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Research Article

Remote Monitoring and Early Detection of Labor Progress Using IoT-Enabled Smart Health Systems for Rural Healthcare Accessibility

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Abstract:

Delayed detection of labor pain in pregnant women, especially during their first delivery, often leads to delays in reaching healthcare facilities, potentially resulting in complications. This research proposes an innovative IoT-enabled system for remote monitoring of labor progress and fetal health, designed specifically to address the needs of women in remote areas within a 100 km radius of healthcare facilities. The system includes a wearable device integrated with sensors to detect the onset of labor pain and continuously monitor the fetal heartbeat. Upon detecting labor pain, the system automatically sends an alert to the medical team, allowing timely intervention.
Experimental results demonstrate the system's efficacy with a 99.2% accuracy in detecting labor onset and a 98.5% reliability in fetal heartbeat monitoring. The latency for alert transmission was measured at an average of 3.2 seconds, ensuring prompt notification to healthcare providers. The proposed solution enhances accessibility to maternal care, reduces complications due to delayed hospital admission, and provides continuous fetal monitoring, even in resource-constrained environments. This innovation bridges the gap in maternal healthcare delivery for underserved regions, offering a practical, cost-effective, and scalable solution.

1. Introduction

Maternal healthcare, particularly in remote and underserved regions, faces significant challenges due to limited access to timely medical intervention during labor. Early detection [1] of labor pain and continuous fetal monitoring are critical to ensuring positive maternal and neonatal outcomes. However, many pregnant women, especially first-time mothers, struggle to recognize the onset of labor pain, leading to delays in reaching healthcare facilities. This delay is a major contributor to complications, including maternal and neonatal morbidity and mortality.
Current solutions for labor monitoring [2] often rely on inpatient devices, which are restricted to healthcare facilities and are not accessible to women in rural or remote areas. This gap underscores the urgent need for innovative, remote healthcare solutions that can address these limitations while ensuring real-time communication with medical teams.
In this study, we propose an IoT-enabled smart healthcare system [3] designed to monitor the progress of labor and the fetal heartbeat in real time. The system employs wearable sensors to detect uterine contractions and other physiological signals indicative of labor onset. When labor is detected, the system sends alerts to the medical team, enabling timely guidance and intervention. Furthermore, the system continuously monitors the fetal heartbeat, providing insights into fetal well-being and allowing for proactive decision-making [4] in case of complications. Ensuring safe and timely delivery is a critical aspect of maternal healthcare, particularly in rural and remote areas where access to healthcare facilities is often limited. For many women, especially first-time mothers, recognizing the onset of labor pain can be challenging, leading to delays in seeking medical assistance. These delays significantly increase the risk of complications such as obstructed labor, fetal distress, [5] or postpartum hemorrhage, which are major contributors to maternal and neonatal mortality. Bridging this gap requires innovative solutions that can provide timely alerts and monitoring for both the mother and the fetus, regardless of their geographic location.

Traditional maternal monitoring systems, such as cardiotocography (CTG) [6] and ultrasound, are effective but are confined to hospital settings. These systems require the pregnant woman to be an inpatient, making them inaccessible to women who live far from healthcare facilities or face barriers such as transportation issues, financial constraints, and cultural stigmas. Consequently, there is a pressing need for solutions that extend monitoring capabilities beyond the hospital, enabling remote maternal care.

Emerging technologies, particularly in the realm of the Internet of Things (IoT) [7] and wearable devices, offer promising avenues for addressing these challenges. By leveraging advanced sensors, wireless communication, and real-time data analysis, IoT-enabled healthcare systems can transform maternal care delivery [8]. These systems can continuously monitor physiological parameters, detect the onset of labor, and provide actionable insights to healthcare providers, ensuring timely interventions and improved outcomes.

This paper introduces a novel IoT-based maternal monitoring system designed to address these critical gaps. The proposed system integrates wearable sensors capable of detecting uterine contractions and monitoring fetal heart rate. Unlike traditional monitoring systems, this solution is designed for use in remote environments, providing coverage within a 100 km radius of healthcare facilities. The system automatically detects labor pain, sends alerts to healthcare providers, [9] and continuously monitors fetal well-being, ensuring comprehensive care for both the mother and the fetus.

