

Maternal HealthCare Using IoT-Based Integrated Medical Device: Bangladesh Perspective

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Abstract

Purpose: The main purpose of this study is to develop a low-cost integrated medical device. This device will help investigate the risk levels of maternal patients as well will reduce the cost involved in medical diagnosis for poor countries like Bangladesh, where maternal healthcare is a great concern.

Methodology: We proposed and developed an integrated medical device that includes all possible sensors to collect raw data from maternal patients. As soon as the data is collected it will be sent to the cloud for processing. In the cloud, there are a set of algorithms (software) for processing raw data received from the device. After processing and analyzing our system will automatically identify the risk levels of those patients. The software is developed in open source code so that in the future it can be updated by researchers.

Results: We developed the system and practically collected raw data from patients and uploaded those data to our cloud system. In the cloud, it was processed and the resultant data were presented in the form of graphs. From these graphs, the risk levels were identified.

Limitations: The proposed system is developed for maternal patients only. This system needs to be authorized by the health regulatory authority. To make it cost-effective some expensive sensors were not used.

Contribution: The main contribution of this study is to minimize the cost involved in maternal healthcare in poor countries like Bangladesh. This, in turn, controls the death of mother and child by improving maternal healthcare facilities.

Keywords: Cloud, Cyber-Physical Systems, Integrated Medical Devices, Open Source Code, Processing Algorithm

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1. Introduction

Bangladesh has made tremendous improvements in maternal healthcare in the last few decades. The death of mother and child has been reduced dramatically, during childbirth. The achievement was due to the increase in maternal healthcare facilities. The government is still working on maternal healthcare to reduce the death rate of mothers and children to zero. One of the main obstacles to such effort is the cost associated with the medical diagnosis equipment used for continuous monitoring in critical cases. This cost cannot be beard by many poor people in rural areas. The diagnosis cost increases because of the cost of medical devices. Such medical devices are developed and manufactured by developed countries where the manufacturing cost is high. Moreover, they release newer models of the same type of machines iteratively. Always the cost increases for the newer model. The production cost of such medical equipment may reduce by manufacturing locally.

Production of such medical devices became a billion-dollar business. They produce from small devices to large machines for diagnosing patients. Every country has its own medical regulatory compliance authority. Since there is no coordination among different authorities, such devices are usually stand-alone and are unable to communicate adequately with each other ([Hameed, Hassan, Shabnam, Miho, & Khalifa, 2008](#)). Manufacturers employ researchers to design new medical equipment that is minimally invasive. However, this research process is costly for the manufacturers, which can have a direct impact on the costs of the medical devices they produce. These costs are ultimately passed on to patients in the form of increased medical expenses. The development of such medical equipment is not governed by a single regulatory authority worldwide, and each country has its own regulatory body that approves the use of such equipment. For example, the FDA ([FDA, 2006](#)) in America is responsible for regulating medical devices. The existence of various regulatory authorities has created a diverse environment for medical devices ([Martin & Barnett, 2012](#)). As a result, interoperability between devices produced by different manufacturers is often not supported, making equipment from one vendor incompatible with that of another. A survey by Medical Devices and Diagnostic Industry (MDDI) ([FDA, 2006](#)) revealed that healthcare innovation faces three main challenges.

1. The cost and complexity improve in optimizing innovation.
2. The duration and amount of follow-up and tracking information required by the FDA.
3. The most frequent grievance voiced by software innovators is likely the challenges encountered in securing publication due to regulatory concerns.

As per our research observation, the challenges of medical devices manufacturer's environment are:

1. **A variety of similar medical equipment:** Various manufacturers develop their own equipment in-house and do not collaborate with others ([www.mddionline.com](#)). This causes to develop a variety of machines for the same purpose. As a result, the diagnosis result varies remarkably.
2. **Developing algorithms for processing raw data:** Raw data are collected with the help of different sensors and are processed by the device ([Zhang, Qiu, Tsai, Hassan, & Alamri, 2015](#)). This algorithm is developed in an individual manufacturer's laboratory which produces many different algorithms for the same purpose. This in turn produces different results.
3. **Huge Volume of Medical Data:** Most modern medical devices generate large amounts of data ([Chen, 2014; Nakajima, Shiga, & Hata, 2012](#)). Such huge data need to be processed in real-time for better diagnosis results. This needs better computational devices (i.e. latest computer hardware).
4. **Getting Optimum Result:** Different manufacturers developing different medical equipment of the same type but some are producing satisfactory results but others are not. This is because some processes or algorithms used are better than others.

The following are the key challenges faced in the development of medical devices:

1. **Developing algorithms for processing raw data:** Raw data is collected by different sensors and processed by the device ([Zhang et al., 2015](#)). Each manufacturer develops its own algorithm in its research center, resulting in different algorithms for the same process, leading to varying outcomes.
2. **A huge volume of medical data:** Most modern medical devices generate a large amount of data ([Chen, 2014; Nakajima et al., 2012](#)). This vast amount of data requires real-time processing, which requires significant computational effort.
3. **Obtaining optimal results:** Different manufacturers develop different medical equipment of the same type, but some devices produce satisfactory results while others do not. This is due to differences in the algorithms or processes used.

