Smart Mobile System for Pregnancy Care Using Body Sensors

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Abstract— **Hypertensive disorders are the most common problems during pregnancy. They cause about 10% of maternal deaths. The world mortality rate has decreased but many women are still dying every day from pregnancy complications. Various technic resources are being used in an integrated manner in order to minimize even more the death of both mothers and babies. Mobile devices with Internet access have a great potential to expand actions of health professionals. These devices facilitate care with people that are living in remote areas, assisting in patient monitoring. Information exchange anywhere and anytime between experts and patients could be an important way to improve the pregnancy monitoring. This paper presents a mobile monitoring solution using body sensors to identify worsens in the health status of pregnant women suffering hypertensive disorders. This mobile application uses Naïve Bayes classifier to better identify hypertension severity helping experts in decision-making process. Results show that the proposed mobile system is promising for monitoring blood pressure disorders in pregnancy.**

***Keywords*— Decision support systems; Mobile Health; Mobile Computing; Bayes methods; Hypertension; Pregnancy**

I. BACKGROUND

Causes of maternal death during pregnancy are very variable and usually occur in events of risk pregnancy or in a premature birth. According to World Health Organization (WHO) about 800 women die every day worldwide from preventable causes related to pregnancy risk. About 99% of these deaths occur in developing countries [1]. Although this maternal mortality worldwide dropped by almost a half only, in 2010, almost about 300,000 women died along and following pregnancy and during childbirth. The majority of these deaths occurred in developing countries and most of them could have been prevented with due medical care.

According to [2] mobile environments along with other technologies open up novel opportunities on healthcare. Thus, the integration and convergence of several technologies could contribute to develop healthcare services anytime and anywhere. Triantafyllidis *et al.* present a system deployed on a mobile device that allows self-management daily activities of chronically ill patients [3]. This system uses unobtrusive vital signs monitoring through a wearable multi-sensing device. Results show the system has been well evaluated by the patients because it is easy to learn and use. It is also considered helpful for disease management and treatment.

Internet of Things (IoT) is a concept in which devices used dairy by people are equipped with sensors capable by capturing aspects of real world, as temperature, humidity, presence, etc., and send data to a repository to receive this information and use them smartly. Catarinucci *et al.* propose an IoT-based smart architecture for patients monitoring and tracking, staff personnel, and biomedical devices inside hospitals [4]. This smart system is capable to collect, in real time, both environmental conditions and patients' physiological parameters using a hybrid sensing network. The achieved results demonstrate the proposed system also provides remote patient monitoring and immediate handling of emergencies. Xu *et al.* propose a semantic data model to store and interpret IoT data [5]. Treatment of data in this IoT-based system is used to provide support to emergency medical services. It accesses data timely and ubiquitously from a cloud and mobile computing platform. Results show that these data accessing method is effective in a distributed heterogeneous data environment.

Considering the above-mentioned context, this paper aims to investigate a mobile solution for high-risk pregnancy monitoring using sensor networks. This application alerts the health staff about any change in hypertension condition during pregnancy. It proposes the use of Naïve Bayes classifier to better classify the seriousness of hypertensive disorder helping a health specialist in emergency moments. These systems applied to healthcare offer the possibility to monitor and evaluate pregnant health state, notifying complications that can occur in a given time. The main contribution of this work includes a mobile healthcare system based on Bayesian networks that uses sensors, as shown in [6-8], to support decision makers in the pregnancy care and its performance evaluation.

The paper is organized as follows. Section II addresses the use of Naïve Bayes classifier on healthcare, while section III shows the system architecture and its modelling using the Naïve Bayes classifier. Performance evaluation of the proposed method and results analysis are considered in Section IV. Finally, Section V provides the conclusion and suggestions for further works.

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II. NAÏVE BAYES ON HEALTHCARE

The performance assessment of three supervised machine learning classification techniques were studied by Kachroo *et al.* [8]. The authors compare these classification methods using real data sets to predict cancer incidence and mortality rates. Results indicate that Naïve Bayes classifier achieved the greatest performance for both cancer incidence and mortality. Ravindran *et al.* propose a system to identify safe and unsafe conditions in usual activities of both children and pregnant women [9]. Results show that data sets are better classified by a Naïve Bayes classifier. Interpretation results by this classifier always show significant and identifiable thresholds.

Parages *et al.* propose a method for to predict perfusion scores given by humans for each myocardium region [10]. The proposed approach is based on a machine-learning algorithm, *i.e.*, the Naïve Bayes classifier. In the proposed approach, the classifier is applied over a set of image features extracted from polar maps. Results show good performance agreement between humans and the proposed method. Shaikh *et al.* propose a smart system that uses data mining techniques. [11] Using the Naïve Bayes classifier this system is able to solve complex queries for diagnosing heart disease. Qian *et al.* developed a framework that predicts cardiac events better than the conventional measures [12]. This system uses Naïve Bayesian method for risk integration. Results showed that this approach significantly improves the predictive accuracy, specificity, and sensitivity level. Brüser *et al.* present a study on the feasibility of the automatic detection of atrial fibrillation through cardiac vibration signals recorded by bed sensors [13]. This research evaluates and classifies seven machine learning algorithms. The Naïve Bayes approach showed that trains and classifies data very quickly.

