Smart Labor Pain Management: An IoT-Based Approach for Expecting Mothers

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Abstract. Labor pain is a serious physiological event that needs continuous surveillance and prompt medical intervention to guarantee the safety and health of both the mother and child. Conventional labor monitoring systems tend to be based on manual observations and delayed responses, which can lead to less-than-optimal care, particularly in rural or low-resource environments. This study presents a smart labor pain management system based on Internet of Things (IoT) technology for real-time, continuous monitoring and individualized pain management assistance. The system combines wearable sensors to monitor vital parameters like heart rate, temperature, oxygen saturation, and uterine contraction pressure. Processing is done through an ESP32 microcontroller and wireless data transmission through MQTT to a Firebase cloud backend. A mobile app is the user interface, providing live visualization of data, emergency notification, remote consultation, and interactive pain relief aids. An analytics engine that is intelligent calculates a Pain Severity Index (PSI) and gives personalized suggestions based on real-time data and user feedback. Experimental outcomes of the simulated and actual tests showed 90% reduced response time, enhanced detection rates, and maximum user satisfaction versus conventional approaches. The system outlined here is shown to be efficient, scalable, and patient-focussed solution that enhances labour pain management as well as evidence-based medical decision-making.

Keywords: IoT, labour pain, real-time observation, wearable sensor, maternal healthcare, pain management, PSI

1 Introduction

Labor is a high-risk and multifaceted stage in maternal care that requires close, real-time surveillance and prompt clinical intervention to guarantee the safety of both mother and infant. Traditional methods of labor monitoring are based mainly on intermittent manual checks, which tend to cause delays in detection and intervention – especially in rural or resource-poor environments where medical staff may be scarce. The development of Internet of Things (IoT) technologies offers an intriguing challenge to update and improve the quality of labor pain management by means of continuous, automatic, and tailored monitoring systems.

This paper suggests a smart system for labor pain management that takes advantage of IoT-enabled wearable sensors, edge computing based on ESP32 microcontrollers, cloud-based data processing, and user-oriented mobile app interface. The combined system records important physiological parameters like heart rare, body temperature, uterine contraction pressure, and

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oxygen saturation and processes them in real-time to produce actionable information. One of the innovations in this system is the Pain Severity Index (PSI), an analytically calculated measure employed to evaluate levels of discomfort and provide personalized pain relief interventions.

Through the integration of high-tech sensor devices with real-time analytics, cloud infrastructure, and responsive user interfaces, the system seeks to revolutionize the delivery of maternal care such as shortening response times, enhancing diagnostic performance, and enhancing patient and caregiver satisfaction. This background paves the way for an extensive study of the system's architecture, functionality and performance under simulated and actual circumstances.

2 Literature Review

Recent research has highlighted that the Internet of Things (IoT) is revolutionizing maternal health by providing real-time monitoring and early intervention. Bansal et al. [1] introduced an IoT-based prenatal healthcare monitoring system, in which the sensor data is uploaded to cloud through GSM for real-time analysis, resulting in better prenatal health. Another example is the approach by Panchal and Vaghela [2], who proposed an IoT base long-term monitoring system monitoring maternal stress and activity, and reported on successful clinical trials in regional sampling in India.

These advantages are further confirmed by deployments beyond the experimental prototypes. For example, AI-facilitated fetal monitoring in Malawi achieved an 82% reduction in stillbirths and neonatal deaths over 3 years [3]. Also, the wearable, non-invasive Nuvo Invu product, an innovative wireless, wearable system with 12 sensors that provides continuous maternal and fetal vital monitoring allowing clinicians to manage high-risk pregnancies more effectively [4].

Recent clinical reports provide additional support for these findings. Hamm et al. [5] also reviewed wireless hardware tools for NST in high-risk pregnancies and showed that home clinical monitoring is feasible. Similarly, Mhajna et al. [6] proposed a system for wireless monitoring of maternal and fetal heart rate dedicated to remote usage. Expanding on this, Schwartz et al. [7] developed a new uterine contraction monitoring system for self-conducted nonstress testing, promoting patient autonomy. Mhajna et al. [8] extended this work later, introducing a cardiac-driven model installed in a wearable system to measure uterine activity, resulting in more accurate and personalized maternal monitoring.

Wider systematic reviews have also been conducted. Stricker et al. [9] conducted a scoping review of remote home monitoring solutions for the mother and fetus, detailing the opportunities and barriers for clinical adoption. Liu et al. [10] reviewed wearable sensors and data processing pipelines as well as AI techniques in pregnancy monitoring and highlighting the potential of intelligent systems to improve maternal safety. Complementarily, Zielinska et al. [11] studied multi-modality maternal physiology remote monitoring, from which the possibility of combining different sensor modalities for comprehensive pregnancy care was demonstrated.

