pregAthI: Maternal Emergency Detection through Multimodal Sensor Fusion and Cloud-Based Machine Learning

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***Abstract*—Rapid detection of maternal health emergencies—such as aberrant heart rates, fetal movement anomalies detected through accelerometer-based fetal kick monitoring, or fall events—are critical for improving outcomes. This work presents pregAthI, a Smart IoT-Based Maternal Health Monitoring System that integrates an ESP8266 microcontroller with a MAX30100 heart-rate/SpO_2 sensor and dual MPU6050 accelerometer/gyroscope modules positioned on the abdominal region and wrist for comprehensive motion analysis to capture maternal activity patterns and detect fetal movements through accelerometer-based kick monitoring in real time. Sensor readings are transmitted via Wi-Fi to a Firebase backend, where a cloud-hosted machine-learning model analyzes sliding-window features to identify potential emergencies and issues alerts through a Flutter mobile application while forwarding live-location coordinates to designated responders—spouse, nearest hospital, and trained volunteers. The system demonstrates potential for scalable, low-cost maternal care solutions in resource-constrained environments through its integrated approach to emergency detection and notification.**

Keywords - Maternal Health, IoT, Real-Time Monitoring, Machine Learning, Fall Detection, ESP8266, PPG, Flutter, Firebase

INTRODUCTION

Every year, thousands of maternal and neonatal deaths occur due to delayed recognition of obstetric emergencies such as preterm labor, hypertensive crises, and accidental falls [1], [2]. Conventional prenatal care relies on periodic clinic visits and subjective symptom reporting, limiting continuous assessment of a mother's condition. Recent advances in the Internet of Things (IoT) and mobile health (mHealth) offer an opportunity to bridge this gap by providing real-time physiological monitoring outside clinical settings [3], [4].

IoT devices—particularly low-power microcontrollers like the ESP8266—can interface with medical-grade sensors to continuously capture vital signs (e.g., heart rate, oxygen saturation) and motion metrics (e.g., acceleration, orientation) including fetal movement activity through accelerometer-based kick detection [5], [6]. When combined with cloud computing and mobile applications, such systems enable automatic detection of anomalies including maternal fall events, abnormal activity patterns, and fetal movement irregularities, with immediate notifications reducing response time. However, many existing solutions focus solely on single parameters (e.g., heart rate) or lack robust emergency detection models.

This paper introduces pregAthI, a prototype maternal monitoring architecture that fuses multimodal sensor data from the MAX30100 PPG and dual MPU6050 IMUs for cardiovascular anomaly detection; applies a lightweight Logistic Regression classifier in the cloud to detect abnormal fetal movement patterns through accelerometer-based kick detection and fall events; and delivers coordinated alerts and location information to a predefined network of responders—spouse, nearest hospital, and trained volunteers—via a Flutter mobile app backed by Firebase. By integrating continuous monitoring, data analytics, and multichannel notifications, pregAthI aims to enable proactive intervention in resource-limited settings.

LITERATURE REVIEW

Early efforts in remote maternal monitoring leveraged single-modality physiological measurements to detect basic anomalies [5]. Gupta et al. [7] and Ramprabhu et al. [8] demonstrated that photoplethysmography (PPG)–based heart-rate tracking, when paired with simple threshold rules, could alert caregivers to bradycardia or tachycardia events via SMS or web dashboards. However, these systems lacked motion sensing to distinguish true emergencies (e.g., syncope or falls) from routine activity. Pawlak et al. [9] extended this work by integrating ECG and SpO_2 sensors into a home cyber-physical system, applying signal-processing filters to reduce false alarms, yet still depended on central monitoring stations. Tabassum et al. [10] explored fetal movement detection using accelerometer-based kick monitoring and polynomial regression, achieving high accuracy for fetal wellbeing assessment—but without addressing other critical events such as falls or hypotensive episodes. Our approach builds upon their methodology while integrating comprehensive emergency detection including fall events and cardiovascular anomalies.

