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#### **Abstract:**

Preterm birth is a major global health concern and a leading cause of neonatal mortality. Traditional monitoring methods are intermittent and often fail to detect early signs of labor. This paper proposes a non-invasive IoT based maternal monitoring system integrated with Machine Learning for early prediction of preterm birth. The system continuously monitors physiological parameters such as uterine muscle activity, heart rate, oxygen saturation, body temperature, and motion patterns using wearable sensors. Data is transmitted to a cloud platform where an XGBoost algorithm analyzes patterns and predicts risk levels. The system achieved an accuracy of 95.4% with an alert latency below 1.2 seconds, providing a reliable, cost effective, and real time monitoring solution.

**Key Words:** Preterm Birth, Internet of Things (IoT), Machine Learning, XGBoost, Maternal Health Monitoring, Cloud Computing.

#### **1. Introduction:**

Preterm birth, defined as childbirth occurring before 37 completed weeks of gestation, represents one of the most critical challenges in maternal and neonatal healthcare worldwide. According to the World Health Organization, approximately 15 million preterm births occur globally each year, making it a leading cause of neonatal mortality and long term morbidity. Complications associated with premature delivery include respiratory distress syndrome, intraventricular haemorrhage, necrotizing enterocolitis, developmental delays, and increased susceptibility to infections. In countries such as India, preterm birth rates remain significantly high, with a substantial number of neonates requiring intensive medical care annually.

Despite considerable advancements in obstetric and neonatal healthcare, the early prediction of preterm labor remains a complex and unresolved clinical problem. Conventional monitoring approaches rely primarily on hospital based examinations, including periodic cervical assessments, fetal fibronectin testing, and ultrasound based cervical length measurements. Although these methods provide valuable clinical insights, they are inherently intermittent and fail to offer continuous monitoring of maternal physiological conditions. As a result, early signs of preterm labor may go undetected until symptoms become severe, thereby limiting the effectiveness of timely medical intervention.

Recent advancements in Internet of Things (IoT) and Machine Learning (ML) technologies have introduced new opportunities for continuous, remote, and intelligent healthcare monitoring. IoT based systems enable real time acquisition of physiological data through wearable sensors, while machine learning algorithms facilitate predictive analysis by identifying complex patterns within biomedical signals. The integration of these technologies provides a promising framework for proactive maternal health monitoring, addressing the limitations of traditional clinical practices.

In this context, this paper presents a non invasive IoT based maternal monitoring system integrated with machine learning for the early prediction of preterm labor. The proposed system continuously monitors critical physiological parameters, processes the acquired data using intelligent algorithms, and transmits it to a centralized cloud platform for analysis. By enabling real time monitoring and predictive risk assessment, the system aims to improve maternal care, reduce neonatal complications, and enhance overall healthcare efficiency across diverse healthcare environments.

#### **2. System Architecture and Implementation:**

The proposed Preterm Birth Detection System is developed using a modular architecture to enable continuous maternal health monitoring, real time data processing, early risk prediction, and timely alert generation. The system integrates multiple non invasive sensors with an ESP32 microcontroller, including

an EMG sensor for uterine activity, a MAX30102 sensor for heart rate and oxygen saturation (SpO<sub>2</sub>), an MPU6050 sensor for motion detection, and a thermistor for temperature measurement

The acquired sensor data is processed using digital filtering techniques such as low pass and notch filters to remove noise and interference. Relevant features, including contraction frequency, heart rate variability, SpO<sub>2</sub> levels, motion parameters, and temperature variations, are extracted and normalized before being transmitted to a cloud platform. A machine learning model based on XGBoost analyzes the data to predict the risk of preterm labor. To improve signal accuracy, motion artifacts are reduced using adaptive filtering techniques based on accelerometer data.

The system uses Wi-Fi and the MQTT protocol for efficient and secure data transmission, with features such as buffering and automatic reconnection to ensure reliability. The cloud platform stores and manages data using a PostgreSQL database and provides real time visualization through a Hospital Management System interface. Alerts are generated when abnormal conditions are detected, such as high heart rate, low oxygen levels, elevated temperature, or increased contraction frequency, and are delivered through web dashboards, mobile notifications, and SMS. The system also includes a remote monitoring interface that allows healthcare professionals to track patient data, analyze trends, and access historical records. The hardware components include ESP32, sensors, display, and battery, while the software stack consists of Arduino IDE, Python, XGBoost, Scikit learn, Node.js, React.js, PostgreSQL, and MQTT. Overall, the system provides a portable, efficient, and intelligent solution for early detection and management of preterm birth risk.

