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Maternal healthcare using IoT-based integrated medical device: Bangladesh perspective

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Abstract

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

Research Methodology: A device equipped with multiple sensors was developed to collect raw data from pregnant patients. This data is transmitted to the cloud, where open-source algorithms process and analyze it to identify patient risk levels.

Results: We developed the system, collected raw data from patients, and uploaded these data to our cloud system. The data were processed in the cloud, and the resultant data were presented in the form of graphs. From these graphs, the risk levels were determined.

Conclusion: The IoT-based integrated device showed approximately 93% accuracy compared with conventional methods. It is a cost-effective, scalable, and adaptable solution that is suitable for maternal healthcare in developing countries. Features such as plug-and-play sensors, real-time cloud processing, and machine learning-based diagnostics make it a promising innovation for reducing maternal and infant mortality rates.

Limitations: The device is designed solely for use in pregnant patients and requires authorization from health regulators. Some high-cost sensors were excluded to ensure affordability..

Contribution: The main contribution of this study is to minimize the costs involved in maternal healthcare in poor countries such as Bangladesh. This, in turn, controls the death of mothers and children 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 over the last few decades. The deaths of mothers and children during childbirth have been reduced dramatically. This achievement was due to the increase in maternal healthcare facilities. The government is still working on maternal healthcare to reduce the death rates of mothers and children to zero. One of the main obstacles to such efforts is the cost associated with the medical diagnostic equipment used for continuous monitoring in critical cases. This cost cannot be borne by many poor people in rural areas. The diagnosis cost increases because of the cost of the medical devices. Such medical devices are developed and manufactured in developed countries, where the manufacturing cost is high. Moreover, they release newer models of the same type of machines iteratively. The cost of a newer model is always higher. The production cost of such medical equipment may be reduced by local manufacturing.

The production of such medical devices has become a billion-dollar industry. They can be produced from small devices to large machines for patient diagnosis. Every country has its own medical regulatory compliance authorities. Because of the lack of coordination among different authorities, such devices are usually stand-alone and are unable to communicate adequately with each other. Manufacturers employ researchers to design minimally invasive medical equipment. However, this research process is costly for manufacturers, which can directly impact the cost of the medical devices they produce. These costs are ultimately passed on to patients as 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 in the United States is responsible for regulating medical devices. The existence of various regulatory authorities has created a diverse environment for the development of medical devices. Consequently, 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) revealed that healthcare innovation faces three main challenges (Amaral, Paiva, Rodrigues, Veiga, & Bell, 2024; Riesna, Pujianto, Efendi, Nugroho, & Saputra, 2023).

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

According to our research observations, the challenges of a medical device 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. This has led to the development of various machines for the same purpose. Consequently, the diagnostic results vary remarkably.
2. ***Developing algorithms for processing raw data:*** Raw data are collected using different sensors and processed by the device (Zhang, Qiu, Tsai, Hassan, & Alamri, 2015). This algorithm was 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 (Akila1, Parameswari, & Jayakumari, 2022; Dicuonzo, Galeone, Shini, & Massari, 2022; Wang, Kung, & Byrd, 2018). Such large amounts of data must be processed in real time for better diagnostic results. This requires better computational devices (i.e., the latest computer hardware).
4. ***Getting Optimum Result:*** Different manufacturers develop different medical equipment of the same type, but some produce satisfactory results while others do not. This is because some processes or algorithms used are better than others (Khan, Khan, & Nazir, 2022; Palanisamy & Thirunavukarasu, 2019).

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

1. ***Developing algorithms for processing raw data:*** Raw data are collected by different sensors and processed by the device (Fitriana, Rahmadi, & Armin, 2024; Zhang et al., 2015). Each manufacturer develops its own algorithm in its research center, resulting in different algorithms for the same process and leading to varying outcomes.
2. ***A huge volume of medical data:*** Most modern medical devices generate large amounts of data. This vast amount of data requires real-time processing, which requires significant computational effort (Dash, Shakyawar, Sharma, & Kaushik, 2019; Prosperi, Min, Bian, & Modave, 2018; Shakor & Khaleel, 2024).
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 because of the differences in the algorithms or processes used.