Naïve Bayes classifier is probably the Bayesian classifier most widely used in various diagnostic problems. Despite being simplistic, it reports a better performance in several tasks of classification.

III. SYSTEM MODEL

This section presents the system architecture and describes step-by-step the Bayesian model construction used in this study.

A. Model Architecture

The model architecture used in the proposed scheme is shown in Figure 1 with some components. Under this model, pregnant monitoring presenting high-risk pregnancy is performed by sensors presented in [6-9] for collection of physiological data. Other important data for the identification of the hypertension severity is the presence of protein in urine. To collect these data a proteinuria test is performed, as shown in [14]. Then, the data probabilistic inference is made in the mobile system using the Bayesian model.

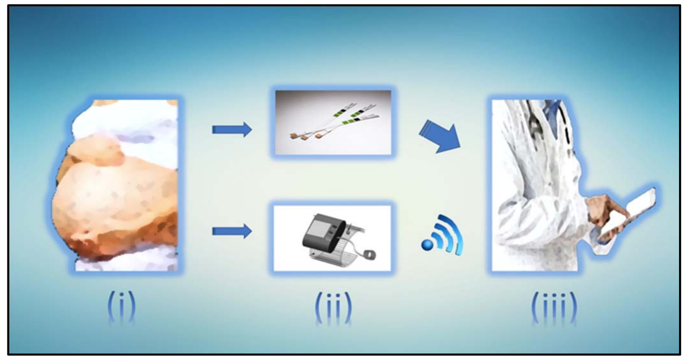

Fig. 1. Architecture model showing a caregiver monitoring a high-risk pregnancy using mobile technologies.

B. Naïve Bayes classifier

The Bayesian model can offer important statistical information for decision-makers regarding to this change. Bayesian classifiers use the Bayes theorem – Eq. 1.

$$P(c_i/d) = \frac{p(d/c_i)p(c_i)}{p(d)} \quad (1)$$

First member of the equation $P(c_j/d)$ represents which the caregiver is trying to identify, *i.e.,* if there were significant changes in the patient's condition. The Bayesian method shows how to change the *a priori* probabilities $(p(c_j), p(d))$ considering new evidences in order to obtain the *a posteriori* probabilities $(p(c_i/d), (p(d/c_i))$. The main idea is calculating the probability of an event A given a B event, e.g., probability of someone having hypertensive disorder, knowing blood pressure and/or proteinuria.

Figure 2 shows the modeled network that is used as the basis of obtained data. This figure presents the Bayesian inference for a patient with preeclampsia. Three types of blood pressure are defined: *i)* normal (less than 139mmHg systolic), *ii)* high (between 140 and 179mmHg systolic), and *iii)* very high (greater than 180 mmHg systolic). Three classifications of proteinuria (in 24 hours) are also defined: *iv)* absent (without protein in urine), *v)* traces (about 0.3 to 1g/24hrs), and *vi)* severe (greater than 3.5g/24hrs). These categories represent the *a priori* probabilities. Two degrees of hypertension severity were considered: *a)* mild and *b)* severe, and the system is capable to identify if this patient suffers with another hypertensive disorder (unknown her previous condition).

Considering that two attributes are required to classify the severity of preeclampsia, the model assumes independent attributes to estimate the desired parameters as showed in Eq. 2.

$$P(Preecl.) = \frac{p(BPres./Preecl.)p(Prot./Preecl.)p(Preecl.)}{p(BPress.)p(Prot.)} \quad (2)$$

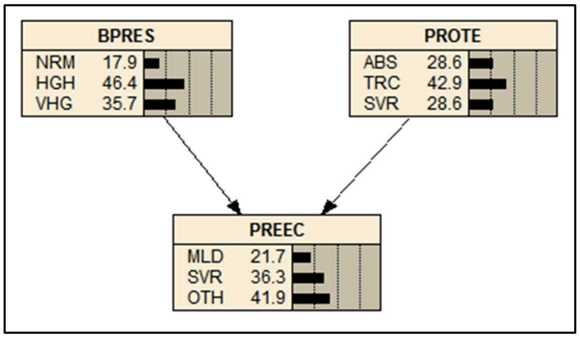

Fig. 2. Bayesian inference built with data collected from 25 pregnants (in percentage).

The *a priori* probability can be firstly calculated constructing a frequency table for each attribute. Then, next step is to use the Naïve Bayes classifier equation to calculate *a posteriori* probability for each class. The class with the highest *a posteriori* probability is the prediction outcome. Figure 3 illustrates the decision-making process.

Fig. 3. Illustration of the inference model showing the probabilities for each severity of hypertensive disorders to the healthcare expert.

