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Smart Health Monitoring System for Pregnant Women of Rural Regions

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ABSTRACT

Enhancements in healthcare abilities improve living standards in the current era. Human resources are vital in technologically advanced and developing countries. In developing countries, maternal deaths occur due to a lack of medical facilities and health infrastructure. The death ratio in pregnant women due to lack of medical facilities in advance and developing countries is 9:1. Most developing countries have poor medical information systems, which causes pregnant women to have very few routine check-ups in the early stages of their confinement. This results in an increased death rate of infants and maternal in backward regions. This is nowadays a major health concern for pregnant women of rural regions in developing countries like Pakistan. Existing medical approaches for such issues consist of devices and wired sensors which are very costly. Ultrasound examinations are performed using Bluetooth devices as well. However, these approaches are costly and not easily available in backward regions. The proposed framework helps to solve this issue using wireless technology. The physical movement of a fetus as well as maternal are measured using commercial-off-the-shelf sensors. These sensors consist of an accelerometer, temperature sensor, heart rate sensor, and blood pressure. Sensor data is forwarded using IoT to the mobile phone. Mobile phones transmit the collected data to the cloud for processing, analysis results, and storage.
The proposed work helps in providing a low-cost method of movement of the fetus and bodily parameters of pregnant women of rural regions in developing countries. The proposed system provides better care using IoT and commercial off-the-shelf sensors.

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Citation:

1. Introduction

In this modern age of technology, pregnancy, and childbirth still causing women to die due to poor medical facilities. According to WHO and UNICEF, the death rate due to this phenomenon is almost 585000 which is due to poor health facilities in backward regions of developing countries [1]. The majority of the deaths due to pregnancy and childbirth occur in backward areas of un-industrialized countries. The ratio of death in Africa is 1:7 which occurs due to several medical hitches in mother and child. This ratio is one in a thousand in developed countries. These hitches can be treated if diagnosed early in pregnancy which can decrease the death rate. Some of these hitches can be even seen before the start of confinement and can be solved if diagnosed at the proper time. Treatment at the proper time can save the life of both the fetus and the mother as well. It is estimated that the majority of deaths (74%) occur due to heavy blood loss, contaminations, impediments, etc. Several other factors are also involved which are preventing women from getting proper medical assistance throughout the pregnancy. These factors include distant hospitals, poor income, absence of awareness, and poor medical amenities. Therefore, providing well-timed health assistance to expecting women is compulsory for a healthy fetus.

An ultrasound scan must be performed during confinement at least two to three times to know the health and growth of the developing baby [2]. Timely medical check-ups will also help in healthy baby growth and improve the health of the mother throughout the pregnancy. Women from distant and backward areas have an absence of awareness about the significance of proper treatment. This absence of awareness causes an enlarged impermanence percentage as well as increased health problems such as sleep disorders, nausea, and faintness.

Ultrasonography is the popular approach to check the movement and growth of a baby. This approach helps in the diagnosis of many health problems of the baby and mother [3]. Growth abnormalities, miscarriage risks, Ratifying confinement, and manifold confinements can be detected using ultrasonography. However, the risks associated with this approach make it less popular in different regions. This approach is expensive and also considered unsafe for the fetus. Though long-standing threats of this approach are ambiguous which causes this method risky for hours of nursing [4].

Several IoT-based I/O and sensing devices are available in the market which has replaced the previous huge size electronic devices. These sensing devices include a gyroscope, voice sensor, temperature sensor, keyboard, light pen, etc. The basic theme of IoT is to control sensors and actuators using the internet. Sensing devices in the IoT network are interconnected and communicate with each other through internet/wireless services [5].

IoT provides health facilities using different sensors and actuators. These sensors and actuators communicate with each other in three main layers as shown in Figure 1. In the first layer, L1 data is gathered from sensing devices and objects. This layer performs data collection and transmission. In Layer L2, data is transferred to the gateways and routing devices that perform transmission and communication in IoT networks. In layer L3 data storage, analysis, and research are performed on cloud/servers, mobile phones, fog computations, etc. as discussed by the author [6].

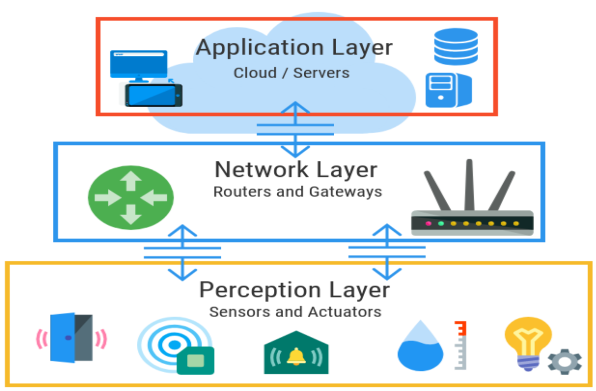

Figure 1: Three-Layer Architecture of the Internet of Things [6]

In previous studies, several monitoring systems have been proposed that help in solving the health-related issues of the fetus and pregnant women from different perspectives. For long-term monitoring, the proposed method is the ideal choice for pregnant women. Because exposure to ultrasonic waves can somehow increase the risks of health issues. For this purpose, an IoT-based health monitoring system for pregnant women is proposed. This proposed approach consists of the latest, low-cost, and easy-to-use sensors which may not harm the developing baby in continuous monitoring of health. The proposed system uses sensors that are effortlessly accessible in the marketplace. Key features of the proposed system are as follows.

1. The proposed health monitoring system consists of an accelerometer, heart rate sensor, blood pressure sensor, and temperature sensor.
2. The proposed health monitoring system uses an intelligent supervised learning approach called Naïve Bayes to predict the results.
3. Accuracy of the proposed health monitoring system is obtained by doing experiments on 4 pregnant women for 6 months of their maternal period.

Proposed health monitoring system for maternal in rural areas to monitor their health parameters using commercial off-the-shelf sensors. These sensors interact with a microcontroller. The microcontroller then interacts with the mobile application and data is transferred to the app. This app forwards data to the cloud for actual processing and results generation. Four pregnant ladies are monitored in this study.