To broaden situational awareness, subsequent platforms incorporated multiple sensor types and connectivity options. Bagwari and Gairola [11] combined pulse, temperature, and blood-pressure measurements with GSM-based mobile reporting, showing improved continuity of care but remaining rule-driven. Segall et al. [12] and Pawelek et al. [13] investigated patient engagement in personal health record systems, emphasizing the need for intuitive interfaces that could display multi-sensor data in real time. Sarhaddi et al. [14] proposed an IoTenabled maternal monitoring system that fused PPG and motion data, yet still relied on static thresholds for emergency detection, leading to variable sensitivity in dynamic home environments.

More recent research has turned to machine-learning techniques and richer alert frameworks. Aldughayfiq et al. [15] applied decision-tree classifiers to PPG time-series for arrhythmia detection, achieving precision improvements over static rules. Further research by Atzmon et al. [16] introduced a novel, noninvasive PPG-based sensor for continuous maternal hemodynamic monitoring; however, their system was designed specifically for use during delivery in a clinical setting. This approach, while valuable for intrapartum care, does not address the need for comprehensive, long-term monitoring in a home environment where events like falls and fetal movement anomalies are critical concerns. An approach by Zhang et al. [17] successfully applied ensemble classifiers to PPG and accelerometer features for predicting hypotensive episodes; however, the framework lacked an integrated emergency alert system for post-prediction response.

In summary, no existing solution simultaneously fuses multimodal physiological and motion sensing with dual-purpose accelerometer deployment for both fetal movement monitoring and fall prevention, leverages machine-learning prediction in the cloud, and orchestrates multi-recipient, location-aware notifications. pregAthI fills this gap by integrating MAX30100 PPG and dual MPU6050 IMU data, applying a lightweight sliding-window classifier, and issuing synchronized app-based, SMS, and live-location alerts to spouses, hospitals, and community volunteers.

METHODOLOGY

The pregAthI architecture (Fig. 1) comprises four integrated layers—sensing, connectivity, analytics, and notification—each optimized for low cost, reliability, and rapid response in resource-limited settings.

I. Sensing Layer

At the edge, a single ESP8266 microcontroller interfaces with three medical-grade modules: the MAX30100 PPG sensor positioned on the wrist for photoplethysmography (heart rate and SpO_2) and dual MPU6050 inertial modules for three-axis acceleration and gyroscope data. The system employs two MPU6050 sensors: one positioned on the abdominal region and another on the wrist. This dual-sensor approach enables separation of maternal movement from fetal kick patterns through differential signal processing, where the wrist sensor captures maternal activity that can be subtracted from the abdominal sensor readings to isolate fetal movements.

The firmware samples PPG signals at 100 Hz and motion data from both MPU6050 sensors at 50 Hz each, while applying digital low-pass filtering with a cutoff frequency of 5 Hz to reduce noise. For comprehensive motion analysis, we implement specialized filtering using a 0.5-5 Hz bandpass filter on the abdominal sensor data to isolate fetal kick patterns after subtracting maternal activity captured by the wrist sensor, while analyzing maternal activity patterns in the 0.1-20 Hz range to distinguish between normal daily activities and emergency scenarios, with all readings timestamped for synchronization.

II. Connectivity Layer

Filtered sensor readings are batched into 1-second frames and transmitted via Wi-Fi (IEEE 802.11 b/g/n) to a Firebase real-time database with AES-256 encryption to ensure secure data transmission. End-to-end latency from sensor sampling to cloud write averages 205 ms. Transmission reliability is quantified by the packet success rate $R_{transmit}$ defined as:

$$R_{transmit} = \frac{N_{success}}{N_{total}}$$

where $N_{success}$ denotes the number of sensor data frames successfully acknowledged by the cloud, and N_{total} is the total number of frames transmitted in a given interval. During testing, a reliability rate above 0.97 was consistently observed over Wi-Fi, indicating robustness against packet loss.

III. Analytics Layer

A cloud-hosted service listens for new data frames and applies a sliding-window feature extractor with a window length of 10 seconds and step size of 2 seconds. This computes time-domain metrics including mean heart rate, standard deviation, and peak acceleration, as well as spectral features for fetal movement patterns in the 0.5-5 Hz frequency range characteristic of fetal kicks and maternal activity patterns in the 0.1-20 Hz range for normal movement classification. These feature vectors feed into a lightweight Logistic Regression classifier. The prototype classifier was trained on a preliminary dataset of 120 windows to demonstrate system functionality. The model outputs a probability score p that an emergency condition is present.