This study is motivated by the concept of "plug and play" (PnP), which is widely used in computing. 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 the device driver. Once the device driver is installed, the operating system synchronizes with the device, and it becomes operational. 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, users 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 can be integrated into a single computer that can be shared with the cloud (Internet). However, to implement such an idea, the challenges of heterogeneous data fusion and open platform access must be addressed. Each manufacturer's device processes data using its own algorithm, resulting in slightly different outputs. Integrating these different processes into a single integrated environment is a significant challenge (Seth et al., 2025; Torab-Miandoab, Samad-Soltani, Jodati, & Rezaei-Hachesu, 2023).

2. Literature Review

Numerous studies have been conducted worldwide to integrate medical equipment. Most of these studies have focused on specialized medical conditions, such as the ICU and CCU. However, it has been observed that not all patients require such critical care. Most patients only need to be diagnosed continuously with special medical equipment. Some relevant studies are as follows: The Medical Device and Diagnostic Industry (MDDI) is a prominent journal that covers healthcare devices, their advancements, and reports on new inventions in the healthcare industry. According to Dey, Ashour, Shi, Fong, and Tavares (2018), cyber-physical systems and their implementation in healthcare have been explained in detail. They conducted a survey of CPS in healthcare applications proposed by academia and industry. They also presented a comprehensive taxonomy that categorizes the different components and methods required for the application of CPS in healthcare (Alzahrani, Alshehri, AlGhamdi, & Sharma, 2023; Shaikh, Rasool, & Verma, 2023). 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, this study identifies areas that require further research. According to 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 their contribution to the product development process. The results of this study influenced the development of this technology. Hameed, Hassan, Shabnam, Miho, and Khalifa (2008) concentrated 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, and live audio and video coverage. Although the author addressed the integration of medical record systems, equipment integration was not mentioned. Hence, the problem of a lack of interoperability persists.

Zhang et al. (2015) proposed 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 any particular standard. The system features 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 the individual. In their paper, Nakajima, Shiga, and Hata (2012) propose a new and more effective approach for developing healthcare systems called System Health Care. The authors suggest integrating smart devices to create a smart healthcare system and emphasize the importance of continuous development of valuable solutions tailored to individual health dynamics and dependency. Their proposed solution is suitable for the co-evolutionary integration of smart devices and services into the smart grid. Although this study discusses important health issues and system development approaches, it does not address the integration of medical equipment used for diagnosing patients. The ‘Center for Medical Interoperability’ (medicalinteroperability.org) is actively engaged in the integration of medical devices. The organization has brought together a consortium of industry leaders to disrupt the current healthcare landscape in the United States. Through their collective efforts, they are propelling the healthcare industry toward a brighter future (Amadea, Suryaputra, & Sondakh, 2022; Khuluqa, Mardwita, & Yuliawati, 2025; Putri, Budiarti, Huboyo, & Haryanti, 2024).

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: The three parts are outlined below.

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

The working procedure of a typical medical equipment is shown in Figure 1.

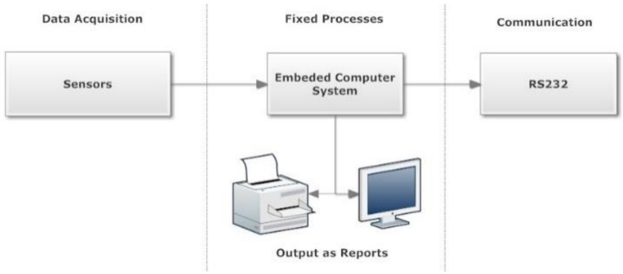

Figure 1. Conventional Medical Device working process

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 diagnostic reports. Medical equipment of this type is typically sold as a complete set, including an embedded processor or computer. Consequently, if a new algorithm is developed, it cannot simply be installed on an old machine. Instead, a completely new set of similar machines with only different model numbers must be developed, which can be costly. Different models of the same machine may exist owing to differences in the algorithms used to process raw data. Manufacturers must develop new devices to support the development of such algorithms. Because 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 (Cecelya, Rahmadi, & Armin, 2025; Pratama & Armin, 2025).