Section 2 of the paper describes the literature work. The proposed approach is enlightened in section 3. Section 4 discusses the implementation specifics and outcomes of the proposed methodology. Section 5 lastly provides the conclusion and future work.

2. Related Work

Women's health is considered a matter of concern for the wellbeing of the public. According to the report of the World Health Organization, 98% of women die in rural areas of developing countries due to a lack of medical facilities [1]. The maternal death rate is 14 times higher in developing countries as compared to other countries [7]. These numbers are very high and unacceptable in this modern age of technology. In the paper [8,9,10] several risk factors that are linked to pregnancy are discussed. Factors linked to pregnancy include increased levels of blood pressure, increased heart rate, increased body temperature, etc. Such factors are creating several diseases like Polycystic Ovary Syndrome, Preeclampsia, Eclampsia, Thyroid, Heaviness, miscarriage, low birth weight, etc. In the paper [11], the author explains how a high level of blood pressure affects the health of pregnant women in their confinement period. High blood pressure decreases the chances of normal birth. Several technologies are available in the health sector which can help to solve these issues related to maternal mortality.

Medical conditions like diabetes, heart rate, blood pressure, body temperature, viral infections, complications during previous confinements, body weight, and STIs are the main factors that can cause pregnancy loss [12].

2.1 IoT in Health Monitoring System

The Internet of Things has revolutionized the health sector by providing several smart technologies. Collected data from IoT devices are treated in different ways using machine learning, deep learning, etc. These smart devices provide health facilities to distant areas using the internet. The status of a patient's health can be viewed remotely [13]. Table 1 shows a comparison of the basic architecture composition of the Internet of Things network discussed in articles [4-8].

Table 1: Comparison of IoT architectures composition in the health system [4-8]

		Features				
Article	**Layers**	*-site data process*	*Communication management*	*User Interface*	*rror manageme*	*ower and Securi*
[4]	*IoT Sensors*	Acquisition syster	Data Transition	Big Data	-	-
[5]	*Perception Layer*	-	Network Layer	Application laye	-	-
[6]	*Perception Layer*	Translator	Network Layer	Application Laye	-	-
[7]	*Node Level*	-	Link Level	-	Network Level	-
[8]	*Sensor Manageme*	Identification Management	Network Access management	Intelligent application	-	Power and Secu management

Cloud computing is one of the major trends in the health sector. In [14], the author discussed the architecture, trends, technologies, and paradigms used in cloud health. Another author [15] describes wireless integration in healthcare devices. Security and authorization issues are also resolved using blockchain, encryption, and encoding techniques [16].

Figure 2 shows a list of several IoT devices that are used in the health sector for the diagnosis and treatment of patients [42]. These devices can be hospital-based or home-based. Both types of monitoring are nowadays available with the help of IoT devices and cloud computing.

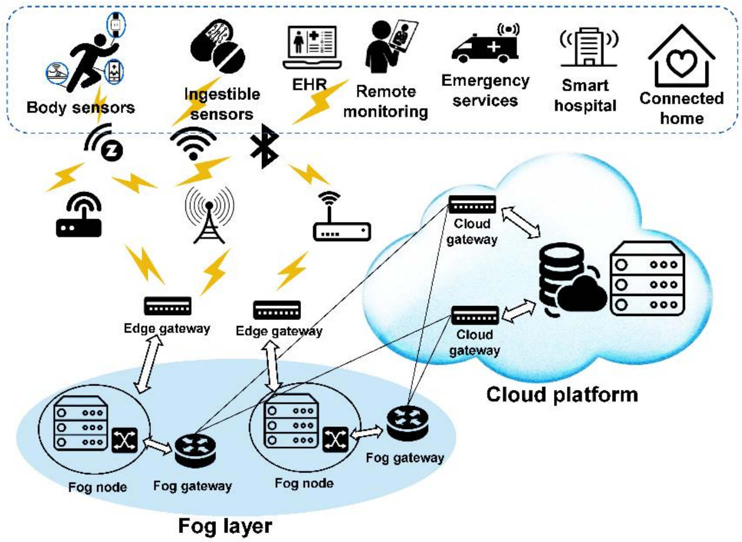

Figure 2: Cloud-based health system devices and components [42]

2.1.1 Maternal Monitoring

Long-term maternal health monitoring is a matter of concern nowadays because of the risks associated with childbirth. Chen et. al.[17] introduces a heart rate monitoring system during pregnancy. Maternal monitoring in this study is carried out in the last trimester of confinement. Real-time monitoring is performed using smart sensors integrated into the pillow. [18] Moreira et. al. suggested long-term health monitoring systems measure the psychological parameters of maternal. Hypertension symptoms are monitored using sensors. Data is forwarded to health specialists for necessary actions. Variations in a heartbeat during exercise are monitored by Carpenter et al. [19].

Heart rate and other bodily parameters of pregnant women can be forwarded using mobile phone technology [20]. Electronic circuit-based heart rate monitoring consists of a Wi-Fi modem and a messaging service. The heart rate sensor used in this study works by analyzing the heart rate from the finger which should be placed on the sensor. A three-layer health system is proposed by Paul et al. which evaluates the health conditions in three different layers. Processing of data is performed on the cloud.

[21] Khanum et al. projected a maternal health care system that allows intercommunication between the doctor with the maternal. In this paper, the communication channel of the system is discussed only.

Bluetooth-based personal health care system is designed in the study [22]. In this system, wearable sensors are used which include heartbeat, blood pressure, and body temperature.

Gayathri S.et.al. established an e-health system for home-based monitoring. [23]. The data mining approach is used for training and testing the model. A supervised learning mechanism is used in it. [24] Another remote health monitoring system is proposed for the psychological assessment of pregnant ladies. S. Subalakshmi.et.al. proposes a biological behavior monitoring system for maternal to monitor uterine reduction, heartbeat, and blood flow [25]. A fetal monitoring system to calculate the important bodily values of a fetus is proposed by Shruthi.T.et.al. This data is forwarded to the clinic for necessary actions [26].