This study is motivated by the concept of "plug and play" (PnP), which is widely used in computers. PnP means that any device (such as a keyboard, mouse, printer, or webcam) connected to a computer is automatically recognized and prompts the user to install a device driver. Once the device driver is

installed, the operating system synchronizes with the device, and it becomes usable. There is no need to configure the device each time it is used. Similarly, if all medical equipment could be manufactured to attach to any general computer and provide device drivers, the user could easily obtain results from the device. This would be as simple as buying a webcam for a PC. In this way, all medical equipment could be integrated into a single computer that could be shared with the cloud (internet). However, to implement such an idea, the challenges of heterogeneous data fusion and open platform access need to be addressed ([Chandola, Sukumar, & Schryver, 2013](#); [Chen, Ma, Ullah, Cai, & Song, 2013](#)). Since each manufacturer's device processes data using its own algorithm, resulting in slightly different output. Integrating these different processes into a single integrated environment is a significant challenge.

2. Literature Review

Numerous studies have been conducted worldwide to integrate medical types of equipment. Most of these studies have focused on specialized medical conditions such as ICU and CCU. However, it has been observed that not all patients require such critical care. The majority of patients only need to be diagnosed continuously with special medical types of equipment. Some relevant studies are as follows:

MDDI (Medical Device and Diagnostic Industry) is a prominent journal that covers healthcare devices, their advancements, and reports on new inventions in the healthcare industry.

[Haque, Aziz, and Rahman \(2014\)](#) provided a detailed explanation of cyber-physical systems and their implementation in healthcare. They have conducted a survey of CPS in healthcare applications proposed by academia and industry. They also presented a comprehensive taxonomy that categorizes different components and methods required for the application of CPS in healthcare. The taxonomy highlights the similarities and differences between state-of-the-art technologies utilized in CPS for healthcare from the perspective of Wireless Sensor Networks (WSN) and Cloud Computing. Additionally, the study identifies the areas that require further research.

[Martin and Barnett \(2012\)](#) conducted a research study to investigate how medical devices could be integrated. They explored the shortcomings and applied a descriptive approach to investigate the contribution to the product development process. The results of this work influenced the development of the technology.

The study by [Hameed et al. \(2008\)](#) concentrates on creating an integrated Emergency, Healthcare, and Medical Information System (IEHMS) that can resolve numerous issues in existing systems. The goal was to combine real-time and mobility technologies with medical emergency systems using SMS, MMS, live audio, and video coverage. Although the author addressed the integration of medical record systems, there was no mention of equipment integration. Hence, the problem of lacking interoperability still persists.

In their research, [Zhang et al. \(2015\)](#) put forth a patient-centric cyber-physical system called "Health-CPS" for healthcare applications and services. They utilized cloud and big data analysis technologies for data collection but did not specify a particular standard. The system featured a data management layer for distributed storage and a data-service layer with parallel computing. The primary objective of this study was to demonstrate how cloud and big data technologies can improve the performance of healthcare systems, resulting in an array of intelligent healthcare applications and services for individuals.

In their paper, [Nakajima et al. \(2012\)](#) propose a new and more effective approach for developing healthcare systems called Systems Health Care. The authors suggest integrating smart devices to create a smart healthcare system and emphasize the importance of continuous development with valuable solutions tailored to individual health dynamics and dependency. Their proposed solution is suitable for the co-evolutionary integration of smart devices and services. While the paper discusses

important health issues and system development approaches, it does not address the integration of medical equipment used for diagnosing patients.

The ‘Centre for Medical Interoperability’ (medicalinteroperability.org) is actively engaged in integrating medical devices. The organization has brought together a consortium of industry leaders to disrupt the current healthcare landscape. Through their collective efforts, they are propelling the healthcare industry toward a brighter future.

2.1 The typical medical equipment

The working procedure of most traditional medical equipment can be broadly categorized into three parts, although not all equipment follows the same process. These three parts ([FDA, 2006](#)) are outlined below:

1. First, raw data is collected from the patient's body through the use of sensors, rays, blood samples, and tissue samples, among other methods.
2. Next, computer programs process the data using algorithms that have been developed by the manufacturer's own research laboratory.
3. Finally, the medical equipment generates reports in the form of printed values or graphs as output.

A typical medical equipment's working procedure can be viewed as shown in Figure 1.

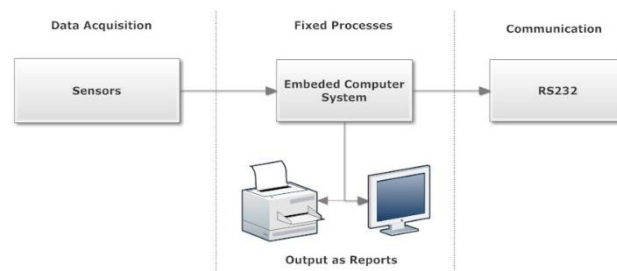


Figure 1. Conventional Medical Device working process

Although these machines are equipped with communication ports, their purpose is not to provide raw data. Instead, they are used to obtain processed data in the form of values, graphs, or images, which are known as diagnosis reports.