2.2 Related Work

In maternal healthcare, some patients require continuous monitoring during pregnancy and childbirth. During pregnancy, some medical conditions are treated as critical and are considered risky. Such risk factors include blood pressure, heart conditions, diabetes, and hormonal changes that cause changes in behavioral, psychological, and physical health risks. A lot of research has been carried out and is still ongoing on how to detect and take quick action to avoid serious health conditions for the mother and baby. Maternal health care seeks to identify the classic causes of risk factors and the mental health of a patient. Such risks can be detected using devices that integrate medical equipment into a single unit for patient monitoring.

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

One specific area that requires continuous monitoring is maternal care during the childbirth process. Consequently, research in this field has been conducted. Some related studies in this area are listed below.

2.2.1 Review of Risk Factors

In pregnant women, some issues must be addressed. Such issues include the age of the patient, body weight, body mass index (BMI), oxygen level in the blood (BO), blood pressure (BP), body temperature, and physical activities. Some diagnostic results, such as ECG, vaginal discharge in the first trimester, contraction in the third trimester, abnormal fatal protein, electrical uterine activity (EUA), mechanical uterine activity (MUA), dental heart rate (FHR), and fatal movement activity, need to be considered. Some threshold values are defined for each medical test that doctors follow for pregnant patients (Zhang et al., 2015). Research is still ongoing to determine which factors require further medical attention, clinical diagnosis, or medications.

Depending on the risks during pregnancy, they may be classified into three categories: normal, moderate, and high risk. In the case of age, women younger than 18 years and older than 40 years are always in the high-risk zone during pregnancy. A study showed a method for comparing the age factor in pregnant women and BMI that classified as underweight (<18.5), normal (18.52-24.99), obese (30-34.99), and morbidly obese (>35). Another study showed that hypertensive disorders in pregnancy fall into the following segments: gestational hypertension, chronic hypertension, and pre-eclampsia. The accepted guidelines state that the treatment of hypertension during pregnancy varies (Perejón et al., 2024). Oxygen saturation is another important factor that must be considered while caring for a pregnant patient. A value under 93% is very risky for both the patient and the baby.

A study showed that the presence of high sugar levels in the blood or diabetes may cause harm to pregnant women if not controlled. Hyperthermia is a risk factor for pregnant women. Patients must be aware of hyperthermia for the betterment of the mother and child. Maternal serum screening (MSS) is another factor used by doctors to better identify the risk for pregnant women. Some studies have suggested that the MSS level is considered in the distribution of MSAFP levels. Such as with fatal neural tube defects as 7.0 (unaffected), 2.3 (spina bifida), and 5.0 (anencephaly). The MSS level for the distribution of MSAFP levels with fetal Down syndrome was 0.5/LR-2.0 (Down syndrome), 0.8/LR-1.0 (normal), and 1.4/LR-5.0 (upper syndrome) during the second trimester of pregnancy. Another new method was developed to detect uterine contractions using changes in several electromyography (EMG) parameters. The fatal heart rate (FHR) is another important factor to measure. This was observed using a methodology based on the "Delayed moving windows" algorithm. It was set with a normal heart rate of 120–160 bpm (Zhang et al., 2015).

Body issues such as weight, age, blood pressure, heart rate, physical activity, and body temperature need to be analyzed for treating a pregnant woman. These parameters, their corresponding values, and their levels may cause the intensity of risks for a specific patient. These factors are key to identifying the risk level of women during pregnancy. For example, patterns of risk and relationships between medical factors are related to pregnancy and precautions. The IoT is an important part of data transfer through the hardware layer between person-to-person and machine-to-machine, to minimize the size of the health monitoring system. The hardware layer manages the interconnections between devices. Because many devices are connected to a network, bandwidth and electromagnetic spectrum are challenges that can hinder efficient data transfer. Sensors can be controlled by an Arduino controller, which is used to analyze the data from the sensors (i.e., temperature sensors, heart rate sensors, etc.). The IoT is a compact system of computing devices used to transfer data over a physical network without requiring human-to-human or human-to-computer interaction. With this technology, data transfer is possible over long distances (Munyao, Maina, Mambo, & Wanyoro, 2024; Sarhaddi et al., 2021; Suliswor o et al., 2025; Yang, Liu, & Wang, 2024).