### **3. Uterine Contraction Analysis:**

Preterm labor remains one of the most challenging conditions in obstetrics, largely because its earliest sign - uterine contractions - can be subtle and easily mistaken for benign Braxton Hicks contractions. However, careful assessment of contraction features reveals distinct patterns that separate true preterm labor from false labor.

Clinically, preterm contractions feel similar to term labor contractions but are often less intense, more closely resembling menstrual cramps or a dull backache. The key distinguishing features are frequency, duration, and progression. In true preterm labor, contractions occur regularly, typically every five to twenty minutes, with a threshold of six or more contractions in one hour. Each contraction lasts between forty and sixty seconds. Unlike Braxton Hicks, true preterm contractions do not stop with rest, hydration, or changes in position. Instead, they progressively grow stronger and more frequent over time, signaling that the cervix may be beginning to change.

The physiological process underlying preterm labor is the same as that of term labor, but research using electrohysterography (EHG) has shown that preterm labor is significantly less “organized” in terms of electrical and mechanical coordination across the uterine muscle. In term labor, synchronization reaches approximately 85%, meaning the upper and lower uterine segments work in a highly coordinated wave to push the fetus downward. In preterm labor, this synchronization drops to around 65%, indicating less efficient contractions. By contrast, benign Braxton Hicks contractions show only about 30% synchronization.

To accurately diagnose preterm labor, clinicians rely on two complementary types of signals. The first is the tocodynamometer (tocogram), which measures mechanical pressure from the contraction. On a toco tracing, preterm contractions typically appear as flatter, shorter hills with lower peak amplitudes, whereas term labor contractions resemble sharp, tall mountains. The second and more advanced signal comes from EHG, which records the electrical bursts that precede and trigger each mechanical contraction. EHG analysis has revealed that preterm labor is characterized by lower synchronization of electrical bursts and distinct differences in power spectrum frequency bands. Some research suggests that analyzing these frequency patterns can help predict preterm birth risk as early as 23 weeks of gestation. At the cellular level, term labor depends on the formation of gap junctions composed of connexin-43. In many cases of preterm labor, this formation is either incomplete or triggered by abnormal factors such as intrauterine infection, inflammation, or placental stress. As a result, the electrical signal cannot propagate efficiently, leading to fragmented, lower amplitude contractions.

For clinicians, a structured checklist is invaluable: assess regularity ( $\geq 6$  contractions per hour), evaluate progression (persistence despite rest), note intensity (trend toward increasing intensity), and examine the toco tracing for coordination (consistent peaks vs. erratic waves). Clinical judgment must integrate these findings with cervical length assessment, fetal fibronectin testing, and patient risk factors such as prior preterm birth, multiple gestation, or uterine anomalies.