Using the data collected by the sensor and the caregiver, below, it is presented a case study to show the model operation. An expert receives data from a sensor on his/her mobile device of a patient who has severe preeclampsia (systolic blood pressure 158mmHg and proteinuria 3.6g/24hrs). Next step is the collection of proteinuria. Computing the new data (systolic blood pressure 142mmHg and proteinuria 3.6g/24hrs) in the classifier system, it calculates the probability of the pregnant having changed her condition. Demonstration of this model inference is shown in Eq. 3.

Despite the improvement of the patient's health condition there were no alterations in the pregnant clinical condition in terms severity with a probability of accuracy about 84%.

$$P(severePE/HighBP, SevereP) = \tag{3}$$

$$= \frac{p(HighBP/severePE)p(SevereP/severePE)p(severePE)}{p(HighBP)p(SevereP)} = 0.84$$

Next section focuses on the performance evaluation of the proposed model. A technique to assess the potential of a model generalization from a set of data was used. This technique is widely used in problems where the modeling goal is prediction.

IV. Performance Evaluation

The cross validation is used to evaluate the proposed method. Tsumoto and Hirano [15] propose a framework for assess the cross-validation methods that use rule induction based on statistical indices. It uses the leave-one-out method. This approach is a special case of *k*-fold cross validation, with *k* equal to the total number of data *N*. In the current approach, *N* error calculations are performed, one for each data. Seize this method have a high computational cost, it is indicated for situations where few data are available. Table I shows the evaluation result performed by this method.

TABLE I. Performance Evaluation from the Naïve Bayes Classifier.

Technique	*k*	TP	FN	FP	TN	Sens.	Espec.	Acc.	AUC
Naïve Bayes	25	3	4	1	17	0.4286	0.9444	0.8000	0.687

Sens.=Sensitivity; Spec.=Specificity; Acc.=Accuracy.

Figure 4 shows the area under ROC (receiver operating characteristic) curve. This curve is a powerful tool to measure performance problems in medical diagnosis. It allows studying the variation of the sensitivity and specificity for different parameters.

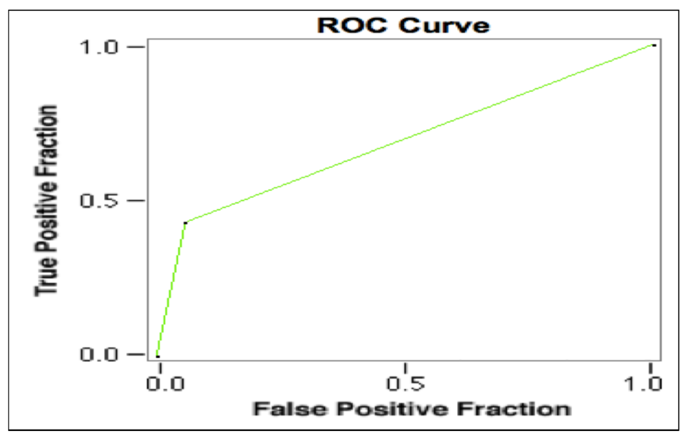

Fig. 4. Area under the ROC curve. Models that present curves closest to the point (0,1) can be considered optimal models.

The model proposed in this paper performed well in terms of specificity, *i.e.*, when the model suggest a negative result for pregnant woman that did not change her condition. Experiments with high specificity are quite useful to confirm the presence of diseases. Regarding the sensitivity, the results are reasonable. Sensitivity means the probability that a model may be positive for pregnant woman that changed her hypertension. This is due to the low quantity of data used to feed the system. With enough amount of data, the system can predict better for positive cases of severe preeclampsia.

The accuracy of the system has shown a good performance. It is the percentage of the results correctly identified by the model. Thus, the more accurate the measurement process closest is the result of the real value measurement.

V. CONCLUSION AND FUTURE WORK

This work discussed the use of a mobile application to support caregivers in pregnancy monitoring. This system receives data from body sensors to measure the blood pressure, in real time, and together with data collected by a healthcare expert through a proteinuria testing makes the inference using the Bayesian classifier Naïve Bayes.

A case study has been performed to demonstrate and validate the inference process. To predict changes in the health status of a pregnant woman that suffering from severe preeclampsia, experienced experts collected a dataset from 25 pregnant. The model shown a percentage of 84% of the pregnant does not changed their clinical condition, despite having a slight improvement.

Performance evaluation of this proposed method showed that this classifier performed well in prediction with an accuracy of 0.8. The method also had a specificity of 0.9444 and a sensitivity of 0.4286. The classifier proved to be a good predictor, but more studies should be performed in order to improve the accuracy of the used approach.

Further works aim to improve the system performance by increasing accuracy and sensitivity. With a larger dataset it is possible to improve these indicators. A comparative study between the different Bayesian classifiers should be conducted using discrete variables. For this research, two probabilities distributions are highlighted: the multinomial distribution and the Bernoulli distribution. Other works addressing the use of other classifiers as fuzzy logic, neural networks, support vector machines, and decision trees can be considered.

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