# Review and Analysis of Risk Factors of Maternal Health in Remote Areas Using the Internet of Things (IoT)

**Chapters** March 2020

DOI: 10.1007/978-981-15-2317-5_30



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# Review and Analysis of Risk Factors of Maternal Health in Remote Areas using the Internet of Things (IoT)

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**Abstract.** IoT is the greatest ingenious innovation in the modern era, which can exploit also in mission-critical like the healthcare industry. This paper demonstrates effective monitoring of pregnant women mostly in a rural area of a developing country, with the help of wearable sensing enabled technology, which also notifies the pregnant woman and her family about the health conditions. There are many researchers have been researched to reduce the maternal and fetal mortality but the mortality rate is not reducing, where it should be in zero tolerance. This research is intended to use machine learning algorithms to discover the risk level on the basis of risk factors in pregnancy. In this research, an existing dataset (Pima-Indian-diabetes dataset) has been used for the analysis of risk factor and comparison of some machine learning algorithms showing that Logistic Model Tree (LMT) gives the highest accuracy in case of classification and prediction of the risk level. Regardless, a few selected pregnant women's data has been collected (through IoT enabled devices) and the same process is also applied for this dataset also by using LMT. Com parison results show that the prediction of risks is the same for the existing and real dataset.

**Keywords:** Maternal Risk Factors, Internet of Things, Wearable Sensors.

## 1 Introduction

Most of the pregnant women, die from the known and preventable complications of pregnancy and childbirth, live in low- and middle-income as such as developing countries who are ignorant about the risks factors that cause maternal mortality [1-2]. Consistently, pregnancy should be monitored to ensure the healthy development of the fetus and the safe delivery of the infant. Regardless, the greater portion of pregnancy related devices is placed in health complex for being expensive and in consequence, passing through all the difficulties as proper transport, huge traffic hours, ruthless weather, environmental pollution, extended queues to attain regular checkups in hospital [3 ]. Pregnancy-related complications will be possible to diminish by classifying risk factors, which is essential at the early stage of the symptoms [4]. The objective of this research is to provide effective care for pregnant women mostly living in a rural area by using smart technology based on IoT.

The IoT is the integration concept of all devices which are readable, addressable, recognisable, locatable and manageable via the Internet through RFID (Radio-Frequency

Identification), wireless local area network, wide area network, etc. Additionally, it provides real-time information and interacts with real-time users. The hardware layer is responsible for the interconnection between the physical devices through the sensors where miniaturization can be a challenge and in the communication layer, lots of devices are connected in a network where bandwidth and electromagnetic spectrum may be a challenge that can be a barrier to transfer data effectively and efficiently. However, the Internet of Things is an important medium for data transfer through the hardware layer with full communication between Person to Person and machine to machine, for providing the health monitoring system for patients [5].

This approach is an attempt to resolve a maternal healthcare problem presently the non-urban area of developing countries is facing. The foremost objective of this paper was to design a remote healthcare system to reduce the complications during pregnancy as well as the birth of an unborn child. It's encompassed three main parts. First one is finding patient's relevant medical data using IoT based medical sensors; second, processing the collected data for predicting maternal health status and the last part was transferring the collected data to medical experts for remote viewing that enables the medical team to monitor the mother and fetal health progress away from hospital pregnancies.

Wearable sensing devices name as Radio Frequency Identification (RFID) tags in Body Area Network (BAN) will be connected by Bluetooth/ZigBee with Personal Area Network (PAN) and the database will be updated for getting monitored in anytime-any where, by the medical staffs.

## 2 Analysis of Risk Factors during Pregnancy

### 2.1 Literature Search and Selecting Risk Factors Intensity

Analyzing medical profiles such as age, weight, blood pressure, existing health condition, heart rate, body temperature, physical activity, etc. these parameters and corresponding values and their intensity of risks for that specific patients can be predictable. It enhances knowledge about the risk level of women in pregnancy, eg patterns of risk, relationships between medical factors related to pregnancy and precautions. Table:1 summarizes the level of risk parameters in pregnancy and their values, weights with references. Initially, analyzing these very basic medical factors in pregnancy to find out the risk level as well as the worst case of these factors.