Time-oriented remote health monitoring system is proposed in another work that is ideal for emergencies [27]. Another time-oriented health monitoring system monitors the physical movement of the mother, sleep quality, heartbeat, and oxygen saturation [28]. Fetal heart level is monitored in another study done by Nur Amira.et.al. In which the fetal heartbeat is remotely forwarded to the doctor [29].

Amit S. Wale et.al. uses a neural-network-based approach for heart-attack prediction in pregnant ladies [30]. Mohamed Fezari.et.al.[31] proposes a monitoring system for heart rate which works with Raspberry PI in real-time. [32] The hemoglobin level of the maternal is monitored to check the correlation between vitamin C intake and hemoglobin level during pregnancy. [33]

Sowmya S.et.al. Proposes a dehydration monitoring system for maternal and fetuses using smart sensors. These values are forwarded to the doctor for the necessary decisions and actions.

The majority of devices discussed in the literature work consist of costly sensors and expensive equipment. Moreover, these devices are not typically designed according to the needs of pregnant women in rural areas in developing countries. These devices are not available in those areas where people with low income are living. To overcome this problem, a cost-effective maternal health monitoring system is proposed which is based on commercial off-the-shelf sensors that are communicating wirelessly.

3. Design of the Proposed System

It is the need of time to monitor the physical health parameters of pregnant women to give them proper medical facilities throughout their confinement period. The proposed system helps in monitoring the health of the baby and mother using commercial off-the-shelf sensors and a secure IoT network. Sensors are interconnected so that their communication can be easily carried out in real-time. Intelligent machine learning algorithms make it possible to remotely monitor the health and show the result on a mobile phone. Predicted results will help to give timely treatment to pregnant women and monitor the baby's health. Figure 3 explains the architecture of the proposed framework for health monitoring of pregnant women.

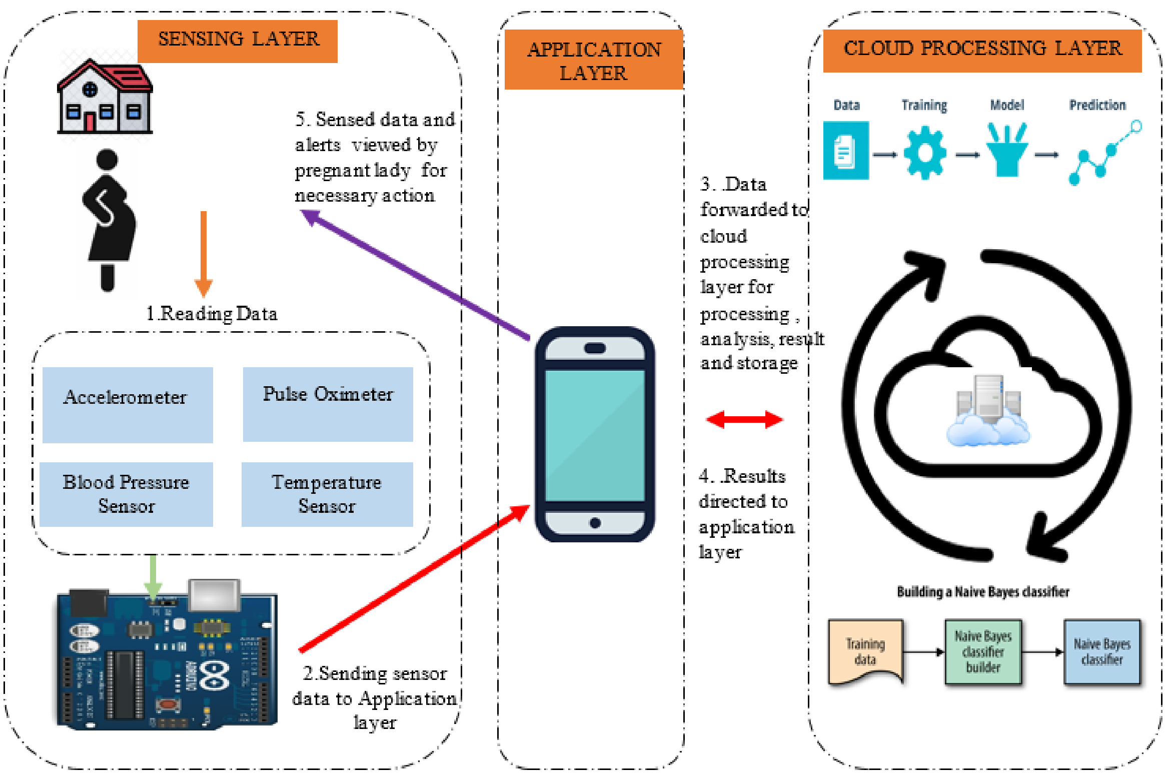

Figure 3: System Design of Proposed Maternal Health Monitoring System

The proposed framework for health monitoring consists of five sensing devices. Data collected through these sensing devices is collected by a microcontroller which is then forwarded to the mobile phone which acts as a gateway. Mobile phone applications forward this data to the cloud for processing, analysis and storage. The result produced by the cloud-based machine learning approach helps in determining the physical conditions of babies and maternal. Layers of system design are described as follows

3.1 Sensing Layer

The proposed maternal health monitoring system consists of sensors, routers, and cloud computing algorithms. Maternal health is an important issue nowadays. For this purpose, proposed system monitors the ambient parameters of the maternal more accurately so that accurate results can be produced. The sensing layer consists of sensing devices which are small commercial off-the-shelf sensors working in a real-time environment. These sensors calculate heart rate, oxygen saturation, body temperature, movement of the baby in the womb, and blood pressure. An accelerometer is placed on the abdominal wall of the mother. IoT surprisingly allowed the use of sensors to monitor physical bodily parameters and provide medical facilities to patients in real time.

3.2 Application Layer

To provide interactivity, the application layer plays an important layer. This layer allows the person to view and interact with the processing system through the graphical user interface. Real-time parameters calculated using the sensing layer are displayed on a mobile phone. Pregnant women can view these values. Any seriousness in these parameters allows women to get timely medical assistance for better health [34]. The application layer of the proposed system consists of a mobile phone, laptop, or iPad. Users can choose the device according to their convenience and feasibility. Mobile devices are more feasible for such interaction of sensors because of speed and portability. Mobile devices are more common as compared to other processing devices. Almost every person in a family has a mobile phone. However other interactivity components also allow sensor integration and connectivity. Computers and desktop devices provide more processing power as compared to portable devices.