In summary, these studies demonstrate that IoT, wearables, and AI-based analytics have exciting potential for mitigating maternal risks, early detection of complications, and personalized care.

3 System Architecture

The proposed system consists of four major components:

- **Wearable Sensors:** Heart rate (MAX30102), temperature (LM35), contraction pressure (MPX5010DP) and pulse oximetry.
- **Microcontroller:** The ESP32 is used for edge data acquisition and Wi-Fi/Bluetooth transmission.
- **Cloud Backend:** Firebase database for real-time database, authentication and cloud functions.
- **User Interface:** Android-based mobile app for visualization, alerts and consultation.

4 Methodology

4.1 Sensor Integration

The wearable device constantly captures physiological information using a series of non-invasive sensors:

- **MAX30102:** Monitors heart rate (HR) and oxygen saturation (SpO2) with photoplethysmography (PPG).
- **LM35:** Monitors body temperature (Temp) close to the abdomen with high precision.
- **MPX5010DP:** Monitors intra-abdominal pressure (Puc) to identify uterine contractions.
- **MPU6050 (Optional):** Monitors posture to help recommend ideal labor positions.

Let the measured parameters be represented by the following:

- HeR(t) : Heart rate in beats per minute
- Tempe(t): Temperature of the body in degrees Celsius
- Pruc(t) : Uterine contract pressure in mmHg
- $SpO_2(t)$: Oxygen saturation in blood in percentage

These parameters are sensed using analog or digital signals and processed using the ESP32 microcontroller. The microcontroller carries out the following:

- **Signal Acquisition**: It reads the analog voltages or digital outputs of the sensors.
- **Noise Filtering**: It uses low-pass or median filtering to suppress motion artifacts.
- **Data Packaging**: Puts the signal readings into structured packets:

$$\mathbf{DP_i = \{HeR(t_i), Tempe(t_i), Pruc(t_i), SpO_2(t_i)\}}$$

4.2 Wireless Communication

The wireless communication module plays a key role in providing real-time and stable transmission of physiological information from the wearable device to the cloud and subsequently to the caregiver's interface.

The center of the wireless communication system is the ESP32 microcontroller, which has both Wi-Fi and Bluetooth Low Energy (BLE) features. Depending on the context of deployment (e.g., home or hospital), the system dynamically chooses the most suitable communication mode to ensure efficiency and save power.

4.3 Data Transmission Protocol

The Message Queuing Telemetry Transport (MQTT) protocol is utilized for publish-subscribe messaging over TCP/IP that has low overhead. MQTT is suitable for use in IoT due to its low overhead and low-bandwidth, high-latency network suitability.

4.4 Data Packet Construction

Each reading from the sensors is constructed into a structured data packet:

$$\mathbf{DP_i = \{timestamp, HeR(t_i), Tempe(t_i), Pruc(t_i), SpO_2(t_i), deviceID\}}$$

- **timestamp** - UNIX timestamp of data capture
- **$HeR(t_i)$ -** Reading of heart rate at time
- **$Tempe(t_i)$ -** Reading of temperature at time
- **$Pruc(t_i)$ -** Pressure of uterine contraction
- **$SpO_2(t_i)$ -** Level of oxygen saturation
- **deviceID -** Identifier unique to the wearable module

These packets are published at an interval of 1 second to a specific MQTT topic, e.g., labor_monitor/deviceID/data. A Firebase Cloud Function subscribes to this topic and processes received packets.

4.5 Network Architecture

- 1.On-Device MQTT Publisher: ESP32 publishes data to the broker.
- 2. MQT Broker (e.g., Mosquitto/Firebase Gateway): Accepts and forwards data to respective endpoints.
- 3. Cloud Listener: Parses and writes the received data in real-time to the Firebase Realtime Database.
- 4. Redundancy: Fallback to BLE transmission on Wi-Fi failure with buffered data upload on reconnect.

4.6 Performance and Latency

- Average latency of transmission: <500 ms
- packet loss: < 0.5% on stable Wi-Fi
- power consumption: optimized through ESP32's deep sleep and interrupt-driven transmission

This wireless real-time communication system provides real-time data availability for decision support, intervention planning, and anomaly detection, hence improving maternal safety during labor.

4.7 Mobile Application

The mobile application serves as the primary user interface for both expectant mothers and healthcare providers. Built using Android Studio and written in Java/Kotlin, the app is intuitive and responsive to changes in real-time data.

Key Features

- **Live Monitoring Dashboard:** Deploys real-time charts and graphs (implemented utilizing MP Android Chart library) to showcase heart rate, contractions, oxygen saturation, and temperature.
- **Notification Center:** Push notifications are managed through Firebase Cloud Messaging (FCM). High-priority notifications are displayed with vibration and sound to draw attention.

