuals with high-risk of developing chronic diseases. These applications are useful tools for planning and conceiving appropriate interventions, thereby reducing the number of unnecessary hospitalizations. The development of better diagnostic and treatment protocols enables an adequate readmissions analysis, and improves the utilization of resources in health institutions. Therefore, it is possible to determine the best treatment possibilities, using the valuable evidence from smart systems that support clinical decisions. The ANN approach has been used to solve the most pressing concern in the health sector, namely, the reduction of cost without decreasing the quality of care. This approach could

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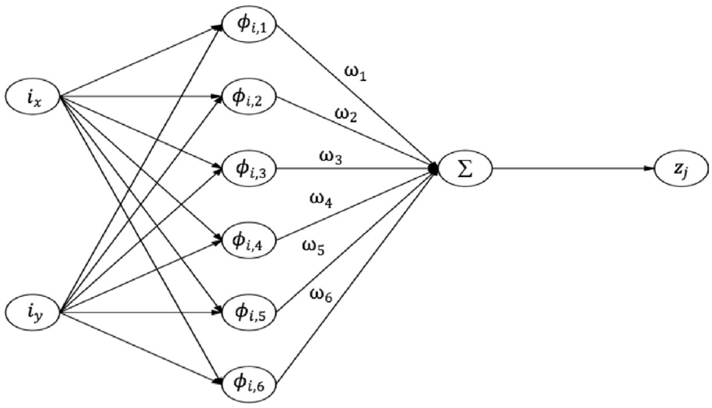

Fig. 1. Example of a radial basis function neural network.

reduce the patients duration of stay in hospitals, and avoid clinical complications that result from hospital infections. This practice improves the patients' outcome and provides valuable information to clinicians, thus reducing costs and increasing the quality of the services rendered [14]. It is also important to identify and understand patients with high health expenses [15]. According to Zheeng et al., ANNs can improve the various aspects of health care management including utilization and allocation of resources, length of hospital stay, and cost incurred at various hospitals, among others. CI techniques can add value to business intelligence (BI), if used in health management for all the financial and health associated costs [16]. In the accompaniment and diagnosis of chronic diseases, such as heart [17,18] and metabolic diseases [19–22], cancer diagnosis [23–25], and other significant illnesses, there exists a broad association to the solutions involving evolutionary CI techniques. Therefore, this paper proposes the application of a CI approach based on neural networks for the prediction of high-risk gestation caused by diabetes mellitus. Its primary goal is to improve pregnant women accompaniment and the governance of hospitals, thus reducing costs without decreasing the quality of the services provided.

Thus, the main contribution of this paper is the adaptation of the algorithm RBFNetwork, which is based on ANN, to the context of business intelligence area. This novel method uses a normalized Gaussian radial basis function network and the k-means clustering algorithm to provide the basis functions. Moreover, this approach learns by linear regression, and can reliably predict possible risks of gestational diabetes mellitus, when considering the output layer of the network. The main idea is to improve the efficiency in the approximation of the functions, simplifying the data treatment process, through a linear combination of translations of an appropriately chosen radial base function. Therefore, this novel method is capable of improving the predictive model accuracy through the solution of the well-know interpolation problem [26,27].

A performance evaluation comparing the presented method with other works in the literature is also presented. This evaluation demonstrates the reliability of this model and its contribution to the advance of the state-of-the-art in this field.

The remainder of this paper is organized as follows. Section 2 elaborates on related work about the topic focusing on the RBFNetwork method in its application on healthcare. Section 3 describes the adaptation of this ANN-based approach to predict the onset of gestational diabetes mellitus. The performance evaluation, comparison of various methods, and the analysis of the results of the proposed approach is presented in the Section 4. Finally, Section 5 concludes the paper and suggests further works.

2. Radial basis function network to predict diabetes mellitus in pregnancy care

RBFNetwork is an ANN that uses the distance between points for interpolation [28]. This method estimates the unknown values using neurons that use radial base activation functions, such as the Gaussian function shown in Eq. (1).

$$\phi(r) = e^{-(\epsilon \cdot r)^2} \quad (1)$$

The commonly used types of radial basis functions include $r = ||x - x_i||$, *i.e.*, where r represents the distance between the points. This method constructs approximation functions using Eq. (2).

$$y(x) = \sum_{i=1}^{N} w_i \phi(\left\|x - x_i\right\|) \quad (2)$$

The approximating function $y(x)$ represents the sum of N radial basis functions. Each function is associated with a different center x_i and weighted by a suitable coefficient w_i. The linear least squares matrix method estimates the weights w_i, considering that the approximating function is linear with respect to the weights. In the RBFNetwork, the point to be interpolated can activate almost every neuron, depending on the distance between the points and the radial basis function center for each neuron, which results in a greater or lesser contribution of the neuron to the final result. The radial basis function measures the activation. The closer the point to be interpolated is to the radial basis function center for a determined neuron, the more this neuron is activated. In other words, the further away from the neuron the radial basis function center is, the less activated the neuron is until it reaches zero activation. Fig. 1 shows an example for the architecture diagram of the RBFNetwork. There are two dimensions in the entry: the horizontal and vertical coordinates, x and y, summarized at the point i. For estimating the activation, the distance between the radial basis function center of each neuron and the input i is used. Then, a weight ω multiplies the resulting value and sums it to generate the output z_j.

RBFNetwork training defines the position of the radial basis function center for each neuron, the neuron quantity used, the radial basis function parameters (spread), and the weights ω using Eq. (2). Regarding the definition of the radial basis function center, the RBFNetwork frequently groups spatially close sample data and defines a single radial basis function to represent them. This method uses the k-means clustering algorithm that creates random groups and iteratively separates the elements based on spatial proximity [29]. Another way is to randomly position the radial basis function centers and adjust the weights and parameters so that they are sufficient for the interpolation to be adequate. When the radial basis function centers are positioned on the sample data, the calculation of weights is simpler; it can be done by solving a system of linear equations, since the same amount of sample and variable data have to be estimated. Each equation represents the interpolation described in Eq. (2), equated to a sampled data. Eq. (3) describes the system of linear equations.

$$\begin{cases} \sum_i \omega_i \phi_{1,i} = z_1 \\ \sum_i \omega_i \phi_{2,i} = z_2 \\ \vdots \\ \sum_i \omega_i \phi_{n,i} = z_n, \end{cases} \tag{3}$$

This system can be rewritten in a matrix form, as given by Eq. (4).

$$\overbrace{\begin{bmatrix} \phi_{1,1} & \phi_{1,2} & \cdots & \phi_{1,n} \\ \phi_{2,1} & \phi_{2,2} & \cdots & \phi_{2,n} \\ \vdots & \vdots & \ddots & \vdots \\ \phi_{n,1} & \phi_{n,2} & \cdots & \phi_{n,n} \end{bmatrix}}^{\Phi} \overbrace{\begin{bmatrix} \omega_1 \\ \omega_2 \\ \vdots \\ \omega_n \end{bmatrix}}^{\Omega_r} = \overbrace{\begin{bmatrix} z_1 \\ z_2 \\ \vdots \\ z_n \end{bmatrix}}^{Z} \tag{4}$$

The function ϕ is the activation function, ω represents the weights, n is the number of neurons, and $\phi_{a,b} = \phi(\left\| a - b \right\|)$, where a and b are the radial basis function centers of the two neurons. The symbols ϕ, Ω_r, and Z represent the elements of the equation in simplified form. It is necessary to invert the matrix ϕ and multiply it by the matrix Z to calculate the weights. Eq. (5) shows the process for calculating the weights ω.

$$\phi \cdot \Omega_r = Z \Rightarrow \Omega_r = \phi^{-1} Z \tag{5}$$

The RBFNetwork algorithm is widely used in the healthcare industry, and it has shown excellent results during performance evaluation. Chandrasekar et al. discussed the major challenges of the RBFNetwork in decreasing the computation time and complexity [30]. This research proposes a dynamic learning method based on the RBFNetwork architecture with the addition of neurons and sample deletion in health parameters to overcome these issues. The practical results of this method in terms of detection accuracy and time have been presented. In [31], Alsalamah et al. use the RBFNetwork algorithm with a Gaussian function as an inference mechanism to classify heart diseases. This work aims to reduce false classifications. The proposed method outperforms the well-known multilayer perceptron neural network approach, demonstrating a simpler and flexible structure. Al-Salamah and Amin implemented an RBFNetwork algorithm to classify the diagnostic data of heart patients [32]. This work uses the Gaussian distribution function as the kernel of radial basis functions to construct the network. In addition, it uses optimization algorithms, and the performance evaluation produced reasonable results. In [33], the authors discuss the three main modules of a recognition method for diagnosing heart diseases, namely, de-noising, feature extraction, and classifier modules. In this paper, the researchers experimented with different classifiers, including the RBFNetwork, in an arrhythmia database to classify the different heartbeats in ECG. The results showed that the proposed method reduces noise from the ECG signals accurately in comparison to classical methods. For the automatic diagnosis of cerebral vascular accidents, Ruano et al. proposed the use of RBFNetwork [34]. This work uses this ANN-based technique in a diagnosis system for automatic identification of cerebral vascular accident by computed tomographic images analysis. The construction of the classifier focuses on the feature selection aspect. This model achieved an excellent specificity and sensitivity. Therefore, the use of RBFNetwork algorithm in medical diagnosis can be useful.

The proposal presented in this work uses a Gaussian radial basis function, given in (1), and the k-means clustering method to calculate the distance of each element from the center of the appropriately chosen radial basis. The estimated output is the sum of the multiplication of the outputs of the hidden layer by their synaptic weights w, as shown in (2). The updating of weights in the network training is performed through the process shown in (5). This process is shown in Algorithm 1.

Algorithm 1. RBFNetwork pseudo-code.

```
begin
for a ⟵ 1 to n do
    for b ⟵ 1 to n do
        ϕ[a, b] ⟵ ϕ(‖x − x_i‖);
    end for
end for
Ω_r ⟵ MultiplyMatrices(InverseMatrix(ϕ),
Z);
for each point j of the points to be
interpolated do
    for a ⟵ 1 to n do
        ϒ[a] ⟵ ϕ(‖x − x_i‖);
    end for

R[j] ⟵ MultiplyMatrices(TransposedMatrix(ϕ_r),
ϒ);
end for
end
```

The algorithm proposed in this paper has some differences concerning traditional ANN proposals. The neurons in the intermediate layer have only radial basis activation functions, while other approaches have sigmoidal functions or other types. The proposed approach presents a single intermediate layer, rather than the multiple layers, such as the multilayer perceptron (MLP) algorithm [35], *i.e.*, the larger the distance between the input and the center, the lesser the neuron activation. In other ANN approaches, the activation is given by the scalar product between the input vector and the weight vector. Therefore, the RBFNetwork requires less training time and scoring, presenting a better predictive capability compared to other classical approaches.

The next section discusses gestational diabetes mellitus, the separation proposal of patients' data into variables and categories, and the neural network modeling approach.

3. Using the RBFNetwork learning algorithm to predict the onset of gestational diabetes mellitus

Gestational diabetes mellitus affects 2–18% of all pregnancies worldwide. The degree of glucose tolerance reduction defines gestational diabetes, whose onset or detection occurs during pregnancy. Its prevalence varies depending on the diagnostic criteria used and the population studied. Every year, there has been an increase in the number of gestational diabetes cases that are diagnosed. The highest prevalence is in high-risk populations [36]. The risk of maternal, fetal, and neonatal unfavorable outcomes increases with increased maternal glycaemia. The most frequent complications associated with gestational diabetes for the mother are cesarean section and preeclampsia, which can result in premature birth, macrosomia, shoulder dystocia, hypoglycemia, and perinatal death [37].

The costs related to this metabolic disease are very high. It is estimated that there has been an increase of 34% in the maternity care expense associated with this pathology [38]. The duration of hospital stay for patients with diabetes is directly related to

Table 1
Classification of the input variables into categories. For the gestational diabetes prediction problem, groups were selected for each of the input variables.

Input variables	# of categories	Categories
Number of pregnancies	3	[0, 2]; [3, 6]; [7, +∞[
Plasma glucose concentration a 2 h in an oral glucose tolerance test	6	[0, 89.1]; [89.2, 107.1]; [107.2, 123.1]; [123.2, 143.1]; [143.2, 165.1]; [165.2, +∞[
Diastolic blood pressure (mmHg)	3	[1, 76.1]; [76.2, 9.1]; [96.2, +∞[
Triceps skin fold thickness (mm)	3	[1, 25]; [26, 32]; [33, +∞[
2-H serum insulin (μU/ml)	4	[1, 110]; [111, 150]; [151, 240]; [241, +∞[
Body mass index (weight in kg/(height in m^2)	5	[1, 22.814]; [22.815, 26.84]; [26.841, 33.55]; [33.551, 35.563]; [35.564, + ∞ [
Diabetes pedigree function	5	[0, 0.244]; [0.245, 0.525]; [0.526, 0.805]; [0.806, 1.11]; [1.12, + ∞ [
Age (years)	5	[21, 24]; [25, 30]; [31, 40]; [41, 55]; [55, +∞[
Outcome	2	1, 0

hospitalization costs. The increase in the average duration of stay increases the hospitalization costs and the use of medical resources, and results in a considerable economic burden for both patients and hospitals. Therefore, it is necessary to control the duration of hospital stay through the identification and early treatment of this disease.

This study enrolled 394 women who were at least 21 years old. This dataset belongs to the National Institute of Diabetes and Digestive and Kidney Diseases (NIDDK) [39]. This research disregarded data with missing attributes. The women participating in this research were native people of the US, who live on the banks of the Gila and Salt rivers in the southern part of Arizona state. The Pima Indians have the highest rate of diabetes worldwide. This group also has elevated levels of obesity (approximately 70%) and hypertension. The mean values of the data for various categories were as follows. Pregnancies: 3.6 ± 3.3, plasma glucose concentration: 122 ± 33, diastolic blood pressure: 69.1 ± 18.1 mmHg, triceps skin fold thickness: 23.1 ± 14.7 mm, 2-h serum insulin: 102.1 ± 126.6 μU/ml, body mass index: 33.3 ± 7.6 weight in kg/(height in m^2), diabetes pedigree function: 0.5 ± 0.3, and age: 32.6 ± 11.5 years. Of these, 130 (33%) were at high risk of developing gestational diabetes mellitus. Table 1 summarizes the categories that were considered.

Table 2
Precision, recall, and *F*-measure values of the RBFNetwork algorithm where the class value "1" is interpreted as tested positive for gestational diabetes mellitus risk.

	TPR	FPR	Prec.	Rec.	*F*-measure	Class
	0.871	0.377	0.824	0.871	0.847	0
	0.623	0.129	0.704	0.623	0.661	1
Weighted avg.	0.789	0.295	0.785	0.789	0.786	

4. Performance assessment and results analysis

For the evaluation of a particular classification method and its comparison with different methods, one of the main criteria considered was the precision (Prec.). This indicator represents the ability of the model to predict a new instance class accurately. For the accuracy estimation, this study used the 10-fold cross-validation to classify the gestational diabetes database into training and test sets [40]. This evaluation method divides the database into k partitions of the same size. During each iteration, one of the k partitions that were generated forms the test set and the remaining $k - 1$ partitions form the training set. The precision corresponds to the average success percentage for k iterations. In practice, cross-validation with k equal to ten is the most commonly used method. This study also used the *F*-measure for indicating the imbalance among the classes. This indicator expresses the harmonic average between precision and recall (Rec.). The recall represents the fraction of relevant cases recovered. Table 2 shows these indicators as well as their weighted averages.

Table 3 compares the performance of the proposed method with similar works in literature. All these studies used the same database, but with different treatments for the data. Information that was not available is left blank in the table.

The results show that for the leading indicator, namely the *F*-measure, the method proposed in this work provides excellent performance in comparison with other methods in literature. Regarding precision, the RBFNetwork algorithm has a performance that is very close to that of the J48 tree-based classifier.

Another important indicator for the classifier evaluation is the area under the receiver operating characteristic curve (ROC Area). This method shows the trade-off between the true positive rate and

Table 3
Precision, recall and *F*-measure values in recent research using the same diabetes database.

	Method	TPR	FPR	Prec.	Rec.	*F*-meas.
Moreira et al.	RBFN	**0.789**	0.295	0.785	**0.789**	**0.786**
Sa'di et al. [41]	NB	0.770	0.317	0.767	0.770	0.768
	RBFN	0.743	0.381	0.735	0.743	0.737
	J48	0.765	0.243	**0.786**	0.765	0.771
Habibi et al. [42]	J48	–	**0.012**	0.717	0.694	0.705
Seera and Limb [43]	Hybrid	–	–	0.784	–	–
Christopher et al. [44]	PART	–	–	0.707	0.713	0.709
	FURIA	–	–	0.747	0.751	0.741
	JRIP	–	–	0.756	0.751	0.733
	DTable	–	–	0.702	0.709	0.703
Rahman and Afroz [45]	MLP	0.778	0.306	0.774	0.778	0.776
	FLR	0.670	0.662	0.582	0.670	0.572

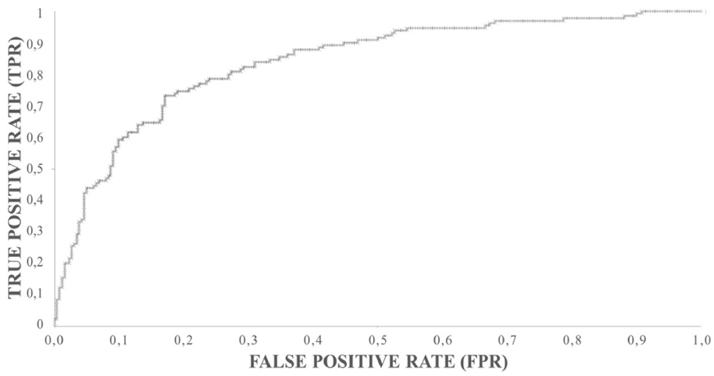

Fig. 2. ROC curve construction for the class "1".

Table 4
ROC area that represents a relation between the TP and FP rates.

	Method	TPR	FPR	ROC area
Moreira et al.	RBFN	**0.789**	0.295	0.839
Sa'di et al. [41]	NB	0.770	0.317	0.845
	RBFN	0.743	0.381	0.764
	J48	0.765	0.243	0.743
Habibi et al. [42]	J48	–	**0.012**	**0.875**
Seera and Limb [43]	Hybrid	–	–	0.732
Christopher et al. [44]	PART	–	–	–
	FURIA	–	–	–
	JRIP	–	–	–
	DTable	–	–	–
Rahman and Afroz	MLP	0.778	0.306	0.813
	FLR	0.670	0.662	0.504

Table 5
Kappa coefficient for the RBFNetwork algorithm.

Kappa coefficient value (k)	Concordance level
<0	There is no agreement
0–0.20	Minimal agreement
0.21–0.40	Reasonable agreement
0.41–0.60	Moderate agreement
0.61–0.80	Substantial agreement
0.81–1.0	Perfect agreement

the false positive rate of a classifier. TPR indicates the proportion of positive instances that are correctly predicted. FPR measures the percentage of negative instances that are incorrectly classified as positive. The ideal rate for these indicators is $TPR = 1$ and $FPR = 0$. Table 4 presents the performance comparison based on this indicator.

Fig. 2 shows the ROC curve for the class "1", *i.e.*, pregnant women who have a significant probability of developing gestational diabetes mellitus during pregnancy. The models that present an ROC curve closer to the point (0, 1) are considered to be excellent predictors.

The kappa coefficient (k) is a statistical method of performance evaluation that indicates the level of agreement among the datasets. Eq. (6) shows the formula for calculating this indicator.

$$k = \frac{p_o - p_e}{1 - p_e} \tag{6}$$

where p_o is the relative acceptance rate and p_e represents the hypothetical acceptance rate. Table 5 lists the different agreement (or reproducibility) levels.

The model proposed in this work has a kappa coefficient $k = 0.5092$, *i.e.*, the proposed algorithm has a moderate concordance. This indicator gives an idea of how far the observations deviate from the expected results, thus indicating how legitimate the interpretations are.

Fig. 3 shows the performance of the proposed method based on the ROC area, TPR, and FPR indicators, in relation to the number of cases in the database. This chart indicates that the increase in ROC area and TPR is related to the increase in the quantity of data (the best values are closest to 1). The FPR decreases with an increase in the amount of data in the dataset (the best values are closest to 0).

It represents a significant result for very large or complex datasets that traditional data-processing applications still cannot handle. This fact indicates the importance of the development of Big Data platforms and applications related to this novel concept. The current trend indicates that traditional data warehouse-based BI tools will migrate to Big Data Analytics technologies.

5. Conclusion and future work

This paper proposed an algorithm based on ANN (known as RBFNetwork) in business intelligence, which uses a normalized Gaussian radial basis function network. This approach uses the k-means clustering algorithm to provide the basis functions and learns by performing linear regression on the output layer of the network to predict possible gestational diabetes risk cases reliably. This CI method can support hospital management in several ways. The main contribution of this approach is that it provides the possibility of handling a large amount of data to find useful results that support health experts in the decision-making process.

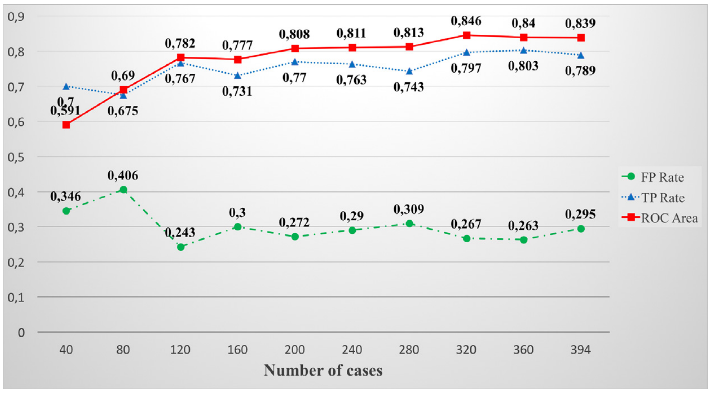

Fig. 3. ROC curve construction for the class "1".

Gestational diabetes mellitus is responsible for early maternal and fetal mortality. The worsening of health problems related to chronic diseases, such as gestational diabetes mellitus, and the lack of prevention programs, increase the number of amputations and hospitalization costs. Therefore, one of the most relevant aspects of this work is an attempt to reduce the impact of this disease on hospital management by providing the knowledge needed for health policy management and planning that can bring improvements to both hospitals and pregnant women. This work presented a robust algorithm to solve the problems related to a significant amount of data in uncertainty moments. This approach can provide health managers with valuable information, and combined with the physicians experience of previous cases, they can identify cases that could induce a risk to pregnancy. The RBFNetwork algorithm achieved excellent results in its performance evaluation using a database with information about symptoms and risk factors related to gestational diabetes. It achieved a precision of 0.785, *F*-measure of 0.786, and area under ROC curve of 0.839. Compared with the other studies in literature, this method, which implements a normalized Gaussian radial basis function network using the k-means clustering algorithm, is a powerful prediction tool. The Kappa coefficient showed the level of agreement for this classifier, *i.e.*, and the authenticity of the interpretations of this algorithm. This approach achieved a moderate concordance degree with $k = 0.5092$, which is considered a good result.

Over the years, there has been a general advance in prenatal care, especially in the area of gestational diabetes. Pregnant women should be encouraged to change their lifestyle, with appropriate diet, prevention of weight gain, and maximal metabolic control. We believe that the decrease in the percentage of women with gestational diabetes reflects the joint effort of the management staff, experts on healthcare, and pregnant women in the improvement of pregnancy care by controlling chronic diseases.