Nowadays health robots assist in providing facilities to people. These robotic devices are more suitable for people with a physical disability. However, such robots are not easily available for rural areas patients. For this purpose, mobile and computers are a better option. Compatibility of sensors with the interactivity device is also a major concern. To solve this issue, it is a better approach to use a combination of interactivity devices in which one can be chosen as the main device. In the proposed framework, the mobile device is used as an interactivity component in which an app is used to represent the sensor's data to pregnant women.

3.3 Cloud Layer

The proposed maternal health monitoring system consists of sensors, routers, and cloud computing algorithms. The Cloud layer of cloud computing is the major component of the proposed framework. User-defined protocols of communication and processing of information are used on the cloud servers [35]. There are two methods to store the raw data on cloud servers. The first one is raw Big Data and the second is organized data. In general cloud computing is performed in three different layers.

1- The integration and preliminary data processing layer serve as the gateway to the cloud module. This layer helps in performing the interaction with collected data products.

2- The Big Data Storing and Analysis layer allows the extraction of meaningful information from the data collected through the sensors or sensing module. Several processing techniques, algorithms, and formulas can be applied to the data to generate results and useful information. Statistical trends in data can be easily observed using this data.

3- The semantic storage and configuration layer deals with high-quality data structures and layouts. In the proposed framework machine learning algorithm is used to perform data structuration and alignment. Algorithms provide useful results and an accuracy of 98.5% which is acceptable for the correctness of the system. This stored data of pregnant women can be used in the future for medical history and research.

3.4 Internet of Things

IoT nowadays is serving as the backbone of many large data networks. Sensing devices in IoT networks are controlled remotely using communication protocols and algorithms. This communication and integration of objects into the network allows more feasible remote networks and computer-based structures. These networks help in providing improved communication, precision, and commercial benefits. Small sensing devices in the IoT network allow information gathering easy and comfortable. Sensors in the IoT network can communicate and store information to other sensing devices by using broadcasting algorithms and decision systems [36].

Several machine learning techniques are available to extract meaningful information from the data collected by these IoT sensing devices. These techniques can be supervised learning and unsupervised learning. Data analysis and prediction techniques can be applied in a real-time environment to generate results. In the proposed health monitoring system, data classification, analysis, and predictions are performed using the Naïve Bayes machine learning algorithm which gives an accuracy of 98.3%.

3.5 **Machine Learning and Cloud Computing**

A subfield of Computational systems in which human intelligence-based algorithms are used to solve real-life problems is called machine learning. Machine learning is reflected as a functional mare in the Big Data field. Machine Learning approaches can be applied in health, business, commerce, aerospace, biomedicine, music, media, and many more real-world applications. Machine Learning has revolutionized the field of health and fitness by providing medical robots and devices. In the proposed health monitoring system, data received from the sensing devices is processed using a supervised machine learning algorithm. Real-time predictions are made and results are forwarded to the mobile phone. These results are then used for the timely diagnosis of health problems predicted by the cloud-based machine learning system [37].

In a supervised learning approach, the algorithm is previously trained on test data and then performs prediction using this knowledge. In the unsupervised approach, previous knowledge is not known [38]. Pattern recognition and feature extraction are performed on real-world data. These two approaches can be applied according to the requirement of the problem.

3.6 Naïve Bayes Classification Algorithm:

In the proposed research, the algorithm used to intelligently classify input data into meaningful information to generate results is the Naïve Bayes algorithm. Naïve Bayes is a supervised learning algorithm that works by intelligently predicting classes using probability. This algorithm works on the principle of Bayes theorem in which attributes are assumed, independent. In the 18th century, a British Mathematician proposed the Bayes theorem. The equation of the theorem is given in equation 1 [39].

$$P(A|B) = \frac{P(A)P(B|A)}{P(B)} \tag{1}$$

In equation 1, P(A|B) represents the likelihood of the existence of event A when event B happens, P(B) is the likelihood of the existence of event B, P(A) is the likelihood of the existence of event A and P(B|A) is the likelihoods of the existence of B when event A happens. In the proposed framework, the Naïve Bayes classifier is applied to the data set which results in a confusion matrix. A confusion matrix is a table in which true labels and predicted labels are arranged according to their classes.

4. Experiment Details

In the previous section, the architecture and complete design details of the proposed maternal health monitoring system are explained. In this section, we will discuss the implementation of the proposed system. System working is explained in three layers. Sensing layer, application layer, and cloud layer.

4.1 Hardware components

Hardware components used in this experiment are cheap and easily available in the market. For the microcontroller, Arduino mega 2560 with built-in Wi-Fi module ESP8266 is used as a processing device that receives data from sensors. Figure 4 shows the list of sensors used in the experiment.

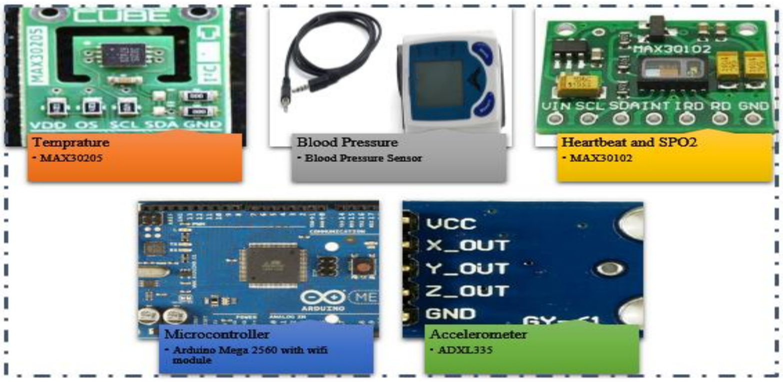

Figure 4: Hardware Components of the proposed system

4.1.1 Accelerometer sensor

An accelerometer is a small electronic sensing device that is used to monitor the physical body movement of objects. The accelerometer works by measuring activity on the x, y, and z-axis. Fetus movement in the abdomen is because of placental ineffectuality in the uterus. In the sixteen weeks of confinement, a baby starts moving and kicking but this movement is unobserved by the mother. These movements help in determining the fitness and growth level of the fetus.