Medical equipment of this type is typically sold as a complete set, complete with an embedded processor or computer. As a result, if a new algorithm is developed, it cannot simply be installed into an old machine. Instead, a completely new set of similar machines with only a different model number must be developed, which can be costly.

Different models of the same machine may exist due to differences in the algorithms used to process raw data. Manufacturers must develop new devices to support the development of these algorithms. Since the machines are sold as an integrated set, older machines cannot be upgraded, and new sets of similar machines with updated model numbers and the same sensors are developed.

One significant disadvantage of these machines is that they do not have the capability to access raw data from the devices.

2.2 Related Work

In maternal health care, some patients need continuous monitoring during their pregnancy period and at the time of childbirth. During pregnancy, some medical conditions are treated as critical and termed as risky. Such risk factors include blood pressure, heart conditions, diabetics, and some hormonal changes that cause changes in behavioral, psychological, and physical health risks. There is a lot of research carried out and still going on how to detect and take quick action to avoid serious health

conditions for the mother and the baby. Maternal health care looks for the classic causes of risk factors and the mental health of a patient. Such risks can be detected by devices that integrate medical equipment into a single unit to monitor patients.

Research has been conducted globally to integrate medical equipment. Much of this research has focused on specialized medical conditions, such as ICU, HDU, and CCU. However, not all patients require such critical care conditions. Only a few special cases require patients to be sent to facilities where ICU, CCU, and other such services are available. The majority of patients do not require such intensive care but still need to be diagnosed continuously using medical equipment.

One specific area that requires continuous monitoring is maternal care during childbirth. As a result, research in this field has also been conducted. Some related works in this area are listed below:

2.2.1 Review of Risk Factors

In pregnancy cases, there are some issues that must be cared for. Such issues are – Age of the patient, body weight, body mass index (BMI), oxygen level in the blood (BO), blood pressure (BP) (FDA, 2006), Body temperature, and physical activities. Some diagnosis results like ECG, vaginal discharge in the first trimester, contraction in the third trimester, abnormal fetal protein, electrical uterine activity (EUA), mechanical uterine activity (MUA), fetal heart rate (FHR), fetal movement activity, etc. result need to be considered.

Some of the threshold value is defined for each medical test that doctors follow for the maternal patient (Zhang, et.al. 2015). Research is still going on which factors need further medical attention or clinical diagnosis or medications.

Depending on risks in pregnancy, they may be distributed into three categories such as normal, moderate, and high-risk. In the case of age, lower than 18 and more than 40 aged women are always in the high-risk zone in pregnancy. A study shows that a method for comparing the age factor in pregnant woman and a BMI that classify as underweight (<18.5), normal (18.52-24.99), obese (30-34.99), and morbidly obese (>35) (Phuong, Hieu, Wang, Lee, & Lee, 2011). Another study shows that hypertensive disorder in pregnancy falls into the following segments: gestational hypertensive, chronic hypertension, and pre-eclampsia. The accepted guideline says that the treatment of hypertension in pregnancy varies (www.mddionline.com).

The oxygen saturation level is another important factor that needs to be considered while caring for a pregnant patient. A value under 93% is very risky for a patient as well as for the baby.

A study shows that the presence of high sugar in the blood or diabetes may cause harm to pregnant women if not controlled. Hyperthermia is another risk factor for pregnant women. The patient must be aware of hyperthermia for the betterment of the mother and child.

Maternal serum screening (MSS) is another factor, which is used by doctors for better identification of risk for the pregnant woman. Some research suggested that MSS level is considered in the distribution of MSAFP levels. Such as with fatal neural tube defects as 7.0 (unaffected), 2.3 (spinal bifida), and 5.0 (anencephaly). MSS level for the distribution of MSAFP levels with fetal Down syndrome as 0.5/LR-2.0 (down syndrome), 0.8/LR-1.0 (normal), 1.4/LR-5.0 (upper syndrome) during the second trimester of pregnancy period.

Another new method has been developed by the researcher to detect uterine contraction using changes in several Electromyography (EMG) parameters. Fetal heart rate (FHR) is another important factor to measure. It is observed with a methodology based on the "Delayed moving windows" algorithm. It has been set with a normal heart rate of 120 bpm to 160 bpm (Zhang et al., 2015).

The body issues like weight, age, blood pressure, heart rate, physical activity, body temperature, etc. need to be analyzed for treating a pregnant woman. These parameters and corresponding values and their level may cause the intensity of risks for a specific patient. These factors are the key knowledge for identifying the risk level of women during pregnancy. For example, patterns of risk, and relationships between medical factors are related to pregnancy and precautions ([Chen, 2014](#)).

IoT is an important part of data transfer through the hardware layer between person to person and machine to machine, for minimizing the size of the health monitoring system ([Chen et al., 2013](#)). The hardware layer manages the interconnection between the devices. Since a lot of devices are connected in a network, bandwidth, and electromagnetic spectrum are a challenge that can be a barrier to data transfer efficiently ([Haque et al., 2014](#)).