2.2.2 Selection of Risk Factor Intensity

Analyzing physical issues such as age, weight, blood pressure, heart rate, and body temperature are parameters for identifying the risk level of a patient. A specific patient can be diagnosed according to the risk level. This analysis provides knowledge on the risk levels of women during pregnancy. The pattern of risk relationships between medical issues is related to pregnancy and preventive measures. 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 and 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 and 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 and Gupta (2014)
Age	20-29	30-35	35-45	Phuong, Hieu, Wang, Lee, and Lee (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) mmol/l(mg/dl)	≥11.1 (≥200) mmol/l(mg/dl)	Lv, Xia, Wu, Yao, and 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 conducted to show a comparative analysis of both data mining and statistical approaches. A data mining tool called 'Weka' was used for this research. In recent years, such risk prediction analyses have been performed using data mining techniques.

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 has been conducted by many researchers, especially for Heart Attack risk prediction. This topic has attracted the attention of many researchers who have used such techniques for diagnosis and prognosis and have been used in the analysis of risk factors in recent days. According to the WHO and UNICEF, many pregnant women die from preventable diseases. Machine learning technologies focus on new researchers' recommendations for handling critical risk conditions (Oh, 2015). Machine learning algorithms can be used to specify and predict high-risk levels. 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 fewer errors (Mehta, Bhatt, & Ganatra, 2016). Data mining and machine learning are the best and fastest-growing features of knowledge discovery in datasets. 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 patients to determine their risk factors. Using conventional medical equipment to determine risk factors among pregnant women is expensive and time-consuming. Moreover, it does not provide raw data. Because raw data are required for machine learning, we need to collect raw data from patients and send them to the cloud. Using big data analysis, we will process such raw data using computer programs (i.e., algorithms) and provide diagnosis results. Such algorithms will be developed in open-source code so that researchers worldwide can further update them. Using a machine learning algorithm, this result will be used to detect risks for a particular patient. A better algorithm may be implemented at any time, and processing the same data will be easy.

Risk level prediction plays a pivotal role in the diagnosis process and will be effective in the preventive health of both mothers and children.

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. Because all the measuring tools are integrated into one device, it is also portable. This healthcare system was used to collect data from pregnant women and send them to the cloud through communication ports. Such communication devices are integrated into our devices, which are used online. Our machine learning-based software will automatically process the collected data online and continuously monitor pregnant women. If any fatal health issues arise, they will be notified immediately.

2.3.2 Working Process of the System

1. **Step 1:** The patient's data will be collected using a wearable device that consists of different sensing modules that collect data, that is, BP, temperature, heart rate, etc. Each module will be a complete data collection device (Arduino Nano) connected to a central computer (ESP32 Module).
2. **Step 2:** The collected data are 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, the data are moved to the cloud.
4. **Step 4:** Inside the cloud, a pre-installed machine learning algorithm is used to process the data.
5. **Step 5:** The diagnosis results are sent to the sources (i.e., hospitals and other emergency services). Machine learning can be used to identify fatal risk conditions. In the case of a fatal risk condition, 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) Raw data are stored in the cloud.
d) Data were analyzed using open-source software.