Several mechanisms are available to monitor the movement of the fetus. One of the most commonly used methods is ultrasonography. But this method is considered expensive and sometimes risks are associated with this method. To overcome this issue, the accelerometer is the best option.

ADXL335 is a small sensing device that calculates the movement safely on the x, y, and z-axis. This sensor provides a high level of acceleration calculation accuracy. This device works wirelessly and is placed on the abdominal wall of the mother so that the fetus's movement can be calculated accurately. Normal fetus kick count represents the normal values of kick count for healthy baby growth. From sixteen weeks, a baby starts making kicks but these kicks are unobserved by the mother. These kicks can be felt by the mother from the 20th week of confinement. If these kicks are less than 10 in twelve hours, then this condition can be an alarming situation. Alerts must be generated for timely treatment. Table 2 describes the normal and abnormal range of fetus movement in hours [44].

Table 2: Fetus movement count [44]

Sr.-No.	Time (Hours)	Fetus movement count Normal range	Fetus movement count Abnormal range
1	2 hours	6 or greater	Less than 6
2	4 hours	8 or greater	Less than 8
4	12 hours	10 or greater	Less than 10

4.1.2 Blood Pressure sensor

The pressure of blood in the human body is also a matter of concern for a healthy life. Many people are facing blood pressure issues which is also a base for many other diseases. Pregnant women need to monitor their pressure of blood flow throughout their confinement period. If blood pressure is not normal it can cause life-threatening problems for both mother and baby. High blood pressure leads to hypertension which can harm both lives. High blood pressure in pregnancy can create many complications that must be treated on time. The most common problem due to high blood pressure is Preeclampsia which usually starts in the fifth month of pregnancy. Preeclampsia can seriously damage many bodily organs. Table 3 shows the classification of Blood pressure according to the lower and upper ranges [43].

Table 3: Blood Pressure Classes [43]

Sr.-No.	Blood Pressure Group	Systolic mm Hg (Upper range)		Diastolic mm Hg (Lower range)
1	Normal	< 120	AND	<80

2	Elevated	120-129	AND	<80
3	High Bp (Stage I Hypertension)	130-139	OR	80-89
4	High Bp (Stage II hypertension)	>=140	OR	>=90
5	Hypertensive Crisis	>180	AND/OR	>120

Heart rate and Oxygen Saturation

Heart rate and oxygen saturation monitoring enable monitoring of heartbeat values. Heart rate varies according to the physical activity. It must be within the normal range throughout pregnancy. Max30102 sensor is used to calculate the heartbeat and oxygen saturation in the proposed framework. It calculates the heartbeat of pregnant women after a specified time interval. The light of the sensor is on when it is in working condition.

Table 4: Heartbeat and SPO2 categories

Sr.-No.	Class	Heart Rate	Spo2
1	Normal	60-100	95-100%
2	Abnormal	Any value other than normal value	Any value other than normal value

4.1.3 Temperature Sensor

Body temperature is also the main factor in determining the health conditions of the mother and baby. Normal body temperature should be maintained for the health of the baby. Any changes in body temperature should be timely observed and diagnosed. MAX30205 temperature sensing module is used in the proposed research. This sensor gives accurate values as compared to a normal thermometer. The temperature range for this sensor is 0°C to 60°C and the humidity range is from 15%.

Table 5:Temperature Categories [44]

Sr.-No.	Class	Body Temperature
1	Normal	96°-100° F
2	Abnormal	Any value other than normal value

4.2 Sensing Layer

The first step in the proposed system is sensing data from sensors in a real-time environment. Microcontrollers with small commercial off-the-shelf sensors work in this layer by generating data. This layer collects data and forwards the data to the next layer called the application/ user interface layer. Body temperature, accelerometer data, oxygen saturation, blood pressure, and heart rate data are produced in this layer. Figure 5 shows the blood pressure data collected in real-time, Figure 6 Shows Temperature, figure 7 shows heart rate, Figure 8 shows Fetal movement and Figure 9 shows a combined real-time data graph with details. This graph shows the data according to time.