The study of other ANN approaches, such as simple logistic, multilayer perceptron, sequential minimal optimization, support vector machines, among others are suggested for further research. Research on other pregnancy-related diseases (e.g., hemorrhages and pregnancy-specific hypertensive crises) is also strongly recommended.

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Chapter 6

Neuro-fuzzy Model for HELLP Syndrome Prediction in Mobile Cloud Computing Environments

This chapter consists of the following article:

Neuro-fuzzy Model for HELLP Syndrome Prediction in Mobile Cloud Computing Environments

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Neuro-fuzzy model for HELLP syndrome prediction in mobile cloud computing environments

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Summary

The exchange of information among health professionals is a common practice among clinics, laboratories, and hospitals. Cloud-based clinical data exchange platforms enable valuable information to be available in real time and in a secure and private manner. The increasing availability of data in health information systems allows specialists to extract knowledge using pattern recognition techniques for the identification and prediction of risk situations that could lead to severe complications for a patient. Hence, this paper proposes the use of a neuro-fuzzy machine learning technique for predicting the most complex hypertensive disorder in pregnancy called HELLP syndrome. This classifier serves as an inference mechanism for cloud-based mobile applications, for effective monitoring through the analysis of symptoms presented by pregnant women. Results show that the proposed model achieves excellent results regarding several indicators, such as precision (0.685), recall (0.756), the F-measure (0.705), and the area under the receiver operating characteristic curve (0.829). This technique can accurately predict situations that could lead to the death of both a mother and fetus, at any location and time.

KEYWORDS

big data analytics, cloud computing, hypertensive disorders, machine learning, mobile health, pregnancy

1 | INTRODUCTION

The rapid development of data processing and storage technologies and increasing spread of Internet access have made computing resources less costly, more powerful, and ubiquitously available.[1] These technological trends have enabled the emergence of a novel computation paradigm called cloud computing in which resources such as processing, storage, and communication capacity are made available in the form of services and used according to specific user demands.[2-4] In parallel to this growth, the use of smart mobile devices, such as tablets and smartphones, has increased in prominence and popularity over recent years.[5] In this sense, cloud computing can provide computational resources such as servers, networks, storage, applications, and services to these devices in a flexible and agile manner, with less management or interaction effort with the service provider required.[6] In this context, the mobile cloud computing (MCC) paradigm has emerged, which aims to provide computational resources from the cloud to extend the capacities of mobile devices. The leading technique in this paradigm is the offloading of applications. This method consists of partitioning a task into components, which can either run locally on a mobile device or using virtualized resources in the cloud. The main idea is that application segments that require intensive processing are moved to the cloud, while small tasks are performed on the mobile device.[7] By employing this method, a user can execute more complex applications and save battery power.

Several health organizations, such as hospitals, clinics, and health plan providers, are seeking to incorporate the practice of electronic health (e-health) strategies for service integration and process digitization.[8,9] The most significant effort in this field has been to develop a single database such that electronic patient records (EPRs) can be accessed online.[10] These are initiatives that require the intensive use of novel technologies, such as the Internet of Things (IoT),[11] mobility,[12] big data analytical tools[13] for handling large volumes of data, and cloud computing for service improvement and cost reduction.[14] E-health seeks to achieve digital healthcare transformation and adopt novel information and communication technologies (ICTs) to improve organizational processes, in order to help medical staff become more proactive. The leading idea is to equip health institutions for the more efficient management of electronic health records (EHRs), prescriptions, diagnoses, and communications among organizations.[15] Data storage and information integrated into a real-time system represents a significant benefit of e-health in the cloud.[16] This method allows the development of big data projects for more assertive decision making. Therefore, the remote patient monitoring through cloud-based mobile devices permits physicians to provide personalized care, principally in the management of complex diseases.

In this sense, with the rapid advancement of cloud-assisted mobile computing paradigms medical professionals can employ these technologies for remote patient monitoring. These novel opportunities allow specialists and health organizations to innovate in the field of patient care, whether in post-hospital monitoring or the management of symptoms of chronic diseases.[17-19] Preventive and prophylactic actions become less complicated with the adoption of more robust applications and monitoring devices, which can be easily integrated into hospitals or clinics, thus improving the obtained results. The significant advantage of using technologies based on mobile cloud-assisted paradigms is in the monitoring of patients suffering from chronic diseases, such as eclampsia and HELLP syndrome (**H**emolysis, **E**levated **L**iver enzymes, and **L**ow **P**latelet count), which have a predefined treatment course. However, these conditions require the closest management of highly specialized professionals. A patient's displacement to a healthcare institution would mean a high increase in the cost of their treatment. The evaluation of new symptoms, adverse reactions, and pregnancy assessments has been becoming less onerous for pregnant women through telemedicine.[20] Current systems use conventional algorithms for the early prediction of HELLP syndrome. Therefore, the main idea of this study is to propose a hybrid algorithm capable of handling both numerical and nominal variables, maintaining the efficiency of these systems as well as their accuracy. Cloud-based mobile care solutions are exceptional when it comes to providing valuable information regarding treatment feedback. The main contributions of this paper are as follows:

- a comprehensive review of the state-of-the-art of MCC in healthcare;
- a study of algorithms based on a neuro-fuzzy approach and their use in the prediction of chronic diseases related to pregnancy;
- a performance assessment of different techniques using a cross-validation method and its related indicators; and
- a comparison of the proposed model with similar studies, to demonstrate the efficiency of the proposed approach.

The remainder of this paper is organized as follows. Section 2 elaborates on related work on this topic, focusing on artificial neural networks (ANNs) and fuzzy logic-based algorithms applied in healthcare. Section 3 describes the adaptation of a hybrid algorithm based on ANNs and fuzzy logic to predict HELLP syndrome in high-risk pregnancies, which can lead to severe complications for both the mother and newborn. A performance evaluation, comparison of various methods, and analysis of the results for the proposed approach are presented in Section 4. Finally, Section 5 concludes this paper and suggests further work.

2 | RELATED WORK

Real-time clinical data analysis and sharing represents a new trend toward the development of large databases. The availability of these databases to researchers, which involves the entire medical history of an individual, contributes to significant advances in medical research. However, EHRs, which store this massive amount of medical information, must guarantee confidentiality, security of data access and transmission, interoperability, and other conditions. Regarding the processing of large volumes of data, cloud computing provides the necessary infrastructure to support novel research initiatives, principally owing to its ability to process a large volume of data in real time, which represents a relevant research topic for the big data concept.[21-23] The leading studies concerning mobile and cloud computing concepts and big data analytics are related to medical diagnosis,[24-26] telemonitoring,[27] and image processing,[28,29]

Concerning medical diagnosis, Chang et al developed an ML-based model, using ontology and a Bayesian classifier, to predict problems related to depression.[24] This study used a multi-agent system to develop the proposed approach for a mobile cloud-assisted environment. Despite the authors not presenting a sensitivity analysis, the integration of an ontology-based method and statistical approach is promising for assessing diseases related to mental conditions. Bourouis et al[25] suggested a novel smart decision support system (DSS) integrated with a little lens for eye examinations and the diagnosis of problems related to vision. This cloud-assisted mobile diagnosis system used an ANN-based approach to analyze retinal images using the mobile lens to identify diseases related to the retina. For the performance evaluation of this proposal, the study considered several medical ophthalmology databases. The results showed that the model could accurately identify various retinal diseases. For the diagnosis and monitoring the Parkinson's disease, Al Mamun et al presented a cloud-based system for identifying and monitoring patients in remote areas who suffer from this condition.[26] A performance assessment showed that this novel approach is capable of identifying Parkinson's disease with high precision.

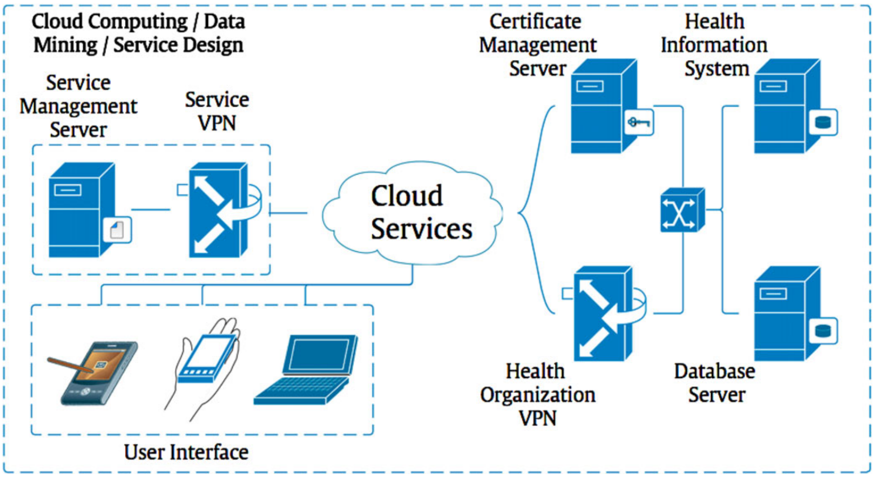

FIGURE 1 The proposed architecture for mobile cloud services in healthcare

The use of mobile cloud-assisted technologies could enable further healthcare services for patients, principally in remote areas where such services are practically inaccessible.

The HELLP syndrome is a rare obstetric complication, which is not well understood and difficult to diagnose, occurring during pregnancy or postpartum, and can result in the death of a pregnant woman. Its main characteristics are hemolytic anemia, elevated liver enzymes, and low platelet count.[30] Usually, HELLP syndrome occurs in conjunction with the worsening of the condition in women who have suffered from preeclampsia, ie, hypertension caused by pregnancy. According to the World Health Organization (WHO), it is estimated that 8% of pregnant women with preeclampsia develop this syndrome.[31] This number indicates that, in general, the problem affects between 0.2% and 0.6% of pregnancies worldwide. At first, the signs and symptoms of this complication can be confused with severe preeclampsia, ie, increased blood pressure and bloating. When the condition worsens, it results in acute pulmonary edema, renal insufficiency, cardiac failure, hemorrhage, and rupture of the liver, leading to maternal death. When the disease is diagnosed through laboratory and clinical examinations, the indicated treatment is to interrupt gestation, regardless of the gestational phase, so that the pregnant woman's general condition can be corrected. Depending on the gestational age of the fetus it often does not survive.

Archibong et al presented a point-of-care mobile-based platform to identify the hemolysis level of a pregnant woman through color measures of blood plasma.[32] In this mobile application, the camera captures images from a capillary tube, and the application examines the color segments of the cell-free plasma layer, based on a calibration curve. Considering that the hemolysis level represents an essential indicator for HELLP syndrome, the aggregation of other clinical indicators related to this syndrome may contribute to its early identification. Konnaiyan et al[33] presented a novel mobile-based colorimeter to measure glucose and protein concentrations in biological samples, combining the image processing of a mobile application with a 3D-printed sample holder. Results showed that the mobile-based colorimeter represents a powerful tool for classifying reagent strip pads.

The studies presented in this section related to this research theme have served as a basis for the solution proposed in this work. Figure 1 presents the proposed architecture of the model using a neuro-fuzzy algorithm for the early identification of HELLP syndrome, which serves as the inference mechanism for a cloud-assisted smart mobile system.

The next section discusses a neuro-fuzzy model that exploits the characteristics of ANNs, such as the ability to learn and generalize, combined with the characteristics of fuzzy logic, which deals logical reasoning based on association functions.

3 | NEURO-FUZZY NETWORKS FOR THE IDENTIFICATION AND PREDICTION OF HYPERTENSIVE DISORDERS DURING PREGNANCY: A CASE-BASED STUDY OF HELLP SYNDROME

Fuzzy logic deals with a high-level computational rationale based on information obtained from experts and converted into linguistic variables.[34] However, diffuse inference systems cannot learn and adjust to new cases. The union of fuzzy inference systems with ANNs in a single integrated system is a promising approach for the construction of artificial intelligence (AI) systems.[35,36] The resulting integrated models, called neuro-fuzzy models, can combine parallel computation with the learning ability and close-to-human knowledge representation ANNs and analytical abilities of fuzzy systems.[37,38]

The neuro-fuzzy model proposed in this work is based on the algorithm proposed by Jang, called an adaptive network-based inference system (ANFIS), which is a multi-layered ANN that is functionally equivalent to the Takagi-Sugeno diffuse inference system.[39-41] Each system layer is associated with a particular step of the inference process. A Takagi-Sugeno diffuse inference system is constituted of five layers. The first hidden layer

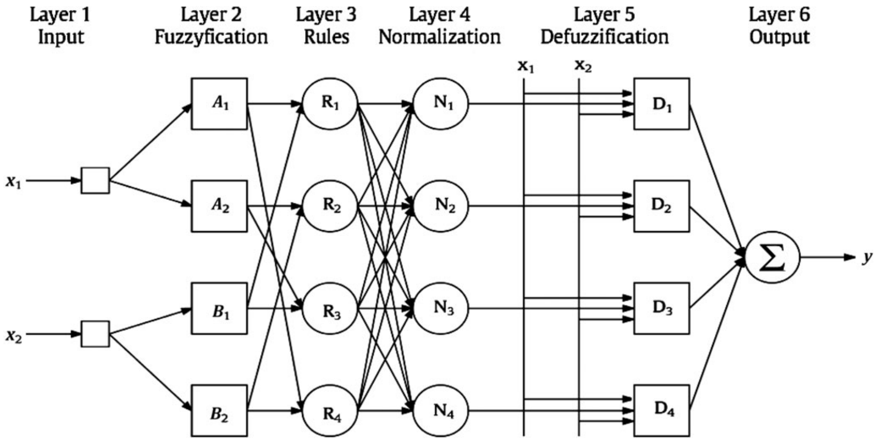

FIGURE 2 Adaptive network-based fuzzy inference system scheme

is responsible for mapping the input variables to the membership functions. The standard operator *T* is applied to the second hidden layer to calculate the antecedents of the rules. The third hidden layer normalizes the degree of compatibility of the entries followed by the fourth hidden layer, where the consequences of the rules are determined. The output layer calculates the global output as the sum of all the signals arriving at this layer. The ANFIS architecture uses the back-propagation learning algorithm to determine the parameters of the input membership functions and the algorithm of the least squares method to determine the parameters in the consequent ones. Each step of the learning algorithm presents two parts. In the first step, the input data pairs are propagated, and the consequent parameters are calculated using the iterative algorithm of the least squares method, whereas the parameters of the premises are considered fixed. In the second part, the input data pairs are propagated again, and at each iteration, the back-propagation learning algorithm is used to modify the parameters of the premises, while the consequent ones remain fixed. This procedure is iterative. The ANFIS is usually presented as a six-layer feed-forward type ANN, as indicated in Figure 2. In this example, two inputs, x_1 and x_2, and one output, y, are considered. Two fuzzy sets represent each input, and a first-order polynomial gives the output.

The fuzzy sets A_1 and A_2 belong to the universal set X_1, the fuzzy sets B_1 and B_2 belong to the universal set X_2. This work considers four rules, described by Equations (1) to (4).

$$Rule\ \ 1: \quad if\ \ \{x_1 \in A_1, x_2 \in B_1\}, \quad then\ \ y = k_{10} + k_{11}x_1k_{12}x_2 \tag{1}$$

$$Rule\ \ 2: \quad if\ \ \{x_1 \in A_2, x_2 \in B_2\}, \quad then\ \ y = k_{20} + k_{21}x_1k_{22}x_2 \tag{2}$$

$$Rule\ \ 3: \quad if\ \ \{x_1 \in A_2, x_2 \in B_1\}, \quad then\ \ y = k_{30} + k_{31}x_1k_{32}x_2 \tag{3}$$

$$Rule\ \ 4: \quad if\ \ \{x_1 \in A_1, x_2 \in B_2\}, \quad then\ \ y = k_{40} + k_{41}x_1k_{42}x_2 \tag{4}$$

In the input layer, the neurons directly pass the external signal to the next layer. Equation (5) indicates the relationship between the input $x_i^{(1)}$ and output $y_i^{(1)}$ of a neuron *i* of the first layer.

$$y_i^{(1)} = x_i^{(1)} \tag{5}$$

In the fuzzification layer, the neurons perform the encoding of the inputs. In the model proposed in this study, the neurons of this layer use an activation function named the sigmoid function. However, any other function can be used as a pertinence function. Equation (6) specifies a sigmoid-type activation function.

$$y_i^{(2)} = \frac{1}{1 + \left(\frac{x_i^{(2)} - a_i}{c_i}\right)^{2b_i}} \tag{6}$$

Here, $x_i^{(2)}$ represents the input, $y_i^{(2)}$ represents the output of the neuron *i*, and the terms a_i, b_i, and c_i represent parameters that control the pertinence function.

In the rule layer, each neuron corresponds to a Takagi-Sugeno diffuse rule. A neuron receives the information from the coding layer as input and calculates each resulting term. The conjunction between the antecedent terms is performed by the product operator. Thus, the output of the neuron *i* from the third layer is obtained from Equation (7).

$$y_i^{(3)} = \prod_{j=1}^{k} x_{ji}^{(3)} \tag{7}$$

In the normalization layer, each neuron receives as input all of the outputs of the rule layer neurons and calculates the normalized value of each rule. This value represents the contribution of each rule to the final result. The output $y_i^{(4)}$ of each neuron i is indicated by Equation (8).

$$y_i^{(4)} = \frac{x_{ji}^{(4)}}{\sum_{j=1}^{N} x_{ji}^{(4)}} \tag{8}$$

In the fifth layer, called the defuzzification layer, each neuron is connected to its respective normalization neuron and receives the input signals x_1 and x_2. The decoding neuron calculates the value of the term resulting from a given rule. Equation (9) describes this process.

$$y_i^{(5)} = x_i^{(5)}[k_{i0} + k_{i1}x_1 + k_{i2}x_2] \tag{9}$$

Finally, the output layer is represented by a single neuron that sums the outputs of all neurons of the defuzzification layer, generating the total output of the algorithm. Equation (10) represents this sum.

$$y = \sum_{1}^{n} x_i^{(6)} \tag{10}$$

The neuro-fuzzy model uses the back-propagation algorithm to calculate the parameters of the antecedent terms of the rules, as shown in (6). This approach also uses the least-mean-squares algorithm to determine the parameters of the consequent terms, as shown in (9). Each iteration of the training consists of two steps. In the first step, the input data are propagated, and the parameters of the following terms are calculated according to the least-mean-squares algorithm. The terms of the previous parameters are set during this step. In the second step, the error rates are retro-propagated. In this manner, the back-propagation of the algorithm is applied to update the parameters of the antecedent terms. In this step, it is the parameters of the ensuing terms that are fixed. In the Takagi-Sugeno inference model, the output y is a linear function. Given the parameters of the pertinent functions and the set of inputs and outputs of training, a set of P linear equations can be defined, as indicated by Equation (11).

$$\begin{cases} y_d(1) = x_1^5(1)f_1(1) + x_2^5(1)f_2(1) + \cdots + x_n^5(1)f_n(1) \\ y_d(2) = x_1^5(2)f_1(2) + x_2^5(2)f_2(2) + \cdots + x_n^5(2)f_n(2) \\ \\ y_d(P) = x_1^5(P)f_1(P) + x_2^5(P)f_2(P) + \cdots + x_n^5(P)f_n(P) \end{cases} \tag{11}$$

Equation (12) rewrites this set of equations in matrix form.

$$y_d = Ak \tag{12}$$

Here, y_d is a vector of desired outputs, with dimension $P \times 1$; A represents a matrix of size $P \times n(m+1)$; and k is a vector of consequent parameters of dimension that is equal to $n(m+1) \times 1$. The set of parameters of the consequent terms is obtained from the pseudo-inverse matrix, which is indicated by Equation (13).

$$k^* = (A^T A)^{-1} A^T y_d \tag{13}$$

Once the parameters of the terms derived from the rules of inference have been determined, it is possible to determine the output vector y of the ANN. Furthermore, it is possible to calculate the error vector, as indicated by Equation (14).

$$e = y_d - y \tag{14}$$

From this vector of errors, it is possible to determine the variation of the antecedent terms. This variation is calculated as a function of the squared error E and the learning rate, as indicated in Equation (15).

$$\Delta a = -\alpha \frac{\delta E}{\delta a} \tag{15}$$

The model proposed in this study, combining the learning capacity of ANNs with the reasoning ability of fuzzy systems, can be used efficiently in the modeling of nonlinear dynamic systems, providing simpler models with fewer approximation errors. This approach allows expert knowledge to easily be incorporated into the structure of a system. At the same time, its connectionist structure avoids diffuse inference, which is a process that requires substantial computational effort.

4 | PERFORMANCE ASSESSMENT AND ANALYSIS OF RESULTS

This study considered 205 parturient women diagnosed with a hypertensive disorder during pregnancy. Of these, seven pregnant women presented HELLP syndrome. The data were collected during May and September of 2017, after project approval by the research ethics committee at the

Maternity School Assis Chateaubriand (from the Federal University of Ceará, Fortaleza, CE, Brazil), under the certificate of presentation for ethical appreciation, number 66929317.0.0000.5050 and receiving assent with protocol number 2.036.062.[42]

HELLP syndrome occurs in approximately one to two women per 1,000 pregnancies, in 4% to 12% of pregnant women with severe preeclampsia and in up to 11% of pregnant women with eclampsia. Most cases affect women with gestation between the 28th and 36th weeks.[43] The correct identification of signs, symptoms, and laboratory evaluation are strongly important for the correct identification of cases. The causes of HELLP syndrome are not yet completely understood, and it is currently considered an acute immunological rejection of the mother regarding the fetus. The clinical presentation of the syndrome is varied. Symptoms develop more frequently in the third trimester, but it is also possible that they occur in the second trimester or postpartum. Earlier conditions are usually of higher severity and are associated with a worse perinatal prognosis, prematurity, and maternal complications due to pregnancy interruption difficulties. Symptoms most commonly present as abdominal pain and exacerbated sensitivity in the epigastrium, right upper quadrant, or retro-sternal. Many patients also present nausea, vomiting, and fatigue and can be treated as having a non-specific viral disease or hepatitis, mainly if the enzymes aspartate aminotransferase (AST) and lactate dehydrogenase (LDH) are at very high levels. It is important to note that, although hypertension (PA > or = 140/90 mmHg) and proteinuria occur in approximately 85% of cases, these conditions may not be associated.

The diagnosis of HELLP syndrome is based on laboratory tests. It is suggested that these tests be conducted in all pregnant women with increased blood pressure, especially when preeclampsia is suspected. The severity of conditions and the importance of early diagnosis mean that the possibilities of these conditions should always be considered in pregnant women with hypertension, symptomatic or not. HELLP syndrome is associated with high maternal morbidity and mortality, and early diagnosis and treatment in specialized services reduces complications and fatal events. All of the following criteria are required for diagnosis: (a) microangiopathic haemolytic anemia with characteristic schizocytes in blood smear and other signs suggestive of haemolysis, including increased LDH or indirect bilirubin levels and decreased serum haptoglobin concentration (= 25mg/dL); (b) platelet count that is equal to or below 100,000 cells/μl; (c) serum LDH concentration that is equal to or greater than 600IU/l, or total bilirubin that is equal to or greater than 1.2mg/dL; and (d) serum AST concentration at or above 70IU/l.[44,45]

For a performance evaluation of the proposed neuro-fuzzy model, this paper considered the 10-fold cross-validation method.[46] The cross-validation technique consists in dividing the database into k parts or folds. Of these, $k-1$ folds are used for training, and one fold serves as a testing base. This process is repeated k times, where each part is used once as a set of tests. Then, the total correction is calculated by the average of the results obtained in each step, thus obtaining a quality estimate of the evaluated knowledge model, allowing a statistical analysis. From this evaluation methodology, a confusion matrix was created. This type of table allows the visualization of the performance of a learning algorithm.[47] Each column of the array represents the instances of a predicted class, while the rows represent the instances of an actual class. The elements that constitute the confusion matrix consist first of true positives (TPs), consisting of pregnant women who are at high risk of developing HELLP syndrome where the model classifies them as positive. Second, there are true negatives (TNs), where the classifier correctly rejects cases in which a patient has no risk of developing the syndrome. In this case, the risk is negative, and the model classifies it as negative. Third, there are false positives (FPs), also known as false alarms. In this case, the risk is negative. However, the classifier classifies the pregnant women as likely to develop the related disorder. Finally, there are false negatives (FNs), where the risk is positive, and the model classifies the pregnant women as not having a risk of developing HELLP syndrome. Table 1 shows the values obtained from the confusion matrix, related to the main performance evaluation indicators of predictive classifiers.

