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SMART WOMB: AI Enabled Maternal Safety Device

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Abstract— **Pre-eclampsia is one of the leading complications during pregnancy that can cause severe maternal and fetal morbidity or even mortality if not detected at an early stage. Traditional methods of diagnosis rely on periodic clinical examinations and blood pressure monitoring, which often fail to capture sudden changes in a pregnant woman's physiological conditions. In this project, a real-time pre-eclampsia prediction system is designed using the Internet of Things (IoT) and machine learning technologies. The proposed system consists of two wearable devices—one is a wrist-based maternal fitness tracker using the ESP32 microcontroller, which records vital parameters such as heart rate, blood pressure, and oxygen saturation (SpO_2) using a MAX30100 sensor. The second device is a wearable abdominal belt that contains a fetal kick detection sensor interfaced with another ESP32 to continuously monitor fetal movement activity. The data collected from both devices are transmitted wirelessly to an IoT server for processing and analysis. A cloud-based machine learning model performs data fusion and pattern recognition to predict the likelihood of pre-eclampsia by analyzing correlations between maternal hemodynamic variations and fetal activity patterns. This system offers an intelligent, low-cost, and non-invasive solution for early detection and alert generation, ensuring that medical intervention can be provided at the earliest possible stage. The use of IoT and artificial intelligence in maternal healthcare can significantly reduce mortality rates, improve prenatal care quality, and support continuous remote monitoring for expecting mothers, especially in rural or low-resource areas.**

Keywords : Pre-eclampsia, Internet of Things (IoT), Machine Learning, Maternal Health Monitoring, Wearable Devices, ESP32 Microcontroller, MAX30100 Sensor, Fetal Movement Detection, Smart Healthcare, Remote Monitoring, Data Fusion, Early Risk Prediction, Non-invasive Monitoring, Pregnancy Care, Artificial Intelligence.

I.INTRODUCTION

Pregnancy complications such as pre-eclampsia remain a major challenge in global maternal healthcare, accounting for thousands of deaths every year. Pre-eclampsia is primarily characterized by hypertension and proteinuria that occur after 20 weeks of gestation. If left undetected, it can lead to severe outcomes including organ dysfunction, seizures (eclampsia), preterm birth, and even maternal or fetal death. The diagnosis and management of pre-cclampsia currently depend on hospital-based monitoring, periodic checkups, and clinical laboratory tests. However, many pregnant women in rural and underdeveloped regions do not have access to continuous monitoring facilities. The rapid advancement in the field of the Internet of Things (loT), sensor technology, and machine learning algorithms now offers a novel solution to this problem. By continuously capturing and analyzing maternal vital parameters such as heart rate, blood pressure, and oxygen levels, as well as fetal movement data, it becomes possible to detect early warning signs long before clinical symptoms appear.

The loT-based wearable devices in this system are designed to collect real-time data, which is then transmitted to a central server through wireless communication. The data are processed by a cloud-hosted machine learning model that predicts pre-eclampsia risk using predictive analytics. The integration of loT with artificial intelligence transforms traditional healthcare into a proactive and preventive framework, allowing doctors and healthcare providers to take timely action. This project aims to create a portable, affordable, and intelligent monitoring systemn that can help reduce maternal mortality and improve the overall safety of pregnancy.

I. RELATED WORKS

Recent research has explored the application of IoT and machine learning in maternal healthcare.Machine learning models such as Random Forest and Support Vector Machines have been used to predict pre-eclampsia with high accuracy using clinical datasets.loT-based maternal monitoring systems have also been developed to track vital parameters like heart rate, blood pressure, and oxygen levels in real time. These systems enable remote monitoring and early warning alerts, particularly beneficial in rural areas.Additionally, wearable fetal monitoring systems using sensors and signal processing techniques have shown promising results in detecting fetal movements and abnormalities. However, most existing systems focus either on maternal or fetal parameters independently.

The proposed system integrates both maternal and fetal monitoring with machine learning-based prediction, providing a more comprehensive and reliable solution.

II. DESIGN

1.SYSTEM DESIGN:

1. Proposed System Architecture

The system consists of two main wearable devices:

- Maternal Monitoring Device:

Measures heart rate, blood pressure, and SpO2 using sensors like MAX30100.