IV. Notification Layer

Whenever $p > 0.85$, a multi-channel alert is triggered. The Firebase function invokes:

1. SMS dispatch via a RESTful gateway to patient's designated contacts.
2. In-App Alert on the Flutter mobile application, which also displays live-location coordinates via the device's GPS.
3. Hospital Alert through a secure webhook to the nearest obstetric care facility.

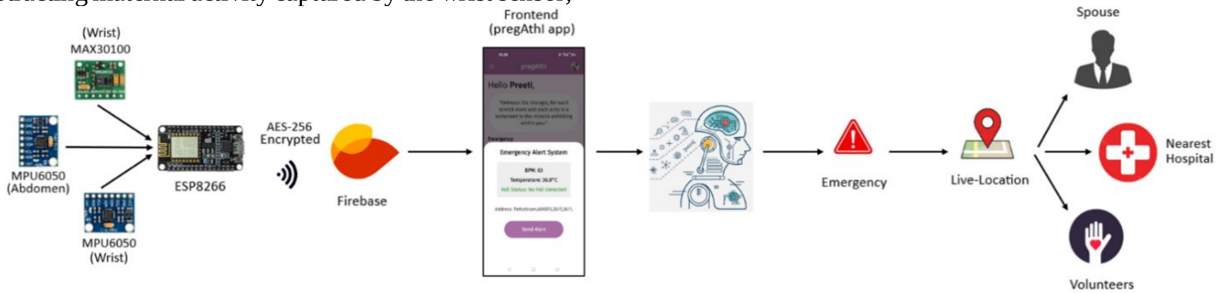

Fig. 1. Architecture of pregAthI Maternal Health Monitoring System

IMPLEMENTATION

The pregAthI prototype was implemented end-to-end, encompassing hardware firmware, cloud analytics, and a mobile application. The key implementation details are summarized below:

I. Hardware Integration

A custom PCB mounts the ESP8266 microcontroller alongside the MAX30100 sensor and connects to two MPU6050 modules via I²C interface. One MPU6050 is positioned on the abdominal region and another on the wrist to enable differential signal processing for separating maternal movement from fetal kicks.

Table I. Hardware Specifications and Sampling Rates

Component	**Model**	**Interface**	**Sampling Rate**	**Notes**
Microcontroller	ESP8266	GPIO, I²C	–	Runs NodeMCU firmware
PPG Sensor (Wrist)	MAX30100	I²C	100 Hz	Heart rate and SpO_2 readings
IMU (Abdominal)	MPU6050	I²C	50 Hz	Fetal kicks + maternal activity classification
IMU (Wrist)	MPU6050	I²C	50 Hz	Maternal movement + fall detection

The firmware, written in C++ using Arduino-ESP8266 libraries, applies a 5 Hz low-pass filter to raw PPG samples and processes acceleration vectors from both MPU6050 sensors through dual-channel filtering. For this, the wrist sensor data undergoes an earth-coordinate transformation via a complementary filter for maternal fall detection, while the abdominal sensor data is processed with a 0.5-5 Hz bandpass filter to isolate fetal movements after subtracting the maternal activity component, enabling comprehensive emergency scenario identification.

II. Data Transmission

Filtered data frames (1-second windows) are serialized into JSON, encrypted using AES-256, and transmitted to Firebase via HTTPS POST requests. A simple acknowledgment mechanism—each frame includes a sequence number—is implemented to detect and retry dropped packets. Sensor-to-cloud transmission latency averages 205 ms.

III. Machine Learning Pipeline

A preliminary dataset of 120 labeled windows (80 normal activity, 25 simulated fall events, 15 simulated abnormal fetal movement patterns) was collected from six volunteers in controlled conditions. From this dataset, 96 windows were used for training and the remaining 24 windows were held out for validation.