The main hypertensive disorders in pregnancy, which represent the predictive classifiers of this study, are as follows: O10—pre-existing hypertension complicating pregnancy, childbirth, and the puerperium; O11—pre-existing hypertensive disorder with superimposed proteinuria; O12—gestational edema and proteinuria (induced by pregnancy), without hypertension; O13—gestational hypertension (induced by pregnancy) without significant proteinuria; O14—gestational hypertension (induced by pregnancy) with significant proteinuria; O14.0—early preeclampsia (placental); O14.1—late pre-eclampsia; O15—eclampsia, O14.1—HELLP syndrome; and finally, O16—unspecified maternal hypertension.

TABLE 1 Performance evaluation of the neuro-fuzzy model used for the prediction of hypertensive disorders of pregnancy with a main focus on HELLP syndrome

	Precision	Recall	F-measure	Class
	0.818	0.643	0.720	O10
	0.931	0.794	0.857	O11
	0.000	0.000	0.000	O12
	0.714	0.952	0.816	O13
	0.333	0.077	0.125	O14.0
	0.736	0.967	0.836	O14.1
	0.692	0.600	0.643	HELLP syndrome
	0.000	0.000	0.000	O15
	0.000	0.000	0.000	O16
Weighted average	**0.685**	**0.756**	**0.705**	

Precision and recall are essential metrics that make it possible to evaluate the performance of classifiers for each class of a database. Precision represents the ability of the classifier to recognize the instances of one class of interest and reject the others, whereas recall represents the classifier's ability to recognize all instances of a class of interest. The F-measure is a harmonic average between the precision and recall. Equations (16) to (18) presents the mathematical models for these metrics.

$$Precision = \frac{TP}{TP + FP} \tag{16}$$

$$Recall = \frac{TP}{TP + FN} \tag{17}$$

$$F\text{-}measure = 2 \times \frac{Recall \times Precision}{Recall + Precision} \tag{18}$$

Another important performance indicator is the receiver operating characteristic (ROC) curve. This curve represents a technique for visualizing and selecting classifiers based on their performance. This evaluation approach has been widely employed in the literature because, in general, evaluating only the success rate of a classifier is a very simple metric.[48] The ROC curve is very useful in dealing with domains where classes are unbalanced and have different classification costs per class. The ROC curve represents the relationship between the TP and FP rates. To compare classifiers, it is recommendable to reduce the ROC curve to a single scalar by calculating the area under the curve (AUC). Table 2 presents the results for this indicator.

Figure 3 shows the ROC curve for the class related to HELLP syndrome. Classifiers with curves closest to point (0, 1) are considered excellent predictors, ie, the more accurate the test, the closer its ROC curve is to the upper-left corner of the graph, which indicates a test threshold with excellent sensitivity and a low FP rate. The closer the ROC curve is to the upper left corner, the larger is the AUC.

To demonstrate the feasibility of the proposed semantic model, Table 3 compares similar approaches used recently in the literature for pregnancy care, using the metrics of the confusion matrix.

TABLE 2 The area under the curve related to each predictive class of hypertensive disorders during pregnancy

	TP Rate	FP Rate	AUC	Class
	0.643	0.010	0.814	O10
	0.794	0.012	0.905	O11
	0.000	0.000	0.500	O12
	0.952	0.043	0.975	O13
	0.077	0.010	0.567	O14.0
	0.967	0.283	0.869	O14.1
	0.600	0.021	0.807	HELLP syndrome
	0.000	0.000	0.487	O15
	0.000	0.000	0.500	O16
Weighted average	**0.756**	**0.136**	**0.829**	

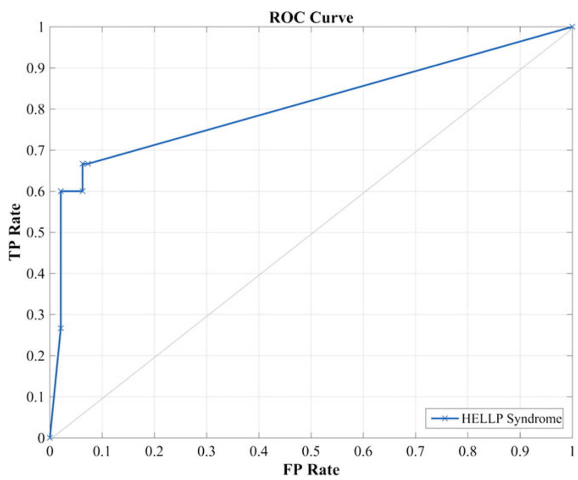

FIGURE 3 Receiver operating characteristic curve for the HELLP syndrome class

TABLE 3 Performance comparison of recent similar methods related to pregnancy care

	Method	TP Rate	FP Rate	Precision
Moreira et al	Neuro-fuzzy	0.756	0.136	0.685
Paydar et al[49]	RBFNetwork	0.533	0.206	0.714
	MLP	0.800	**0.059**	**0.909**
Pereira et al[50]	GLM	**0.890**	0.709	0.586
	SVM	0.856	0.721	0.621
	DT	0.883	0.200	0.839
	NB	0.843	0.370	0.747

These results indicate that the radial basis function network (RBFNetwork) algorithm presents good precision, following almost all other compared methods; however, a TP rate is below the average compared with the other methods. This behavior is due to the classification randomness, which decreases its reliability. This approach also presents a high FP rate, ie, a high false alarm rate. Likewise, the generalized linear model (GLM), support vector machine (SVM), decision tree (DT), and naive Bayes (NB) classifiers present the same characteristic. Concerning the ANN-based algorithm known as MLP, which performs the best results, the neuro-diffuse model has better computational performance, although it presents a slightly lower TP rate. The performance evaluation shows that the proposed neuro-fuzzy-based model is equivalent to algorithms based on ANNs, eg, RBFNetwork, MLP, and SVM. The approach proposed in this work also achieves a performance close to decision tree-based algorithms, eg, DT and statistically based models, as is the case of the NB classifier, among others. The model proposed in this work achieves an excellent FP rate, ie, a low false alarm rate. For this indicator, the values closest to zero are considered ideal.

5 | CONCLUSION AND FUTURE WORK

Regarding the growth of mobile computing, new leading research is being conducted in the area of knowledge considered here, attempting to minimize errors and increase efficiency. The idea has emerged of computing models in the cloud, and subsequently, new paradigms have emerged regarding MCC. The union of the two areas of mobile and cloud computing represents the application of cloud computing in mobile computing, with the aim of filling some gaps in this area. MCC has enhanced the processes and storage that would previously be available on a mobile device, sending them to a robust hardware structure on the cloud, that is, the hardware of the cloud servers. MCC represents an attempt to enhance applications of mobile computing, and it may be applicable to almost all fields. In some areas, MCC can be more effectively applied, introducing further advantages. Mobile devices are evolving quickly, along with their deployment in health services. Models based on long-term real-time health monitoring meet the demands of professionals who need to monitor patient health remotely. Thus, the deployment of mobile devices in various healthcare systems exploits several significant features for a quality medical health system.

A suggestion for further work is to adopt other types of models based on fuzzy logic and ANNs to precisely classify data. It is strongly suggested to develop more hybrid classifiers, targeting the care of pregnant women. Developing a smart DSS that can reach remote areas is also a challenge to be addressed. Other approaches to classifying and clustering data also require further study.

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Chapter 7

Nature-Inspired Algorithm for Training Multilayer Perceptron Networks in e-health Environments for High-Risk Pregnancy Care

This chapter consists of the following article:

Nature-Inspired Algorithm for Training Multilayer Perceptron Networks in e-health Environments for High-Risk Pregnancy Care

Mário W. L. Moreira, Joel J. P. C. Rodrigues, Neeraj Kumar, Jalal Al-Muhtadi, and Valery Korotaev.

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PATIENT FACING SYSTEMS

Nature-Inspired Algorithm for Training Multilayer Perceptron Networks in e-health Environments for High-Risk Pregnancy Care

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Abstract

Nature presents an infinite source of inspiration for computational models and paradigms, in particular for researchers associated with the area known as natural computing. The simultaneous optimization of the architectures and weights of artificial neural networks (ANNs) through biologically inspired algorithms is an interesting approach for obtaining efficient networks with relatively good generalization capabilities. This methodology constitutes a concordance between a low structural complexity model and low training error rates. Currently, complexity and high error rates are the leading issues faced in the development of clinical decision support systems (CDSSs) for pregnancy care. Hence, in this paper the use of a biologically inspired technique, known as particle swarm optimization (PSO), is proposed for reducing the computational cost of the ANN-based method referred to as the multilayer perceptron (MLP), without reducing its precision rate. The results show that the PSO algorithm is able to improve computational model performance, showing lower validation error rates than the conventional approach. This technique can select the best parameters and provide an efficient solution for training the MLP algorithm. The proposed nature-inspired algorithm and its parameter adjustment method improve the performance and precision of CDSSs. This technique can be applied in electronic health (e-health) systems as a useful tool for handling uncertainty in the decision-making process related to high-risk pregnancy. The proposed method outperformed, on average, other approaches by 26.4% in terms of precision and 14.9% in terms of the true positive ratio (TPR), and showed a reduction of 35.4% in the false positive ratio (FPR). Furthermore, this method was superior to the MLP algorithm in terms of precision and area under the receiver operating characteristic curve by 2.3 and 10.2%, respectively, when applied to the delivery outcome for pregnant women.

Keywords Clinical decision support systems · Nature inspired computing · Machine learning · Artificial neural networks · Optimization · e-Health

This article is part of the Topical Collection on *Patient Facing Systems*

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Introduction

In the development of novel computational techniques that use nature as a source of inspiration for computation, concepts, principles, and mechanisms observed in nature are used to find efficient and elegant solutions for solving a wide variety of high complexity issues. Whereas traditional computational techniques cannot solve many of these problems efficiently, biologically inspired methodologies, such as optimization [1] and pattern recognition problems [2], can. A recently introduced research topic involves solutions for adjusting parameter values of machine learning (ML) techniques by using biologically inspired techniques [3]. The main concepts related to these methods are swarm intelligence [4, 5], a paradigm to which the ant colony optimization (ACO) and particle swarm optimization (PSO) algorithms belong [6, 7], the artificial immunology system (AIS) concept [8], with emphasis on the principle of clonal selection, and genetic algorithms (GAs) [9]. Swarm systems constitute the fundamentals of the PSO algorithm, i.e., this approach is related to the existing organization among flocks of birds and shoals of fish, and to human social behavior. In the health field, this algorithm is used in medical systems as a solution to optimization problems related to health condition evaluation [10], incidence of chronic diseases [11], and tomography images [12–15], among other issues.

The influence of independent parameter values on the performance of ML techniques has motivated researchers to develop different algorithms and methods to improve the obtained performance, reduce computational cost, and automate the parameter setting process [16]. For artificial neural networks (ANNs), Gaxiola et al. asserted that the tempt and error method usually finds the best parameter values. According to the authors, the selection of values for the parameters of the back-propagation learning algorithm for ANNs influences the convergence of learning and the overall network performance [17]. The use of nature-inspired algorithms to adjust the parameters of ML techniques is widely found in the current state-of-the-art studies. Hlihor et al. used GAs to adjust the vector parameters of support vector machines (SVMs) [18]. Chen et al. used the PSO algorithm for the same ML technique [19]. In the study presented in [20], the authors adjusted the neural network parameters by using GAs. Different ML techniques can show different sensitivities to the selection of their parameter values. In the same way, various methods used to adjust these parameters can show different performances. Therefore, it was considered interesting to evaluate the use of different methods to adjust the parameters of various ML techniques. Thus, this study investigated the use of a biologically inspired algorithm, named PSO, for adjusting the values of the independent parameters of an ML technique based on ANNs, known as multilayer perceptron (MLP). The use of this hybrid algorithm as an intelligent mechanism in a CDSS for the monitoring of the high-risk pregnancy can support health experts in uncertainty instances, which are more common in the complex disorders related to pregnancy. The main contributions of this paper are as follows.

- The proposal of a hybrid algorithm, based on the PSO technique, for the selection of input and bias weights of the hidden layer of the ANN-based algorithm known as MLP;
- A performance assessment of the MLP algorithm, optimized by a nature-inspired method proposed in this study, and the conventional MLP technique through a 10-fold cross-validation approach, using a healthcare data set;
- A performance comparison of the MLP algorithms, optimized by the nature-inspired method designated PSO, and other methods proposed in the literature for monitoring and risk prediction in pregnancy.

The remainder of this paper is organized as follows. "Related work" elaborates on related work on the topic, focusing on the nature-inspired algorithms as applied in healthcare. "Particle swarm optimization algorithm: A nature inspired approach based on swarm intelligence" describes the adaptation of a biologically inspired algorithm for optimizing the MLP method to predict risks in pregnancy that can lead both mother and newborn to suffer severe complications. The performance evaluation, comparison of various methods, and the analysis of the results of the proposed approach are presented in "Performance evaluation and results". Finally, "Conclusion and future work" concludes the paper and suggests further works.

Related work

The use of nature-inspired algorithms can be commonly found in various medical and healthcare areas. Cheng et al. proposed using the ACO algorithm for rebuilding electrocardiogram (ECG) signals [21]. The authors presented a performance comparison of their proposed optimization method and several algorithms used in state-of-the-art ECG signal reconstruction, using an arrhythmia data base. The results showed that the proposed swarm intelligence algorithm reconstructed ECG signals with great accuracy. Hedeshi and Abadeh discussed how data mining (DM) techniques have become an efficient solution for CDSSs [22]. In their paper, the authors suggested using the PSO algorithm to extract fuzzy rules for identifying heart diseases, using a coronary artery disease data set [23, 24]. In this approach, a boosting mechanism was used to determine the weights from the training set, through newly extracted rules, for misclassified or uncovered instances. The performance assessment showed that the proposed method could detect coronary artery disorders at an acceptable accuracy rate.

Liang and Peng applied the AIS in the field of health by using the characteristics of the immune system and memory related to learning for liver disease diagnosis [25]. The proposed smart model combines the AIS approach and GAs to diagnose the illness in question. In their research study, GAs were adopted for the learning process to infer about antibody population evolution using various health data sets. The results show that the system's accuracy is promising and it could be a useful diagnostic tool for liver-related health problems. GAs are very efficient for searching for optimal, or approximately optimal, solutions in a wide variety of challenges. In [26], Chernbumroong et al. proposed a model based on GAs for recognizing the activity of older adults. This approach could be used to provide knowledge and smart services to several experts related to healthcare through various wrist-worn sensors. In their study, accelerometers were used as the primary sensor for heart rate data acquisition. To find the best fusion weights, the authors proposed a method based on the GAs' selection. The results showed that the suggested algorithm achieved an accuracy similar to that of other classifiers.

Vishnuvarthanan et al. proposed an automated hybrid algorithm for improving magnetic resonance brain images [27, 28]. This technique combined clustering and nature-inspired optimization techniques. The algorithm proposed in their paper could support health experts in the diagnosis of pathological processes through optimization and clustering techniques. The performance comparison of several optimization techniques suggested that the proposed approach achieved excellent sensitivity and specificity values.

According to Zhou, it is possible to improve a system's performance and the user quality of experience (QoE) through optimization algorithms [29]. However, for e-health systems, principally those that use cloud computing in mobile environments, the development of an efficient delay announcement system presents an open and challenging issue [30]. The author discussed conventional convex and stochastic optimization-based models. The results showed that these methods cannot address this problem because of the subjective user response concerning the announced delay. Thus, it is fundamental to analyze which are the best nature-inspired optimization models for solving the gaps related to response time and performance assessment.

The recent research included in the literature served as a contribution to the proposal in this paper and also to support the novelty and innovation of the proposed method.

Particle swarm optimization algorithm: A nature inspired approach based on swarm intelligence

The PSO algorithm is a global optimization technique initially developed for optimization of nonlinear continuous functions. The fact that the sharing of information among individuals offers an evolutionary advantage was essential in its development. This optimization method is based on the social behavior of birds, fish, and, mainly, of humans. In this approach, the particles move through a search space, collecting and sharing information with other particles. These categories of collected and shared information correspond to individual learning and collective transmission, respectively. The PSO method can be applied to binomial or continual problems. Each particle is represented by its current position, velocity, and best position found. Each particle accounts for a point in a D-dimensional space. The particle position i is given by $X_i = (x_{i1}, x_{i2}, \cdots, x_{iD})$, its velocity is given by $V_i = (v_{i1}, v_{i2}, \cdots, v_{iD})$, and the best position found by this particle is given by $P_i = (p_{i1}, p_{i2}, \cdots, p_{iD})$. For the case of a global neighborhood, the best position found among all particles is represented by p_g.

A particle moves in a particular direction depending on its current position, velocity, and the best position found by it and by its neighbors. Equations 1 and 2 determine how the speed and position of the particles are updated, respectively. A speed limit was introduced to avoid the velocity explosion of the particles. The position of the particle may also be restricted to the range of the defined search space. Algorithm 1 describes the steps for this approach.

$$v_{id}(t+1) = w \cdot v_{id}(t) + \phi_1 \cdot r_1 (p_{id} - x_{id}(t)) + \phi_2 \cdot r_2 (p_{gd} - x_{id}(t)) \tag{1}$$

$$x_{id}(t+1) = x_{id}(t) + v_{id}(t) \tag{2}$$

where t represents the iteration, w the inertia weight, the function of which is to balance the global and local search, r_1 and r_2 are independent values uniformly distributed in the interval [0, 1], and ϕ_1 and ϕ_2 are acceleration constants.

Algorithm 1 Particle swarm optimization algorithm pseudo code

$\tau \leftarrow 1$
while Stop criterion is not satisfied **do**
  for each particle i **do**
    if aptitude of $x_{id} > p_{id}$ **then**
      $p_{id} \leftarrow x_{id}$
    end if
    Update particle velocity according to Eq. 1
    Update particle position according to Eq. 2
  end for
  $\tau \leftarrow t + 1$
end while

The advantage of using the PSO is its simple implementation, since it uses only primitive structures and mathematical operators without high computational cost. Naturally,

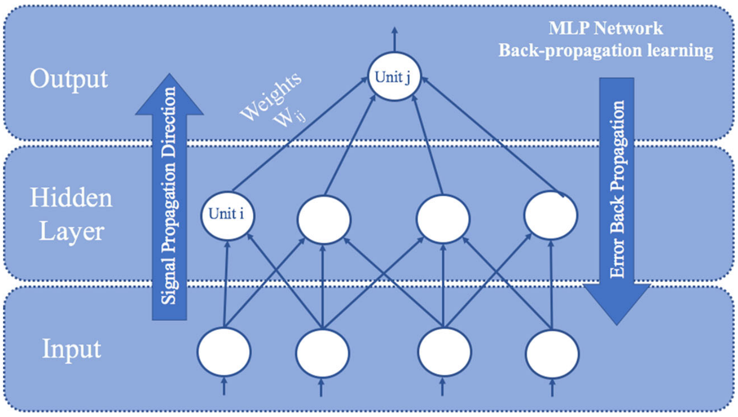


Fig. 1 Two-layer artificial neural network with back-propagation learning

similarly to all heuristics, the PSO does not guarantee an optimal solution, and it is common for the method to fall into local minima. The values of the constants are selected empirically, according to the problem in question. This study considered ϕ_1 and ϕ_2 equal to 2.05 and w equal to 0.5. The random variables r_1 and r_2 were extracted from a uniform distribution and updated with each population velocity calculation. Clearly, the best positions, individual and global, are obtained through the fitness function. Therefore, the steps for this algorithm are as follows. *1)* Initialize a population K of dimension D. This initialization must be uniform if the search space is known. Otherwise, initialize randomly. *2)* Determine the values of the constants. *3)* Check whether the stopping criterion was reached. This criterion can be a predetermined value or number of iterations. If it has been reached, finalize the algorithm. *4)* Randomize the random numbers for r_1 and r_2. *5)* Determine the best global and individual position. *6)* Update the particle velocity. *7)* Update the positions of the particles. *8)* Return to Step 3. Given the algorithms and their two simple equations, it can be seen that the PSO is nothing more than an update of the speed and position in the search space until a sufficiently suitable solution is found.

The leading idea of the PSO algorithm relies on the information exchange among the particles on promising positions, combined with the individual experience of each particle over positions already visited by them. This method can lead the algorithm to find an optimal problem solution. The use of a set of candidate solutions, as in evolutionary algorithms, fast convergence, and simplicity make this approach a promising alternative to other well-known swarm-based algorithms for solving multi-objective problems.

Table 1 Primary information regarding risk factors, symptoms presented before and during pregnancy, and laboratory abnormalities identified during gestation, and hypertensive disorders related to these indicators used to define the nodes applied to the artificial neural network modeling described in this study

Risk factors	Symptoms presented before admission	Symptoms presented and laboratory abnormalities during pregnancy
Gestational age; Personal history of preeclampsia; Family history of preeclampsia; First-time father; Age more than 35 years; Multiple pregnancies; Interval of 10 years or more between pregnancies	Obesity; Hypertension; Migraine; Type I or II diabetes; Kidney diseases; Thrombophilia; Autoimmune disease	Hypertension; Proteinuria; Hemolysis; Liver enzymes increasing; Plaquetopenia; Edema; Hyperreflexia; Headache; Epigastric pain; Nausea or vomiting; Blurred vision; Dizziness; Oliguria
Hypertensive disorder identification		
Pre-existing hypertension complicating pregnancy, childbirth, and the puerperium; Pre-existing hypertensive disorder, with superimposed proteinuria; Gestational [pregnancy-induced] edema and proteinuria without hypertension; Gestational hypertension [pregnancy-induced], without significant proteinuria; Gestational hypertension [pregnancy-induced] with significant proteinuria; Early preeclampsia (placental); Late pre-eclampsia; HELLP syndrome; eclampsia		

Table 2 Cross-validation results for the nature-inspired particle swarm optimization+multilayer perceptron algorithm and the conventional multilayer perceptron method, regarding possible childbirth outcomes for pregnant women

	TPR	FPR	Prec.	Rec.	F-meas.	Class
PSO+MLP	0.946	0.429	0.967	0.946	0.957	Normal
	0.571	0.054	0.444	0.571	0.500	ICU admission
	0.000	0.000	0.000	0.000	0.000	Hemorrhagic c.
	0.000	0.000	0.000	0.000	0.000	Maternal death
Weighted Avg.	0.920	0.402*	0.930*	0.920	0.925*	
MLP	0.968	0.714	0.947	0.968	0.957	Normal
	0.286	0.032	0.400	0.286	0.333	ICU admission
	0.000	0.000	0.000	0.000	0.000	Hemorrhagic c.
	0.000	0.000	0.000	0.000	0.000	Maternal death
Weighted Avg.	0.920	0.667	0.909	0.920	0.914	

*best result

The parameter configuration by means of the PSO algorithm is essential for a better training result of an MLP neural network. This is because the weight optimization of the MLP connections depends directly on the parameter values of this algorithm, which are never constants, and can vary according to the data base used in the network. The presence of at least one intermediate (hidden) layer of neurons characterizes MLP networks. This type of network is one of the most versatile in terms of its applications. It can be used mainly in the following types of problems: to determine the universal approximation of functions, classification of patterns, process identification and control, forecasting of time series, and optimization of systems [31–34].