Sensors can be controlled by an Arduino controller, which is used to analyze the data coming from the sensors (i.e. temperature sensors, heart rate sensors etc.). The IoT is a compact system in computing devices that is used to transfer data over a physical network without requiring the interaction of human-to-human or human-to-computer. With this technology data transfer is possible between long distances([Cheema, Rai, & Gupta, 2013](#)).

2.2.2 Selection of Risk Factor Intensity

Analyzing physical issues like age, weight, blood pressure, heart rate, body temperature, etc. are parameters for identifying the risk level of a patient. According to the risk level, a specific patient can be diagnosed. This analysis is used as knowledge on the risk level of women during pregnancy. The pattern of risk relationships between medical issues is related to pregnancy and precautions. Table 1 summarizes risk intensity parameters in patients.

Table 1. Risk Levels in medical diagnosis

Parameter	Risk level			References
	Low	Mid	High	
Blood Pressure	Systolic 120-139 mm Hg, Diastolic 80-89 mm Hg	Systolic 140-159 mm Hg, Diastolic 90-99 mm Hg	Systolic <90 and >160 mm Hg Diastolic <50 and >100 mm Hg	(Soegijoko, 2013)
Heart Rate	75-80 bpm	90-140 bpm	>70 and <140 bpm	(Blinzakov & Pallikarakis, 2001)
Body Temperature	averages 98.6 F (37 C)	<98.6 F (37 C) and > 102 F (38.9 C)	102 F (38.9 C) or higher (>35 C or >95 F) = Hypothermia	(Karim & Ahmad, 2010)
Fatal Movement	10 movements such as kicks, flutters, or rolls. within 12 hours; 6k/2hrs	10 movements Flutters, or rolls. within 12 hours; 6k/2hrs	>10 movements Such as kicks, flutters, or rolls. within 12 hours; >6k/2hrs	(Banerjee & Gupta, 2014)
Age	20-29	30-35	35-45	(Phuong et al., 2011)
BMI	(18.5–24.9 kg/m ²)	(18.5–24.9 kg/m ²)	<(18.5 kg/m ²) >(25–34.9 kg/m ²)	(Phuong et al., 2011)
Blood glucose AFB	<7.8 (<140) mmol/l(mg/dl)	<7.8 (<140) and ≥7.8 (≥140)	≥11.1 (≥200) mmol/l(mg/dl)	(Lv, Xia, Wu, Yao, &

		mmol/l(mg/dl)		Chen, 2010)
Blood glucose (Fasting)	<6.1 (<110) mmol/l(mg/dl)	≥6.1(≥110) &<7.0(<126) mmol/l(mg/dl)	≥7.0 (≥126) mmol/l(mg/dl)	(Lv et al., 2010)
Blood glucose (HbA1c)	<42 mmol/mol	42-46 mmol/mol	≥48 mmol/mol	(Lv et al., 2010)

2.2.3 Machine Learning in Medical Science

Research has been carried out to show a comparative analysis of both data mining and statistical approaches([Fortino, Guerrieri, Russo, & Savaglio, 2014](#); [Rahmani et al., 2015](#)). A data mining tool called 'Weka' is used for this research. In recent years, such type of risk prediction analysis is done by data mining techniques([Fortino et al., 2014](#); [Meyer, 2014](#); [Mohammed et al., 2014](#); [Rahmani et al., 2015](#)).

For risk analysis, risk prediction, and implementation a device /tool is developing for diagnosing the disease is a common trend nowadays([De la Cruz, Cuellar, Rojas, Molina, & Robles, 2015](#); [Lu, Zhao, Zhao, Li, & Zhang, 2015](#)). Research on developing Smartphone-based risk prediction tools is done by many researchers specially Heart Attack risk prediction was developed ([Rotheram-Borus, Tomlinson, Swendeman, Lee, & Jones, 2012](#)). This topic has drawn the attraction of many other researchers to use such techniques for diagnosis and prognosis and was used in the analysis of risk factors in recent days. According to WHO and UNICEF, many pregnant women die because of preventable diseases. Machine learning technologies focus on the new researcher's recommendations to handle critical risk conditions ([Oh, 2015](#)). Machine learning algorithms can be used to specify and predate high-risk prediction of the unknown level. This case decision tree is the most used technique for better accuracy and prediction rather than the regression model among all other algorithms in the health domain with less error([Mehta, Bhatt, & Ganatra, 2016](#)). Data mining and machine learning are the best and fastest-growing features of knowledge discovery in a dataset. This is why it is broadly used for predicting risk by following different steps([Abegaz & Habtewold, 2019](#)).

2.3 Proposed System

In health monitoring systems it is necessary to collect samples from the patient to determine their risk factors. Using conventional medical equipment, it is very expensive and time-consuming to determine risk factors among pregnant women. Moreover, it doesn't provide raw data. Since raw data is required for machine learning, we need to collect raw data from patients and send it to the cloud. Using big data analysis, we will process such raw data by using computer programs (i.e. algorithms) and provide diagnosis results. Such algorithms will be developed in open-source code so that the researchers around world can further update such algorithms. By using a machine learning algorithm, this result will be used for detecting risks for a particular patient. A better algorithm may be implemented at any time for processing the same data will be easy.