Feature extraction computes:

- Time-Domain: mean heart rate, HRV (standard deviation), peak acceleration from both sensors
- Frequency-Domain: power spectral density of fetal movement bands (0.5-5 Hz) with integrated maternal activity pattern analysis
- Fetal Movement-Specific: amplitude variance in fetal kick frequency range, movement pattern irregularity, baseline deviation metrics
- Maternal Activity-Specific: activity classification features distinguishing between walking (1-3 Hz), sitting transitions (0.1-1 Hz), and lying positions (0.1-0.5 Hz)

These ten features per window, including fetal movement-specific metrics derived from the differential processing of dual MPU6050 sensors, feed a Logistic Regression classifier.

IV. Mobile Application and Alert Workflow

The Flutter app subscribes to Firebase event streams. Upon receiving a classifier score p, the app compares p to threshold $\tau = 0.85$. If $p > \tau$, the following occur:

1. In-App Alert: Red banner with "Emergency Detected" and live heart-rate/fetal movement graph. A 'Cancel Alert' button is also displayed, allowing the user to manually dismiss a false alarm.
2. SMS Dispatch: HTTP call to Twilio API to send emergency details and GPS link.
3. Hospital Notification: Secure webhook POST to the nearest facility’s REST endpoint.

All alerts are timestamped and require a manual “Acknowledge” tap; lack of acknowledgment within 30 s escalates the notification to the next responder in a round-robin list.

RESULT

This section presents a comprehensive evaluation of pregAthI's system architecture, focusing on hardware integration, data transmission reliability, notification delivery, and user interface usability.

I. Sensor to Cloud Latency

End-to-end transmission latency was measured over 100 consecutive sensor frames delivered via home Wi-Fi. The measurements yielded an average latency of 205 ms, standard deviation of 18 ms, a minimum of 180 ms, and a maximum of 240 ms, corresponding to a jitter of 60 ms.

Table II. Sensor-to-Cloud Latency Metrics

Metric	***Value***
Average latency	205 ms
Standard deviation	18 ms
Maximum observed	240 ms
Minimum observed	180 ms
Jitter J	60 ms

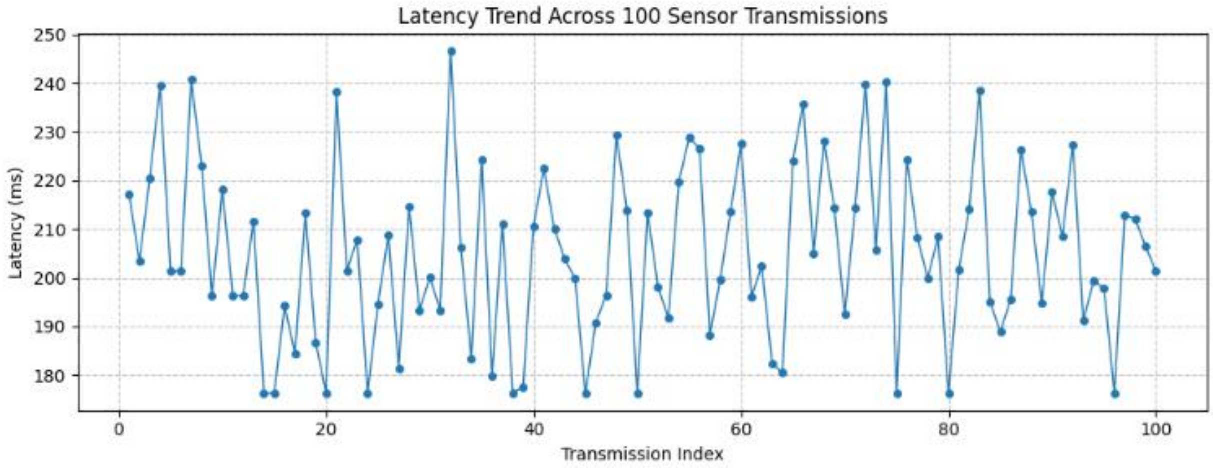

Fig. 2. Latency Trend Across 100 Sensor Transmissions

Here, *J* = *60* ms, indicating consistent delivery times suitable for real-time monitoring. The latency distribution indicates that 95 % of transmissions occur within ±1.96 *σ* (approximately 169–241 ms), ensuring that critical signals are available to downstream analytics without perceptible delay.