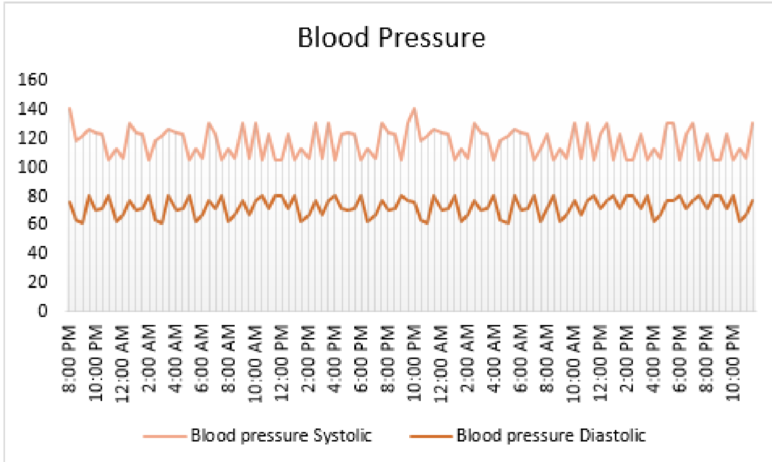

Figure 5: Blood Pressure

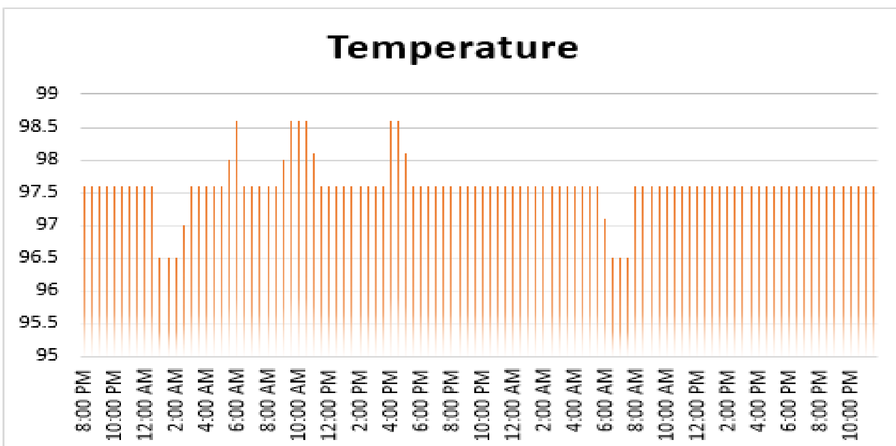

Figure 6: Temperature

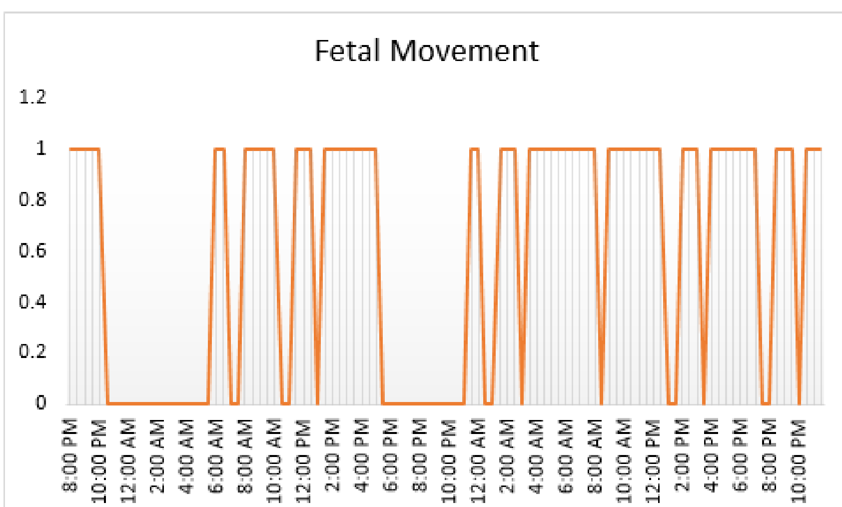

Figure 7: Fetal Movement

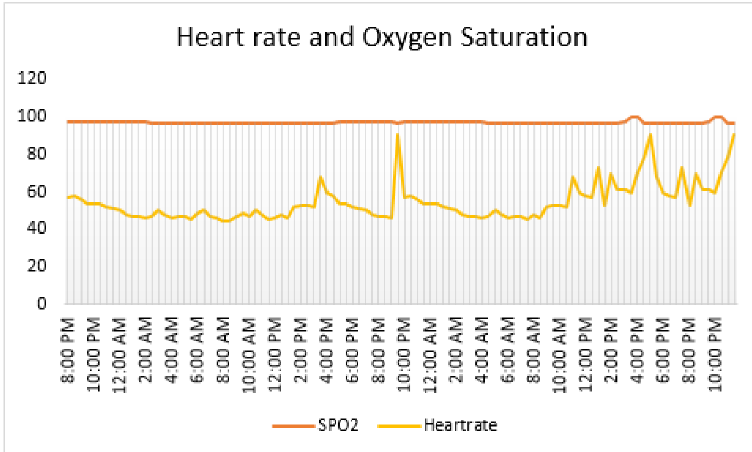

Figure 8: Heart rate and Spo2

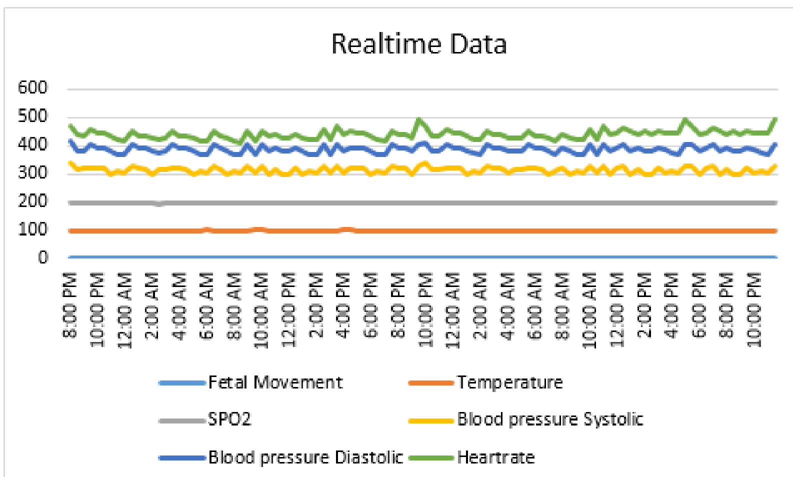

Figure 9: Real-time Data

4.3 Application Layer

The application layer at this level deals with data communication and transmission. Several communication devices are available in the market which include 3G, 4G, and 5G, fiber optic communication, and Wi-Fi devices. Ethernet devices also provide fast transmission. The proposed model consists of 5G mobile phones, computers, and tablets as communication devices that are easily available in homes.

4.4 Cloud Layer

The Cloud Layer of the proposed health monitoring system is considered the most important layer. Processing is done on the cloud. Data received from the application layer is processed and converted into meaningful results at this level. The intelligence of Machine Learning is applied at this stage and transfers the results to users. Data storage is also available which is achieved using MS Azure or Amazon S3.

4.5 Naïve Bayes implementation in the experiment

The proposed health monitoring system works with the Naïve Bayes algorithm. The data set consists of two parts. One is for training and the second is for testing. Our training data consists of 1989 records. Labeled data is used in training. Figure 10 shows the implementation of the Naïve Bayes model. Five input parameters in the training data set are classified into three classes (good, normal, alert) using the Naïve Bayes rulemaking system.

In this implementation, Training data is imported the classification app is configured according to this data, and the model is trained. The result of this trained model is exported for future use which can also be viewed on the model display.