The prediction of risk level plays a pivotal role in the diagnosis process and will be effective in the preventive health of both mother and child.

2.3.1 Proposed System Model

In our project, we developed an integrated medical device that collects commonly used raw data (i.e. blood pressure, blood glucose level, ECG, temperature, etc.). This device is cost-effective and user-friendly. Since all measuring tools are integrated into one device, it is portable too. This healthcare system will be used to collect data from pregnant women and send it to the cloud through communication ports. Such communication devices are integrated into our devices which world online. Our machine learning-based software will automatically process the collected data online and

will monitor pregnant women continuously. And if any fatal health issue arises, it will immediately notify you.

2.3.2 Working Process of the System

1. **Step 1:** The patient's data will be collected by using a wearable device that consists of different sensing modules that collect data i.e. BP, Temperature, Hart beat, etc. Each module will be a complete data collection device (Arduino Nano) which will be connected to a central computer (ESP32 Module).
2. **Step 2:** Collected data will be identified and stored in the local central computer (ESP32 Module) until communication is established with the cloud.
3. **Step 3:** As soon as the data communication link is established, data will be moved to the cloud.
4. **Step 4:** Inside the cloud, a pre-installed machine learning algorithm will be used to process those data.
5. **Step 5:** Diagnosis results will be sent to the sources (i.e. hospital and other emergency services). Machine learning is used to identify fatal risk conditions. In case of fatal risk condition arises the machine will send a notification to the doctors for necessary actions.

2.3.3 Modules of the System

- a) Data collection through sensors
- b) Accumulating data and setup communication links with the cloud
- c) Store raw data on the cloud.
- d) Analyzing data using open-source software.