Several algorithms exist that can be used for MLP training. Among these, the best-known learning algorithm for training these networks is the back-propagation of the observed error gradient. This algorithm constitutes a supervised learning method, which uses the desired output for each input provided to adjust the parameters, called weights (and indicated by w), of the network according to the delta rule. In addition, the weight adjustment uses the gradient back-propagation method to define the corrections to be applied. Equation 3 shows this adjustment process.

$$w_j(n+1) = w_j(n) + \Delta w_j(n) \tag{3}$$

where neuron j represents an output node in iteration n. Equation 4 represents the calculation of the descending gradient.

$$\Delta w_j(n) = -\eta \frac{\partial \epsilon(n)}{\partial w_j(n)} \tag{4}$$

where η represents the learning rate and $\epsilon(n)$ the instantaneous sum of the quadratic errors in iteration n.

The training occurs in two moments, namely, the forward and backward phases. In the forward phase, an output set is produced as the actual response of the network, and in the backward phase, the synaptic weights are updated via the delta rule so that the real network response moves close to the desired response. Equation 5 shows the generalized delta rule that is applied.

$$\Delta w_{ij}(n) = \alpha \Delta w_{ij}(n-1) + \eta \delta_j(n) y_i(n) \tag{5}$$

where $\delta_j(n)$ represents the local gradient and $y_i(n)$ the functional sign that appears in neuron i in iteration n. In this study, the moment constant α was considered in order to increase the learning rate η and decrease the instability. Figure 1 shows the schema of a feed-forward neural network, that is, a network where the processing flow is strictly from the input to the output. Therefore, the back-propagation algorithm consists of two computational steps, to determine direct and reverse processing. In the first step,

Table 3 Cross-validation results for nature inspired particle swarm optimization+multilayer perceptron algorithm and the conventional multilayer perceptron method, regarding possible childbirth outcomes for newborn

	TPR	FPR	Prec.	Rec.	F-meas.	Class
PSO+MLP	0.915	0.276	0.890	0.915	0.903	Normal
	0.667	0.110	0.692	0.667	0.679	ICU admission
	0.000	0.010	0.000	0.000	0.000	Neonatal death
Weighted Avg.	0.830	0.226*	0.819	0.830	0.824	
MLP	0.915	0.345	0.867	0.915	0.890	Normal
	0.630	0.096	0.708	0.630	0.667	ICU admission
	0.500	0.000	1.000	0.500	0.677	Neonatal death
Weighted Avg.	0.830	0.271	0.827*	0.830	0.826*	

*best result

Table 4 Area under receiver operating characteristic curve results for nature-inspired particle swarm optimization+multilayer perceptron algorithm and the conventional multilayer perceptron method, regarding possible childbirth outcomes for all predictive classes

	TPR	FPR	AUC	Class
Delivery outcome for preg. women				
PSO+MLP	0.946	0.429	0.959	Normal
	0.571	0.054	0.952	ICU admission
Weighted Avg.	0.920	0.402	0.958*	
MLP	0.968	0.714	0.869	Normal
	0.286	0.032	0.865	ICU admission
Weighted Avg.	0.920	0.667	0.869	
Delivery outcome for newborn				
PSO+MLP	0.915	0.276	0.892	Normal
	0.667	0.110	0.871	ICU admission
	0.000	0.010	0.918	Neonatal death
Weighted Avg.	0.830	0.226	0.887*	
MLP	0.915	0.345	0.850	Normal
	0.630	0.096	0.857	ICU admission
	0.500	0.000	0.980	Neonatal death
Weighted Avg.	0.830	0.271	0.855	

*best result

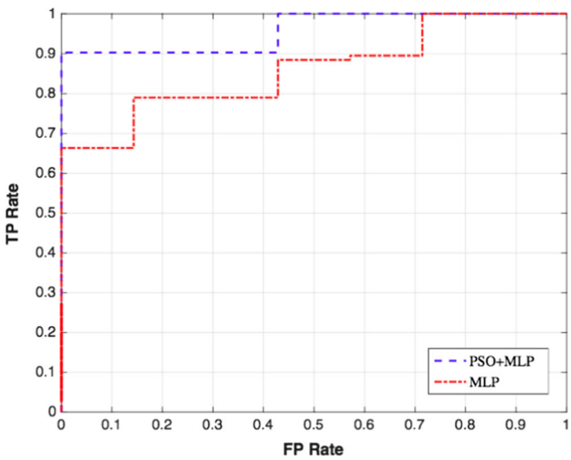
an input is applied to the neural network, and its effect is propagated by the network, layer by layer. During this stage, the network weights remain constant. In the reverse processing, a calculated error signal at the network output is propagated in the reverse direction, layer by layer, and at the end of this process, the weights are adjusted according to an error correction rule. The back-propagation algorithm converges when the Euclidean norm of the error gradient is below a prespecified and arbitrarily small threshold.

In the following section, the use of the combination of the PSO and MLP methods is discussed and compared with that of the conventional MLP algorithm. This section also presents the data base of hypertensive pregnant women used to evaluate the proposed method. A performance comparison of the proposed method and other similar approaches in the literature is presented to show the efficiency in healthcare environments of the proposed model, which combines a biologically inspired algorithm and an algorithm based on ANNs.

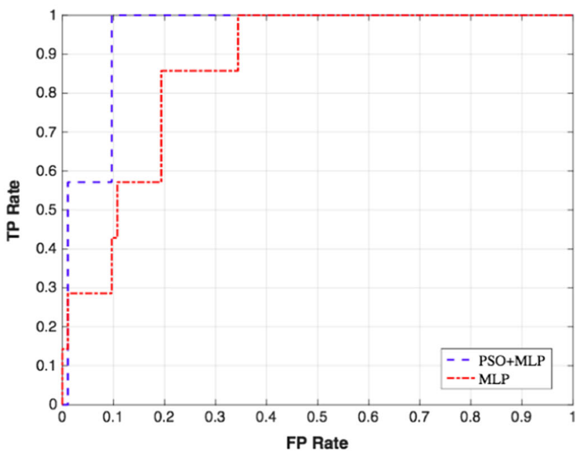
Performance evaluation and results

This study considered 100 parturient women diagnosed with a hypertensive disorder during pregnancy. First, the approval of the project by the research ethics committee at the Maternity School Assis Chateaubriand (from the Federal University of Ceará, Fortaleza, CE, Brazil) under the certificate of presentation for ethical appreciation, number 66929317.0.0000.5050 was obtained. The protocol number of the received assent is 2.036.062. The data were then collected during May 2017. Table 1 summarizes the principal information used to compose the nodes applied in the ANN modeling in this study.

When this valuable information is introduced into the ANN, it is possible to predict when the delivery will occur (before or after 34 weeks of gestation). It is also feasible to predict the type of delivery, the outcome for the pregnant woman, the outcome for the neonate, and whether the neonate will be small for gestational age

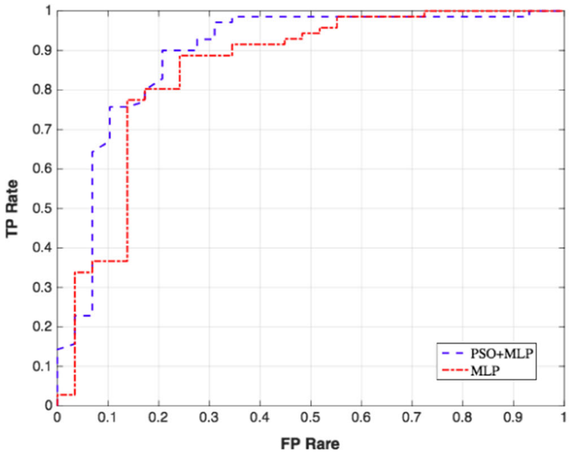


(a) Normal delivery outcome

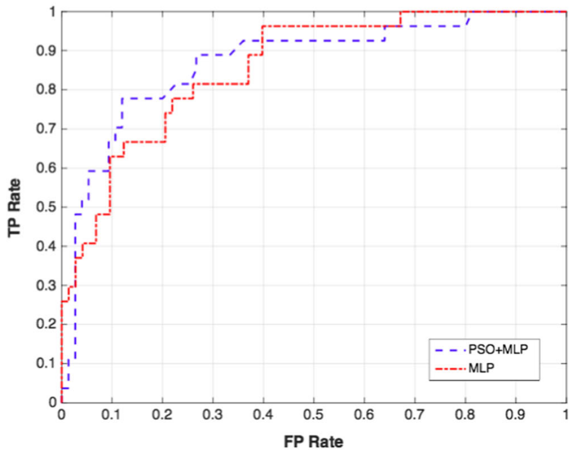


(b) ICU admission

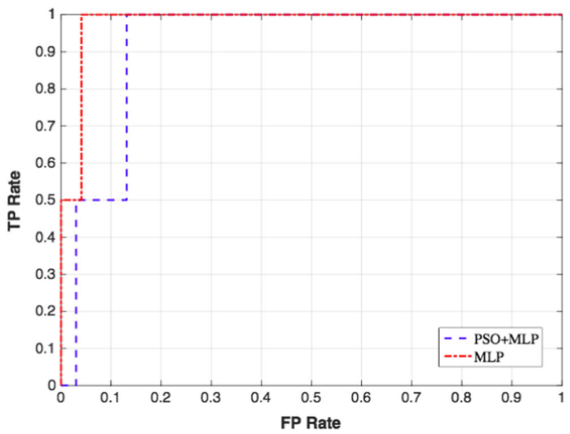
Fig. 2 Receiver operating characteristic curves related to possible childbirth outcomes for pregnant women



(a) Normal delivery outcome



(b) ICU admission



(c) Neonatal death

Fig. 3 Receiver operating characteristic curves related to possible childbirth outcomes for the fetus

(SGA), and whether the indicators on the Apgar scale will be less than 7 for the first five minutes after childbirth. Intrauterine fetal growth retardation, which results in live births of babies considered SGA, represents a significant risk factor for neonatal mortality. The risk factors associated with intrauterine fetal growth retardation are low maternal weight gain during pregnancy, low maternal weight before pregnancy, and short stature of the mother, which are considered indicators of possible maternal malnutrition. The Apgar scale is the most commonly used method to evaluate the immediate adjustment of the newborn to life outside the uterus, assessing its vitality conditions. It consists of the assessment of five items of a physical examination of the infant, at one, five, and ten minutes of life. The evaluated aspects are heart rate, respiratory effort, muscle tone, reflex irritability, and skin color. For each of these items, a score of 0 to 2 is assigned. A score of 8 to 10, present in about 90% of live births, means that the newborn was born in optimal condition. A score of 7 indicates that the newborn has a slight difficulty. A score from 4 to 6 translates as a difficulty of moderate degree, and from 0 to 3 as a difficulty of dangerous degree. If these difficulties persist for a few minutes without treatment, they can lead to metabolic changes, generating a potentially severe situation, called anoxia (lack of oxygenation).

For performance evaluation of the proposed model, in this study the 10-fold cross-validation technique was used [35]. In this well-known method for evaluation of classification models, the data base is randomly divided into k mutually exclusive partitions (folds) of size approximately equal to n/k cases. Cases that belong to $k - 1$ folds are used for training, and the induced hypothesis is tested on the remaining fold. This process is repeated k times, considering a different fold for each testing. Then, the error in the cross-validation is the average of the calculated errors in each of the k folds. In this study, $k = 10$ was considered. Table 2 shows the cross-validation results for the considered algorithms regarding the possible childbirth outcomes for pregnant women.

The results show an improvement in significant indicators. The nature-inspired algorithm obtained a substantial reduction in the false positive rate (FPR), i.e., this method yields a reduced number of cases where the conventional model predicted a particular outcome for the pregnancy, but the true result was different. The lower the FPR, the fewer the false alarm cases predicted by the model. The proposed approach also shows improvements in precision (Prec.), which represents the percentage of examples classified as positive that are indeed positive. In terms of the recall (Rec.) indicator, which is the percentage of positive examples classified as positive, the model did not show improvement. However, it showed, as did the conventional method, an excellent rate. The F-measure represents a weighted harmonic mean between precision and recall. An increase in the value of this indicator represents an improvement in the relationship between the two leading indicators. No cases were found in the data base for the hemorrhagic complications and maternal death classes. Table 3 shows the performance evaluation for the delivery outcome for the newborn.

The performance results of the hybrid algorithm for the delivery outcome of the neonate were similar to those of the conventional method. The biologically inspired approach showed a small reduction in the FPR.

The receiver operating characteristic (ROC) curve is a visualization technique for assessing ML techniques based on their performance [36]. This technique has been widely used by the scientific community, since an evaluation of only the accuracy rate of a classifier is quite superficial. ROC curves are useful for handling domains, the classes of which are unbalanced, and the grading costs per class are different. Table 4 shows the performance of the algorithms examined in this study in terms of the area under ROC curve (AUC). Approaches that achieve an AUC close to 1 are considered excellent predictors.

Figures 2 and 3 present a comparison of the ROC curves of the biologically inspired hybrid PSO+MLP algorithm and the classical ANN-based MLP method. These curves were constructed for each possible outcome for both pregnant woman and neonate.

The performance comparison of the examined algorithms in terms of the ROC curves shows that the hybrid algorithm, which is nature-inspired, showed a better performance than the conventional model, except for the "neonatal death" class. To confirm these excellent results, Table 5 presents a performance comparison of the proposed method and other similar algorithms in the literature.

Table 5 Performance comparison of several algorithms in the literature for the prediction of the type of delivery in a risky pregnancy

	Model	Precision	TP rate	FP rate
Moreira et al.	PSO+MLP	0.9300*	0.9200*	0.4020
Pereira et al. [37]	GLM	0.5857	0.8904	0.7086
	SVM	0.6206	0.8557	0.7208
	DT	0.8391	0.8828	0.1995
	NB	0.7469	0.8429	0.3702
Paydar et al. [38]	RBFNetwork	0.7140	0.5330	0.2060
	MLP	0.9090	0.8000	0.0590*

*best result

Based on the presented results, it is possible to affirm that the algorithm inspired by nature, namely PSO, considerably improves the performance of algorithms based on ANN by selecting the best attributes and adapting the synaptic weights during the training phase.

Conclusion and future work

Nature-inspired computing includes all strategies developed from (or inspired by) a biological or natural mechanism. It is important to emphasize that cognitive aspects and human reasoning themselves represent natural mechanisms of fundamental importance. Therefore, the scope of natural computing includes symbolic artificial intelligence. In this context, this paper presented the use of a technique that is biologically inspired by the cooperative behavior and information exchange seen in groups of several animal species, such as flocks of birds, schools of fish, and swarms of bees.

The results showed that the PSO algorithm considerably improved the well-known technique based on ANNs, known as MLP, through the best parameters selection and value adjustment of weights. This hybrid algorithm presented a precision of 0.930, recall of 0.920, F-measure of 0.925, and AUC of 0.958. This method was compared with other algorithms used in studies in the literature The performance evaluation showed that biologically inspired techniques represent an efficient mechanism for optimization of commonly used ANN techniques.

The results show that the PSO algorithm is a suitable tool for the optimization of ANN architectures, presenting a low computational cost and excellent precision. However, the major limitation of this method concerns its sensitivity to the choice of parameters through the existence of the possibility that there is no convergence. Another limitation is the fact that PSO algorithm can converge prematurely to a local minimum. On the other hand, there can be a dispersion of the particles. It is suggested that further work should include the application of the other techniques based on the nature referenced in this paper to adjust weights and select the best parameters for other ANNs-based techniques.

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Compliance with Ethical Standards

Conflict of interests The authors declare that they have no conflict of interest.

Ethical approval The ethics board approval was obtained by the Research Ethics Committee of the Maternity School Assis Chateaubriand of the Federal University of Ceará, Fortaleza, CE, Brazil under the certificate of presentation for ethical appreciation, number 66929317.0.0000.5050, and receiving assent with protocol number 2.036.062.

Informed Consent Informed consent was obtained from all individual participants included in the study.

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Chapter 8

Averaged One-dependence Estimators on Edge Devices for Smart Pregnancy Data Analysis

This chapter consists of the following article:

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Averaged one-dependence estimators on edge devices for smart pregnancy data analysis☆

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A B S T R A C T

The development of edge computing has allowed the Internet of Things (IoT) to reach higher levels of operational efficiency, knowledge generation, and decision-making through a better relationship between applications and their users. The principal idea is the processing of large amounts of data close to the network edge, where these data are generated. Hence, in this paper, the use of a machine learning technique, known as averaged one-dependence estimators, is proposed for real-time pregnancy data analysis from IoT devices and gateways. This statistical technique is useful for decentralized pre-processing of data and its intermediate storage, reducing the amount of data to be transferred to the cloud and ensuring operability, even in an event of network failure. The results show that this technique presents accurate results with a low computational cost and could be a useful tool to better take advantage of the potential of IoT solutions in healthcare.

1. Introduction

The concept of cloud computing refers to the usage of shared memory, storage, and processing resources, which are interconnected by the Internet. However, the Internet of Things (IoT) applications that are sensitive to communication latency, such as medical emergency applications, are not feasible with the use of cloud computing, because the execution of all calculations and actions requires the exchange of messages between devices and the cloud [1]. Two concepts have emerged to address this limitation in the use of cloud computing. The first concept is fog computing, which creates a federated processing layer in the local network of the computing devices of the network extremities [2]. The second concept is edge computing, which operates directly in the device layer, performing some processing, albeit of low computational complexity. In this way, edge computing further reduces the communication volume, in addition to collaborating to provide autonomy in the decision-making in the device layer. A significant challenge for both fog and edge computing, within the IoT scenario, is the definition of a system architecture that can be used in

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different application domains, such as healthcare.

The growing data generation by IoT devices requires that much of the information that is stored in the cloud be relocated back to the network edge. This reallocation occurs because, currently, there is a demand for real-time processing, capable of providing rapid responses that are relevant to the operation and decision-making [3]. To improve the response time in processing data collected by IoT devices, these data should be treated, stored, and analyzed near the end user. The optimal manner to achieve this result, with respect to data processing and response time, is to develop computing solutions at the network edge. Edge computing, in its most fundamental form, brings the user's computing closer, by implementing data storage at the network edge. With edge solutions, it is no longer necessary to transfer a significant amount of data for processing in a data center in the cloud, e.g., to then return the decoded data. Through faster, more responsive local solutions, edge computing leads to a higher-quality experience with faster response times for end users [4]. Regarding the advent of this novel paradigm, the higher computational performance of IoT smart devices combined with increasingly accurate machine learning (ML) techniques, tend to substitute public cloud infrastructure primarily, i.e., infrastructure based on the software as a service (SaaS) concept [5]. However, in this new scenario, the need for a centralized cloud persists. In the cloud, information is discharged and stored for a more extended period, where this information can be accessed and analyzed by robust ML algorithms [6].

Regarding healthcare, fog and edge computing could be particularly valuable for patient monitoring and rapid response to an epidemic crisis in difficult-to-reach areas. An alert from the system could trigger a protocol for coordinated care, or even trigger emergency services, in real time, if the patient's vital signs fall dramatically [7]. The development of IoT interfaces that meet the particular demands of the clinical workflow remains a challenge [8]. Defining the limits of what constitutes useful data for patient care represents another important task [9]. The creation of medical devices, which are safe and approved by health authorities for data collection, is not an easy task to accomplish. The distribution of these smart devices and the education of patients about their use also represent an exciting challenge [10]. The fog and edge computing models represent an excellent initiative that can be quickly executed to address all these fundamental gaps.

This study seeks to solve the problem of the computational limitation of IoT devices, considering their energy constraints, in the local execution of sophisticated algorithms. Patient's collected data are transmitted to more powerful platforms on edge, where aggregation and processing are feasible. Transferring this responsibility to an edge platform allows IoT devices to save energy by accessing external services on demand. Besides, its virtually unlimited processing makes it possible to perform health data analysis in real-time and the monitoring of high-risk situations. Therefore, the main contributions of this paper are the following:

- A comprehensive review of the state of the art of edge network architectures, applications, and trends in IoT-based healthcare solutions;
- A study of algorithms based on ML techniques and their use in conjunction with edge devices in prediction of pregnancy-related risk situations;
- A performance evaluation of various ML approaches using a 10-fold cross-validation method and its related indicators;
- A comparison between the Bayesian model suggested in this study and similar works to demonstrate the efficiency of the proposed approach.

The remainder of the paper is organized as follows. Section 2 elaborates on related work on the topic, focusing on ML algorithms for fog and edge computing as applied in the healthcare sector. Section 3 describes the adaptation of the averaged one-dependence estimators (AODE) algorithm, which is based on Bayes' theorem, to process smart pregnancy data over edge devices. The performance assessment, comparison of various methods, and analysis of the results of the proposed approach are presented in Section 4. Finally, Section 5 concludes the paper and suggests directions for future work.

2. Machine learning on the edge: real-time intelligent analysis at the network edge

Currently, real-time ML at the network edge represents one of the leading trends for the analysis of large amounts of information. Intelligent edge devices, based on the IoT paradigm, are already capable of collaborating and analyzing data in conjunction with other devices. The use of real-time ML algorithms within distributed data applications has increased in recent years, i.e., algorithms that can support peer-to-peer (P2P) decisions in real-time.

In this context, Farahani et al. discussed IoT applicability in healthcare. In this study, the authors introduced an architecture for electronic health (e-Health) environments based on the IoT paradigm, fog and cloud computing, and ML applications [11]. This research, based on a patient-centric e-Health model, is composed of a multilayer architecture, consisting of the device, fog, and cloud layers to handle a vast amount of information. The conclusions addressed the IoT challenges in e-Health environments, focusing on the analysis of large volumes of data with respect to its variety, volume, and velocity. The results showed that there is a tendency to partition the networking layer into two sublayers, i.e., fog and cloud layers, owing to different requirements of quality-of-service (QoS), storage, and latency. In [5], Kumar and Gandhi presented several IoT-based applications for continuous patient health condition monitoring, considering the need to manage a considerable quantity of data generated by wearable sensor devices. This study also proposed a three-layer architecture to store and process the collected wearable sensor data. These layers focus on collecting data from IoT wearable sensor devices, storing these data in cloud environments, and using a logistic regression-based prediction model for early detection of heart diseases. For performance evaluation, this study considered the receiver operating characteristic (ROC) analysis to identify significant clinical parameters for identification and prediction of heart-related diseases. The results showed that ML techniques are useful, accurate, and quickly responsive tools for IoT edge devices and that a fog layer application can further

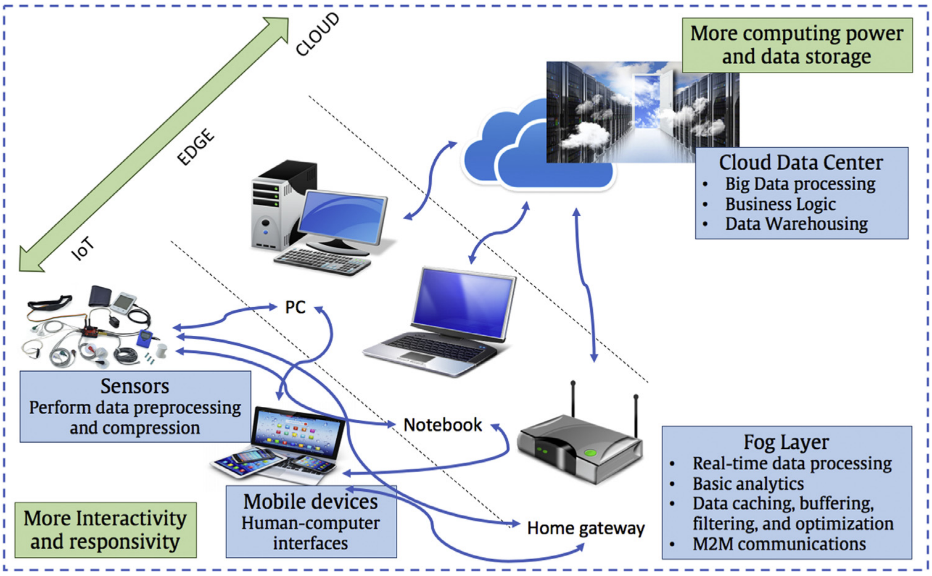

Fig. 1. Edge computing architecture.

improve the performance of conventional architectures. In the same way, Liu et al. discussed the development of novel deep-learning-based algorithms for pattern recognition. In this paper, the authors also presented an image recognition system, based on edge computing paradigms, to overcome well-known inherent problems of conventional mobile cloud computing, such as system latency and low battery life of mobile devices [12]. The results showed that the proposed model achieved excellent performance, concerning the accuracy, response time reduction, and low energy consumption, compared with existing recent works.