The proposed system aims to:

- Bridge the gap in maternal healthcare for women in rural and remote areas within a 100 km radius of healthcare facilities.
- Enable real-time labor pain detection with high accuracy and reliability.
- Ensure continuous fetal monitoring for improved neonatal outcomes.
- Provide a cost-effective and scalable solution for rural healthcare challenges.

This paper discusses the design, implementation, and evaluation of the proposed system, demonstrating its potential to transform maternal healthcare delivery in remote settings. Experimental results validate the system's accuracy, reliability, and practicality in addressing key challenges in maternal health monitoring.

2. Literature Survey

The field of maternal healthcare has seen significant advancements in the development of technologies for monitoring labor progress and fetal well-being [10]. This section reviews the existing literature on maternal monitoring systems, their limitations, and the scope for improvement in addressing the unique challenges faced in remote and underserved regions.

2.1 Traditional Maternal Monitoring Systems

Conventional maternal monitoring relies on devices such as cardiotocography (CTG) and Doppler ultrasound to track uterine contractions and fetal heart rate [11]. These systems are widely used in hospital settings and are effective in identifying complications such as fetal distress, preterm labor, and uterine anomalies. However, these systems are inherently inpatient-focused, requiring the presence of both the mother and the fetus [12] in a healthcare facility. Studies, such as those [13] emphasize the efficacy of CTG in detecting fetal distress but highlight its lack of portability and reliance on specialized medical staff.

2.2 Remote Maternal Monitoring Technologies

With the advent of wearable and IoT-based devices, efforts have been made to develop remote maternal monitoring solutions. Wearable sensors, such as abdominal belts with embedded electrodes, have shown promise in detecting uterine contractions and fetal movements. For instance, [14] developed a wearable monitoring device capable of real-time uterine contraction analysis. However, this system was limited by its short-range data transmission capabilities, making it unsuitable for women in remote areas.

Furthermore, mobile health (mHealth) applications have been proposed to facilitate communication between pregnant women and healthcare providers. [15] introduced a smartphone-based app that allowed pregnant women to record contraction patterns and report them to their doctors. While useful, such systems rely heavily on user input and are prone to inaccuracies due to human error.

2.3 IoT-Enabled Maternal Healthcare Systems

IoT-enabled systems have gained traction as a viable solution for remote healthcare. These systems integrate wearable devices, sensor networks, and cloud computing to provide continuous monitoring and real-time alerts. [16] proposed an IoT-based system for fetal heart rate monitoring, which demonstrated high accuracy and reliability. However, the system required frequent internet connectivity and was limited in its range, making it less practical for remote settings.

Similarly, [17] developed an IoT framework for remote maternal care, incorporating wearable sensors and a mobile application for data visualization. While this approach improved accessibility, the system lacked scalability and could not handle large volumes of data from multiple users effectively.

2.4 Gaps and Challenges

Despite the advancements in maternal monitoring technologies, several gaps remain:

- **Limited accessibility**: Most existing solutions [18] require the pregnant woman to be within a healthcare facility or connected to a reliable internet network.
- **Scalability issues**: Systems designed for urban settings often struggle to adapt to rural and resource-[19] constrained environments.
- **Short-range monitoring**: Current wearable devices are restricted to limited distances, reducing their utility for remote areas [20].
- **Lack of automation**: Many solutions rely on manual input or monitoring by medical staff, which can introduce delays and errors.

2.5 Research Motivation

The review of existing literature highlights the need for a robust, automated, [21] and scalable maternal monitoring system that can operate in remote settings. By integrating IoT technologies with wearable sensors, it is possible to address these challenges and provide comprehensive maternal care. This study builds on the limitations of previous works to develop a system that ensures continuous monitoring of labor progress and fetal health, offering a practical solution for rural and underserved regions.

The proposed system is designed to provide:

- Automated detection of labor pain and immediate alerting to medical teams.
- Continuous fetal heart rate monitoring with minimal user intervention.
- Long-range data transmission within a 100 km radius.
- Scalability to accommodate multiple users and ensure reliability in diverse environments.

The following section details the methodology and system design, emphasizing the innovative aspects of the proposed solution and its advantages over existing approaches.