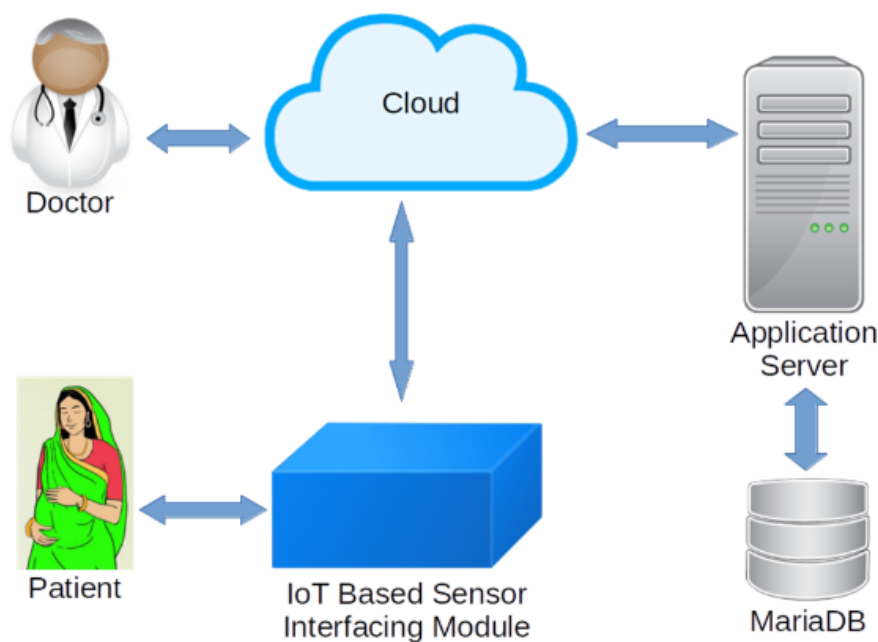


Figure 2. Modules of system

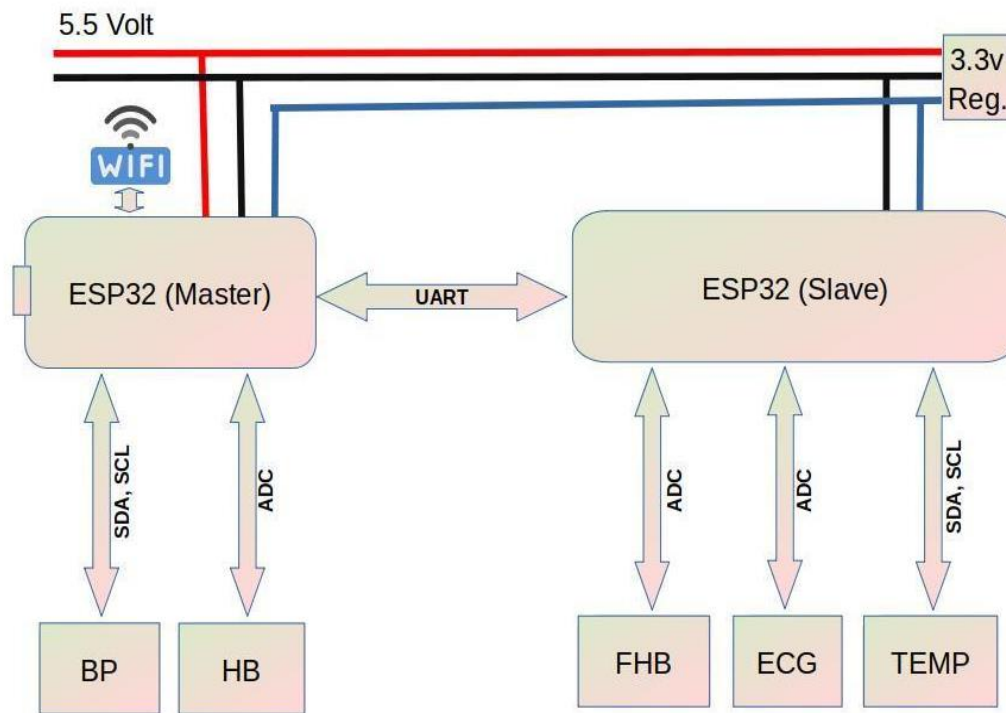


Figure 3. Block Diagram of Proposed Model

Figure 3 describes the block diagram of the data collection module with different sensors and a communication link with the WiFi module. As soon the link is established, data are transferred to the cloud and saved there in the database.

2.3.4 System Implementation

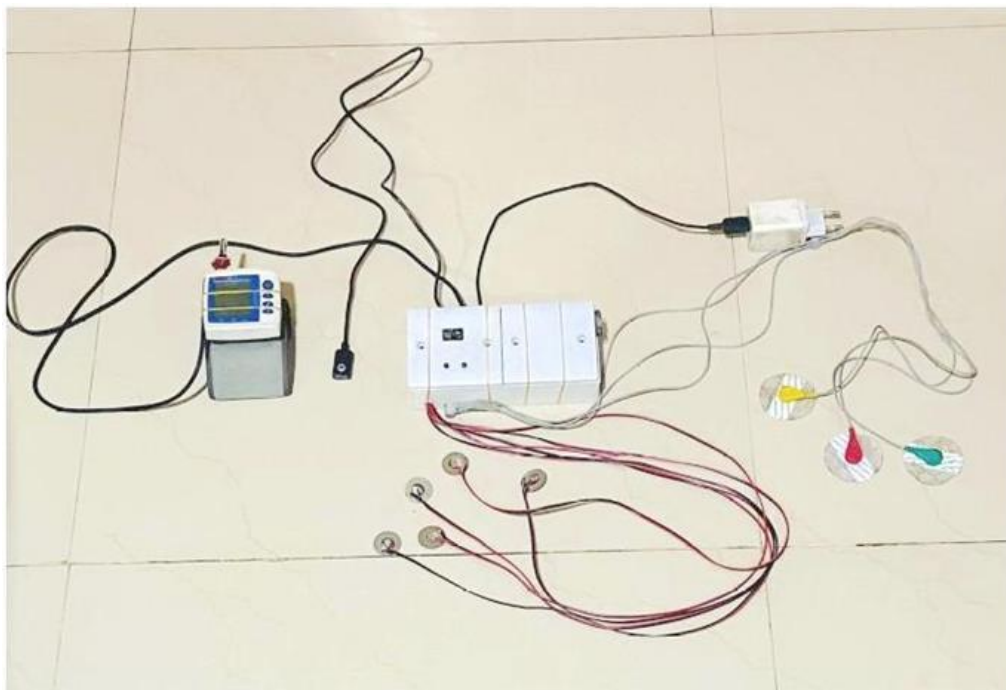


Figure 4. Developed Device with different sensors

In our project, we have developed an integrated device that includes different sensors for collecting raw data from a patient for the maternal patient for her diagnosis. The sensors used for our system are given in the following table:

Table 2. List of sensors used in Medical device

Sensor Type	Device Model No	Description
Microcontrollers	ESP32 Module	ESP32 is a series of low-cost, low-power system-on-chip microcontrollers with integrated Wi-Fi and dual-mode Bluetooth.
ECG Module	AD8232ecg	The AD8232 is an integrated signal conditioning block for ECG and other biopotential measurement applications.
Temperature	GY906 Infrared Temperature Sensor	MLX90614 is an infrared thermometer for non-contact temperature measurements. Both the IR-sensitive thermopile detector chip and the signal conditioning ASIC are integrated.
Heart Rate &Oximeter	MAX30102 Heart Rate and Pulse Oximeter Sensor	The MAX30102 is an integrated pulse oximetry and heart-rate monitor biosensor module. It includes internal LEDs, photodetectors, optical elements, and low-noise electronics with ambient light rejection.
Blood pressure	Blood pressure machine	The wrist blood pressure monitor is used to carry out a non-invasive measurement and monitoring of arterial blood pressure values in human adults.
	Pressure Sensor Module HX710B	HX710B Air Pressure Sensor Module adopts a high-precision AD sampling chip. It has a 0-40KPa air pressure sensor. Pressure Sensors measure fluctuations in the pressure exerted by the atmosphere.
Piezoelectric Sensor	Piezoelectric Sensor	A sensor that operates using the principle of piezoelectricity is referred to as a piezoelectric sensor.
Voltage Regulator	AMS1117Voltage Regulator	3.3V Voltage Regulator
Power Adapter	Power Adapter	5 VoltPower Adapter

The primary distinction between conventional systems and our proposed system is that conventional systems consist of separate devices for each type of diagnosis, whereas our system employs a single integrated device equipped with all necessary sensors for gathering raw data from patients. The data collected is then transmitted to the cloud module.