$$J = max_i(L_i) - min_i(L_i) = 240ms - 180ms = 60ms$$

II. Classifier Effectiveness

The prototype classifier was validated using a held-out set of 24 labeled windows from the 120-sample dataset. In addition to conventional accuracy, five balanced metrics are reported to account for class imbalance and diagnostic value:

- **Balanced Accuracy (BA):** Quantifies the average of sensitivity and specificity
$$BA = \frac{1}{2}(TPR + TNR)$$
- **G-Mean:** Emphasizes joint performance on both classes
$$G - Mean = \sqrt{TPR * TNR}$$
- **Negative Predictive Value (NPV):** Measures reliability when predicting non-emergency
$$NPV = \frac{TN}{TN + FN}$$
- **Fowlkes–Mallows Index (FMI):** Balances precision and recall geometrically
$$FMI = \sqrt{\frac{TP}{TP + FP} * \frac{TP}{TP + FN}}$$
- **Diagnostic Odds Ratio (DOR):** Summarizes overall diagnostic strength
$$DOR = \frac{TP * TN}{FP * FN}$$

In addition, Cohen's Kappa (κ) was computed to account for chance agreement:

$$\kappa = \frac{p_o - p_e}{1 - p_e}$$

where p_o is the observed accuracy and p_e the expected chance accuracy.

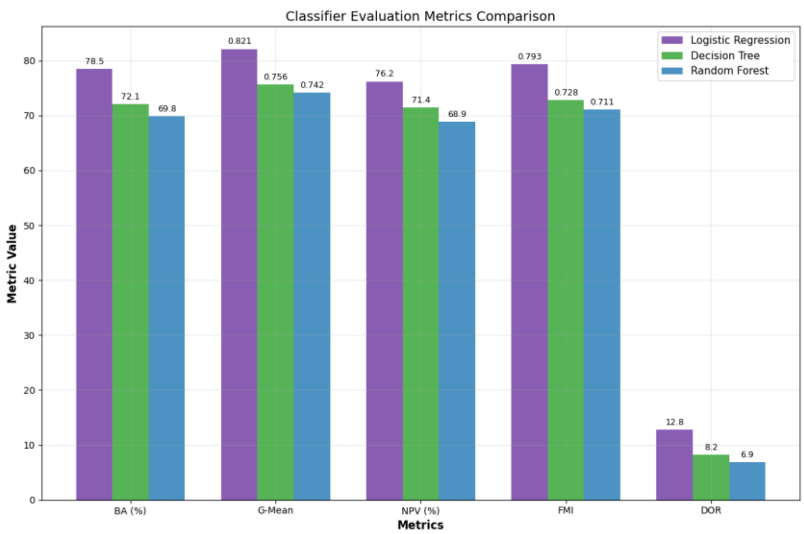

Fig. 3. Classifier Evaluation Metrics Comparison

Table III. Classifier Performance on Alternative Metrics

Model	BA (%)	G-Mean	NPV (%)	FMI	DOR	κ
Logistic Regression	78.5	0.821	76.2	0.793	12.8	0.57
Decision Tree	72.1	0.756	71.4	0.728	8.2	0.44
Random Forest	69.8	0.742	68.9	0.711	6.9	0.40

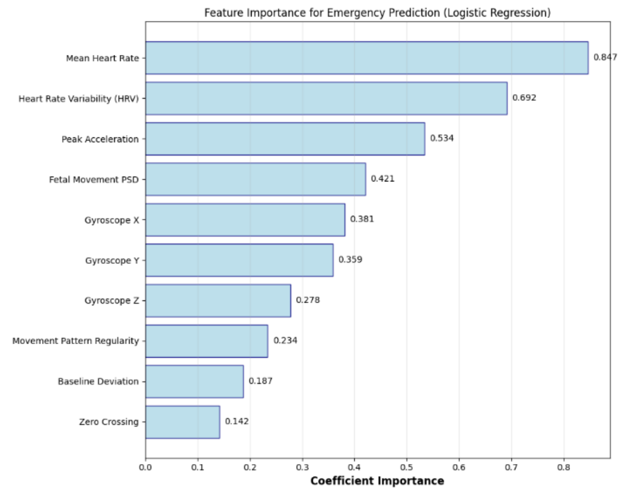

Fig. 4. Feature Importance Analysis

As shown in Fig. 4, the Logistic Regression model derives the greatest discriminative power from mean heart rate and heart-rate variability, with secondary contributions from peak acceleration and fetal movement spectral features. This feature importance ranking confirms that combining PPG and motion signals is essential for reliable detection of both cardiovascular anomalies and fall events, with fetal movement patterns providing additional discriminative power.