**Table 1.** Pregnancy-related medical parameters with corresponding values and their weights.

| Parameters tert | Low | Mid | high | Ref erences |
|---|---|---|---|---|
| **Blood pressure** | Systolic 120-139 mm Hg, diastolic 80-89 mm Hg | Systolic 140-159 mm Hg, diastolic 90-99 mm Hg | Systolic 160 mm Hg or greater, diastolic 100 mm Hg or greater | [6] |
| **Heart Rate** | Heartbeat 75-80 bpm | Hear beats 90-140 bpm | Heartbeat >70 and <140 bpm | [7] |
| **Body Temperature** | averages about 98.6 F (37 C) | < 98.6 F (37 C) and > 102 F (38.9 C) | 102 F (38.9 C) or higher And (>35 C or >95 F) = Hypothermia >10 moves Such | [8] |
| **Fetal move ment** | 10 movements such as kicks, flutters, or rolls. within 12 hours; 6k/2hrs | 10 moves Flutters, or rolls. within 12 hours; 6k/2hrs | kicks, flutters, or rolls. within 12 hours; >6k/ us 2hrs 35-45 underweight (,18.5 kg/m 2 ) | [8] |
| **age** | 20-29 | 30-35 | | [9] |
| **BMI** | (18.5–24.9 kg/m 2 ) | (18.5–24.9 kg/m 2 ) | Overweight (25–29.9 kg/m 2 ), obese (30–34.9 kg/m 2 ) | [9] |
| **Blood glucose (2-hour glucose)** | <7.8 (<140) mmol/ l(mg/dl) | <7.8 (<140) andÿ7.8 (ÿ140) mmol/l(mg/dl) ÿ6.1(ÿ110) & | ÿ11.1 (ÿ200) mmol/ l(mg/dl) | [10] |
| **Blood glucose (fasting glucose)** | <6.1 (<110) mmol/l(mg/dl) | <7.0(<126) mmol/ l(mg/dl) | ÿ7.0 (ÿ126) mmol/l(mg/dl) | [10] |
| **Blood glucose (HbA1c)** | <42 mmol/mol | 42-46 mmol/mol | ÿ48 mmol/mol | [10] |

### 2.2 Analyzing the Common Risk Parameters from an Existing Diabetes Dataset for Women

In this research an existing dataset has been used [10]. Since the dataset was prepared for the diabetes patients and after analyzing it is found that some of the risk factors are common and after preprocessing and filtering this dataset, it is included into risk intensity level and categorized the risk according to the literature search and with the help of medical experts.

One of the data mining software named Waikato Environment for Knowledge Analysis (Weka), developed by 'University of Waikato' in New Zealand, which contains a large number of algorithms and imagining tools for data preprocessing and predicting the accuracy of the new model. It supports data mining tasks such as classification, regression, visualization, clustering, and feature selection. [10]
Two functionalities of 'weka' are focused, first one is for mining information from existing medical datasets; and another is to classify the risk level accurately with the help of machine learning algorithms for better prediction of the risk level. *Fig:1* shows the comparisons of machine learning algorithms belonging to different types of groups to observe which part will provide better classification accuracy through the existing data set.

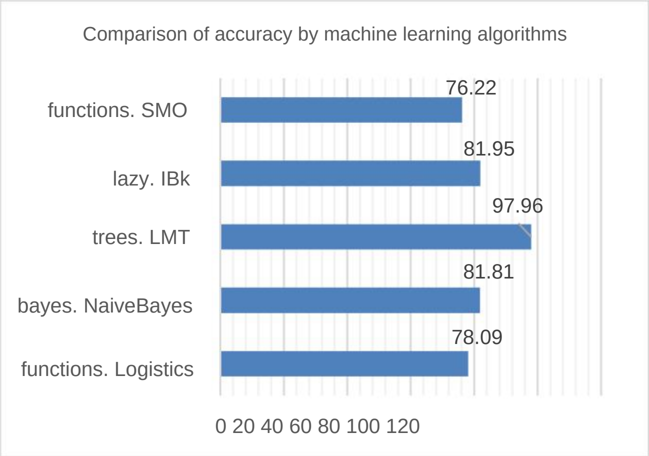


**Fig. 1.** Comparisons between machine learning algorithms.

LMT (logistic model tree) is one of the algorithms under the trees group of machine learning algorithms with the highest accuracy of almost 98%. The classifier for constructing 'logistic model trees', which are classification trees with logistic regression functions at the leaves. One of the more convenient ways to deal with classification tasks is the combination of the logistic regression model and a tree structure in a single tree. There fore, using logistic regression estimates class probability rather than just a classification. The algorithm can deal with binary and multi-class target variables, numeric and nominal attributes and missing values.