Regarding all the presented results, edge computing paradigms and ML approaches represent an essential pathway to solve several issues related to IoT and e-Health environments, showing excellent response time and accuracy for the early identification and prediction of complex diseases. Fig. 1 shows the architecture proposed by this study, based on the edge-of-things paradigm.

Concerning high-risk pregnancies, several health information systems (HISs) were proposed based on the paradigm of knowledge discovery in databases (KDD). This paradigm has been shown to be useful for information management. The KDD is a process composed of data selection, pre-processing, transformation, and establishing useful patterns in the knowledge extraction, i.e., interpretation of raw data into relevant information. For that, the data mining (DM) techniques consist of the interpretation of patterns and knowledge generation after the analysis of the obtained results. DM is an emerging area of computational intelligence used in the analysis of large databases for pattern recognition and information extraction.

Pereira et al. used the risk factors acquired from real data for childbirth outcome prediction using DM methods [13]. The primary purpose of this study was to improve the QoS through specific practices to guide pregnancy care decision-making, and thereby facilitate better results for both the pregnant woman and fetus. The results showed that a decision tree (DT)-based approach could achieve high sensitivity and specificity values, providing to hospitals a HIS capable of accurately predicting the childbirth outcome. However, this study was limited insofar as there are several challenges to using a DT efficiently, including the practical limitation of the method to analyzing a small number of decision options with a limited range of possible risks. Conventional approaches involve many decisions at different levels, each with a wide range of associated risks, and trying to demonstrate these with only a simple DT can result in an enormous and useless model. Paydar et al. proposed a clinical decision support system (CDSS) to predict the pregnancy outcome in women affected by systemic lupus erythematosus [14]. The primary objective of this study was to improve the pregnancy outcome through DM techniques, e.g., logistic regression and artificial neural network (ANN)-based approaches. Comparative results showed that the multilayer perceptron (MLP) algorithm had presented a better performance with respect to other studied approaches. The main limitation of this approach, as well as many other types of ANNs, refers to the training time of neural networks using the backpropagation algorithm, which tends to impose a high computational cost. In this approach, several cycles are necessary to reach acceptable error levels. In this case, the processor must calculate the functions for each node and its connections separately, which can be problematic in extensive networks, or with a significant amount of data.

The use of algorithms based on probability, which present a low computational cost and excellent precision, such as the AODE algorithm, for edge devices represents a promising solution. Approaches based on Bayes' theorem thus avoid a significant demand for computational time, an inherent characteristic of ANN- and DT-based methodologies.

3. Averaged one-dependence estimators for IoT-edge devices: high performance allied to high precision

The algorithm proposed by Webb et al. named AODE, aims to address the attribute independence problem of the well-known naive Bayes (NB) classifier [15]. This algorithm represents an efficient technique that uses a weaker attribute independence

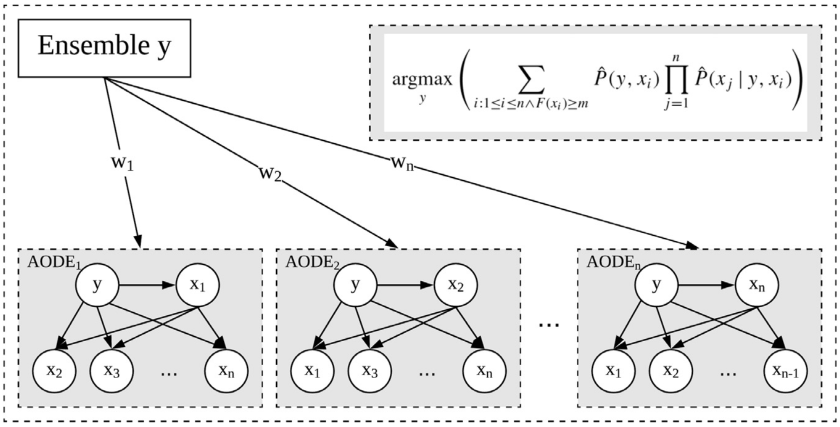

Fig. 2. Classifier model based on one-dependence estimators.

assumption than the NB classifier, thereby improving the prediction accuracy without generating an unnecessary computational cost. The AODE algorithm is restricted to the exclusive use of a single-dependency estimator to maintain its efficiency. This approach can be considered a set of super-parent one-dependence estimators, because each attribute depends on the class and another shared attribute, designated as a super-parent. Graphically, all classifiers based on the AODE algorithm have a structure as shown in Fig. 2, where this method combines all the possibilities of classifiers with this pattern of structure. This approach is often used in bioinformatics to align protein sequences [16], diagnosis of thyroid-related problems [17], and diseases related to structural degradation and decreased bone mineral density [18].

In health, classifiers based on Bayes' theorem categorize an ensemble of attributes $x = \langle x_1,\ldots,x_n\rangle$, such as symptoms, risk factors, and physiological indicators, by selecting

$$\underset{y}{argmax}\,(P(y|x_1,\ldots,x_n)), \tag{1}$$

where x_i represents the ith attribute value and $y \in c_1,\ \ldots, c_k$ are the k predictive classes. In this study, the number k represents the different types of childbirth delivery for pregnant women that developed some hypertensive disorder during pregnancy. Under the attribute independence assumption, this may be expressed as

$$\underset{y}{argmax}\left(P(y)\prod_{i=1}^{n}P(x_i|y)\right). \tag{2}$$

Regarding classification, the NB algorithm uses the formula presented in Eq. (2). Considering that the NB classifier assumes an interdependence between attributes, the AODE approach takes into account a weaker attribute independence assumption, avoiding the model selection. This method has a substantially lower systematic error than the NB classifier, but shows a minimal increase in variance. Eq. (3) presents the definition of the conditional probability.

$$P(y|x) = P(y, x)/P(x) \propto P(y, x) \tag{3}$$

Concerning any attribute value x_i, this equation can be rewritten as follows.

$$P(y, x) = P(y, x_i)P(x|y, x_i) \tag{4}$$

Eq. (4) holds for each value of x_i. Therefore, for any ensemble $I \subseteq \{1, \cdots, n\}$,

$$P(y, x) = \frac{\sum_{i\in I}P(y, x_i)P(x|y, x_i)}{|I|}. \tag{5}$$

Hence,

$$P(y, x) = \frac{\sum_{i:1\le i\le n\wedge F(x_i)\ge m}P(y, x_i)P(x|y, x_i)}{|\{i\colon 1 \le i \le n \wedge F(x_i) \ge m\}|}, \tag{6}$$

where $F(x_i)$ represents the frequency of attribute-value x_i in the training set. Concerning classification, Eq. (7) presents the expression used by the AODE method for the selection.

$$\underset{y}{argmax}\left(\sum_{i:1\le i\le n\wedge F(x_i)\ge m}P(y, x_i)\prod_{j=1}^{n}P(x_j|y, x_i)\right) \tag{7}$$

The classifier selects the class by Eq. (7). The algorithm operation is showed as follows. For each possible class value and parent attributes, determine the correct index for the parent node in the `m_CondiCounts` matrix. If the attribute value does not have a frequency of `m_Limit` or higher, continue. Calculate the prior probability for each attribute and the conditional probability using (7). Add this probability to the overall probability. Then, unblock the parent node. If at least one is not parent node, do plain NB conditional probability. Else, divide by numbers of parent attributes to get the mean. Return AODE probabilities $P(y)$.

In the training step, the AODE algorithm generates a table of probability estimates for each attribute-value, i.e., for each symptom, risk factor, and clinical condition, conditioned by each other attribute-value and each predictive class. The resulting space complexity is $O(k(nv)^2)$, where k represents the number of classes, n the number of attributes, and v the mean number of values per attribute. The time complexity, regarding the table construction, is $O(tn^2)$, where t represents the number of training cases.

The basic idea of the AODE algorithm is to achieve lower classification error than NB classifier for the following reasons. First, this method involves a weaker attribute independence assumption, $P(y, x_i) \prod_{j=1}^{n} P(x_j|y, x_i)$, providing a better estimate of $P(y, x)$ than $P(y) \prod_{i=1}^{n} P(x_i|y)$. This method affords a better estimative for each of the base models that constitute the AODE model, except when the estimates of the base probabilities in the respective models are inaccurate. Second, the aggregation of multiple reliable base models leads to improved prediction accuracy. Third, the AODE model avoids model selection, such as the NB classifier, and hence it avoids the well-known attendant variance problem.

4. Performance evaluation and results

For this study, approval was obtained from the Research Ethics Committee of the Maternity School Assis Chateaubriand of the Federal University of Ceará, Fortaleza, CE, Brazil, under the certificate of presentation for ethical appreciation, number 66929317.0.0000.5050, and assent received with protocol number 2.036.062. This research considered 205 parturient women diagnosed with a hypertensive disorder during pregnancy.

The metrics for evaluation of classification models represent a way of assessing whether the predictive model is behaving in the manner in which it was intended, i.e., evaluating not only whether the approach is correctly classifying cases but also to what extent the model is abstracting the wrong information. For this, the confusion matrix of a hypothesis h offers an adequate classification model measure, by showing the number of correct classifications in comparison to the predicted classifications for each class, over a set of examples T. The matrix entries are represented by $M(C_i, C_j)$, indicating the number of examples of T that are of class C_i but which were classified by hypothesis h as being of class C_j. Eq. (8) presents this relation.

$$M(C_i, C_j) = \sum_{\{\forall(x,y)\in T: y=C_i\}} \left\| h(x) = C_j \right\| \tag{8}$$

The number of acceptances for each class is situated on the main diagonal of the confusion matrix. The other matrix elements, i.e., those for which $i \neq j$, represent the errors in the classification. The confusion matrix of an ideal classifier has every element off the principal diagonal equal to zero, because this predictive method does not present errors. From the confusion matrix, it is possible to define several metrics to evaluate a predictive model. The most common metrics for classification problems are the accuracy, recall (or sensitivity), and specificity, which calculate the success rate for all model classes, the true positive rate (TPR), and the true negative rate (TNR), respectively. The precision calculates the probability, given that the model classified a given case as positive or negative, that this case really belongs to the class predicted. The F-measure is a weighted harmonic mean between the precision and recall. This metric measures the model efficiency, taking into account the error in these indicators.

The ROC curve is a technique for visualizing and selecting classifiers based on their performance. This strong indicator has been widely used by the scientific community to evaluate ML-based classifiers because, in general, evaluating only the classifier accuracy rate is quite a simple metric. The ROC curve is convenient for dealing with domains in which classes are unbalanced and have different grading costs per class. The knowledge extracted from the area under the ROC curve (AUC) makes it possible to quantify an algorithm's accuracy, which is proportional to the area under the curve, and allows the comparison among several models [19]. The AUC is one of the most frequently used indicators to summarize the quality of a curve. This indicator represents a performance measure for ML-based approaches. A model entirely incapable of discriminating the normality or severity of childbirth outcomes would have an AUC close to 0.50 (this would be the null hypothesis), whereas an algorithm with an AUC above 0.70 is considered as a model with satisfactory performance.

This study also considered the cross-validation method for training and testing the algorithms. The k-fold cross-validation technique divides the training data into k equal parts, designating $k - 1$ parts for the training and 1 part for the calculation of the error measurement. This process occurs for each of the k parts, i.e., all parts are used for training and validation. Eq. (9) presents the formula for combining the obtained results of the error calculation.

$$CV_k = \sum_{k=1}^{K} \frac{n_k}{n} Err_k, \tag{9}$$

where

$$Err_k = \sum_{i \in C_k} \frac{(y_i \neq \hat{y}_i)}{n_k} \tag{10}$$

Eq. (10) represents the incorrect classification rate. The specific case of n-fold is known as the leave-one-out method. Under this

Table 1
Performance evaluation of the AODE algorithm concerning the childbirth outcome for pregnant women.

TPR	FPR	Prec.	Rec.	F-meas.	AUC	Class
0.967	0.652	0.921	0.967	0.944	0.864	Normal
0.400	0.021	0.600	0.400	0.480	0.888	ICU[a] admission
0.000	0.010	0.000	0.000	0.000	0.686	Hemorrhagic compl.
1.000	0.000	1.000	1.000	1.000	1.000	Maternal death
0.898	**0.581**	**0.872**	**0.898**	**0.883**	**0.862**	**Weighted Avg.**

[a] Intensive care unit.

method, in every process stage, only one observation is left out of the calculation. However, this study considered $k = 10$. Tables 1 and 2 present the performance evaluation of the AODE algorithm, in terms of the confusion matrix indicators for childbirth outcome for the pregnant woman and the fetus, respectively, using the 10-fold cross-validation method.

The performance assessment shows excellent results for the “normal” and “maternal death” classes concerning all the evaluation indicators of the confusion matrix. The “normal” class has a high false positive rate (FPR), i.e., false alarms occur frequently in this class. These false alarms occur because the different classes present the same symptoms, risk factors, and clinical indicators. Regarding the FPR, the best algorithms present values close to 0 for this indicator. The low performance for the class “hemorrhagic complications” is due to the fact that these complications occurred in only 3% of the cases, i.e., six occurrences. Another consideration is that there is insufficient information in the medical records analyzed regarding indicators of the hydroelectrolytic, acid–base, and, mainly, coagulation disorders.

Regarding the childbirth outcome for the fetus, the Bayesian algorithm achieved an excellent result for normal outcomes and a good result for other classes.

This study compared the AODE algorithm with other well-known ML algorithms to verify the efficiency of the proposed method. These algorithms are divided into three main subgroups, namely algorithms based on the Bayes’ theorem (AODE, NB, and tree-augmented naive Bayes (TAN)), algorithms based on ANNs (support vector machine (SVM), MLP, and radial basis function network (RBF)), and DT-based algorithms (C4.5 and random forest (RF)). Tables 3 and 4 summarize the performance evaluation, in terms of a weighted average, for each of these approaches.

The results show that the AODE classifier presents, in terms of a weighted average, better performance than the other approaches regarding precision for the risk prediction for pregnant women suffering from hypertensive disorders during pregnancy. Concerning the other ML approaches, this method presents a result relatively close to the result presented by the other classification algorithms. Regarding the risk prediction for the fetus, the AODE technique shows a better relation between the TPR (sensitivity) and FPR (1−specificity), as shown by the AUC. The results for the other indicators are also quite close with respect to the other approaches. Table 5 shows a performance comparison of recent research to evaluate the proposed solution concerning the accuracy, sensitivity, and specificity indicators.

Figs. 3 and 4 show a comparison of the most promising approaches, through the ROC curve, concerning the “ICU admission” class for childbirth outcome for both the pregnant woman and fetus.

The comparative analysis of this study also takes into account the viability of the chosen algorithm regarding its execution in edge devices, i.e., it evaluates whether this method is also able to predict the outcome of the delivery in an acceptable time. The complexity analysis measures the amount of effort required for an algorithm’s execution, independent of the technology used (hardware and software), through a simplified mathematical model that represents the most relevant factors [20]. It is possible to express the computational complexity through basic operations, which vary according to the algorithm and the volume of data. This study considered the asymptotic notation, which is also known as big-O notation [21]. Table 6 presents the computational complexity of the leading studied algorithms based on big-O notation.

In the table, k represents the number of classes, n is the number of attributes, v is the average number of values per attribute, and t is the number of training cases. N_T represents the number of DTs in the RF method. Fig. 5 shows the performance of the classification algorithms in terms of the computational time and amount of training data, using the pregnancy database.

The results show that although algorithms based on one-dependence have inferior performance in terms of accuracy compared to algorithms based on DTs and ANNs, these Bayes-based algorithms present superior performance in terms of computational time. From these results, the proposed AODE algorithm represents an essential solution for edge devices, because it is simultaneously flexible, to be applied to several contexts with low computational cost, and robust, to satisfactorily explore the search space, thereby finding viable and precise solutions.

Table 2
Performance evaluation of the AODE algorithm concerning the childbirth outcome for the fetus.

TPR	FPR	Prec.	Rec.	F-meas.	AUC	Class
0.961	0.238	0.885	0.961	0.921	0.857	Normal
0.488	0.074	0.636	0.488	0.553	0.787	ICU admission
0.400	0.015	0.571	0.400	0.471	0.949	Fetal death
0.834	**0.282**	**0.817**	**0.834**	**0.822**	**0.847**	**Weighted Avg.**

Table 3
Performance evaluation of ML-based algorithms concerning the childbirth outcome for the pregnant woman.

Method	TPR	FPR	Prec.	Rec.	F-meas.	AUC
AODE	0.898	0.581	**0.872**	0.898	0.883	0.862
NB	0.854	0.583	0.846	0.854	0.850	0.850
TAN	**0.907**	0.619	0.870	**0.907**	**0.885**	0.792
SVM	0.902	0.619	0.865	0.902	0.881	0.642
MLP	0.883	**0.504**	0.868	0.883	0.873	0.758
RBF	0.873	0.621	0.851	0.873	0.861	0.596
C4.5	0.893	0.773	0.843	0.893	0.859	0.594
RF	0.898	0.734	0.849	0.898	0.864	**0.888**

Table 4
Performance evaluation of ML-based algorithms concerning the childbirth outcome for the fetus.

Method	TPR	FPR	Prec.	Rec.	F-meas.	AUC
AODE	0.834	0.282	0.817	0.834	0.822	0.847
NB	0.839	0.257	0.831	0.839	0.830	**0.858**
TAN	0.795	0.304	0.778	0.795	0.785	0.832
SVM	**0.849**	**0.239**	**0.835**	**0.849**	**0.839**	0.805
MLP	0.780	0.333	0.764	0.780	0.771	0.810
RBF	0.805	0.302	0.781	0.805	0.790	0.805
C4.5	**0.849**	0.255	**0.835**	**0.849**	0.834	0.785
RF	0.829	0.310	0.805	0.829	0.810	0.854

Table 5
Performance comparison among recent similar works related to pregnancy care.

Authors	Approach	Accuracy	Sensitivity	Specificity
Moreira et al.	AODE	0.872	**0.898**	0.419
Paydar et al. [14]	RBF	0.714	0.533	0.794
	MLP	0.909	0.800	**0.941**
Pereira et al. [13]	DT	0.839	0.883	0.801
	GLM[a]	0.774	0.843	0.676
	SVM	0.621	0.856	0.279
	NB	0.747	0.843	0.630

[a] Generalized linear model.

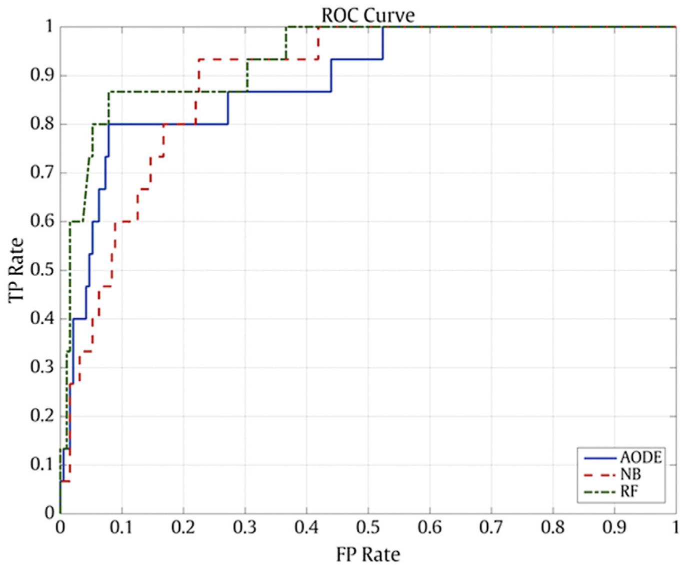

Fig. 3. ROC curves concerning the AODE, NB, and RF algorithms, which showed a better relationship between FP and TP rates.

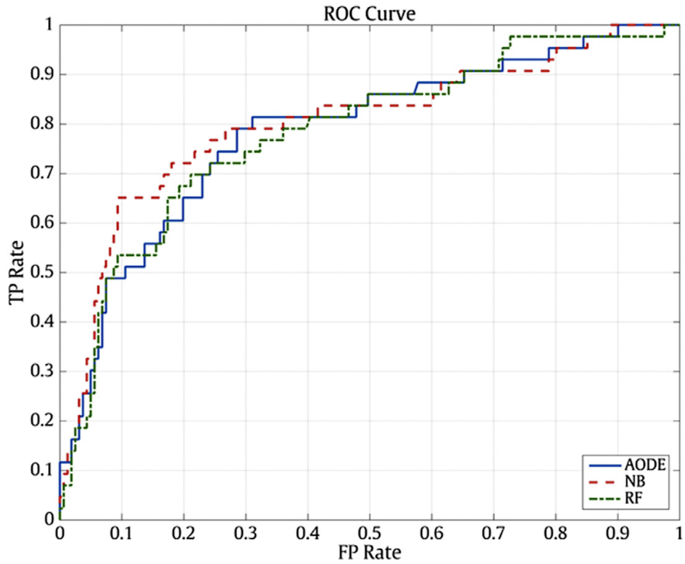

Fig. 4. ROC curves concerning the AODE, NB, and RF algorithms, which showed a better relationship between FP and TP rates.

Table 6
Computational complexity of ML-based algorithms in terms of big-O notation.

Algorithm	Complexity	Algorithm	Complexity
AODE [15]	$O(tn^2)$	SVM [22]	$O(n^3)$
NB [15]	$O(tn)$	MLP [23]	$O(n^2)$
TAN [15]	$O(tn^2 + kn^2v^2 + n^2 \log n)$	RBF [23]	$O(n^3)$
RF [24]	$O(N_T n \log n)$	C4.5 [25]	$O(n^2)$

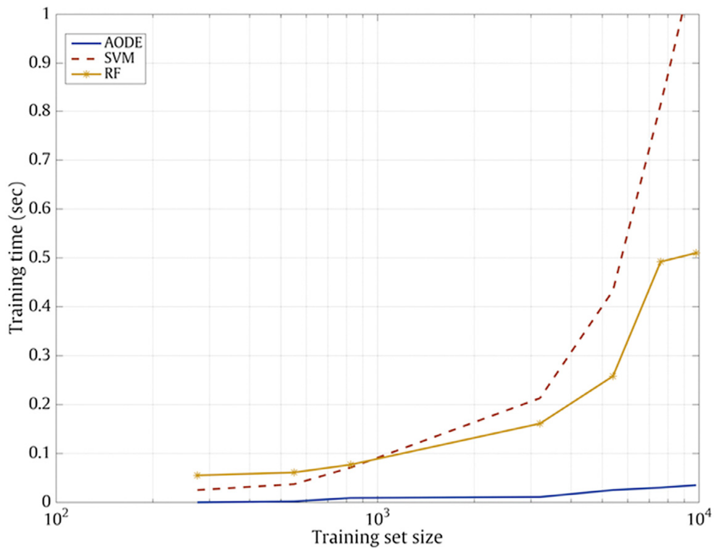

Fig. 5. Computational performance analysis of the leading studied ML approaches. This comparison relates the training set size and the time to execute this training.