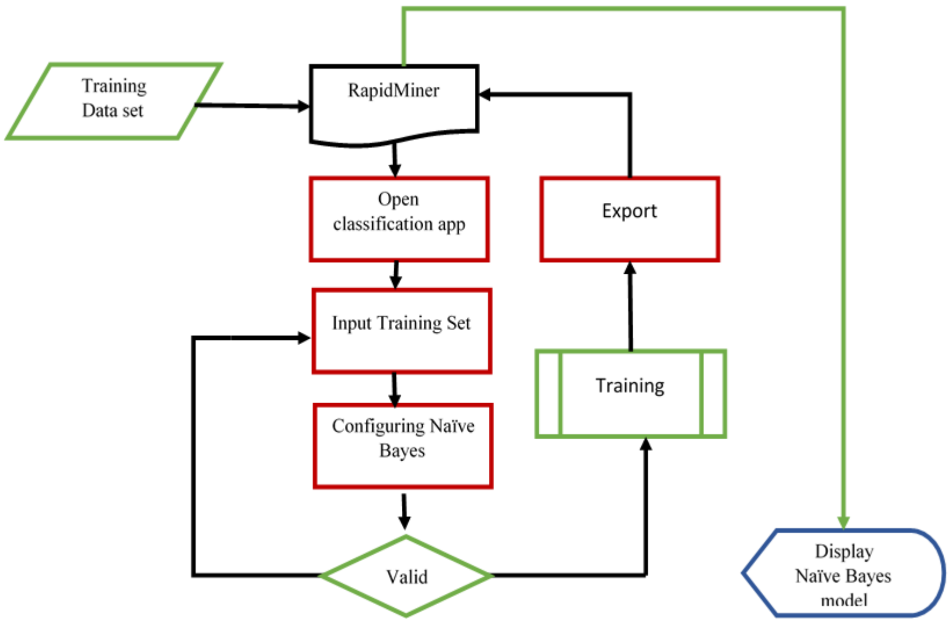

Figure 10: Naive Bayes implementation Flowchart

4.6 Health Monitoring System Experiment:

In this experiment, four pregnant ladies are studied and a model is tested on them. Sensor data which consist of temperature, fetal movement, heart rate of women, oxygen saturation, and blood pressure are collected using a microcontroller which is then transmitted to the application layer. This collected data is displayed in a mobile app that helps pregnant lady monitor their parameters. Further, these parameters are forwarded to the cloud layer for processing, evaluation, and storage. IoT provides intercommunication of these sensing devices and allows data transfer without human involvement.

5. Results and Discussion

A list of sensors and machine learning methodology is discussed in the previous section. In this section results of the proposed health monitoring system for pregnant women in rural areas will be debated in detail. The accuracy of the system is evaluated using two assessment parameters i.e. Confusion matrix and ROC curve. The naïve Bayes model is applied to four different pregnant women data and accuracy is compared in the graph for comparison.

5.1 Naïve Bayes Model Assessment

The proposed Naïve Bayes model provides an overall accuracy of 98.3%. The confusion matrix of the trained Naïve Bayes model depicts true and predicted classes of data provided to the model as shown in Table 7. Class precision for the normal, good, and alert categories is 98.39%, 95.68%, and 100% respectively. Similarly, class recall is also shown in the confusion matrix for three categories.

Table 6: Confusion Matrix for Naive Bayes Classifier

True Class / Predicted	Normal	Good	Alert	Class Precisior

Classes				
Normal	1486	0.0	0.0	98.39%
Good	6.8	433	9.8	95.68%
Alert	3.0	0.0	67	100%
Class Recall	99.32%	97.39%	93.16%	

In table 7, the confusion matrix for the Naïve Bayes classifier is shown which indicates the accuracy of the proposed machine learning algorithm. True classes are shown as columns and predicted classes are shown as rows. Classification of data is performed by using three classes good, normal, and alert. In this classification process, 98.3% accuracy is achieved which is the best for use in the health monitoring decision-making process

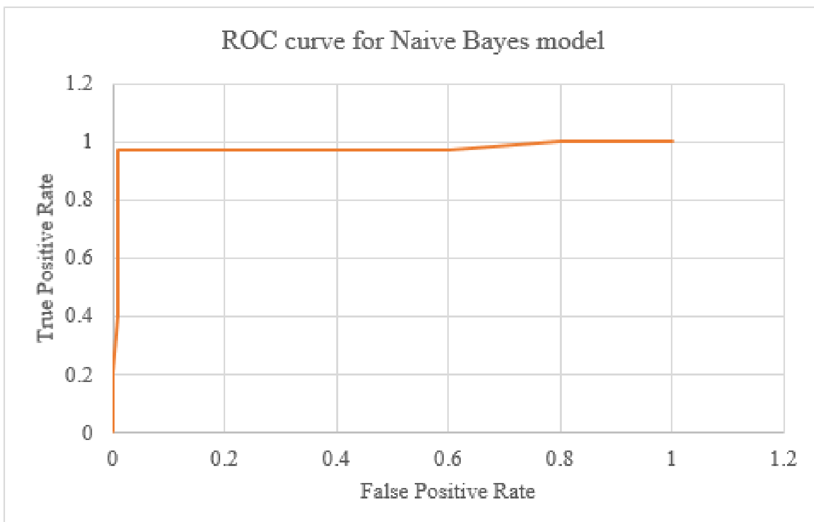

Figure 11: ROC for Naive Bayes model

In Figure 12 above, the ROC curve of our proposed Naïve Bayes model is shown. This graph shows the number of true positive instances and the number of false-positive instances predicted by the Naïve Bayes model. True positive cases are shown on y and false positives are shown on the x-axis. The area under ROC is 0.9865.

5.2 Naïve Bayes Classification Data

Naïve Bayes classification is performed on 1989 records which are provided to the model to check performance. Input from four different pregnant ladies is collected and system performance is evaluated with this data. This collected data sample is shown in the following Figure 13.