### 2.3 Analyzing sample real data to explore the status of accuracy

Selected sample data are collected through IoT enabled devices and verified by a medical expert to provide notification to the pregnant woman and family about her risk level and health conditions.

The following algorithms are used to determine the classification of risk level accuracy. Few selected pregnant women's data have been collected and with the help of medical experts, the risk level is determined whether it is high, mid or low. *Fig. 2* shows the accuracy of correct identification of risk level in pregnancy for the given dataset of risk parameters. Among the entire machine learning algorithm, LMT provides the highest accuracy for correct classification in both training set data and cross folding validations.

At last, our proposed approach obtained 90% accuracy for the diagnosis of risks in pregnancy with faster training time and there is no misclassification in prediction be cause false positive (FP) and false negative (FN) is almost zero that shows in the below *Fig .2.*

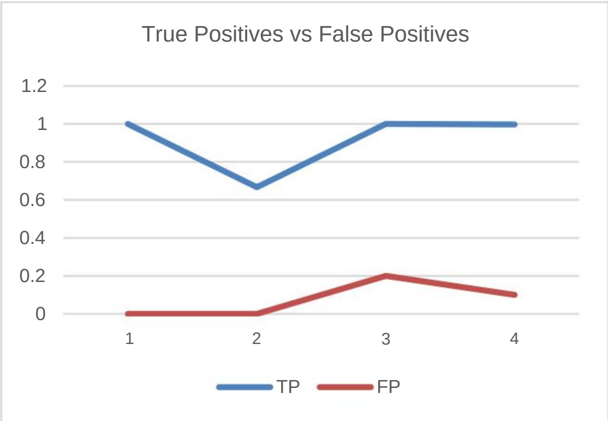


**Fig. 2.** The detailed outcome of LMT for real datasets.

## 3. The experimental result over Pima-Indians-diabetes data set

### 3.1 Classification Accuracy

In *Fig:3* LMT is applied in the existing dataset and got almost 98% accuracy. LMT is the combination of logistic regression and tree induced machine learning algorithms.
In the y-axis of this bar chart representing the risk intensity level of the existing dataset that is labeled as 3 instead of mid-level risk, 2 instead of low-level risk and 1 instead of a high-level risk for the better representation of the result.

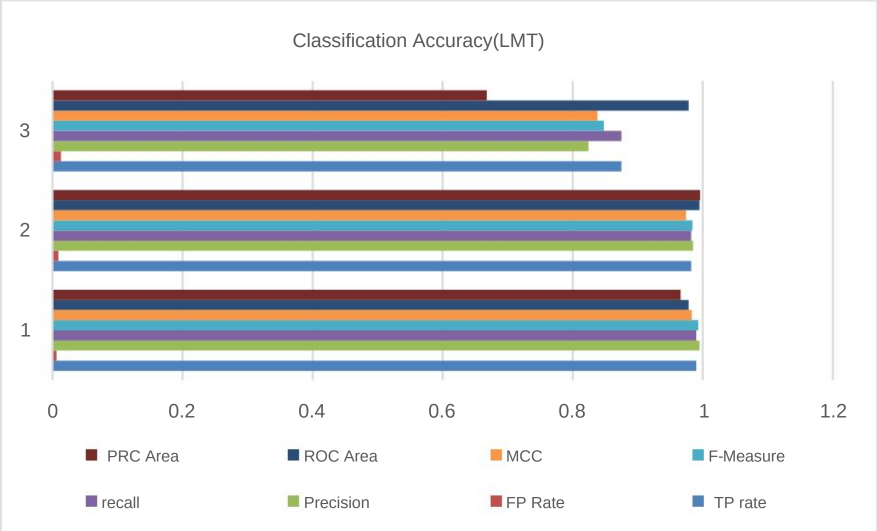


**Fig. 3.** Classification accuracy summary for an existing dataset.

The confusion matrix for this dataset represents the false positive and true positive rate clearly where the false positive rate is very low that maximizes the accuracy and performance of this algorithm.

| Confusion Matrix | | high | Low | Mid |
|---|---|---|---|---|
| predicted class | Low | 408 | 0 | 4 |
| | Mid | 0 | 271 | 5 |
| | high | 2 | 4 | 42 |