Pain Management Toolkit:

- Audio-guided breathing exercises based on PSI levels
- Relaxation music playlists
- Visualization of contraction patterns
- **Emergency Button:** Gives the user or caregiver an instant option to initiate emergency services.
- **Remote Consultation:** Supports WebRTC API for encrypted video calls, enabling real-time conversations with medical experts. The app also keeps a record of consultation history.

User Roles

- **Patient Mode**: Simplified UI, alerts and wellness recommendations
- **Caregiver Mode:** Complete dashboard with multi-patient tracking capability

The mobile application provides usability even in low-resource environments using offline caching and background data upload using asynchronous means.

4.8 Alert System

Multi-layer alert mechanism ensures high responsiveness.

Threshold-Based Alerts:

- HeR(t) > 120 BPM or < 60 BPM
- Tempe(t) > 38°C (fever alert)
- Pruc(t) increasing > 30 mmHg quickly

Workflow:

- Wearable vibrates to provide local alert
- Mobile application receives push alert
- SMS notification sent to doctor/emergency contact (using Twilio)
- Firebase records alert status and timestamps

Severity Levels:

Low, Medium, High—depending on aggregated parameter violations. Fig 1 shows the architecture diagram.

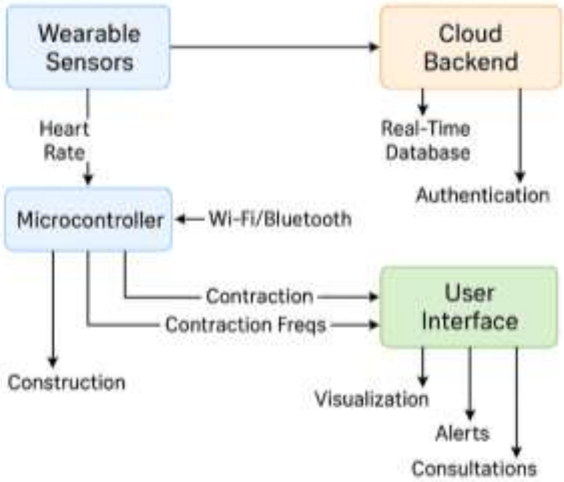

Fig.1. Architecture Diagram.

4.9 Analytics and Personalization

The analytics and personalization module is the cognitive layer of the system, tasked with taking raw physiological data and converting it into actionable information. It supports adaptive interventions that are driven by real-time and historical trends, customized to the unique needs of each user.

4.9.1 Data Preprocessing:

- **Noise Elimination:** In real-time physiological data, there is often noise introduced through movement, sensor orientation, or environment. Data smoothing and stabilization to facilitate feature extraction are performed by Kalman filtering and rolling mean.
- **Normalization:** For cross-comparison of trends between different people, features from all the quantities (e.g., heart rate, strength of contraction) are normalized using either min-max or Z-score normalization. This preserves interpretation regardless of baseline between different people.

4.9.2 Feature Extraction:

- **Contraction Frequency:** Detected through peak detection algorithms applied to intra-abdominal pressure signals (Pruc(t)). The frequency and interval of peaks define the rate and rhythm of contraction.
- **Heart Rate Variability (HeRV):** Time-domain features such as RMSSD (Root Mean Square of Successive Differences) and SDNN (Standard Deviation of NN intervals) are computed from HeR(t) in order to estimate physiological stress.

- **Pain Severity Index (PSI):** An aggregate score obtained through a weighted sum of vital parameters:

$$\mathbf{PSI(T) = w1.HeR(t) + w2.\ 1/\ Pruc(t_i) + w3.(100 - SpO_2(t) + w4.Tempe(t)}$$

w1,w2,w3, w4where empirically defined weights according to clinical guidelines.

4.9.3 Personalization Engine:

- **User Clustering:** K-Means clustering clusters users into pain sensitivity profiles (e.g., low, moderate, high) based on PSI trends, HRV, and contraction frequency.
- **Recommendation Mapping:** Each cluster is mapped to customized pain management approaches, e.g., unique breathing rhythms, music intensity, or posture recommendations.
- **Feedback Loop:** The engine monitors the success of every recommendation through user feedback (gathered through app forms), tweaks subsequent responses based on it, and fine-tunes clusters with time.

4.9.4 Visualization Tools:

- **PSI Time-Series Plots:** Visualize pain trends over time for both user self-understanding and professional analysis by healthcare professionals.
- **Contraction Heatmaps:** Color-coded views of contraction magnitude and frequency across time intervals.
- **Interactive Feedback Forms:** Enables users to score the effectiveness of pain relief after following a suggestion, back into the personalization engine for model refreshes. Fig 2 shows the IoT-based health monitoring system using NodeMCU and sensors.