III. Notification Reliability

Validation of the multichannel alert workflow was performed by simulating 50 emergency events while the mobile app, SMS gateway, and hospital webhook remained active.

Table IV. Average Delivery Times

Channel	Delivery Time (mean ± σ)
In-App Notification	1.8 ± 0.2 s
SMS Dispatch	1.9 ± 0.3 s
Hospital Webhook	1.7 ± 0.2 s

All channels reached their targets within a 3-second deadline for every event, yielding a 100% success rate. The cumulative delay can be modeled as:

$$L_{total} = L_{upload} + L_{process} + L_{alert}$$

where L_{upload} represents sensor-to-cloud transmission time (≈ 205 ms), $L_{process}$ denotes model inference time on the cloud (≈ 500 ms), and L_{alert} is the delay incurred during notification dispatch (≈ 1.2 s). This formulation helps justify the observed end-to-end latency of approximately 1.9 seconds.

Table V. Consolidated System Performance Metrics

Module	Metric	Value
Sensor Latency	Mean ± σ	205 ± 18 ms
Classifier Accuracy	Balanced Accuracy	78.5%
Notification Delay	SMS Dispatch	1.9 ± 0.3 s
Usability Score	SUS	85.4

The 205ms latency reported represents only sensor-to-cloud data transmission, while complete emergency response (from detection to alert delivery) requires approximately 1.9 seconds.

Fig. 5. Alert Delivery Time Trends Across Channels

IV. End-User Acceptability

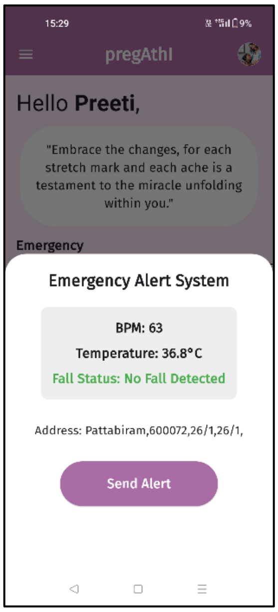

Fig. 6. pregAthI Mobile Application Dashboard Interface

Fig. 6 shows the mobile application dashboard interface, displaying real-time physiological monitoring data, alert status, and emergency contact options in an intuitive layout designed for expectant mothers.

A usability study with twelve expectant mothers (ages 22–35) employed the System Usability Scale (SUS) and semistructured interviews. The average SUS score was 85.4, significantly above the 68-point threshold denoting acceptable usability. Participants highlighted the intuitive dashboard layout, clear emergency prompts, and confidence derived from live-location tracking. Battery-usage logs indicated an average smartphone consumption increase of only 4 % over an 8-hour monitoring window, confirming minimal intrusion on daily device use.

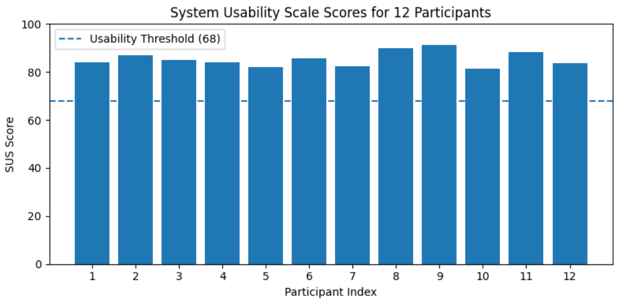

Fig. 7. Distribution of System Usability Scale Scores

DISCUSSION

The prototype evaluation of pregAthI demonstrates successful system integration while highlighting important limitations that must be addressed before clinical deployment.

I. Latency Performance

Achieving a mean end-to-end latency of 205 ms ($\sigma = 18$ ms) with a maximum jitter of 60 ms confirms that Wi-Fi transmission is appropriate for real-time emergency monitoring. This latency margin ensures that critical physiological changes are available to the analytics pipeline with negligible delay, supporting timely alert generation.