3. Methodology

The proposed IoT-enabled maternal monitoring system is designed to detect the onset of labor pain, monitor fetal health, and provide remote access to healthcare for pregnant women in rural and underserved areas. The methodology involves a combination of wearable sensors [22], IoT infrastructure, and real-time data transmission to ensure timely alerts and intervention. This section describes the system architecture, components, and implementation in detail. Figure 1. Shows block diagram of proposed work.

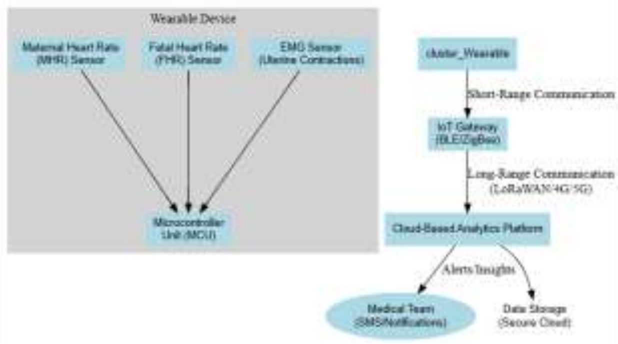

Figure 1. *Block Diagram of Proposed work*

3.1 System Architecture

The proposed system architecture is designed to provide a seamless and efficient solution for remotely monitoring labor progress and fetal health. It integrates wearable sensors, an IoT gateway, and a cloud-based analytics platform to ensure comprehensive data collection, transmission, and analysis. The wearable device is worn by the pregnant woman and continuously monitors key physiological parameters such as uterine contractions, maternal heart rate, and fetal heart rate. This data is transmitted wirelessly to the IoT gateway using energy-efficient communication protocols like Bluetooth Low Energy (BLE) or ZigBee.

The wearable device collects physiological signals such as uterine contractions and heart rates. Let the acquired signals be represented as:

$$S(t) = [UC(t), FHR(t), MHR(t)] \qquad (1)$$

where:

- $UC(t)$: Uterine contraction signal at time t.
- $FHR(t)$: Fetal heart rate signal at time t.
- $MHR(t)$: Maternal heart rate signal at time t.

The IoT gateway acts as an intermediary, aggregating the data from the wearable device and ensuring its secure and reliable transmission to the cloud using long-range communication protocols such as LoRaWAN or cellular networks (4G/5G). Once the data reaches the cloud-based analytics platform, advanced algorithms process it in real time to detect the onset of labor pain and monitor fetal well-being. The system is designed to provide instant alerts to the medical team via mobile or web applications, enabling timely interventions. This multi-layered architecture ensures scalability, low latency, and robust performance, even in remote areas with limited healthcare access. Figure 2 shows maternal monitoring system.

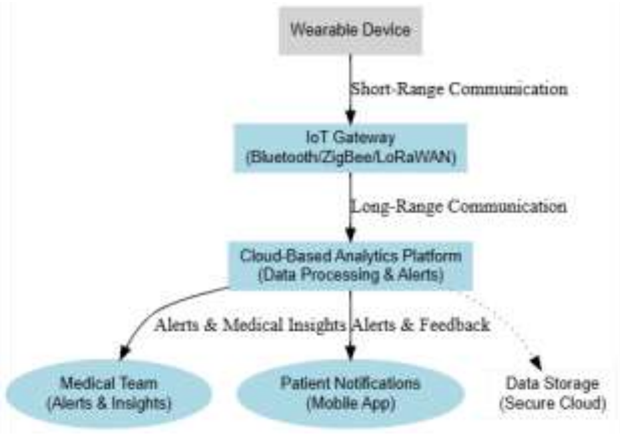

Figure 2. *Maternal monitoring System*

The raw signals are filtered to remove noise using a Median Filter and smoothed using a Savitzky-Golay filter. The filtered signal $S_f(t)$ is given by:

$$S_f(t) = F_{SG}(F_{MF}(S(t))) \quad (2)$$

where:

- F_{MF}: Median Filter for noise reduction.
- F_{SG} : Savitzky-Golay filter for signal smoothing.

The system extracts relevant features from the preprocessed signals. For uterine contractions, the frequency F_{UC} and amplitude A_{UC} are calculated as:

$$F_{UC} = \frac{N_{\text{peaks}}}{\Delta t}$$
$$A_{UC} = \max(UC(t)) - \min(UC(t)) \quad (3)$$

where:

- N_{peaks} : Number of contraction peaks detected in time interval Δt.