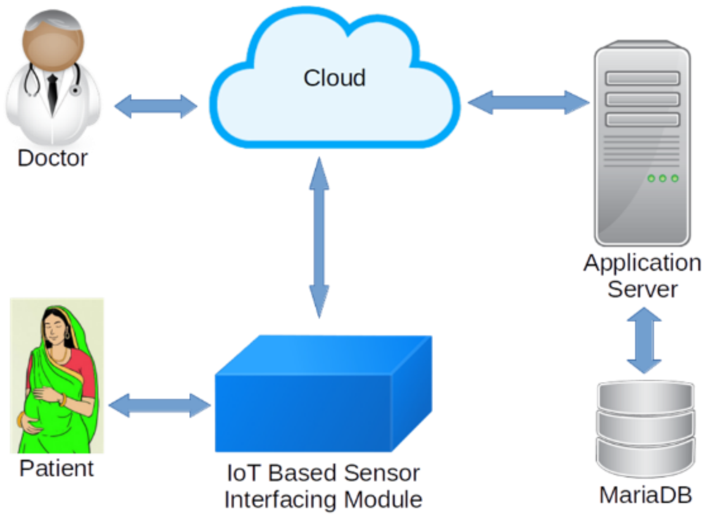

Figure 2. Modules of system

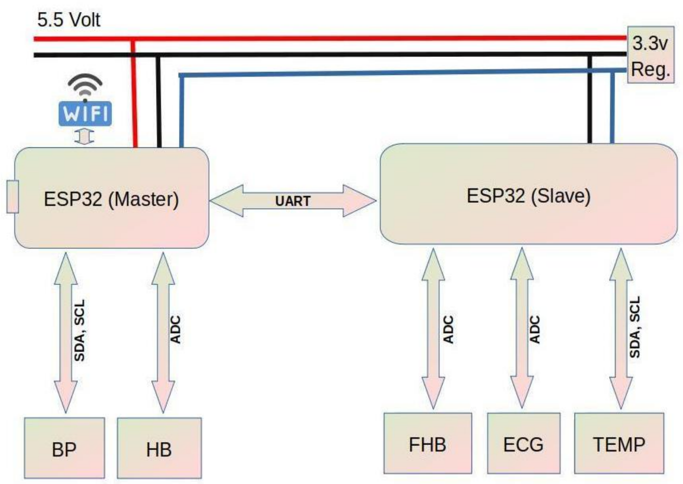

Figure 3. Block Diagram of Proposed Model

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

2.3.4 System Implementation

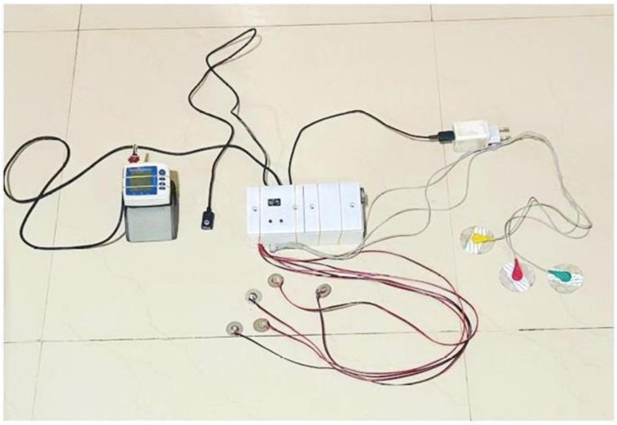

Figure 4. Developed Device with different sensors

In our project, we developed an integrated device that includes different sensors for collecting raw data from a patient for the maternal patient for diagnosis. The sensors used in our system are listed 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 the necessary sensors for gathering raw data from patients. The collected data were then transmitted to the cloud module. In the cloud module, process modules or algorithms are used for processing. Using machine learning, the processing module intelligently analyzes the patient's report and sends the report to the doctors. Depending on the test report, the risk factor will be calculated using statistical analysis. Because all modules are integrated and available, they can be used easily and reliably.

2.3.5 Functional Modules of the System

The following functional modules were used in this system:

1. ***Sensor Module Interface:*** In setup, all the sensors work in unison to gather raw data from the patient's body.
2. ***Sensor Detection:*** In section, individual sensors are automatically detected and help collect raw data from patients.
3. ***Internal Workstation Interface:*** The workstation contains all intricate procedures required to process raw data obtained from sensors. In this context, a single sensor can be used for multiple purposes. For instance, a pulse rate measuring sensor can also be employed to measure blood pressure or perform electrocardiography (ECG).
4. ***Internal Database (NoSQL):*** The 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 C programming language.
6. ***Interface with OS Kernel:*** To ensure seamless access to hardware resources, we employed a Linux-based OS kernel as our operating system (for example, Ubuntu, Fedora, and Red Hat). Given that our source code will be open-source, a Linux-based kernel is the most suitable for our needs.
7. ***Ethernet Interface:*** By sensor module can supply raw data to the OSP system via the Ethernet interface. When adding devices to our system, it is advisable to use the Universal Serial Bus (USB) interface. These interfaces will also be used to obtain processed data from the machine.
8. ***Hardware:*** Our hardware comprises the physical components employed for our purposes, including computers and sensors. We used cost-effective hardware, specifically desktop computers, which are readily available in the market.

3. Results and discussions

Different correlations were found from the experimental data using different statistical equations. This correlation can be used to identify the risk level of pregnant women.