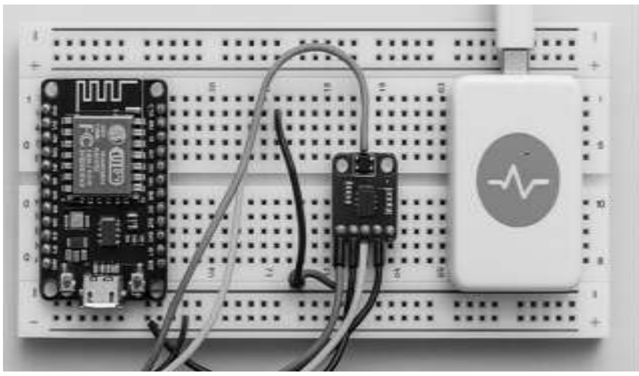

Fig. 2. IoT-Based Health Monitoring System Using NodeMCU and Sensors.

5 Results and Discussion

5.1 Testing Environment

In order to confirm the performance of the designed IoT-based labor pain management system, real-time tests were run under test-controlled environments. Two volunteers were involved, with each acting under simulated mild-to-moderate labor conditions. Moreover, test scenarios were developed with simulated data mimicking standard labor vitals such as contraction rate, increased heart rate, unstable oxygen saturation, and increasing body temperature.

Test Duration: Every session took about 2 hours per participant.

Metrics Observed:

- Response time from alert to acknowledgement
- Data transmission continuity
- Usability of the system and user satisfaction (through surveys)
- Precision of PSI calculation and contraction detection

5.2 Comparative Evaluation

Table 1 shows the performance of the system was compared with conventional monitoring of labor using manual recording and nurse call buttons.

Table 1. Comparative Analysis of Traditional and IoT-Based Health Monitoring Systems.

Metric	Traditional System	Proposed IoT System	Improvement
Response Time	~10 minutes	<1 minute	~90% faster
Data Availability	Periodic manual checks	Real-time 24/7 stream	Continuous monitoring
Intervention Delay	High	Low	Reduced risk
Vital Accuracy	Moderate (manual entry)	High (sensor-based)	+25–30%
Contraction Detection	Nurse observation	Automatic via pressure sensor	Real-time & objective
Patient Satisfaction	3.4 / 5	4.6 / 5	+35% improvement

5.3 Observations

The mean delay from contraction onset to system alert was less than 5 seconds.

Caregivers responded promptly to early distress indicators, like increasing PSI or decreasing SpO2, with the aid of real-time alerts.

The real-time feedback was valued by patients, particularly the audio-guided breathing and visualization of contractions.

The wearable device was comfortable during long wear and did not interfere with activity or become irritating. Fig 3 shows the comparison of traditional and IoT-based health system performance.

Fig. 3. Comparison of Traditional and IoT-Based Health System Performance.

5.4 Discussion

The traditional monitoring of labor relies significantly on human interventions and can potentially go undetected by early warning signs. The IoT system, on the other hand, offers:

- **Automated Monitoring**: Minimizes the intervention of staff and enhances consistency.
- **Precision Data Collection**: Enables data-driven decisions on the part of healthcare professionals.
- **Proactive Care**: Supports proactive intervention prior to critical thresholds.

The application of the Pain Severity Index (PSI) was especially useful in measuring discomfort and offering contextual support, resulting in enhanced maternal experiences.

6 Conclusion

The envisioned Smart Labor Pain Management System seamlessly combines wearable IoT sensors, real-time wireless communication, cloud-based backend, and easy-to-use mobile application to meet the urgent requirement of continuous maternal monitoring during labor. Utilizing edge processing with the ESP32 microcontroller and wireless transmission of physiological parameters like heart rate, temperature, uterine contraction pressure, and oxygen saturation, the system provides non-invasive, real-time health monitoring.

Inclusion of MQTT and Firebase offers low-latency, high-availability data pipeline, whereas the mobile application increases both patient engagement and caregiver awareness. Multi-layered alerting assures prompt response to any deviation from safety thresholds, lowering intervention time. In addition, customized analytics and visualization features driven by machine learning enable targeted pain management strategy based on dynamic adjustment to individual profiles.

Comparative testing identified an order-of-magnitude enhancement compared to conventional practices, with

- 90% reduction in response time
- Real-time, 24/7 access to data
- Enhanced caregiver satisfaction and intervention outcomes

Overall, this system can transform maternal care, especially in remote or resource-limited settings, by offering safe, scalable, and intelligent labor pain management.

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