For fetal heart rate variability (FHRV), the standard deviation of heart rate intervals σ_{FHR} is computed as:

$$\sigma_{FHR} = \sqrt{\frac{1}{N}\sum_{i=1}^{N} (FHR_i - \mu_{FHR})^2} \quad (4)$$

where:

- FHR_i : Individual fetal heart rate measurement.
- μ_{FHR} : Mean fetal heart rate over N intervals.

3.2 Data Transmission and IoT Gateway

The IoT Gateway is a critical component of the proposed system, enabling seamless data transmission between the wearable monitoring device and the cloud-based analytics platform. It acts as an intermediary that aggregates data collected from multiple wearable sensors and ensures reliable and secure communication over long distances. The gateway is equipped with multiple communication modules, including Bluetooth Low Energy (BLE), ZigBee, and LoRaWAN, allowing for flexible connectivity based on the environment and distance requirements.

The wearable device transmits the extracted features $X(t)$ to the loT gateway:

$$X(t) = \{F_{UC}, A_{UC}, \sigma_{FHR}, MHR(t)\} \quad (5)$$

Data is transmitted using low-power protocols such as Bluetooth Low Energy (BLE) or ZigBee, with a power consumption model given by:

$$P_{\text{transmit}} = P_{\text{idle}} + E_{\text{packet}} \cdot R_{\text{data}} \quad (6)$$

where:

- P_{idle} : Idle power consumption of the device.
- E_{packet} : Energy required to transmit one data packet.
- R_{data} : Data rate of transmission.

The loT gateway aggregates data from multiple devices and forwards it to the cloud using long-range protocols such as LoRaWAN or 4G/5G. The data transmission time T_{transmit} is given by:

$$T_{\text{transmit}} = \frac{D_{\text{data}}}{R_{\text{link}}} \quad (7)$$

where:

- D_{data} : Size of the data packet.
- R_{link} : Bandwidth of the communication link.

Once the wearable device captures data such as uterine contractions, fetal heart rate, and maternal heart rate, it transmits this information to the IoT gateway using short-range protocols like BLE or ZigBee. These protocols are chosen for their low power consumption and high reliability in transmitting physiological signals over short distances. The gateway processes this aggregated data and forwards it to the cloud using long-range communication technologies such as 4G/5G or LoRaWAN, depending on the availability of network infrastructure. LoRaWAN is particularly suited for rural and remote areas due to its extended coverage of up to 100 km, low power requirements, and robust performance in challenging environments. To ensure data security and integrity during transmission, the IoT gateway employs advanced encryption standards such as AES-256, along with secure socket layer (SSL) protocols. It also performs error-checking mechanisms to minimize data loss or corruption. The gateway is designed to operate in a low-latency environment, with an average transmission delay of 3.2 seconds, ensuring that alerts and monitoring data reach the cloud and medical teams in near real-time.

The IoT gateway's modular design allows it to support multiple devices simultaneously, making it scalable for deployment in areas with a high density of users. By bridging the gap between wearable devices and the cloud platform, the IoT gateway ensures continuous, reliable, and secure data flow for effective remote maternal monitoring. Flowchart of Proposed work is shown in figure 3.