- Fetal Monitoring Belt:

Detects fetal movements using a kick sensor.

Both devices use ESP32 microcontrollers to collect and transmit data.

2. Data Communication and Processing

- Data is transmitted via Bluetooth/Wi-Fi to a smartphone
- The smartphone acts as a gateway to the cloud
- Cloud platform stores and processes data
- Machine learning model predicts risk levels

3. Working Principle

- Sensors collect real-time physiological data
- Data is transmitted to cloud server
- Machine learning model analyzes patterns
- Risk level is predicted
- Alerts are generated if abnormalities are detected

System Architecture

The overall architecture of the proposed Pregnancy Risk Prediction System is organized into multiple functional layers, as shown in Fig. 1.1. The layered design ensures modularity, efficient data processing, and accurate prediction of pre-eclampsia risk.

Fig 1.1: Block Diagram

Sensor Layer

The sensor layer is responsible for collecting real-time physiological parameters from the pregnant woman. It includes sensors such as blood pressure sensor, heart rate sensor, temperature sensor, SpO2 sensor (MAX30100), and a fetal kick sensor. These sensors continuously monitor both maternal and fetal health conditions. The collected analog and digital signals are interfaced with the ESP32 microcontroller, which acts as the primary data acquisition unit.

Embedded System Layer

The embedded system layer consists of the ESP32 microcontroller programmed using Embedded C. This layer performs sensor interfacing, analog-to-digital conversion (ADC), and real-time data sampling. The ESP32 processes raw sensor data and prepares it for further analysis while also enabling wireless communication through Wi-Fi and Bluetooth.

The power supply design of the Trash Trek Robot ensures stable and isolated delivery of energy to the control electronics, sensors, actuators, and motor system. The platform is driven by a 12 V primary source, which directly powers the DC mthrough the L298 motor driver to provide adequate torque for mobility.

Data Pre-processing Layer

In this layer, the collected raw data undergoes preprocessing to improve accuracy and reliability.Noise filtering techniques are applied to remove unwanted disturbances, and normalization is performed to standardize the data. Feature extraction is then carried out to obtain key parameters such as blood pressure (BP), heart rate (HR), oxygen saturation (SpO2), and fetal movement count (kicks, which are essential for prediction.

Machine Learning Layer

The machine learning layer is responsible for analyzing the proces data and predicting the risk of pre-eclampsia. This layer consists of two stages: offline training and real-time prediction. In the offline phase, historical datasets are used to train a Naïve Bayes model. During real-time operation, live sensor datais fed into the trained model to classify the risk level.

Risk Analysis and Decision Layer

Based on the output of the machine learning model, the system categorizes the condition into different risk levels such as low risk, medium risk, and high risk (pre-eclampsia). This decision-making layer plays a crucial role in identifying potential complications at an early stage.

Output and Alert Layer

The final layer provides user interaction and alert mechanisms. The results are displayed on an LCD screen for immediate monitoring. Additionally, the data is transmitted to a cloud dashboard and mobile application for remote access. In case of high-risk detection, alert notifications are sent to healthcare providers, enabling timely medical intervention.

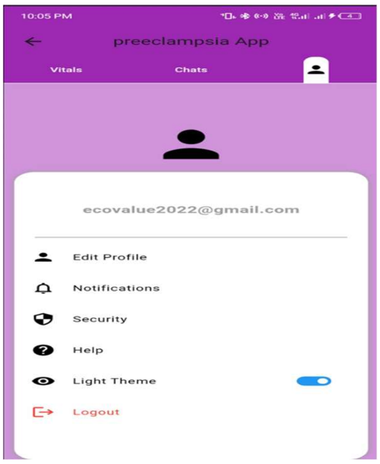

Fig 3.1: Pre-eclampsia mobile application

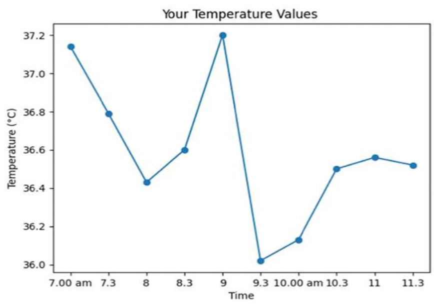

Fig 3.2: mobile application display

3.SOFTWARE & HARDWARE REQUIREMENTS

The implementation of the proposed smart wombsystem requires a combination of embedded hardware components and supporting software tools to enable real-time monitoring, data processing, and communication. The design focuses on reliability, low power consumption, and seamless integration with IoT platforms**.**