5. Conclusion and future work

The worldwide demand for data is increasing. With the new paradigms of the Internet of Things, millions of devices such as smartphones, sensors, and drones are already connected to the cloud. Most of these devices are continuously processing and connected. This growing demand for information is sufficient to cause reduced performance. High latency, network failure, and downtime are issues that are expected as a result of the high volume of access and information flow. To address this problem, the edge computing concept is gaining importance. Currently, all data are sent directly to the cloud; however, with edge computing, the information first goes to a gateway, i.e., an intermediary machine that interconnects the networks, and then to the cloud. This gateway would be closer to the network edge, thereby optimizing the connection and improving the response time.

To this end, a one-dependency algorithm, which is based on Bayes' theorem, for IoT devices in the context of edge computing, is proposed. This algorithm can predict risk situations for pregnant women suffering from hypertensive disorders of pregnancy, which can cause severe complications, including death, for both the pregnant woman and fetus. The averaged one-dependence estimators algorithm represents a leading solution for edge devices in several health contexts, presenting a low computational cost and excellent accuracy. This method presented an accuracy of 0.872, sensitivity of 0.898, and specificity of 0.419, showing quite similar performance to other state-of-the-art machine learning algorithms used to solve similar issues.

Further works suggest the use of other data mining and machine learning techniques, such as lazy learning classifiers, fuzzy logic, and rule-based algorithms. Research into nature-inspired computing paradigms for the optimization of artificial neural network algorithms, such as genetic algorithms and swarm intelligence, are also strongly encouraged, as well as other pregnancy-related complications.

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Supplementary material

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Chapter 9

Computational Learning Approaches for Personalized Pregnancy Care

This chapter consists of the following article:

Computational Learning Approaches for Personalized Pregnancy Care

Mário W. L. Moreira, Joel J. P. C. Rodrigues, Vasco Furtado, Kashif Saleem, and Valery V. Korotaev.

Article submitted for publication in an international journal.

Computational Learning Approaches for Personalized Pregnancy Care

Mário W. L. Moreira, *Student Member, IEEE,* Joel J. P. C. Rodrigues, *Senior Member, IEEE,* Vasco Furtado, Kashif Saleem, and Valery V. Korotaev

***Abstract*—The increasing use of interconnected sensors to monitor patients with chronic diseases, integrated with tools for the management of shared information, can guarantee a better performance of health information systems (HISs) through performing personalized healthcare. The early diagnosis of chronic diseases such as hypertensive disorders of pregnancy represents a significant challenge in women's healthcare. Computational learning techniques are useful tools for pattern recognition in the assessment of an increasing amount of integrated data related to these diseases. Hence, in this paper, the use of machine learning (ML) techniques is proposed for the assessment of real data referred to hypertensive disorders in pregnancy. The results show that the averaged one-dependence estimator algorithm can help in the decision-making process in uncertain moments, thus improving the early detection of these chronic diseases. The best-evaluated computational learning algorithm improves the performance of HISs through its precise diagnosis. This method can be applied in electronic health (e-health) environments as a useful tool for handling uncertainty in the decision-making process related to high-risk pregnancy.**

***Index Terms*—Health information systems, Decision support systems, Machine learning, Data analysis, Healthcare, Pregnancy.**

Introduction

CURRENTLY, numerous medical organizations have adopted HISs with the purpose of reducing costs and increasing the quality of services provided [1]. However, these systems have heterogeneous architectures, databases, and infrastructures. Solutions that involve interoperability, *i.e.*, the system capability to interact with another system without effort for the user, represent a significant research topic that has been growing over the years. Interoperability has facilitated the communication, exchange, and use of patient information between healthcare providers. The amount of clinical information has increased considerably with the development of interoperable devices such as wireless sensor networks and wearables, which can be remotely usable and programmable, making it easier for health experts to access information anywhere and anytime [2]. However, there is still extensive research to be conducted to address some gaps from the cloud computing perspective of systems based on the principles and paradigms of the Internet of Things (IoT) [3]. Regarding data collected through remote devices, clinical exams, and physician diagnoses, it is possible, through advanced Big Data analysis tools, to identify risk situations and perform faster and more accurate decisions, thus avoiding problems that can lead the patient to severe problems, including death. Big Data analytical tools are critical for an innovative healthcare model. These tools allow preliminary diagnoses to be performed in a more personalized way, mainly in the early identification of diseases related to pregnancy and the health monitoring of pregnant women.

The amount of information needed for a physician to decide a patient's diagnosis has grown exponentially in recent years. Regarding the development of novel technologies and devices that collect clinical data from the patient, it is impossible, even for a health expert, to treat all this collected information accurately, especially when dealing with the monitoring and identification of complex diseases. This vast information requires health professionals and hospital managers to have more specialization and skills to handle these large volumes of data.

Data mining (DM) is a computational learning process for discovering patterns in large data sets [4]. This process involves techniques and methods from several areas such as artificial intelligence (AI), ML, statistics, and database systems. The primary objective of this approach is to extract data and transform them into useful information. DM processes focus on the application of statistical and AI techniques for the interactive analysis of data [5]. Such techniques aim to identify patterns, trends, or predictions.

In the midst of this new scenario, scientific research is increasingly focused on Big Data paradigms where the amount of information produced requires more dynamic mechanisms to transform this vast amount of knowledge into useful information [6]. In this context, computational learning techniques are presented as a solution capable of classifying these data, since these methods are useful tools in recognizing patterns and improving the costly and unfeasible conventional analysis process.

Keeping all the above issues in sight, the fusion of Big Data paradigms with computational learning techniques could

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improve the medical diagnosis accuracy of complex diseases in decision-making moments that involve uncertainty. Hence, the following major contributions are presented in this paper:

- Proposal of an architecture for the integration of large amounts of medical data from several sources. Using the proposed architecture, physicians can make their best decisions about a patient's medical condition regarding hypertensive disorders in pregnancy.
- Discussing several ML approaches capable of classifying pregnancy complications through risk factors, symptoms presented by pregnant women, and clinical exams.
- Performance assessment of the proposed ML-based algorithms and comparing them with other studies available in the literature considering various metrics.

The remainder of this paper is organized as follows. The next section discusses the proposed architecture for medical data acquisition and management using ML algorithms for pattern recognition. Then, we present the main state-of-the-art computational learning-based algorithms that are currently used for personalized healthcare. Following that, we conduct a performance evaluation and compare these different algorithms using a 10-fold cross-validation technique. Finally, we conclude the paper, presenting suggestions for future work.

Architecture for Data Integration and Acquisition for Health Information Systems

Figure 1 shows a generalized architecture for clinical data integration, acquisition, and classification, considering a Big Data scenario through ML-based inference mechanisms. In this scenario, most of the devices, *e.g.*, tablets, smartphones, and laptops, used for data exchange and communication with the proposed network are mobile.

Although the Big Data revolution in health is only just beginning, it is now possible to identify three promising areas for the coming years: precision medicine, electronic patient records (EHRs), and the IoT . Regarding these three perspectives for the use of Big Data analytics, the IoT represents, at the moment, the most developing reality, presenting recent essential advances. The promise is that one day, most everyday objects will somehow be connected to the Internet. The use possibilities in the specific area of health are immense. In the case of pregnant women, for example, the use of sensors connected to the Internet can recognize a blood pressure increase and generate an automatic alert for health experts and, in critical situations, for the health system [7]. Another promising possibility is the use of wearables, electronic objects connected to the body that can identify the imminence of convulsions caused by eclampsia [8]. The amount of data generated by the IoT is immensely useful to obstetricians/gynecologists since it identifies all immediate and distant situations that lead to the development of hypertensive diseases related to pregnancy.

The proposed architecture is composed of three primary levels, each level supporting a set of associated activities. These activities range from data acquisition to the availability to the user of the results obtained by the analyses performed on the data. The three levels that compose the architecture are data integration and processing, data analysis and visualization, and data storage. As can be seen in the figure, the conceptual architecture proposal is presented with a description of the activities associated with each of the levels. The first level is responsible for the process called extract transform and load (ETL), which comprises the activities of extracting the data from various sources, and transforming and cleaning them to ensure that the treated data is subsequently loaded into a storage area. The different data sources can have several sources, and the data can be structured, semistructured, and unstructured. The level of data analysis and visualization is responsible for the definition of the medical indicators for analysis. In this way, it is possible to define a set of metrics that allow support of the health experts. The results obtained with the data analyses are presented through the Cloud, with the results available through the Web. The relevance of this data visualization component is related to the need for quick access to data from anywhere and at anytime, thus allowing any Internet-connected device to access these results. The Big Data database stores the data that have been processed and will be used for the analytical treatment at the second level. The Big Data database is the result of the entire ETL process performed at the data integration and processing level. An important aspect associated with this third level is that it is a repository capable of storing several types of data.

Machine Learning Perspective for Big Data Analytics in Pregnancy Care

There is no doubt that the AI subfield known as ML has obtained more and more popularity in recent years. Because Big Data is the hottest trend in the technology industry at the moment, ML techniques are incredibly powerful for making predictions or calculated suggestions based on large amounts of data. ML algorithms can be divided into three categories: supervised, unsupervised, and reinforcement learning [9]. Supervised learning is useful in cases where a property is noticeable for a given data set. Unsupervised learning is useful in cases where the issue is in discovering implicit associations in a given nonlabelled data set. Reinforcement learning is between these two extremes, *i.e.*, there is some form of feedback available for each step or predictive action, without a predefined label or error message. The main supervised learning algorithms for classification problems are based on the Bayes theorem, the support vector machine (SVM) approach, induction of decision trees, and the nearest neighbors (kNN) method. The main strategies for extracting characteristics for supervised classification that are commonly used by health researchers are discussed below.

Supervised Learning Algorithms Based on the Bayes' Theorem

The Naïve Bayes (NB) algorithm follows a variation of Bayesian decision theory. Bayesian probability enables the fundamental knowledge of a domain and logic to be applied to new examples. The NB algorithm assumes that all attributes used to represent an example x are independent. To associate a new example x with a class C_k, it considers the class $C^* = argmaxP(C_k|x)$ with the greatest probability. Otherwise, the averaged one-dependence estimators (AODE) method adopts

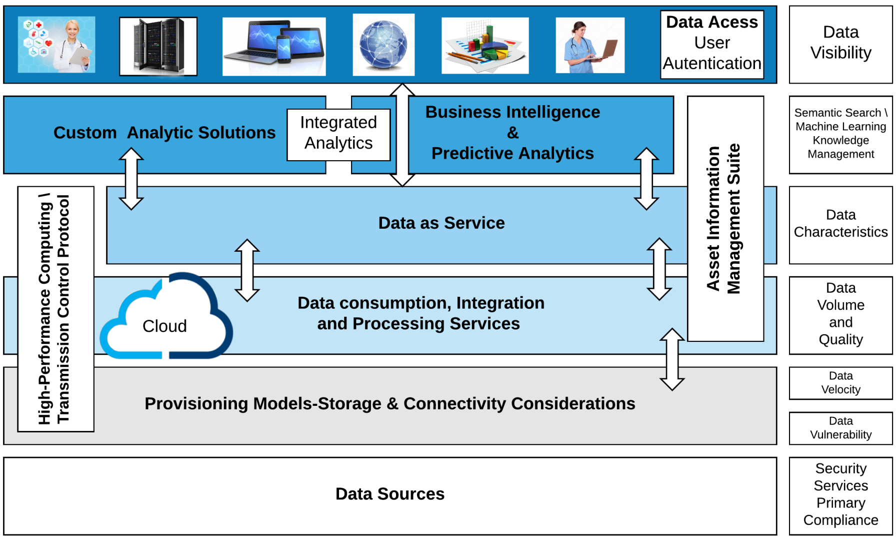

Fig. 1. Architecture proposal regarding Big Data analytics solutions for healthcare.

an approach to minimize the dependence on attributes [10]. In fact, it extends the structure of the NB classifier, including the dependency of each attribute with another attribute.

Application of Decision Tree Induction Algorithms in Health

Decision tree induction algorithms are one of the leading inductive inference methods used. These algorithms consist of discrete target approximation methods, *e.g.*, ID3, C4.5, and random forest (RF), where the learning function is represented by a decision tree, which can be represented as a set of if-then rules [11]. For health diagnosis, the decision tree is constructed by an iterative process, creating a characteristic vector formed by data of symptoms, risk factors, and clinical exams, among others. For each iteration, the division provides the error concerning the data used and, finally, the tree size is defined.

Algorithms Based on Support Vector Machine and Artificial Neural Networks (ANN) in Healthcare

In simple cases with two groups of data, the groups are named linearly separable if there is a hyperplane that separates them. The hyperplane is the decision limiter because on one side is information that belongs to one class, and on the other side, information that belongs to a different class. These separator lines may furthermore have their average distance minimized concerning such data. However, the idea is to find points that are as far away from the separator line as possible. The points that separate the hyperplane are known as support vectors. However, several problems are not linearly separable. For this, we use a nonlinear SVM map of the training data set from their original space to a new space of larger dimensions. This is called the feature space. Let $\Phi : X \rightarrow \Im$ be a mapping, where X denotes the original space and $\Im$ the characteristic space. The appropriate choice of the function Φ causes the data mapped to X to be separated by a linear SVM in $\Im$.

The kNN algorithm is an instance-based method that learns from the simple storage of training data. Regarding a new instance, this method retrieves the data in memory and sorts this new example. From the k nearest neighbors to the instance to be classified, the algorithm evaluates the dominant class and assigns this class to the new instance. The proximity of neighbors can be defined, for example, according to Euclidean distance.

An ANN is formed by simple structures called neurons, similar and autonomous, that have the output connected through a relation to all other inputs of the other elements. Therefore, if there is a loss of an element, the information is not lost. In such a case, this method can present a reduction in processing efficiency. However, it does not lose information. This feature is known as parallelism. The main strength in the structure of ANNs is their ability to adapt and learn. This ability demonstrates that ANN models can handle inaccurate data and not fully defined situations. A well-trained network can generalize when it is presented to entries that are not present in the data already trained.

In health, the leading algorithms used for the monitoring of gestational diseases such as gestational diabetes mellitus are the radial basis function network (RBFNetwork) and multilayer perceptron (MLP) algorithms [12].

Performance Assessment and Results

This study considered 205 parturient women diagnosed with a hypertensive disorder during pregnancy. First, the approval of the project by the research ethics committee at the Maternity School Assis Chateaubriand (from the Federal University of Ceará, Fortaleza, CE, Brazil) under the certificate of presentation for ethical appreciation, number 66929317.0.0000.5050, was obtained. The protocol number of the received assent is 2.036.062. The data were then collected during May and September 2017. Table I lists the risk factors, symptoms presented by the pregnant women, and laboratory exams considered in this study.

TABLE I
RISK FACTORS, SYMPTOMS, AND CLINICAL INDICATORS CONSIDERED IN THIS STUDY TO PREDICT HYPERTENSIVE DISORDERS IN PREGNANCY.

Medical indicators	Brief description
Risk factors	Personal and family history of preeclampsia; New paternity; Age; Multiple pregnancy; Interval of 10 years or more between pregnancies; Obesity; Body Mass Index (BMI); Pre-existing hypertension; Migraine; Diabetes; Kidney disease; Thrombophilia; Autoimmune disease
Symptoms presented	Hypertension; Proteinuria; Edema; Hyperreflexia; Headache; Epigastric pain; Nausea or vomiting; Blurred Vision; Dizziness; Oliguria
Laboratory diagnosis	· Hemolysis (Bilirubin above 1.2mg/dL) · Elevation of liver enzymes ((AST, TGO) > 70U/L and lactic dehydrogenase (DHL) > 600U/L) · Thrombocytopenia less than 100,000/mm^3, with greater severity when less than 50,000/mm^3

Diseases related to hypertensive disorders of pregnancy are indicated by the ICD-10 code list [13]. These diseases are identified as follows. O10 - Pre-existing hypertension complicating pregnancy, childbirth, and the puerperium; O11 - Pre-existing hypertensive disorder with superimposed proteinuria; O12 - Gestational [pregnancy-induced] edema and proteinuria without hypertension; O13 - [pregnancy-induced] Gestational hypertension without significant proteinuria; O14.0 - Early preeclampsia (placental); O14.1 - Late preeclampsia; O15 - Eclampsia; O14.1 - HELLP syndrome; and O16 - Unspecified maternal hypertension.

Concerning the performance evaluation, this work considered the 10-fold cross-validation method [14]. This evaluation method is commonly used to select the best model among a set of algorithms. The k-fold method involves randomly dividing the training set into k groups of approximately equal size. In the first iteration, one of the k groups is named the validation set, and the model is adjusted with the remaining $k-1$ groups. The average prediction error is calculated for the group that was previously removed. The process is repeated k times, and in each iteration, a group of observations is treated as a validation set. In the end, this method presents k average prediction errors, and the average of these represents the error estimate. Therefore, it is possible to select the model based on the k-fold estimate. It is interesting to emphasize the k choice. In the literature, it is common to find k equal to 10. Table II presents the results based on this evaluation method for several ML methods.

The AODE Bayesian classifier presented a better performance concerning the most of classifiers. Its performance was similar to the well-known C4.5 classifier, which is based on decision trees. The significant advantage of the first method is its low false positive rate (FP Rate), *i.e.*, the AODE classifier presents a low false alarm rate and its precision. Table III presents the results of this Bayesian approach regarding all hypertensive diseases related to pregnancy.

This study performs a comparative analysis using algorithms presented by Pereira *et al.* in [15] to validate the model based on Bayes' theorem to determine the AODE classifier. This recent literature study is similar to the proposal of this research. Although the classifier known as the generalized linear model (GLM) has excellent accuracy, also known as the true positive rate (TP Rate), this classifier presents a high FP Rate. The DT method, which is based on decision trees, presents excellent accuracy. However, its FP Rate is also very high. Figure 2 shows this comparison.

A more efficient method of demonstrating the ordinarily antagonistic relationship between TP and FP rates of tests that present continuous results is the receiver operating characteristic (ROC) curve. This curve is a powerful tool for measuring and specifying problems in the performance of medical diagnostics because it allows for the study of the sensitivity and specificity variations for different cutoff values. Figure 3 shows a comparison between the ROC curves constructed from the results of the most promising algorithms used in this study for the late preeclampsia class. Curves close to the point (0, 1) represent the classifiers with the best predictive ability. Likewise, classifiers with an area under the ROC curve (AUC) with values close to 1 are considered optimal.

It is notable that the AODE classifier performance outperforms other types of classifiers for almost all evaluation metrics. The results demonstrate that the AODE classifier can be an important piece of Big Data environments since it presents excellent performance computational and accuracy. This algorithm presents a computational complexity of $O(ln^2)$, where l represents the number of training examples, and n is the number of features. Concerning the training time, this approach presents $O(kn^2)$ as complexity at classification time, where k is the number of classes. The limitation of this method is more related to the inviability for application to high-dimensional data. Besides, its complexity is linear concerning the number of training examples and, therefore, can efficiently process a large volume of data.

CONCLUSION AND FUTURE WORK

Hypertensive disorders are the most pressing problems that occur during pregnancy. These complications are the cause of most maternal and fetal deaths worldwide, mainly in developing countries. Smart DSSs used for realizing personalized healthcare in the era of IoT and Big Data can represent an essential solution for monitoring these chronic diseases. This paper presented several computational learning techniques for large volumes of data acquired from several sources. These techniques may help health experts in moments of uncertainty, where the lack of information may be the difference between success or failure of the delivery outcome for both pregnant women and newborns. Further work suggests the study of other ML techniques as well as optimization methods to improve the performance of some algorithms. A study of the computational performance of these algorithms with an

TABLE II
WEIGHTED PERFORMANCE EVALUATION OF SEVERAL CLASSIFIERS BASED ON MACHINE LEARNING TECHNIQUES, USING DATA COLLECTED FROM PREGNANT WOMEN WHO SUFFERED FROM HYPERTENSIVE DISORDER DURING PREGNANCY.

Classifier	TP Rate	FP Rate	Precision	Recall	F-measure	ROC Area
AODE	0.732	0.123	0.700	0.732	0.706	0.892
NB	0.751	0.119	0.718	0.751	0.722	0.885
C4.5	**0.776**	0.124	**0.722**	**0.776**	**0.735**	0.822
RF	0.722	0.117	0.670	0.722	0.690	0.894
MLP	0.702	**0.104**	0.679	0.702	0.688	**0.897**
RBFNetwork	0.693	0.168	0.563	0.693	0.590	0.815
SVM	0.751	0.119	0.715	0.751	0.721	0.816
kNN	0.620	0.274	0.589	0.620	0.539	0.836

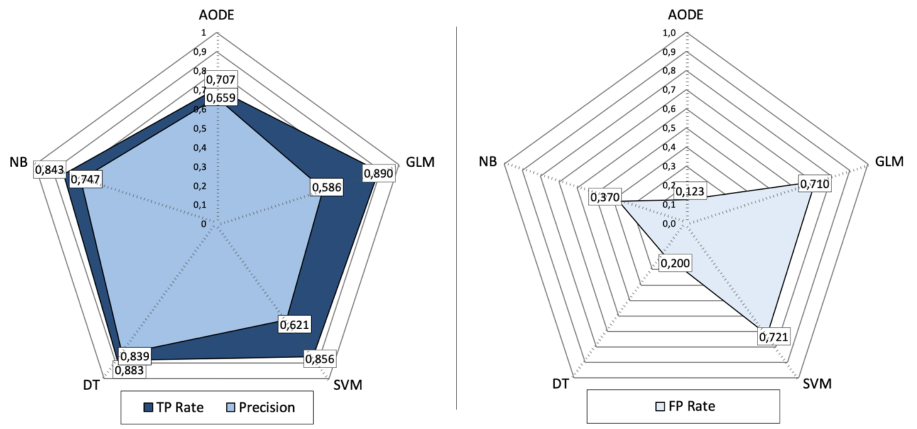

Fig. 2. Performance comparison between recent similar works related to pregnancy care.

TABLE III
PERFORMANCE EVALUATION OF AVERAGED ONE-DEPENDENCE ESTIMATORS REGARDING HYPERTENSIVE DISORDERS IN PREGNANCY.