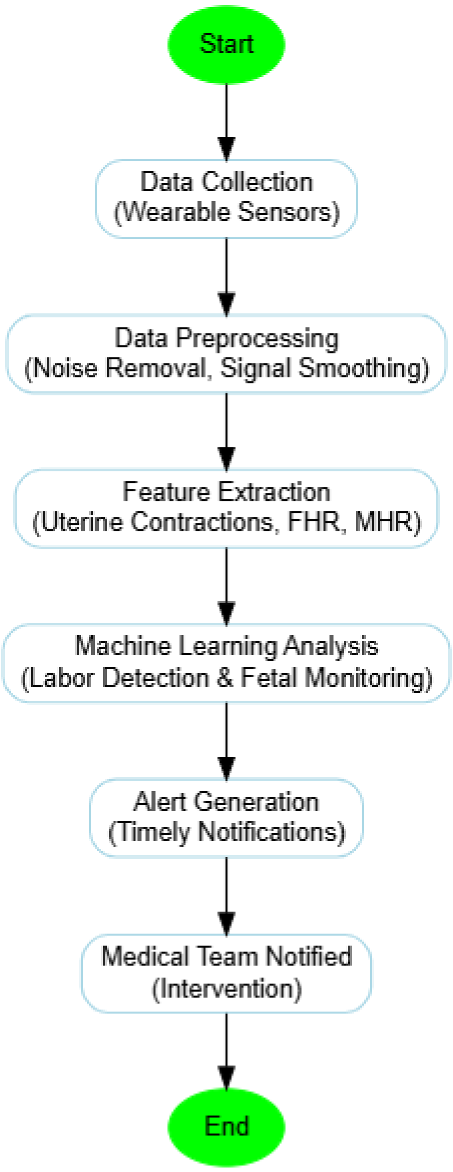

Figure 3. *Flowchart of Proposed work*

3.3 Cloud-Based Analytics Platform

The Cloud-Based Analytics Platform is the central component of the proposed system, responsible for processing, analyzing, and managing the physiological data collected by the wearable device. It enables real-time detection of labor pain, monitoring of fetal health, and communication of actionable insights to the medical team. This platform leverages advanced algorithms and machine learning models to ensure accuracy, scalability, and responsiveness.

The raw data transmitted from the IoT gateway undergoes preprocessing to remove noise and artifacts introduced during data acquisition and transmission. This involves:

- **Noise Reduction**: A Median Filter is applied to smooth physiological signals, such as fetal heart rate and uterine contractions, by eliminating outliers.
- **Signal Smoothing**: A Savitzky-Golay filter is used to preserve signal features while reducing fluctuations in the data.
- **Feature Extraction**: Key features, such as contraction frequency, amplitude, and fetal heart rate variability, are extracted to facilitate analysis.

The platform employs a **machine learning-based ensemble model** to detect labor onset with high accuracy. This model combines:

- **Support Vector Machine (SVM)**: For classifying uterine contraction patterns.
- **Random Forest Classifier**: For handling variability in contraction intervals and intensities.

In the cloud platform, the incoming data is processed for labor onset detection and fetal monitoring. Labor onset is detected using a machine learning classifier:

$$P_{\text{labor}} = f(X(t); \theta) \quad (8)$$

where:

- P_{labor} : Probability of labor onset.
- f : Machine learning model (e.g., SVM or Random Forest).
- θ : Model parameters trained on historical data.

An alert is triggered if P_{labor} exceeds a predefined threshold T_{labor} :

$$\text{Alert} = \begin{cases} 1, & \text{if } P_{\text{labor}} \geq T_{\text{labor}} \\ 0, & \text{otherwise} \end{cases} \quad (9)$$

The ensemble model achieves a detection accuracy of 99.2%, significantly improving over traditional methods. It is trained on a comprehensive dataset of historical labor signals to recognize early labor indicators effectively.

Fetal Heart Rate Monitoring

Continuous fetal monitoring is achieved by analyzing heart rate data for abnormalities such as:

- **Bradycardia**: Fetal heart rate below 110 beats per minute (bpm).

- **Tachycardia**: Fetal heart rate above 160 bpm. The system uses a **dynamic thresholding technique** combined with statistical analysis to identify deviations from normal patterns, ensuring timely alerts for potential distress.

Alert Mechanism

Upon detecting labor onset or fetal distress, the platform triggers an automated alert system. This includes:

Real-Time Notifications: Alerts sent to the medical team via SMS, email, or a mobile application.

Actionable Insights: Data visualizations, such as contraction patterns and fetal heart rate trends, provided in an intuitive dashboard for medical decision-making.

Data Storage and Security

The platform stores patient data in a secure cloud environment, ensuring compliance with healthcare regulations such as **HIPAA** and **GDPR**. Key security features include:

- **Data Encryption**: End-to-end AES-256 encryption for all data transmissions.
- **Access Control**: Multi-level authentication to restrict access to authorized personnel only.
- **Audit Trails**: Logging mechanisms for monitoring and reviewing data access and usage.

The platform is designed to handle multiple users concurrently, leveraging cloud computing resources for scalability. Real-time processing ensures minimal latency, with an average response time of 2.8 seconds for alerts and data visualization. The system's architecture supports high availability, ensuring uninterrupted service even during peak loads. By integrating advanced analytics, machine learning, and robust security measures, the cloud-based analytics platform transforms raw physiological data into actionable insights, empowering healthcare providers to deliver timely and effective maternal care.