Hardware Components

The hardware architecture of the system is centered around the ESP32 microcontroller, which serves as the main control unit responsible for sensor interfacing, data acquisition, and wireless communication. The ESP32 is selected due to its integrated Wi-Fi and Bluetooth capabilities, making it suitable for continuous health monitoring applications.

To monitor maternal health parameters, the system incorporates the MAX30100 sensor, which measures both heart rate and oxygen saturation (SpO2) using photoplethysmography techniques. In addition, a blood pressure sensor is included to track systolic and diastolic pressure levels, which are critical indicators for detecting pre-eclampsia. A separate heart rate sensor is also used to ensure continuous and accurate pulse monitoring.

For fetal monitoring, a dedicated fetal kick sensor is integrated into the wearable abdominal belt.This sensor detects movement patterns and counts fetal kicks, providing important insights into fetal well-being. The collected data from both maternal and fetal sensors are processed by the ESP32 and transmitted to the cloud for further analysis.

A 16x2 LCD display is incorporated into the system to provide real-time visualization of key parameters, allowing the user to monitor health conditions directly from the device. The entire system is powered using a regulated power supply module consisting of a rechargeable battery and voltage regulation circuitry, ensuring stable and uninterrupted operation.

Software Requirements

The software environment plays a crucial role in enabling data processing, communication, and predictive analysis. The Arduino Integrated Development Environment (IDE) is used for programming the ESP32 microcontroller. It provides an easy-to-use platform for writing, compiling, and uploading embedded C/C++ code to control sensors and communication modules.

An IoT cloud platform is utilized for storing and managing the real-time data collected from the wearable devices. The cloud enables remote access, data visualization, and integration with analytical models. It also facilitates communication between the patient and healthcare providers by providing continuous updates and alerts.

The system further incorporates a machine learning-based prediction model that analyzes both historical and real-time data to assess the risk of pre-eclampsia. Algorithms such as Naïve Bayes, Random Forest, or Support Vector Machines can be employed to improve prediction accuracy and reliability.

In addition, a mobile or web-based interface is used to display processed data, generate alerts, and allow healthcare professionals to monitor patient conditions remotely. This integration of hardware and software ensures a complete and intelligent healthcare monitoring system.

IV.IMPLEMENTATION

1. DATA ACQUISITION AND MONITORING

The implementation of the proposed system begins with real-time data acquisition using multiple sensors integrated with the ESP32 microcontroller. The sensors continuously measure physiological parameters such as blood pressure, heart rate, oxygen saturation (SpO2), temperature, and fetal movements. These sensors are interfaced with the ESP32, which collects and processes the incoming signals.

The ESP32 performs initial data handling, including sampling and conversion of analog signals into digital form. The collected data is then prepared for further processing and transmission. The system ensures continuous monitoring, allowing real-time tracking of both maternal and fetal health conditions.

2. DATA PROCESSING AND FEATURE EXTRACTION

Once the sensor data is acquired, it undergoes preprocessing to improve its quality and reliability. Noise filtering techniques are applied to eliminate unwanted disturbances and ensure accurate readings. The data is then normalized to maintain consistency across different parameters.

Feature extraction is performed to identify key health indicators such as blood pressure levels, heart rate, oxygen saturation, and fetal movement count. These features are essential inputs for the machine learning model and play a crucial role in predicting pre-eclampsia risk.

3. MACHINE LEARNING-BASED PREDICTION

The processed data is transmitted to the machine learning module, where predictive analysis is carried out. The system utilizes a Naïve Bayes algorithm trained on historical maternal health datasets. During real-time operation, the live sensor data is fed into the trained model to classify the risk level.

The model analyzes correlations between different physiological parameters and identifies patterns associated with pre-eclampsia. Based on this analysis, the system predicts whether the condition falls under low, medium, or high risk.