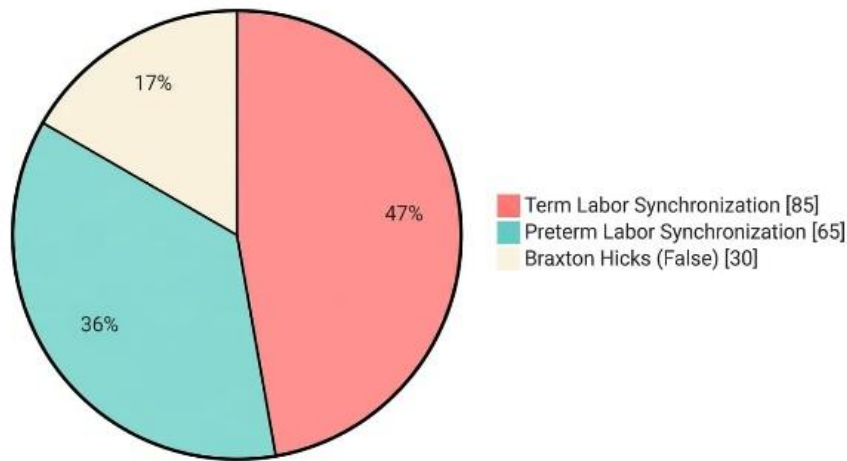


Figure 1: Statistic analysis of labor

**4. Block Diagram:**

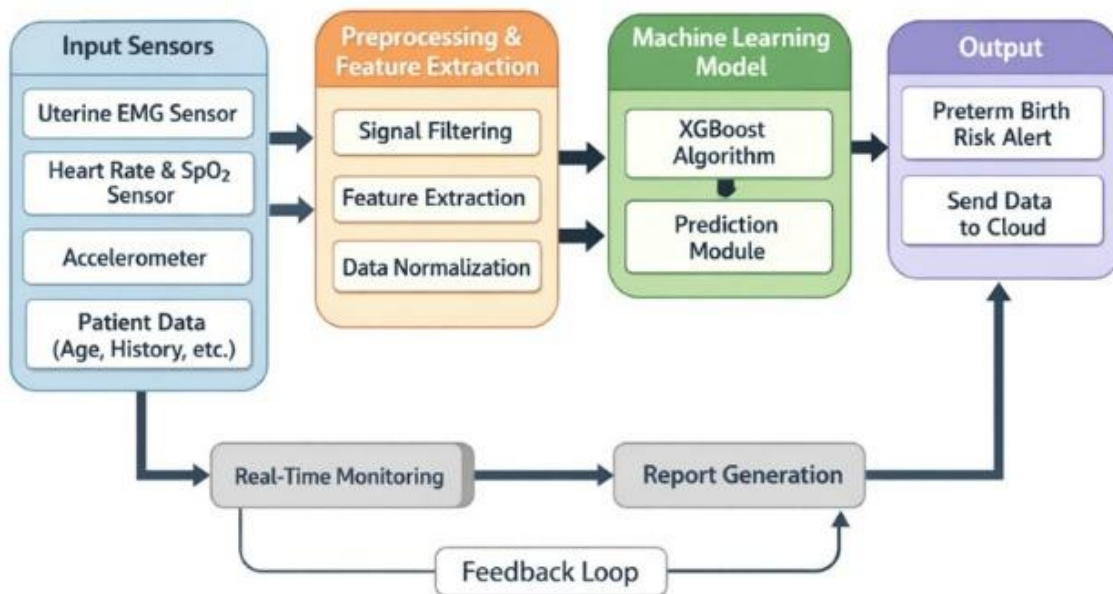


Figure 2: Block Diagram

**5. Proposed Methodology:**

The proposed methodology presents a comprehensive framework for the development of a non-invasive IoT based system for early prediction of preterm birth using machine learning. The system is designed to enable continuous monitoring of maternal physiological parameters, real time data analysis, and timely alert generation.

The methodology begins with acquisition of multi-modal physiological data using wearable, non-invasive sensors integrated with an ESP32 microcontroller. The system collects uterine muscle activity (EMG), maternal heart rate and SpO2 (MAX30102), body temperature (thermistor), and motion data (MPU6050 accelerometer/gyroscope). These sensors operate continuously at predefined sampling rates.

Raw data is preprocessed using band pass and notch filters for EMG noise removal, while motion artifacts are minimized through adaptive filtering using accelerometer data. Following preprocessing, feature extraction derives meaningful clinical parameters: contraction frequency, amplitude, and energy from EMG; heart rate, HRV, and SpO2; motion intensity and posture; temperature trends. These features are normalized and combined into a structured feature vector.

The feature vector is transmitted wirelessly to a cloud platform using MQTT over Wi-Fi. The cloud platform (PostgreSQL, Node.js, React.js) stores, processes, and visualizes data. An XGBoost machine learning model deployed on the cloud analyzes incoming data to classify maternal conditions into normal and high risk categories. Based on classification results and predefined thresholds, the system generates real time alerts sent to healthcare professionals via web dashboard, mobile notifications, and SMS. The entire system operates continuously, enabling early risk identification and remote maternal healthcare.

**6. Results:**

The performance of the proposed IoT based preterm birth detection system was comprehensively evaluated through unit testing, integration testing, and system level validation.