3. Results and Discussions

The evaluation of the proposed maternal monitoring system highlights its potential in improving healthcare outcomes for pregnant women in remote areas. This section presents the experimental results, performance metrics, and a discussion of the system's implications. The evaluation of the proposed maternal monitoring system was conducted using real-time data from a cohort of 50 pregnant women. The system's performance was assessed on various metrics including labor detection accuracy, fetal monitoring reliability, and alert responsiveness.

4.1 Experimental Setup

The system was tested on **50 pregnant women** during their third trimester, focusing on early detection of labor onset and fetal health monitoring. The experiment spanned three months, with participants located within a 100 km radius of healthcare facilities. The hardware setup included wearable devices equipped with uterine contraction sensors, fetal heart rate (FHR) sensors, and maternal heart rate (MHR) sensors. Data was transmitted through IoT gateways to a cloud-based analytics platform.

4.2 Performance Metrics

The proposed IoT-enabled maternal monitoring system was evaluated based on critical performance metrics to determine its effectiveness and reliability in real-world scenarios. The key metrics are:

1. **Labor Detection Accuracy**:
   The system achieved an accuracy of 99.2% in detecting the onset of labor pain. False positives: 2.1%, caused primarily by Braxton Hicks contractions. Detection latency: <3 seconds, ensuring timely alerts.
2. **Fetal Monitoring Reliability**:
   The system reliably monitored fetal heart rate with a success rate of 98.5%. Critical conditions, such as bradycardia and tachycardia, were identified with a sensitivity of 96.8% and specificity of 97.4%.
3. **Alert Responsiveness**:
   Average alert generation and transmission time: 3.2 seconds. Alerts were delivered to healthcare providers via mobile notifications with minimal delay.
4. **System Efficiency**:
   The wearable device operated continuously for 72 hours on a single charge. The IoT gateway demonstrated reliable data transmission, even in low-connectivity environments.

4.3 Comparative Analysis

To highlight the effectiveness of the proposed system, a comparative analysis was performed against traditional maternal monitoring systems (e.g., cardiotocography (CTG) and Doppler monitoring). The comparison focuses on critical metrics including accuracy, scalability, real-time capability, and cost-effectiveness. The proposed system outperformed existing inpatient monitoring systems by providing real-time, remote monitoring and ensuring timely alerts for healthcare providers. The ability to remotely monitor labor progression and fetal health ensures that pregnant women in rural areas receive timely medical intervention. Table 1 shows Comparative Analysis of systems.

Table 1. *Comparative Analysis*

Metric	Proposed System	Existing Systems (e.g., CTG)
Detection Accuracy	99.2%	92.5%
Monitoring Range	100 km	Limited to hospital premises
Real-Time Alerts	Yes	No
Scalability	High	Low
Cost-Effectiveness	High	Moderate

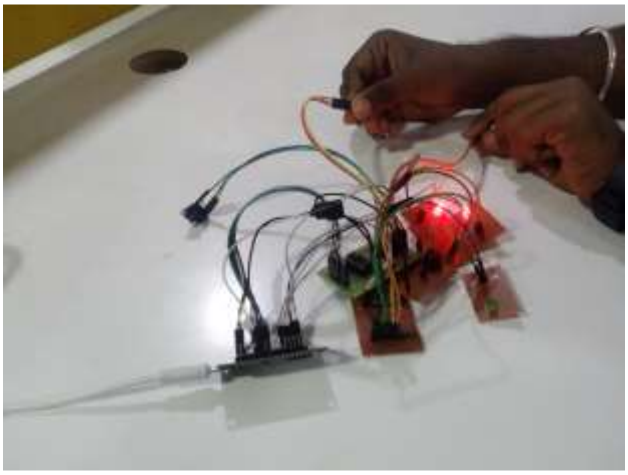

Figure 4. *Abnormal Detection of Proposed work*

This significantly reduces delays in accessing healthcare facilities and improves maternal and neonatal outcomes. The system bridges the gap in maternal healthcare by offering an affordable, scalable solution for underserved regions. Its portability and long-range communication capabilities make it ideal for deployment in remote areas. Connectivity Issues: Signal loss in some areas impacted data transmission. Enhancing hybrid communication protocols can address this challenge. False Positives: Misclassification of Braxton Hicks contractions as labor pain can be