4. IOT COMMUNICATION AND CLOUD INTEGRATION

The ESP32 microcontroller enables wireless communication by transmitting data to a cloud server using Wi-Fi. The cloud platform stores and processes the incoming data, allowing real-time access and monitoring.

A web-based dashboard or mobile application is used to visualize the data, making it accessible to both patients and healthcare providers. The loT integration ensures continuous connectivity and supports remote health monitoring.

5. ALERT GENERATION AND USER INTERFACE

Based on the prediction results, the system generates appropriate alerts. If a high-risk condition is detected, immediate notifications are sent to the user and healthcare providers. This enables timely medical intervention and reduces the chances of complications.

The system also includes an LCD display that shows real-time health parameters, providing instant feedback to the user. The combination of on-device display and cloud-based alerts enhances usability and reliability.

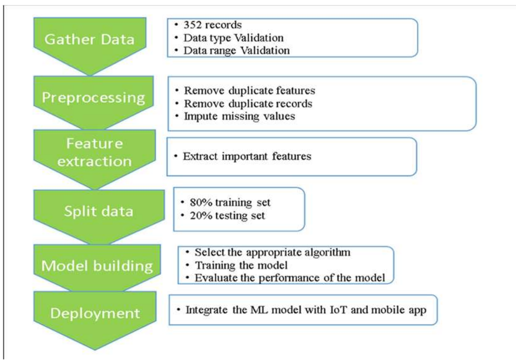

Fig 4.1 : Implementation

VI. RESULTS AND DISCUSSION

The proposed AI-enabled pregnancy risk prediction device was designed and tested using simulated and real-time sensor inputs. The system integrates physiological parameter monitoring with intelligent analysis to identify potential risk conditions during pregnancy.

The hardware module, consisting of sensors such as heart rate sensor, temperature sensor, and motion/activity tracking unit, successfully acquired real-time data from the user. The collected data was processed using a microcontroller and transmitted for analysis.

The software model, based on machine learning algorithms, analyzed the input parameters and classified the risk levels into categories such as normal, moderate risk, and high risk. The system demonstrated reliable performance in detecting abnormal variations in physiological parameters.

The output was displayed through a user interface, enabling easy monitoring for both patients and healthcare providers. Alerts were generated when the parameters exceeded predefined thresholds, ensuring timely intervention.

The experimental results indicate that the system is capable of:

- Continuous real-time monitoring
- Early detection of potential complications
- Providing user-friendly outputs and alerts of pregnancy risk prediction.

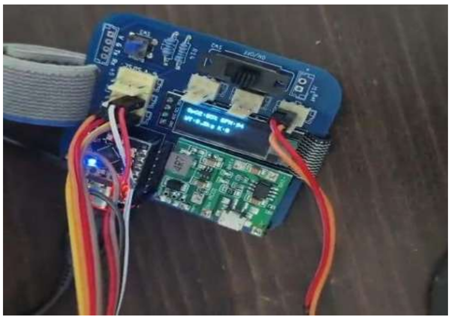

Figure 5.1 : Data receiver

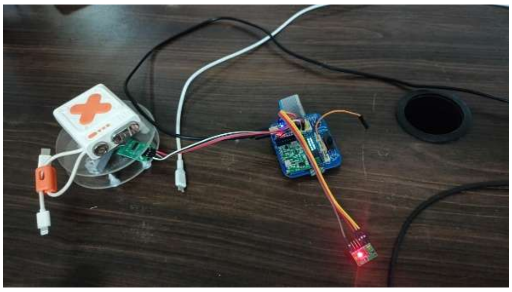

Figure 5.2 : Prototype

VII. CONCLUSION

In this work, an innovative AI-based wearable system for early pregnancy risk detection has been developed. The proposed system combines sensor technology with intelligent data analysis to monitor maternal health parameters effectively.

The device offers a non-invasive, cost-effective, and real-time monitoring solution, making it suitable for both urban and rural healthcare applications. By enabling early detection of potential risks, the system can help reduce complications and improve maternal and fetal outcomes.

The results obtained from the implementation confirm that the system performs efficiently in identifying abnormal conditions and generating timely alerts.

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