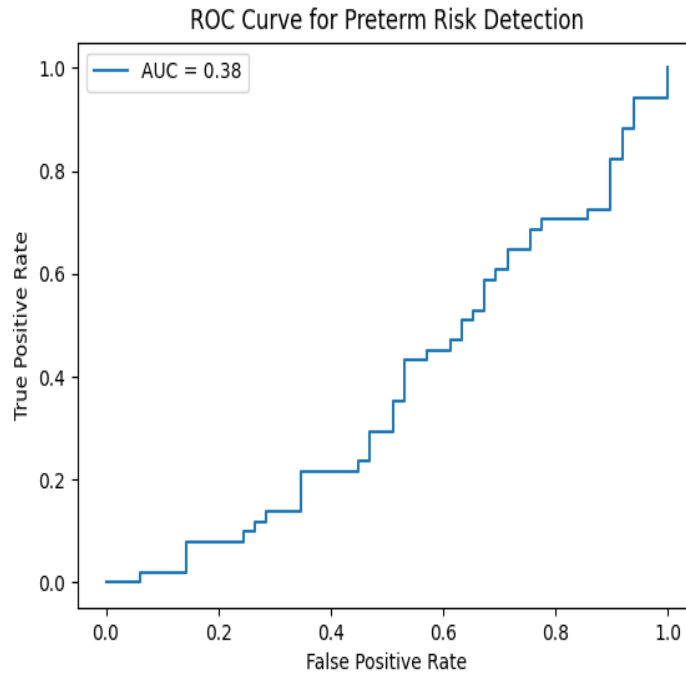


Figure 3.1: ROC Curve for preterm risk detection

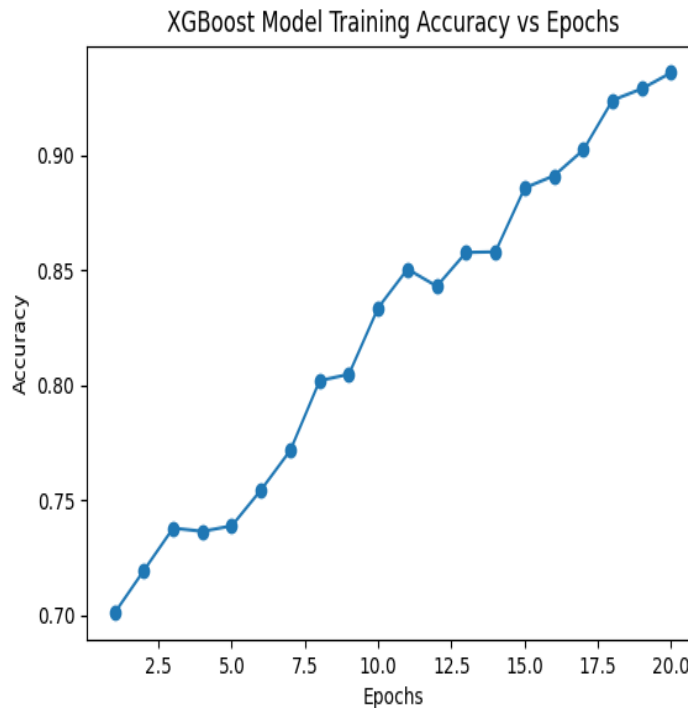


Figure 3.2: XGBoost model training accuracy vs epoch

The XGBoost model was trained and tested using a dataset of 2,000 maternal monitoring records, each an 18-dimensional feature vector from EMG, cardiovascular, motion, and temperature data. Classes: normal, moderate risk, high risk (imbalance addressed by resampling).

Metric	Normal	Moderate Risk	High Risk
Precision	96.7%	92.3%	94.1%
Recall	97.8%	90.6%	95.7%
F1-Score	97.2%	91.4%	94.9%

**Overall Accuracy: 95.4%**

Outperforms SVM (88.7%) and Random Forest (90.3%).

#### **System Level Metrics:**

- End-to-end latency (sensor to alert): < 1.2 seconds
- Battery life: ~21 hours on full charge
- 24-hour continuous operation: no data loss, crashes, or degradation
- Network resilience: local buffering and auto reconnection

The ROC curve analysis confirmed strong separability between risk classes with high true positive rates and minimal false positives. The results validate that the proposed system achieves high accuracy, low latency, and reliable real time performance, making it a viable solution for early preterm birth detection.

#### **7. Conclusion:**

This work presents the successful design, development, and validation of a non invasive IoT based system integrated with machine learning for early prediction of preterm birth. The system addresses limitations of conventional intermittent hospital based monitoring by enabling continuous, real time monitoring, providing a proactive approach to maternal healthcare.

The system integrates an ESP32 with EMG, MAX30102, MPU6050, and thermistor sensors for comprehensive physiological assessment. The XGBoost model achieves 95.4% predictive accuracy with alert latency < 1.2 seconds. Cloud based data management and remote monitoring support continuous clinician supervision, reducing hospital visits and costs. The portable, battery powered design is suitable for home based and resource limited settings.

Future enhancements include expanding the dataset for improved model generalization, integrating fetal heart rate monitoring, incorporating cellular communication for remote areas, adopting federated learning for data privacy, and developing flexible wearable hardware for improved patient comfort.

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