### 3.2 Making Predictions

Prediction of risk level is determined by LMT without any errors which are shown in *Fig:4.* The model has been trained by the existing dataset and five new patients' data has been supplied as test data. Evaluating the model on current test data using LMT predict the risk level accurately according to our standard categorization of risk level in Table:1.

| == Predictions on user test set === | | | | |
|---|---|---|---|---|
| inst# | actual | predicted | error | prediction |
| 1 | 1:? | 1:High | | 1 |
| 2 | 1:? | 2:low | | 1 |
| 3 | 1:? | 1:High | | 1 |
| 4 | 1:? | 2:low | | 1 |
| 5 | 1:? | 1:High | | 1 |

**Fig. 4.** Prediction of risk level using LMT

## 4 Proposed System Models

### 4.1 Integrated Models

Timely diagnosis and proper medication of pregnant women is the critical process during pregnancy. This proposed model attempts to provide better and real-time medical care with lower cost and easier. *Fig. 5* shows the proposed system model.

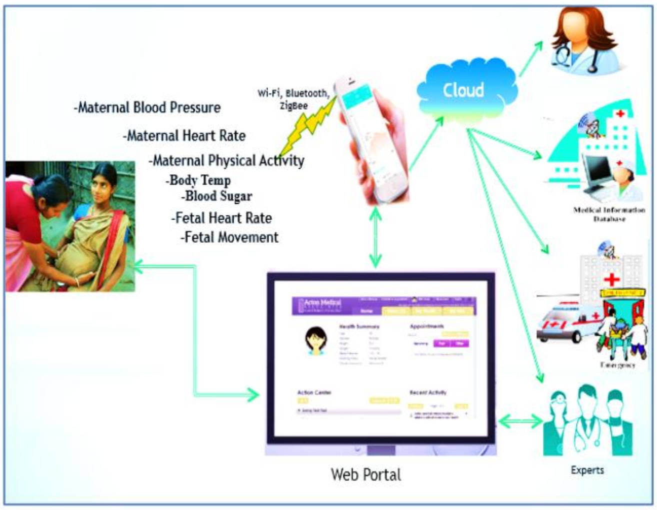


**Fig. 5.** Proposed system models

Reducing maternal mortality and taking care of pregnant women in rural areas is the primary goal of our proposed system model. Mostly, non-portable, sophisticated and expensive devices are used by the hospitals. Development of a compact assist system is the main goal of our proposed system model for accessing and assessing the vital signs such as blood pressure, physical activity, heart rate of rural pregnant women and the movement count, heart rate of the fetus with the help of RFID tags also named as wearable sensing devices. The continuous medical data will be stored in a database for analyzing. Finally, pregnant women and the respective doctors will get a notification for the patient's current health status.

**4.2 Models of IoT devices.**

The developed system in *Fig. 6* represents the temperature, pulse and heart rate reading of patients properly.

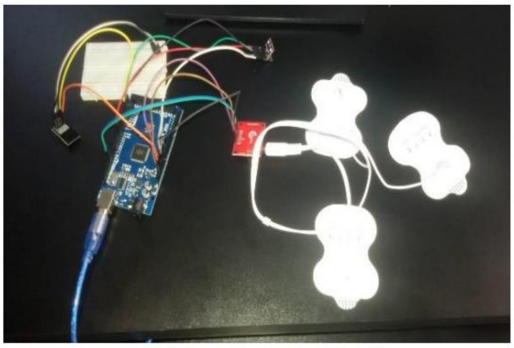

**Fig. 6.** Reading heart rate, pulse data using Arduino mega 2560, ECG, Heartbeat sensors.

## 5 Conclusion

In this research, different risk factors are identified and categorized with the help of medical experts. Machine learning algorithms have been used to classify and predict the risk level of an existing dataset. The result of the prediction has been coordinated with the selected sample data collected through the IoT enabled devices. The outcomes of this coordination have shown that the prediction of risk level has been successful in both cases without any errors. A crowdsourcing approach can be adopted in this research for broadcasting risk factors to analyze and to provide better health monitoring for the patients and their families.

## 6 Acknowledgments

Thanks to Dr. Shirin Shabnam for helping to prepare the categorization of risk parameters in a pregnancy-related medical dataset on the basis of intensity. This research work is supported by research grant RDU1703125 funded by Universiti Malaysia Pahang, http:// www.ump.edu.my/. The authors would also like to thank the Faculty of Electrical & Electronics Engineering, Universiti Malaysia Pahang for financial support.

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