TPR	FPR	Prec.	Rec.	F-meas.	AUC	Class
0.571	0.010	0.800	0.571	0.667	0.974	O10
0.765	0.041	0.788	0.765	0.776	0.961	O11
0.000	0.000	-	0.000	-	0.010	O12
0.857	0.043	0.692	0.857	0.766	0.972	O13
0.231	0.016	0.500	0.231	0.316	0.773	O14.0
0.902	0.239	0.755	0.902	0.822	0.886	O14.1
0.167	0.026	0.286	0.167	0.211	0.778	O15
0.667	0.016	0.769	0.667	0.714	0.951	HELLP Synd.
0.000	0.000	-	0.000	-	0.343	O16

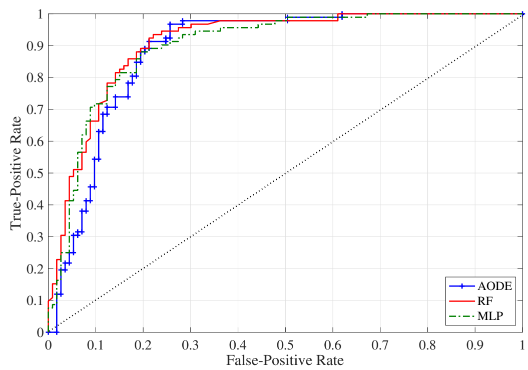

Fig. 3. ROC curves for AODE, RF, and MLP classifiers.

extensive amount of clinical data also represents an interesting topic. This work strongly suggests the application of these approaches to the study of other chronic diseases related to gestation.

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Chapter 10

Postpartum Depression Prediction through Pregnancy Data Analysis for Emotion-aware Smart Systems

This chapter consists of the following article:

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Mário W. L. Moreira, Joel J. P. C. Rodrigues, Neeraj Kumar, Kashif Saleem, and Igor V. Illin.

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Postpartum depression prediction through pregnancy data analysis for emotion-aware smart systems

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ABSTRACT

Emotion-aware computing represents an evolution in machine learning enabling systems and devices process to interpret emotional data to recognize human behavior changes. As emotion-aware smart systems evolve, there is an enormous potential for increasing the use of specialized devices that can anticipate life-threatening conditions facilitating an early response model for health complications. At the same time, applications developed for diagnostic and therapy services can support conditions recognition (as depression, for instance). Hence, this paper proposes an improved algorithm for emotion-aware smart systems, capable for predicting the risk of postpartum depression in women suffering from hypertensive disorders during pregnancy through biomedical and sociodemographic data analysis. Results show that ensemble classifiers represent a leading solution concerning predicting psychological disorders related to pregnancy. Merging novel technologies based on IoT, cloud computing, and big data analytics represent a considerable advance in monitoring complex diseases for emotion-aware computing, such as postpartum depression.

1. Introduction

Concerning the advent of Internet-of-Things (IoT), more and more everyday objects are being integrated through intelligent devices, which share a vast quantity of data [1]. These devices can generate meaningful information about a person's emotional state by capturing behavioral data. In health, the use of this data in emotion-aware smart systems can be applied in several scenarios [2], especially in those related to patients' monitoring who are at high-risk of developing emotional disturbances caused by a temporary condition, such as postpartum depression (PPD) and anxiety in pregnancy [3]. Research on emotion-aware computing is subdivided into two primary fields. The first studies the human emotional state through computational techniques, while the second seeks to develop computational systems capable of expressing artificial emotions in response to external stimuli [4,5]. Concerning both areas, analysis of big emotional data requires an high processing power and exceptional analytical capability. Therefore, to handle this volume of information, techniques that use advanced statistical and computational knowledge are necessary, i.e., algorithms and technologies that enable smart systems to recognize patterns in complex data, then, assisting experts in the decision-making process [6]. Therefore, it is necessary a performance evaluation of several algorithms used in state of the art in artificial intelligence (AI). These algorithms should be capable of helping to identify, through risk factors, clinical, and sociodemographic data, those pregnant women that present a higher risk of developing PPD.

Depression is today a serious public health problem that affects about 154 million people worldwide, being twice as common in women as in men [7,8]. The puerperal pregnancy period is the phase of higher prevalence of mental disorders in women, with depression being the most frequent disorder [9]. Approximately 20% of pregnant women present depression, and most of these women are not adequately diagnosed and treated [10]. During pregnancy, depression can cause problems not only to maternal health, although also to the health and development of the baby, such as prematurity, low birth weight, and problems with child development [11,12]. PPD cases are directly associated with the presence of high blood sugar concentrations during pregnancy [13]. This condition, known as gestational diabetes, affects

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about 4% of pregnancies and, despite the discrete symptoms, can increase the preeclampsia risk and turn the baby more probably to develop overweight and type 2 diabetes in the future [14]. Women who have pre-gestational diabetes and a previous history of mental disorder are at a higher risk of developing PPD, especially in cases of preterm childbirth. Among women without a history of psychological problems, on the other hand, cesarean delivery and age are determinants, since younger mothers who need surgical intervention are more susceptible to suffer from this type of depression [15].

The technology behind innovations brought by IoT encompasses the evolution of high-performance processors and sensors that have lower cost and lower power consumption [1,16,17]. Combined with mobile platforms [18], cloud connectivity, and Big Data, this technology allows the development of more complex applications [19]. In risk situations, the faster the doctors have access to information about the patient's clinical condition and its real situation, the higher the success chance in health care. Therefore, an intelligent solution that uses IoT concepts, Big Data, and AI is critical to improving the decisions by doctors and nurses more safely and quickly [20]. This solution must be capable of capturing and integrating data from different devices that monitor the patient in real time [21], giving the doctor access also to various types of information, such as the result of examinations, patient's medical records since hospitalization, and medication administered [22]. Using AI and Big Data to analyze all information in the briefest possible time allows inferring about the risk possibility, indicating the severity levels of the patient's health [23]. Hence, this study proposes an improved algorithm for emotion-aware smart systems, capable for predicting the risk of PPD in women suffering from hypertensive disorders during pregnancy through clinical data analysis. The main idea of this study is the possibility of identifying pregnant women' needs through real-time data analysis, allowing better management for the treatment of patients that can develop PPD by the use of clinical data for aiding medical staff in uncertainty moments. The main contributions of this paper are as follows:

- PPD prediction using real pregnancy database;
- Performance assessment of several algorithms based on decision trees (DTs), support vector machines (SVMs), nearest neighbor (NN), and ensemble classifiers.
- Classification mechanism for the primary PPD indicators: diabetes mellitus, childbirth method, obstetric and newborn-related problems.
- Use of a real patient dataset from the Maternity School Assis Chateaubriand and the 10-fold cross-validation method.

The remainder of this paper is organized as follows. Section 2 elaborates on related work about the topic focusing on emotion-aware smart systems in its application on healthcare. Section 3 describes the use of machine learning (ML) techniques for pattern recognition in predicting PPD in women suffering from hypertensive disorders in pregnancy. The performance evaluation, comparison of various methods, and the analysis of the results of the proposed approaches is presented in Section 4. Finally, the Section 5 concludes the paper and suggests further works.

2. Related work

Emotion-aware computing has been recently considered as a leading topic regarding human-computer interaction. This field is usually focused on approaches incorporating facial expression and speech recognition, as well as, human motion analysis. Another important research topic concentrates on giving to computers the ability to recognize human welfare, i.e., manners to understand a person's feelings.

In [3], Lin et al. discussed the emergence of health monitoring systems in recent years, showing a trend in the user's emotion use as an essential factor to impact human welfare. In this sense, the authors proposed an emotion-aware smart system for Big Data application in healthcare using both logical reasoning and emotion-based computing. This model is based on software-defined network (SDN) and 5G technologies as well as cloud computing environments, to improve resource utilization and global network performance. Performance evaluation used data generated by wearable devices and sensors. Results showed an interesting relation between the emotion and user's health state. Alhussein discussed the importance of the emotion recognition for initial analysis of the patient [24]. The author also presented an emotion-aware system for facial recognition using Weber local descriptors for the pattern recognition. The presented approach subdivides a static facial image into several blocks to obtain a histogram for this image. Results demonstrated that the proposed model achieved a high recognition rate. From a medical perspective, identifying patients with emotional deficits can help health professionals identify those who are most vulnerable to psychological disorders, i.e., patients who could benefit from a timely individualized intervention. Cheng et al. proposed a smart clothing based on cloud technology for next-generation healthcare systems [25,26]. This study presented a design of a practical mechanism for wearable computing-based emotional interaction for sentiment analysis using predicting models in controllable affective interactions. Results showed that the use of components to collect physiological data and receive analysis results about patient's emotional condition, provided by cloud-based machine intelligence and wearable devices, can improve the quality of experience and service for users considerably. Zhang *et al.* discussed issues related to interoperability, processing time, and stored data characteristics for emotion-aware smart systems [27]. The authors proposed a patient-centric cyber-physical system for applications and services in health. This model is based on cloud computing and Big Data analytics technologies. The results showed that cloud-based technologies and Big Data environments enhance the performance of conventional models, allowing several smart applications and services anywhere and anytime.

Concerning psychological disorders, Valenza et al. propose a wearable system with integrated fabric electrodes and sensors capable to acquiring physiological data and body posture information to pattern recognition, supporting health experts in the bipolar disorder diagnosis [28]. Lanata et al. presented a personalized wearable monitoring system to provide information and communication technologies to patients suffering from mental disorders, allowing health experts to manage their psychological disorders through a mobile-based interactive platform [29]. In [30], Liu et al. proposed a real-time emotion-aware system. This study considered emotional categories and analysis of brain waves from electroencephalograms for emotion recognition. This model showed excellent accuracy and capability to recognize various similar emotions. Regarding depression prediction, Yang et al. presented a mobile smart health recommendation system capable of predicting emotional disorders [31]. This emotion-aware system has as primary objective the improvement of patient's condition through personalized therapy solutions. This study used the Pearson correlation analysis to describe five main external depression characteristics using emotional data of users suffering from the depressive mood. Table 1 provides a summarization of existing emotion-aware smart systems and their AI algorithms.

The trends in the recent state-of-art in emotion-aware smart systems suggests the use of mobile devices, storage, and cloud computing, new approaches in AI for Big Data analytics, as well as the development of novel IoT platforms. Fig. 1 presents an architecture aimed at the remote monitoring of a pregnant woman at risk of developing psychological disorders due to gestation.

In the first few days after the childbirth, hormonal changes are the principal responsible for changes in women' emotional state. Reactions such as distress and sadness are typical in the puerperium. However, health experts, as well as the relatives, should beware to recognize when a woman's behavior indicates depression, a severe illness that

Table 1
Comparison among existing emotion-aware smart systems and their artificial intelligence algorithms.

Authors	Proposal	Approach	Main goals	Key aspects
Valenza *et al.* [28]	· A mood recognition in bipolar disorder.	· Markov chain.	· Wearable model composed of textile technology and biosignal processing.	· It takes exponentially extended period to reach their stationary distribution.
Lanata *et al.* [29]	· A personalized wearable monitoring system for evaluating remission.	· Statistical algorithms.	· Continuous biofeedback to physicians and patients, improving the psychiatric disorder management.	· It cannot respond appropriately to changes that might occur during the signal.
Liu *et al.* [30]	· Real-time discrete emotion recognition from electroencephalogram signals.	· SVM	· This method successfully classified positive and negative emotions presenting reasonable accuracy.	· The choice of the kernel and its parameter setting remains an important issue.
Yang *et al.* [31]	· Emotional health through depression prediction.	DT, SVM.	· This study presented a decision-making solution using different external factors related to depression.	· Limitations concerning to handle with discrete data.

requires medical monitoring. Even in childbirth without complications, some women experience sadness and melancholy. In most cases, it is called the baby blues syndrome [32]. A minor group, between 10 and 15% of the new mothers, faces an even more serious problem, namely the PPD. While the baby blues syndrome is transient, caused only by the abrupt hormonal changes that the woman suffers in the postpartum period and it does not need any treatment, the DPP has antecedents, i.e., it is not caused by the pregnancy or by the childbirth and needs medical monitoring, including chemical treatment. The scheme shown in Fig. 1 shows how the sociodemographic, medical history, and physiological pregnant woman data are collected, processed, and analyzed to assist the decision maker in recognizing changes in the pregnant woman's emotional state. Hospitals and medical centers hold the pregnant woman's data, which is stored in a private cloud and can be safely accessed and kept confidential by obstetricians/gynecologists through credentials. The information fusion occurs in the service manager, which joins data collected from several sources to quantify the observations. For pregnancies identified as at risk, real-time data are collected through IoT sensors, sent and analyzed through the use of ML algorithms, in a healthcare cloud service provider for an evaluation of the pregnant woman's current condition. A report is generated for the specialist physician with statistical inference and recommendations about the psychological state of the pregnant woman. This report allows the physician to make the best decision regarding the severity of the case, notifying the medical center in cases of emergency. In minor risk cases, a personal consultation is scheduled. Inference results are stored long-term in the private cloud for later queries.

3. Current state-of-the-art machine learning algorithms for big data analytics

This section presents the main algorithms used in the state-of-the-art in ML. These methods are divided into four main groups, as shown below.

3.1. Decision trees

The models generated by algorithms based on DTs assume a tree form, which is constructed through different tests that divide the data in the different nodes [33]. The most well-known DT-based algorithms are ID3, C4.5, and CART [34–36]. A DT has three types of nodes, namely root, internal, and leaf nodes. The DT-based algorithm goes from the tree root node and goes through the rules of the internal nodes until reaching a leaf node, which indicates the corresponding class. Besides obtaining the class, a significant advantage of this method is that the trajectory traversed until the leaf node represents a rule, facilitating the decision-making by the expert. Thus, it is possible to use a DT to classify a pregnant woman as healthy or as at risk of developing some emotional disturbance. A DT construction is called induction process. This process is formally defined as given a training set T consisting of an attribute vector $\bar{x} = x_1, x_2, \cdots, x_n$ is an objective variable y with an unknown distribution, the objective is to induce an optimal classifier with a minimum of generalized error. The algorithms based on DTs choose which predictive attribute will be used in each tree node. This choice is based on different criteria such as impurity, distance or dependence. Most of the algorithms divide the data of a node to minimize the impurity degree of child nodes. If a node is entirely pure, it means that all the examples that are part of this node belong to the same class. The DT algorithms use entropy as a measure of impurity. Eq. (1) shows the entropy of a node N.

$$Entropy(N) = -\sum_{C=1}^{n} p(C|N)\log_2(p(C|N)) \tag{1}$$

where $p(C|N)$ represents the fraction of elements belonging to the class C at node N, and k represents the number of classes. The entropy

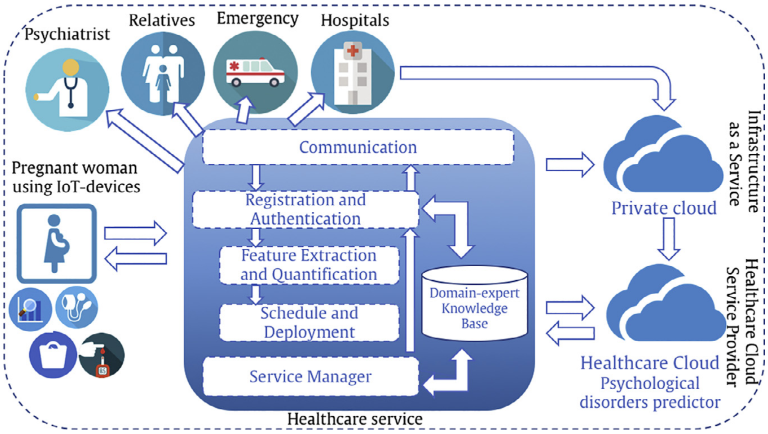

Fig. 1. Architecture proposal based on the Internet of things and cloud computing paradigms for emotion-aware smart systems in pregnancy care.

assumes a value in the interval [0,1], where 0 is the entirely pure node and 1 when a node is impure. It is necessary to resort to the gain concept that explains the difference between the parent node impurity and the impurity sum of the resulting partitions multiplied by their probabilities to determine how much a predictive attribute is useful. Eq. (2) defines the gain associated with a division S.

$$EntropyGain(S) = Entropy\left(N_{parent} - \sum_{j=1}^{n} \frac{|N_j|}{|N_{parent}|} Entropy(N_j)\right) \quad (2)$$

where n is the number of child nodes resulting from the division, $|N_{parent}|$ represents the data partition data associated with the parent node, and $|N_j|$ is the number of elements associated with the child node N_j.

Another widely used measure is the classification error. Eq. (3) presents this measure.

$$ClassificationError(N) = 1 - max_C(p(C|N)) \quad (3)$$

Where $max_C(p(C|N))$ represents the maximum of the fraction of elements of the different classes in the node.

3.2. Support vector machines

The SVM is a category of the artificial neural networks (ANNs) feedforward, i.e., networks whose outputs from a layer neurons feed the posterior layer neurons, not occurring the feedback. This technique initially developed for binary classification seeks to construct a hyperplane as a decision surface. Therefore, the separation between examples is maximal. This considering linearly separable patterns. For non-linearly separable patterns, an appropriate mapping function ϕ is sought to make the mapped set linearly separable. The most well-known SVMs-based algorithms use linear, quadratic, or cubic kernels, and methods that use fine, medium, or coarse Gaussian kernel [37,38].

A linear classification consists of determining a function $f: X \subseteq \mathbb{R}^N \to \mathbb{R}^N$, which assigns a label (+1) if $f(x) \geq 0$ and (−1) otherwise. Eq. (4) represents the formula for this function.

$$f(x) = \langle w{\cdot}x \rangle + b = \sum_{i=1}^{n} w_i x_i + b \quad (4)$$

where w and $b \in \mathbb{R}^N \times \mathbb{R}^N$, are known as the weight and bias vector, these parameters are responsible for controlling the function and the decision rule. The learning process obtains the values of w and b from the input data. The weight vector and bias can be interpreted geometrically on a hyperplane. A hyperplane represents an affine subspace, which divides the space into two parts, corresponding to data from two distinct classes. The weight vector defines a direction perpendicular to the hyperplane. Thus a linear SVM seeks to find a hyperplane that perfectly separates the data of each class and whose margin of separation is maximum, being this hyperplane called the optimum hyperplane. The optimal hyperplane is given by minimizing the norm $\|w\|$, considering the constraint presented by Eq. (5).

$$y_i(\langle w \times x_i \rangle + b) \geq 1, \{i = 1, 2, \cdots, n\} \quad (5)$$

In real problems, linearly separable patterns are hardly encountered, most of which are complex and nonlinear. Real functions were introduced, which map the training set into a linearly separable space, called feature space, to extend the linear SVM to the solution of nonlinear problems. Let the input set S be represented by the pairs $\{(x_1, y_1), \cdots, (x_n, y_n)\}$, with y_i, $i = 1, 2, \cdots, n$ the label of each pattern i, the set of data training. The feature space is a higher dimensionality space in which a function ϕ maps the input set S to obtain a new linearly separable data set S', represented by $\{(\phi(x_1), y_1), \cdots, (\phi(x_n), y_n)\}$. A kernel function ϕ receives two input data x_i and x_j and calculates the internal product of these data in the feature space. Eq. (6) presents the formula for this calculation.

$$\kappa(x_i, y_i) = \langle \phi(x_i){\cdot}\phi(x_j) \rangle \quad (6)$$

It is necessary that the function $\phi(\cdot)$ belong to a domain, where it is possible to calculate the internal product. Table 2 describes some of the most commonly used kernel functions in the state-of-the-art in ML.

Some choices should be conducted to obtain an SVM, such as the Kernel function, the function parameters, besides the algorithm for determination of the optimal hyperplane. Some considerations about the kernel functions described in Table 1 are necessary, to know, in the polynomial learning machine, the power of p is specified a priori by the user. In the radial basis function network the amplitude σ^2, common to all kernels, is also specified by the user. In the two-layer perceptron, only some values of β_0 and β_1 satisfy the Mercer's Theorem [39].

Table 2
Summary of the most commonly used kernel functions in recent literature.

Type of kernel	Function $\kappa(x_i, x_j)$	Type of classifier
Polynomial	$(\langle x_i{\cdot}x_j \rangle + 1)^p$	Polynomial learning machine
Gaussian	$exp\left(-\frac{\| x_i - x_j \|^2}{2\sigma^2}\right)$	Radial basis function network
Sigmoid	$\tanh(\beta_0 \langle x_i{\cdot}x_j \rangle) + \beta_1$	Two layer perceptron

3.3. Nearest neighbor classifiers

The kNN algorithm is a classifier where the learning is based on analogy. The training set consists of n-dimensional vectors, and each element of this set represents a point in n-dimensional space [40]. To determine the class of a new case that does not belong to the training set, the kNN classifier seeks for k elements of the training set that are closer to this element, i.e., which have the shortest distance. These k elements are called NNs. Then, it is verified the classes of these k neighbors and the most frequent class is assigned to the class of the new case. Let $X = (x_1, x_2, \cdots, x_n)$ and $Y = (y_1, y_2, \cdots, y_n)$ two points of $\mathbb{R}^N$. Eq. (7) presents the Euclidean distance, which is the most common metric in calculating the distance between two points.

$$d(x, y) = \sqrt{(x_1 - y_1)^2 + (x_2 - y_2)^2 + \cdots + (x_n - y_n)^2} \tag{7}$$

If each variable has a weight relative to its importance, the weighted Euclidean distance can be represented as in Eq. (8).

$$d(x, y) = \sqrt{w_1(x_1 - y_1)^2 + w_2(x_2 - y_2)^2 + \cdots + w_n(x_n - y_n)^2} \tag{8}$$

The kNN method has only one free parameter (the number of k-neighbors) that is controlled by the user to obtain a better classification. This classification process can be computationally exhaustive if considered a set of extensive data. Concerning some applications, however, the process is quite acceptable [41,42].

3.4. Ensemble classifiers

Ensemble classifiers are an ML paradigm in which several classifiers are trained to solve the same problem [43]. In an ensemble, a set of hypotheses is induced separately, being combined through a consensus method/operator. An ensemble generalization ability is, in general, higher than that of the isolated classifiers that compose it, usually called base classifiers [44]. The most commonly used ensemble approaches are the bootstrapping aggregating (bagging) method, which generates a sampled bootstrap data set, and the boosting method, more specifically adaptive boosting (AdaBoost). In the boosting approach, similar to bagging, each classifier is trained using a different training set. The main difference concerning the bagging approach is that the re-sampled datasets are explicitly constructed to generate mutual learning, and the voting importance is weighted based on the performance of each model rather than the attribution of the same weight to all votes.

In the bagging algorithm the classifiers are trained independently by different training sets through the bootstrap method. To construct them it is necessary to assemble k identical training sets and replicate this training data at random to build k independent networks by re-sampling with replenishment. Next, the k networks must be aggregated by an appropriate combining method, such as the majority of votes. Algorithm 1 shows the bagging pseudo-code.

Similar to the bagging method, in the boosting algorithm, each classifier is trained using a different training set. The main difference concerning the bagging method comes from the fact that the re-sampled datasets are explicitly built to generate mutual learning, and the importance of voting is weighted based on the performance of each model, rather than the attribution of the same weight to all votes. Algorithm 2 presents the boosting pseudo-code.

Despite its instability, the bagging method is directed towards the optimization of classification processes. However, this method can degrade the performance of stable operations being particularly useful when the subjacent model is a DT. The boosting method attempts to produce new classifiers with increasing classification capacity, based on the previous classifier error until a limit is reached on the number of models built or on the precision. Overall, this classification technique consists of creating a strong classifier by combining several weaker classifiers.

4. Performance assessment and results

For this study, approval was obtained from the Research Ethics Committee of the Maternity School Assis Chateaubriand of the Federal University of Ceará, Fortaleza, CE, Brazil, under the certificate of presentation for ethical appreciation, number 66929317.0.0000.5050, and assent received with protocol number 2.036.062. This research considered 205 parturient women diagnosed with some pregnancy-related problem such as hypertensive disorders, diabetes mellitus, obesity, among others.