In the cloud module, there will be process modules or algorithms for processing. By using machine learning the processing module intelligently analyze the patient's report and send the reports to the

doctors. Depending on the test report the risk factor will be calculated by using statistical analysis. Since all the modules are integrated and available, they can be used easily and reliably.

2.3.5 Functional Modules of the System

In this system the following functional modules have been used:

1. **Sensor Module Interface:** In this setup, all the sensors will work in unison to gather raw data from the patient's body.
2. **Sensor Detection:** In this section, will automatically detect individual sensors and will help collect raw data from patients.
3. **Internal Workstation Interface:** The workstation will contain all the intricate procedures required to process the raw data obtained from sensors. In this context, a single sensor can be utilized for multiple purposes. For instance, a pulse rate measuring sensor can also be employed to measure blood pressure or perform an electrocardiogram (ECG).
4. **Internal Database (NoSQL):** Implementation of a big data processing concept will be facilitated by an internal database designed to accumulate an enormous amount of online data.
5. **Virtual Machine:** As our OSP system is expected to be platform-independent, it will utilize a virtual machine to perform complex processes. This virtual machine will be specifically designed to process the raw data gathered from the sensors and will be developed using the C programming language.
6. **Interface with OS Kernel:** To ensure seamless access to our hardware resources, we will employ a Linux-based OS kernel as our operating system (e.g. Ubuntu, Fedora, Red Hat, etc.). Given that our source code will be open-source, a Linux-based kernel is best suited for our needs.
7. **Ethernet Interface:** By means of the Ethernet interface, a sensor module can supply raw data to the OSP system. When adding devices to our system, it is advised to use the USB (Universal Serial Bus) interface. These interfaces will also be utilized to obtain processed data from the machine.
8. **Hardware:** Our hardware comprises the physical components employed for our purposes, including computers and sensors. We use cost-effective hardware, specifically desktop computers, which are readily available in the market.

3. Results and discussions

Different correlation is found from the experimental data by using different statistical equations. This correlation can be used for identifying the risk level of a pregnant woman.

Some of the correlations are shown here:

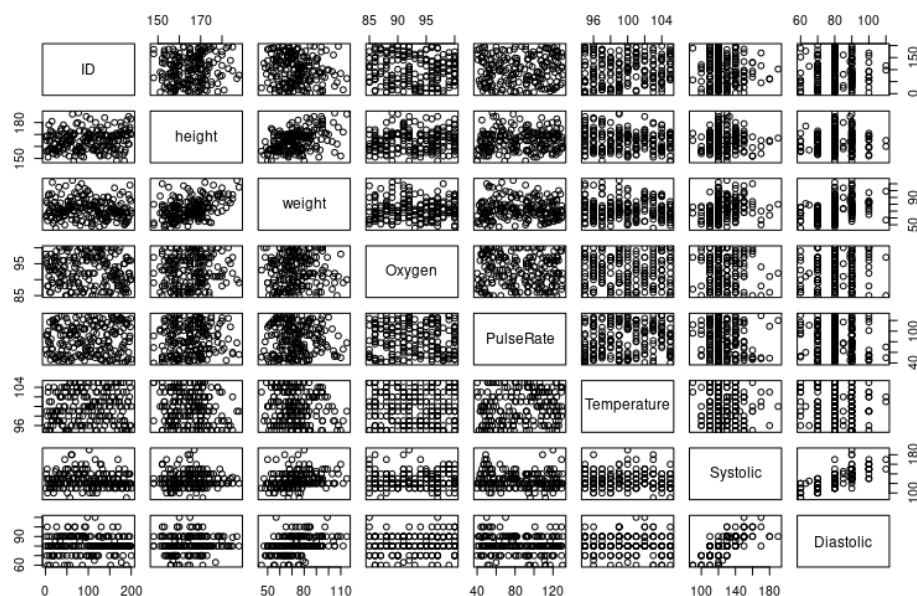


Figure 5. Representation for correlation matrix of raw data stored on the cloud

A matrix called a ‘correlation matrix’ is defined from the data (patient’s height, weight, oxygen level, pulse rate, temperature, systolic, and diastolic). The correlation between the two variables is compared in each figure. These correlations are used for diagnosis by complex analyses.