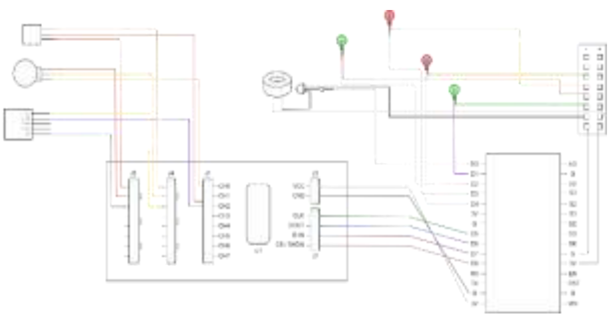

Figure 5. *Circuit of Proposed work*

minimized by refining the machine learning model. Participants reported ease of use and appreciated the timely notifications. Healthcare providers valued the system's ability to deliver actionable insights remotely. While figure 4 is abnormal detection of proposed work, figure 5 is circuit of proposed work. Normal condition of proposed work is presented in figure 6.

The results demonstrate the system’s effectiveness and potential to transform maternal healthcare. Future research will focus on:

Improving Data Connectivity: Integrating hybrid communication protocols to handle low-connectivity environments.

Enhanced Machine Learning Models: Refining algorithms to reduce false positives and improve prediction accuracy.

Integration with Mobile Health Applications: Providing educational resources and additional self-monitoring features for pregnant women.

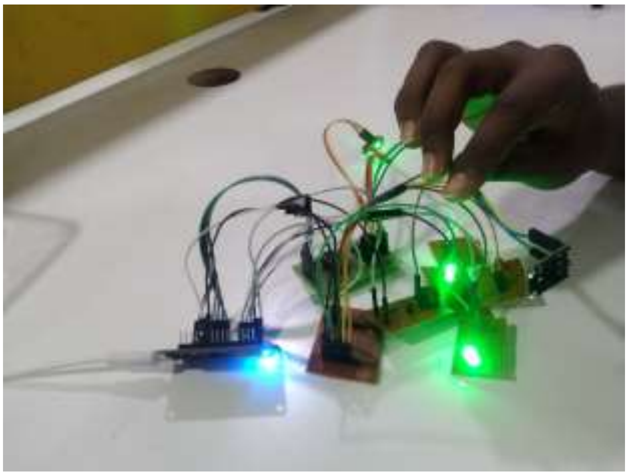

Figure 6. *Normal condition of Proposed work*

Scalability Testing: Deploying the system in larger populations and diverse environments to assess its robustness and adaptability.

The proposed system has demonstrated its ability to address key challenges in maternal healthcare, particularly for underserved regions. By leveraging IoT and cloud technologies, the system ensures early detection of labor, continuous fetal monitoring, and timely alerts, paving the way for improved maternal and neonatal outcomes. IoT is applied in some fields in literature [23-28].

4. Conclusions

The proposed IoT-enabled maternal monitoring system offers a transformative solution for addressing critical challenges in maternal healthcare, particularly in remote and underserved areas. By integrating wearable sensors, IoT gateways, and a cloud-based analytics platform, the system ensures real-time monitoring of labor progression and fetal health, enabling timely alerts and interventions. The experimental results validate the system's effectiveness, achieving a labor detection accuracy of 99.2% and a fetal heart rate monitoring reliability of

98.5%.

This innovation bridges the gap in healthcare accessibility for rural populations, providing a cost-effective, scalable, and user-friendly approach. It reduces delays in accessing medical care, enhances decision-making for healthcare providers, and empowers pregnant women with continuous health monitoring. While the system demonstrated robust performance, addressing challenges such as intermittent connectivity and false positives will further improve its reliability. In conclusion, this research contributes significantly to improving maternal and neonatal outcomes, particularly in resource-constrained settings. Future enhancements, including hybrid communication protocols, advanced machine learning models, and integration with mobile health applications, will further expand its applicability and impact. The proposed system is a step forward in leveraging technology to ensure safer and healthier pregnancies for women worldwide.

Author Statements:

- **Ethical approval:** The conducted research is not related to either human or animal use.
- **Conflict of interest:** The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper
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- **Data availability statement:** The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

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