For the performance evaluation of the proposed algorithms, this study considered the classification matrix [45]. A classification matrix is created by arranging all cases of the model into categories, determining whether the predicted value corresponded to the actual value. All cases in each category are counted, and totals are displayed in the matrix. A classification matrix is a conventional tool for evaluating predictive models and it is often called the matrix of confusion. The created array compares real and predicted values for each class. The rows represent the predicted values for the model, and the columns represent the real values. The categories used in the analysis are false positive (FP), true positive (TP), false negative (FN), and true negative (TN). This evaluation technique represents an essential tool for evaluating ML algorithms. This method facilitates the understanding and responds to effects of erroneous predictions.

Concerning the division of the pregnancy database, this study considered the 10-fold cross-validation method [46]. This approach is commonly used to select the best model from a given set of algorithms. The k-fold method involves randomly dividing the data set into k groups of approximately equal size. In the first iteration, one of the k groups is removed, called the test set, and the model is trained with the remaining $k - 1$ groups. The average forecast error is calculated for the group that was removed. The process is repeated k times, and in each iteration, a different fold is treated as the testing set. Finally, it is possible to have k average predictive errors, and the average of these errors gives the k-fold estimate. In this way, it is possible to select the model/parameter based on this estimate. In recent literature, it is quite common to adopt k equal to 5 or 10 [47]. This work considered $k = 10$.

Depressive symptomatology can be predicted by the physical complications of childbirth, history of obstetric problems, the time it takes to relate with the newborn, a worse postpartum experience, and concerns about newborn's health. PPD can still be associated with newborns' low weight, early gestation or advanced age, the number of sons, psychiatric history, thyroid problems, as well as socioeconomic factors. A significant risk factor is the diabetes mellitus. When untreated this

1: Input: Dataset $D = \{(x_1, y_1), (x_2, y_2), \cdots, (x_m, y_m)\}$:
2: Number of learning rounds T.
3: Process: For $t = 1, 2, \cdots, T$:
4: *(i)* Constitute sets bootstrap of S_t data selecting m random examples of the training set with substitution and *(ii)* Let h_t be the training base result of the algorithm based on S_t
5: End.
6: Output: Combined classifier: $H(x) = majority(h_1(x), \cdots, h_T(x))$

Algorithm 1. Bagging algorithm pseudo-code.

Input: Dataset $D = \{(x_1, y_1), (x_2, y_2), \cdots, (x_m, y_m)\}$:
Algorithm of learning base L; Number of learning rounds T.
Process: $D_1(i) = 1/m$. %Initializes the distribution of weights.
For $t = 1, 2, \cdots, T : h_1 = L(D, D_t)$;
Train the learning base h_t for D using the D_t distribution
$\epsilon_i = Pr_{i \cong D_i}[h_t(x_i \neq y_i)]$;
Measures the error of h_t
$\alpha_t = \frac{1}{2} ln \frac{1-\epsilon_t}{\epsilon_t}$
Determines the weight of h_t
$D_{t+1}(i) = \frac{D_t(i)}{Z_t} \begin{cases} exp(-\alpha_t) & if \quad h_t(x_i) = y_i \\ exp(\alpha_t) & if \quad h_t(x_i) \neq y_i \end{cases}$
Updates the distribution
$= \frac{D_t(i) exp(-\alpha_t y_i h_t(x_i))}{Z_t}$ %Normalization factor allowing D_{t+1} to be a distribution
End.
Output: $H(x) = sign\left(\sum_{t=1}^{T} \alpha_t h_t(x)\right)$

Algorithm 2. Boosting algorithm pseudo-code.

disease can cause problems to both mother and newborn, such as macrosomia, hypoglycemia, jaundice, preeclampsia, urinary tract infection, fetal death, and premature childbirth, caused by the excess of amniotic fluid in the uterus. Another risk factor is high blood pressure in pregnancy, which can bring complications to the mother, such as multiple organ failures, placental dislocation, and death and, concerning the fetus, prematurity, reduced growth, and death. Mothers of children with visible malformations are also at higher risk for PPD and anxiety. Prevalence of major depressive disorder in hypertensive patients was higher than that found in the general population. These indicators need more significant attention to the diagnosis of depressive disorders in hypertensive pregnant women in both primary and outpatient care.

Regarding the prediction of hypertensive disorders of pregnancy, the attributes used were age, where pregnant women older than 35 years were at higher risk of developing these disorders, gestational week when the pregnant woman was admitted to the emergency services, the gestational age before or after 32 weeks was considered essential for the prediction of hypertensive disturbances. Furthermore, family and personal history of hypertensive disorders in pregnancy, new paternity, multiple pregnancy, 10-year interval between pregnancies, obesity, pre-pregnancy hypertension, migraine, diabetes, kidney disease, tendency to develop blood clots (thrombophilia), autoimmune disease such as rheumatoid arthritis, scleroderma and lupus, hypertension during pregnancy and proteinuria. This work also considered three clinical indicators, namely hemolysis, elevation of liver enzymes, and thrombocytopenia for the prediction of the HELLP syndrome. The following symptoms were also considered, namely, edema, hyperreflexia, headache, epigastric pain, nausea or vomiting, blurred vision, dizziness, and oliguria.

Table 3 summarizes the results of the main indicators related to the classification matrix for the prediction of hypertensive disorders during pregnancy. Seventeen classifiers were considered, three based on DTs, six based on SVMs, four based on NN classifiers, and four ensemble classifiers.

Table 3
Performance evaluation of algorithms that present the best results in the prediction of the main problems related to hypertensive disorders of pregnancy, namely, severe preeclampsia and HELLP syndrome.

Approach	Type	Acc.	AUC	TPR	FPR	Class
Simple Tree	DT	84.7%	0.801	0.978	0.233	O14.1
Linear SVM	SVM	86.5%	0.850	0.967	0.200	
Weighted kNN	NN	78.5%	0.879	0.957	0.307	
Bagged Trees	Ensemble	86.5%	0.900	0.967	0.200	
Simple Tree	DT	96.7%	0.690	0.600	0.005	HELLP synd.
Linear SVM	SVM	95.8%	0.889	0.400	0.000	
Weighted kNN	NN	94.5%	0.893	0.267	0.005	
Bagged Trees	Ensemble	96.2%	0.927	0.600	0.010	

The ensemble-based Bagged Trees classifier presented the best performance among the seventeen tested algorithms for the prediction of one of the primary DPP indicators, namely the gestational hypertensive disorders. The main advantage of this approach is its low FP rate (FPR), i.e., this method presents a low index of false alarms. The lower the FPR, the better the predictive algorithm. Accuracy (Acc.) is the percentage of instances classified correctly, while the TP rate (TPR) means a correct classification in the positive class, i.e., the pregnant woman presented preeclampsia, a pregnancy disorder characterized by high blood pressure and significant protein loss in urine (O14.1 second the international code of diseases, tenth revision (ICD-10)), during pregnancy and the predictive model classified this case as true. Eq. (9) presents the formula for the accuracy calculation.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{9}$$

The area under the receiver operating characteristic (AUC) curve also represents a significant indicator because it provides a measure of the overall accuracy independent of a particular threshold [48]. The value of the area below the diagonal of the receiver operating characteristic (ROC) curve equal to 0.5 has no validity because accuracy and errors are in the same proportion and are due to chance. A value equal to 1.0 is not reached since there is always an overlap in the distribution of the proportions of the groups. The validity of diagnosis relies on the ability of the predictive algorithm to increase the number of acceptances as possible (TPR) and to minimize errors (FPR). In other words, maximizing sensitivity and minimizing the FP diagnoses. This relation is conveniently evaluated by the ROC curve, with all values of sensitivity (TPR) on the y-axis being registered apposite the values corresponding to the FPR (calculated as 1-specificity) on the x-axis. Invariably, there is a trade-off between sensitivity and specificity when a cutoff value is set for quantitative test results. If a test were perfect, there would be a complete separation of values between patients with and without the condition, the cutoff would be the lowest value in patients with the disease, and the AUC would be equal to 1. However, since there are no perfect tests in healthcare, there will ever FP or FN results. The AUC is related to the Gini coefficient (G_1) by the formula $G_1 = 2AUC - 1$. Eq. (10) shows the method for the calculation of this coefficient.

$$G_1 = 1 - \sum_{k=1}^{n} (X_k - X_{k-1})(Y_k + Y_{k-1}) \tag{10}$$

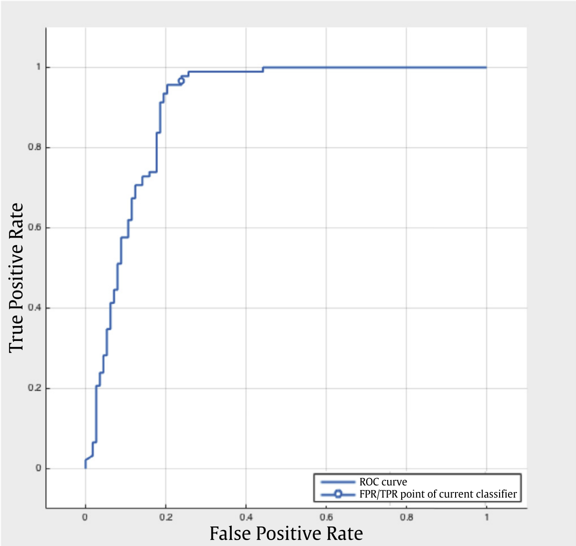

Fig. 2. Receiver operating characteristic curve of the Bagged Tree classifier for the severe preeclampsia class.

Hence, it is possible to calculate the AUC through an average of some trapezoidal approximations. Fig. 2 presents the ROC curve for the Bagged Trees algorithm concerning the severe preeclampsia class.

Table 4 presents the best approaches for predicting the type of delivery for pregnant women. For that, this study added information about the period during which labor occurred (in gestational weeks), considering the 34th week as a critical indicator. Births with some surgical intervention increase the risk of PPD.

The regular results showed in Table 4 are due that, in Brazil, the pregnant woman has the option of choosing the delivery type in cases with less severity. Thus its prediction is quite complicated. On the other hand, the accuracy of the algorithms used in the prediction of the cesarean type is higher for the emergency cesarean than for the antepartum cesarean since, in this second situation, there is an imminent health risk to the fetus and/or to the parturient. The risk factors that have influenced this emergency clinical situation are more difficult to predict than urgency situations, such as eclampsia.

Table 5 presents the childbirth outcome for the pregnant woman. The categories considered were hemorrhage complications, intensive care unit (ICU) admission, normal, and maternal death.

The results of the Complex and Boosted Trees algorithms performed better than the SVM and kNN algorithms since these methods based on DTs present a lower FP rate, i.e., a lower frequency of false alarms.

Fig. 3 presents the ROC curve for the Boosted Trees algorithm concerning the ICU admission childbirth outcome class.

Finally, Table 6 presents the childbirth outcome for the fetus. The categories added were small to gestational age and the Apgar score for the first five minutes after childbirth [49]. The response classes are normal, neonatal ICU admission, and neonatal death.

Fig. 4 presents the ROC curve for the Bagged Trees algorithm concerning the ICU admission childbirth outcome class for the fetus. The choice of a cutoff point should be based on an optimal combination between sensitivity and specificity, since part of the assumption that the classification of an individual as event, given that it is a non-event (FP), and the classification of an individual as non-event, given it is an event

Table 4
Performance evaluation of algorithms that present the best results in the prediction of the antepartum and urgency cesarean.

Approach	Type	Acc.	AUC	TPR	FPR	Cesarean
Simple Tree	DT	73.2%	0.523	0.893	0.412	Antepartum
Coarse SVM	SVM	74.3%	0.533	0.985	0.479	
Coarse kNN	NN	73.7%	0.605	1.000	0.500	
Bagged Trees	Ensemble	70.5%	0.629	0.856	0.421	
Simple Tree	DT	84.0%	0.548	0.250	0.070	Urgency
Coarse SVM	SVM	86.5%	0.568	0.000	0.000	
Coarse kNN	NN	86.5%	0.638	0.000	0.000	
Bagged Trees	Ensemble	85.1%	0.585	0.094	0.034	

Table 5
Performance evaluation of algorithms that present the best results in the prediction of ICU admission and normal childbirth outcome.

Approach	Type	Acc.	AUC	TPR	FPR	Outcome
Complex Tree	DT	93.6%	0.747	0.400	0.025	ICU adm.
Linear SVM	SVM	92.3%	0.788	0.067	0.015	
Weighted kNN	NN	92.8%	0.734	0.000	0.005	
Boosted Trees	Ensemble	94.5%	0.831	0.467	0.020	
Complex Tree	DT	92.3%	0.829	0.984	0.350	Normal
Linear SVM	SVM	89.5%	0.754	0.978	0.426	
Weighted kNN	NN	89.9%	0.957	0.995	0.478	
Boosted Trees	Ensemble	92.7%	0.780	0.967	0.256	

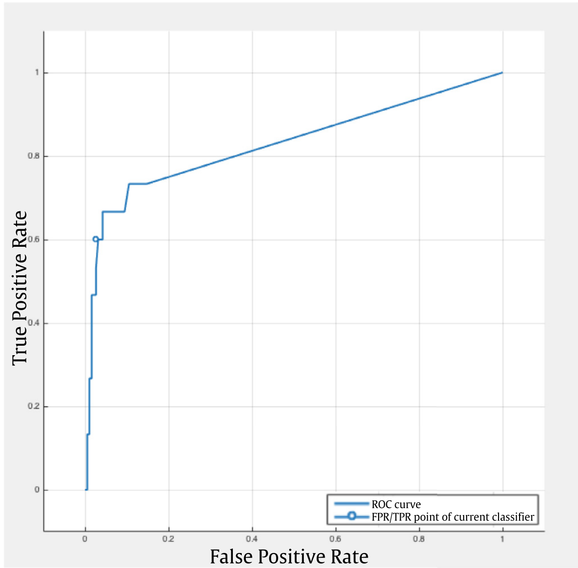

Fig. 3. Receiver operating characteristic curve of the Boosted Trees classifier for the ICU admission childbirth outcome class.

Table 6
Performance evaluation of algorithms that present the best results in the childbirth outcome prediction for the fetus.

Approach	Type	Acc.	AUC	TPR	FPR	Outcome
Simple Tree	DT	86.5%	0.729	0.628	0.083	ICU adm.
Linear SVM	SVM	85.8%	0.770	0.604	0.087	
Medium kNN	NN	83.7%	0.753	0.233	0.035	
Bagged Trees	Ensemble	86.9%	0.790	0.558	0.062	
Simple Tree	DT	91.1%	0.813	0.961	0.192	Normal
Linear SVM	SVM	89.5%	0.852	0.954	0.221	
Medium kNN	NN	0.837%	0.827	0.987	0.409	
Bagged Trees	Ensemble	90.3%	0.870	0.967	0.227	
Simple Tree	DT	94.4%	0.897	0.000	0.010	Neo. death
Linear SVM	SVM	95.3%	0.895	0.000	0.000	
Medium kNN	NN	95.4%	0.790	0.000	0.000	
Bagged Trees	Ensemble	95.8%	0.892	0.300	0.010	

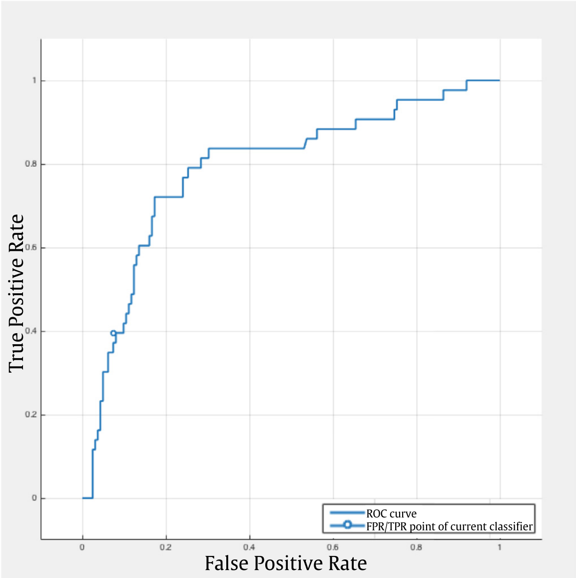

Fig. 4. Receiver operating characteristic curve of the Bagged Trees classifier for the ICU admission childbirth outcome class for the fetus.

(FN) effects equivalent failures for the predictive analysis. By analyzing the ROC curve presented in Figs. 3 and 4, considering that the cutoff point referring to the best combination of sensitivity and 1-specificity is closer to the upper left corner of the graph, this study concludes that the algorithms based on ensemble learning present an excellent reliability in predicting risk events for both pregnant women and neonates. The AUCs reached by the Boosted and Bagged Trees algorithms, concerning the ICU admission, also corroborate with this statement, presenting values close to 1, i.e., 0.831 and 0.790 respectively.

5. Conclusion and future work

Postpartum depression (PPD) is surprisingly common. It is estimated that it affects about 10% of women who have had a baby. Symptoms include anxiety, lack of energy, and changes in sleep and eating patterns. Depression is a disease like any other, which requires treatment, including medicaments and therapy. Above all, PDD is not the woman's fault, and it does not mean a baby rejection. It is crucial that a woman or family member recognize PPD symptoms immediately to assure the mother receives the necessary support. Without an accurate treatment, the PPD can persist for months or even years. Experts do not have an exact explanation for PPD. However, health experts believe it is a combination of hormonal, environmental, psychological, and genetic factors. Emotion-aware smart systems can facilitate an early identification of this disease. With the paradigms of IoT and cloud computing, it is possible monitoring the emotional state of the new mother through devices that interact with each other intelligently. This paper proposed on the use of various artificial intelligence techniques to offer to medical specialists exceptional guidance regarding critical indicators that can support the decision-making process for the emotional state monitoring of the pregnant woman during and after pregnancy. This study seeks to contribute to the United Nations Millennium Development Goals, concerning the topics of reduction in more than 50% the under-five mortality rate, reduction in the maternal mortality rate worldwide, and improvement in the pregnant women's health care [50]. The fulfillment of these goals provides a healthy life through the promotion of the pregnant women well-being of all ages.

Further work proposes the study of other ensemble classifiers to improve the accuracy of more complex indicators, especially those related to urgency, such as intensive care unit admission. The study of other related-diseases to psychological disorders associated with gestation using machine learning techniques is also suggested.

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Supplementary material

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.inffus.2018.07.001.

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Chapter 11

Conclusion and Future Work

This chapter presents the main conclusions that result from the research work described in this thesis. Furthermore, it discusses several research topics related to the work developed along the doctoral programme that can be addressed in further research works.

11.1 Final Conclusions

Throughout the present thesis, it was studied and evaluated the performance of several algorithms based on ML through the application of data partitioning strategies, optimization of algorithms, and classification through ensemble learning. This topic summarizes the work done and signalize some suggestions that can be followed as guidelines for further research on this topic.

The first part of this work is described in detail in Chapter 2 of this document. It was conducted an in-depth study of the thesis research subject to understand and analyze in detail state of the art. Then the primary objectives were defined and described, as well as this research work focus was delimited. Chapter 2 presents a comprehensive study on the evolution of DSSs for health, especially in the area of medical diagnosis. Through this study, it was possible to identify the main limitations and open problems in these type of systems. This chapter also identified classification algorithms based on ML that supported the proposal of a viable solution to the problems analyzed. After analyzing and identifying the main limitations of the existing solutions, this study has identified and discussed some open questions.

The second part of this work is presented in Chapter 3 and relates to one of the primary objectives of this thesis, the proposal of a novel methodology for semantic interoperability in SOA to health services. This proposal integrates semantically acquired data of different EHRs using different archetypes and infers on this knowledge base through ontology rules predicting high-risk situations that can lead to severe problems during pregnancy. This methodology serves as the basis for an SOA that integrates and classifies new cases from a knowledge base. The performance evaluation of the proposal was performed through cross-validation that requires the partitioning of the database into ten subsets of similar sizes involving 133 data from pregnant women. The metrics used for performance evaluation of the ontology rules were precision, recall, F-measure, and AUC. The major types of hypertensive disorders of pregnancy were analyzed during the trials, assuming as the worst-case accuracy of 0.714 for the eclampsia prediction. The results were quite encouraging. As a result, it has been observed that the use of ontologies to address semantically acquired patterns from different EHRs has the potential to influence an SOA implementation for CDSSs significantly. For the worst case, the mean probability for the eclampsia prediction was 71.4%, and the AUC was 0.976. It should be noted that algorithms that have an AUC curve close to 1 are considered ideal for classification tasks. These values are all influenced by the predicting complexity some types of risk situations, such as eclampsia, for example, where, despite an extensive line of research in the area, its cause remains unknown [1].

The third part of this work is described in detail in Chapters 4-9 and concerns the construction and performance evaluation of a solution using AI for health applications in various environments. Chapters 4 and 9 present the proposal using one-dependence estimators using Bayesian algorithms to ensure accuracy, precision, and a low FPR from the classification of data from pregnant women who developed some hypertensive disorder during pregnancy. Chapters 5-8 present the performance evaluation of solutions based on ANNs. This evaluation involved 100 to 400 participants who provided their medical records for the development of proposals based on ML for ANNs. The performance evaluation concluded that the MLP algorithm, optimized by the PSO algorithm, presented the best performance regarding accuracy. However, this method also presents a high computational cost because it is a model that uses a back-propagation algorithm to feed the ANN. The optimization of the MLP algorithm by a nature-inspired technique on average exceeded other approaches by 26.4% concerning accuracy and 14.9% concerning the TPR and showed a reduction of 35.4% in the FPR. Besides, this method was superior to the classic MLP algorithm regarding accuracy and AUC by 2.3 and 10.2%, respectively, when applied to the delivery outcome for pregnant women.

The fourth and final part of this thesis is presented in Chapter 10 and concerns a proposal for an algorithm based on ensemble learning for emotion-aware systems to predict risk situations before, during and after childbirth. This proposal has as primary objective to offer a hybrid model based on DTs and the bootstrapping aggregating and adaptive boosting algorithms to identify any risk situation and for medical obstetricians/gynecologists to easily follow the development of the health status of the pregnant woman, as well as gestation. To performance evaluation of this proposal, the same metrics were used in a real database involving 205 pregnant women. The results were very positive, with the proposed algorithm presenting 94.5% of accuracy for the prediction of admission to intensive care units (ICUs) in the delivery outcome for the pregnant woman and 86.8% of accuracy for the prediction in the ICU admission for the delivery outcome for the fetus.

The primary purpose of this thesis and all partial objectives have been entirely fulfilled. A model proposal for health services and applications enables medical experts to accurately assess the health status of pregnant women who have developed some hypertensive disorder during pregnancy. Through a hybrid prediction algorithm, it is possible to make decisions in uncertainty times anytime and anywhere. Given the complexity of the data and medical information used in this work, the proposed solution was successfully evaluated. As an extension of the realized work, a generalized application model was proposed for any situation related to pregnancy-related problems, which presented an excellent performance in several indicators.

11.2 Future Work

To conclude this research work, it remains to suggest future study topics resulting from the developed research work:

- To extend this study to larger and geographically distinct data universes, as well as apply other ensemble learning techniques based on relational statistical learning.

- To solve problems involving the treatment of large volumes of data, present an ideal solution involving the use of a parallel and distributed processing model that suits any volume and degree of complexity [2].
- To use techniques based on deep learning to contribute to the solution of new challenges regarding pregnancy care, *e.g.*, Zika virus, which represents a potential cause for the birth of newborns with microcephaly, especially in underdeveloped and developing countries [3].
- To develop a single sensor to measure high blood pressure as well as the protein loss in the urine for monitoring risk pregnancies [4].
- To implement and evaluate the results of the proposals presented in this thesis in a real hospital environment, for their validation and comparison with the results obtained by the proposed models.

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