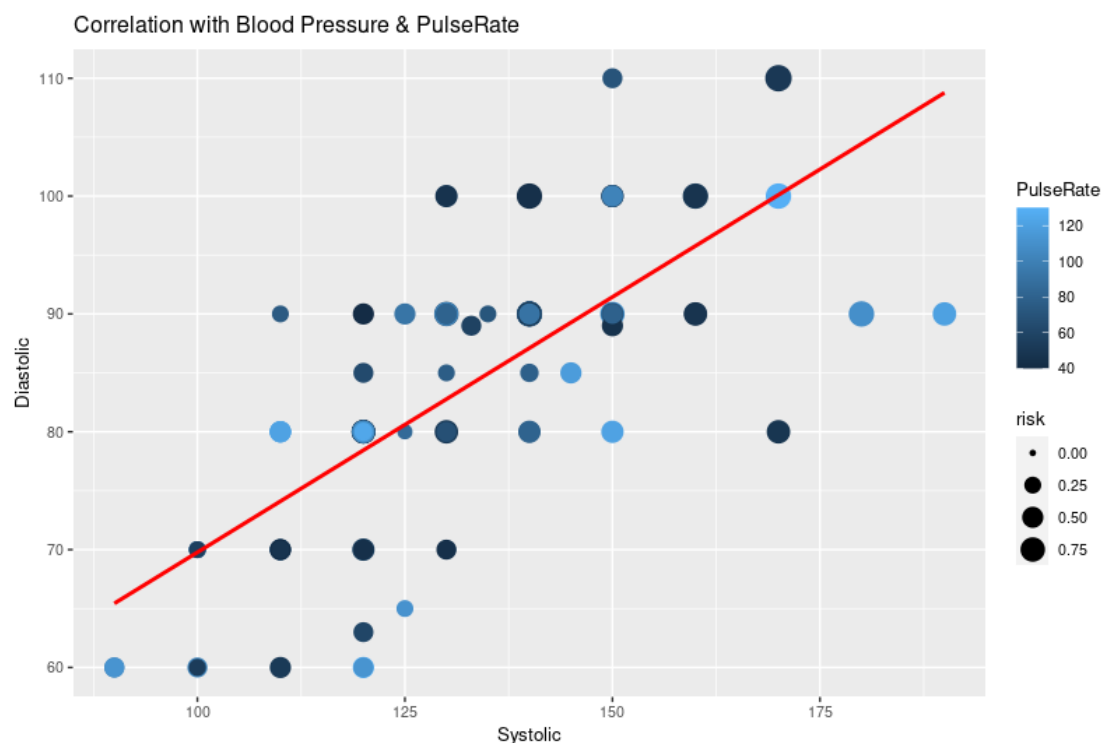


Figure 6. Risk Level and correlation between Blood Pressure & Pulse Rate

Figure 6 shows the correlation between Systolic & Pulse Rate variables for diagnosing risk levels. The red curve identifies the moving average (local polynomial regression) line of the relation between systolic and diastolic. Deep blue identifies the low pulse rate & blue color identifies the high pulse rate. Small circles are the low-risk points and bigger circles identify the high risks.

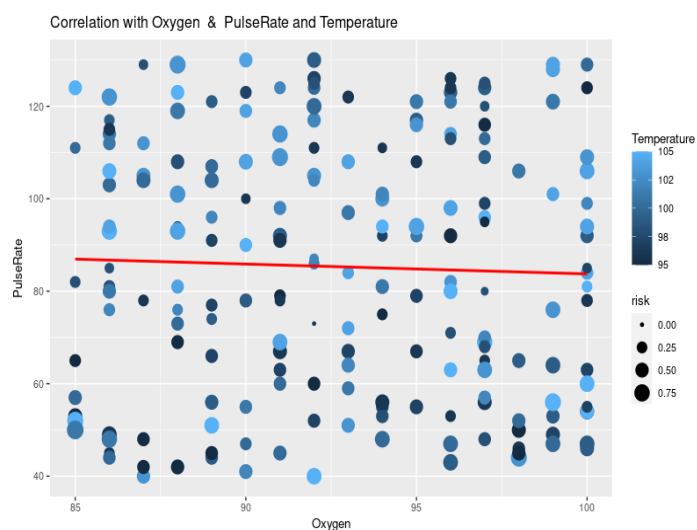


Figure 7. Risk Level and Correlation between Pulse Rate, Oxygen Level & Temperature

Figure-07 shows the relation between pulse rate oxygen level and temperature. The red curve identifies the moving average (local polynomial regression) line of the relationship between pulse rate and oxygen level. Deep blue circles identify the low-temperature blue circles identify the high temperature. Here the small circles are identified as low risk and bigger circles are identified as high risk.

4. Conclusion

The development and experiment were done successfully. The result was compared with the conventional diagnosis methods and was found about 93% accurate. We hope that the experimental result will inspire the regulatory authority, the manufacturers, and the practitioners to accept and use our device in reality. This device can accommodate an increasing number of sensors as per specific requirements, as the sensors are of the plug-and-play type. Our future objective is to incorporate all possible process algorithms into our system. The advantages offered by our system include:

1. Enhancing operational efficiency, precision, and control across various globally-dispersed medical devices.
2. Boosting the production of medical equipment to provide cost-effective services to all individuals.

We have a lot of work ahead of us to fully realize the potential benefits of our system. In the near future, our aim is to integrate more medical devices into a single unit for convenient access to medical services by both wealthy and underprivileged populations across the globe.

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