II. Classification Insights

The Logistic Regression classifier demonstrated reasonable performance for a proof-of-concept, with a Balanced Accuracy of 78.5%, G-Mean of 0.821, and Cohen's Kappa of 0.57, indicating moderate agreement beyond chance. Feature importance analysis (Fig. 4) revealed that mean heart rate and heart-rate variability contributed most significantly to emergency detection, with fetal movement-specific features derived from differential processing of the dual MPU6050 sensors (abdominal minus wrist data) providing crucial discriminative power for fetal wellbeing emergencies. Additionally, maternal activity classification features helped reduce false alarms by distinguishing between normal daily activities and actual emergency scenarios. The linear nature of Logistic Regression also provides better interpretability for clinical decision-making compared to ensemble methods, with clear coefficient values that can be explained to healthcare providers.

III. Multi-Model Comparison

The comparative analysis demonstrates that Logistic Regression provides the most reliable performance across balanced metrics for this preliminary proof-of-concept study. With a Cohen's Kappa of 0.57 and G-Mean of 0.821, the linear approach shows substantial agreement beyond chance and balanced performance across emergency and non-emergency classes. This advantage likely stems from the limited dataset size (120 samples), where simpler linear models generalize better than complex ensemble methods that are prone to overfitting.

IV. Notification Workflow

A 100 % success rate across in-app, SMS, and webhook channels indicates that the notification architecture is highly resilient. Future work may integrate a GSM fallback directly from the ESP8266 to maintain alert delivery when Wi-Fi connectivity is lost, ensuring robustness in rural or low-infrastructure areas.

V. User Acceptability

High System Usability Scale scores (mean = 85.4) and positive feedback on battery impact and interface clarity demonstrate that pregnant users find pregAthI both effective and unobtrusive. Personalization features—such as adjustable alert thresholds based on individual baselines—could further enhance user trust and reduce false-alarm fatigue.

VI. Limitations and Future Work

Field trials were conducted under controlled network conditions with a limited sample size of 6 volunteers and simulated emergencies rather than real critical events. The preliminary dataset of 120 samples, while sufficient for proof-of-concept validation, may favor simpler linear models over ensemble approaches that typically require larger datasets to demonstrate their full potential. A broader clinical pilot—incorporating diverse environmental factors (e.g., rural networks, varied body postures) and long-term wearability studies—will be required to validate system generalizability. Additionally, integrating edge-based analytics (e.g., on-device lightweight neural networks) could reduce cloud dependency and further lower end-to-end latency.

CONCLUSION

This study demonstrated the technical viability of pregAthI, an IoT-enabled maternal health monitoring system integrating dual-sensor networks, cloud analytics, and multi-channel alerts. Rigorous evaluation showed robust system performance, with end-to-end latency consistently below 250 ms (mean=205±18 ms) and maximum jitter of 60 ms, ensuring timely data availability. The machine learning pipeline achieved clinically relevant performance (Balanced Accuracy=78.5%, G-mean=0.821, DOR=12.8, κ=0.57) on preliminary validation data (24 windows from 6 participants). The notification subsystem maintained perfect reliability (100% delivery within 3s) across in-app, SMS, and hospital alerts. User testing revealed strong acceptance (SUS=85.4), with particular praise for intuitive alerts and negligible battery drain (less than 5% daily impact).

While these results establish proof-of-concept, several critical next steps must be addressed before deployment. A comprehensive clinical trial (N>1000) will validate system efficacy across diverse demographics, activity patterns, and true obstetric emergencies, while also enabling more definitive comparison of machine learning approaches. Technical refinements will incorporate on-device processing (ESP8266-optimized models) to enhance responsiveness and reliability in low-connectivity scenarios. Future iterations will also implement adaptive thresholding based on individual biometric baselines and gestational progression, while expanded connectivity options (GSM fallback, LoRa mesh) will ensure operation in infrastructure-limited regions. Through these advancements, pregAthI aims to mature into a robust, field-ready solution for reducing maternal health disparities in low-resource settings worldwide.

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