Case id	Time	Fetal Movement	Temperature (F)	Heart Rate(bpm)	SPO2(%)	Blood Pressure Systolic(mmHg)	Blood Pressure Diastolic(mmHg)
P1	8:00:24 PM	present	97.6	64	98	112	80
	8:45:36 PM	Present	97.5	59	98	117	69
	11:20:30 PM	Present	96.5	69	98	110	71
	12:16:35 AM	Not present	98	76	97	127	76
P2	7:05:45 AM	Present	97	77	98	113	79
	9:06:32 AM	Not present	98.6	78	98	118	78
	11:36:12 AM	Not present	97.6	76	100	125	80
	01:30:14 PM	Present	98	74	100	135	87
P3	12:08:49 AM	Present	98.7	67	98	138	88
	12:59:01 AM	Present	98.6	65	97	110	69
	02:04:43 AM	Not present	96	69	98	109	68
	09:23:12 AM	Not present	96	68	96	119	79
P4	04:08:12 PM	Not present	97	80	98	136	74
	05:25:34 PM	Not present	98.9	81	98	139	78
	05:59:09 PM	Not present	98.9	89	97	140	76
	07:19:08 PM	Present	98	89	99	145	80

Figure 12: Collected data of four pregnant ladies at a different time interval

5.3 Naïve Bayes Classification Results

Recorded data of four pregnant ladies are forwarded to the model for prediction and results. This input data consists of randomly chosen 150 instances of each pregnant lady at different time intervals. Figure 14 shows the results of the model for these four cases of data. Performance is evaluated using Precision and Recall which are two arithmetical methods to estimate performance. Precision is the percentage of true predictions divided by the total prediction of the proposed Naïve Bayes model. The formula for precision is given below

$$P = \frac{TP}{TP+FP} \qquad (2)$$

$$R = \frac{TP}{TP+NP} \qquad (3)$$

[40] In equation 3, P means precision, TP denotes true predicted and FP signifies False predicted examples. [41] In equation 4, R means Recall, TP symbolizes true predicted, and NP symbolizes not predicted examples. Figure 14 shows the performance of the Naïve Bayes model using precision, recall, and error rate for four cases that are studied in this experiment. These results showed the excellent performance of the model in predicting health conditions.

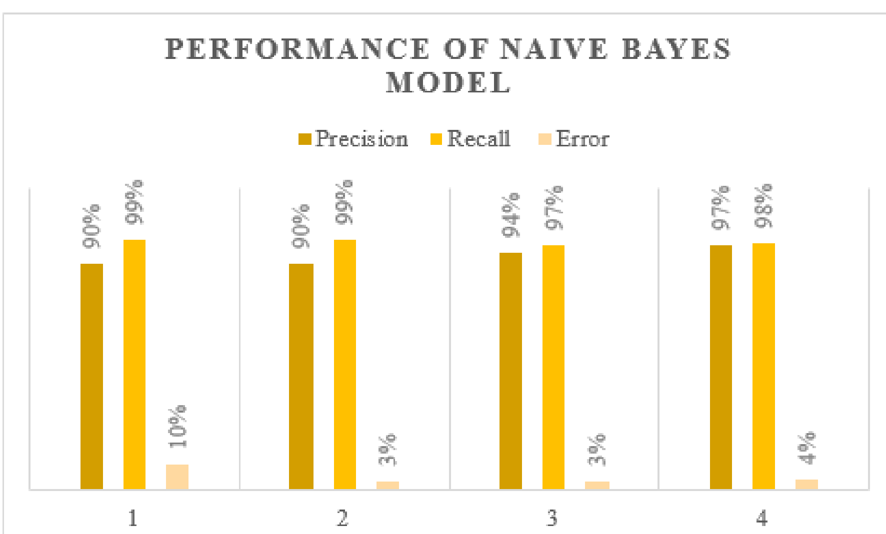

Figure 13: Performance of the Naive Bayes model

5.4 Mobile Application

Figure 15 shows the interface of the mobile application of the maternal health monitoring system using intelligent machine-learning techniques. Parameters of pregnant women can be shown on the app interface of Figure 15(B). it shows the Normal health condition of the pregnant women which is predicted using intelligent Naïve Bayes cloud-based processing technique.

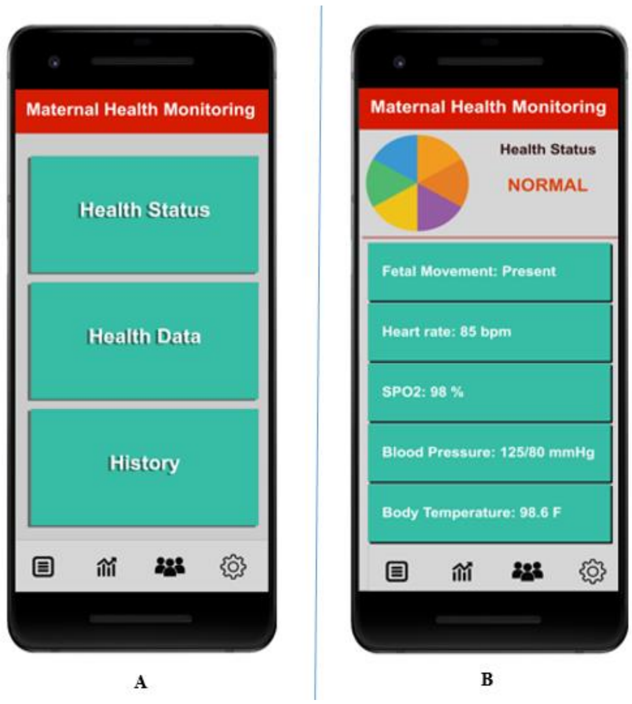

Figure 14: GUI of Maternal Health Monitoring mobile app

Results evaluated using an intelligent algorithm show that the proposed maternal health monitoring system for rural areas is smart and intelligent enough that it can be used effectively during the pregnancy period. It provides an accuracy of 98.3%. it consists of cheap sensors that are easily available in the shop.

6. Conclusion

Results evaluated using an intelligent algorithm show that the proposed maternal health monitoring system for rural areas is smart and intelligent enough that it can be used effectively during the pregnancy period. It provides an accuracy of 98.3%. it consists of cheap sensors that are easily available in the shop.

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