Some of the correlations are as follows:

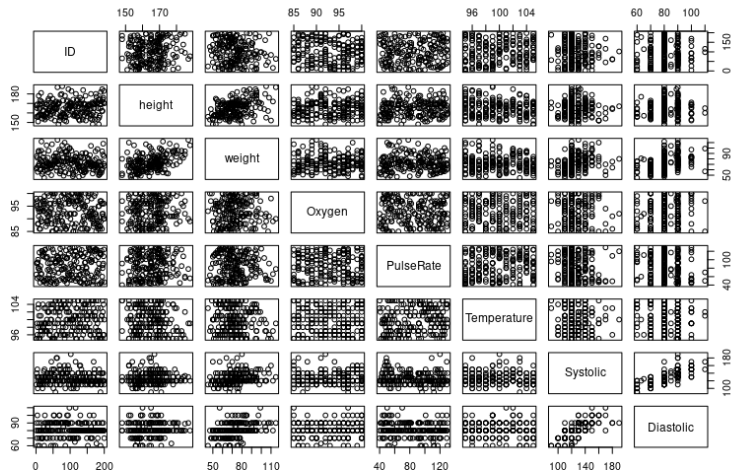

Figure 5. Representation for correlation matrix of raw data stored on the cloud

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

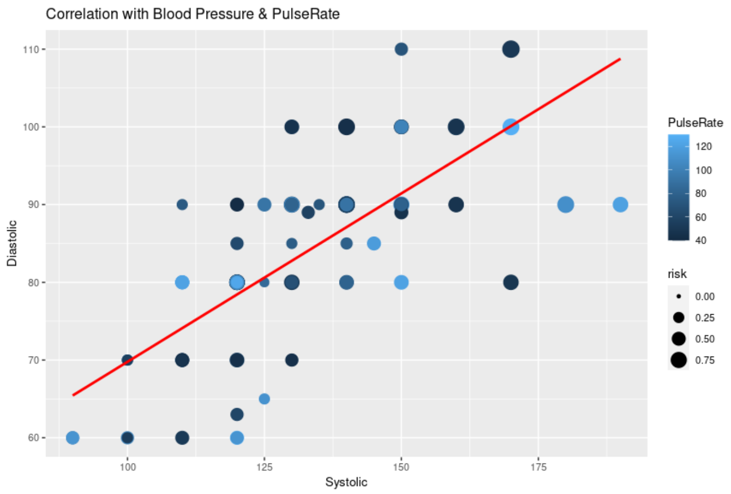

Figure 6. Risk Level and correlation between Blood Pressure & Pulse Rate

Figure 6 shows the correlation between the Systolic & Pulse Rate variables for diagnosing risk levels. The red curve identifies the moving average (local polynomial regression) line of the relationship between systolic and diastolic blood pressure. Deep blue identifies a low pulse rate, and blue identifies a high pulse rate. Small circles represent low-risk points, and larger circles represent high-risk points.

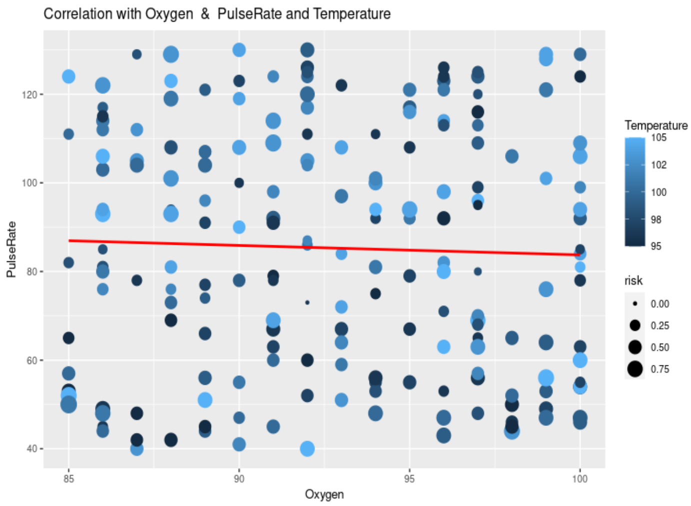

Figure 7. Risk Level and Correlation between Pulse Rate, Oxygen Level & Temperature

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

4. Conclusion

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

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 is also important.

We have a lot of work ahead of us to fully realize the potential benefits of our proposed system. In the near future, we aim 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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