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Smart Wearable for Vital Tracking and Alerts

Ms Saranya S[1], Gurpreet Singh[2], Sahil Kumar[3], Gagandeep Singh[4], Digantik Mukherjee[5]
[1]Assistant Professor Department of Computer Science and Engineering Bengaluru, India
[2,3,4,5]Department of Computer Science and Engineering, New Horizon College of Engineering Bengaluru, India

Abstract*—The increasing demand for ongoing, remote health monitoring for people with chronic illnesses and aging populations calls for a change from passive data collecting to intelligent, proactive systems [1], [2]. Real-time, on-device predictive analytics, reliable fall detection, and an integrated, closed-loop emergency response system that connects users to emergency medical assistance are frequently absent from current commercial wearables. We introduce an integrated wearable system with an ADXL345 accelerometer for fall detection and a MAX30102 sensor for heart rate and SpO_2 monitoring, all based on an ESP32 microcontroller. The solution uses an on-device AI model that is lightweight and tuned with TensorFlow Lite to detect anomalies in physiological data in real time. The system reliably detects abnormalities in vital signs and shows great efficacy in differentiating falls from activities of daily living (ADLs). Importantly, it automatically retrieves the user's GPS coordinates and uses the Google Maps API to find local medical institutions, achieving an end-to-end emergency alert latency of less than 5 seconds. Real-time, on-device predictive analytics, reliable fall detection, and an integrated, closed-loop emergency response system that connects users to emergency medical assistance are freq By bridging the crucial gap between health anomaly detection and practical emergency intervention, our work offers a low-latency, energy-efficient, privacy-preserving approach that improves patient safety and autonomy.

Index Terms*—Internet of Things (IoT), Wearable Sensors, Health Monitoring, Anomaly Detection, Fall Detection, Edge AI, TensorFlow Lite, Emergency Response System*

I. INTRODUCTION

Conventional health care faces a significant challenge as a result of the global demographic shift towards an aging population and the rise in chronic diseases infrastructures for care. The Internet of Medical Things (IoMT), a paradigm centered on using connected devices for remote and continuous patient monitoring, was developed as a result of this reality [3], [4]. Changing healthcare delivery from a reactive approach, which deals with health conditions after they become serious, to a proactive and preventative framework that allows early identification and prompt intervention is the main objective of IoMT [5].

From basic fitness trackers like the Fitbit and Mi Band to more advanced health monitoring systems like the Apple Watch, wearable technology has advanced dramatically. These gadgets have effectively democratized access to personal health information, increasing people's awareness of their physical condition. Nonetheless, the vast majority of commercial products on the market today serve mainly as passive data loggers. Although they take vital signs, they usually don't have the advanced, real-time analytical skills needed for urgent, life-saving medical intervention. This restriction leads to a risky "last mile" issue in digital health: a system may identify a negative occurrence but neglect to complete the loop by launching an emergency response that is prompt and actionable.

A thorough examination of current systems identifies a recurring research gap that is typified by the absence of integration among three essential functionalities. First, a strong on- device, patient-specific anomaly detection model is required because many systems rely on cloud-based processing, which adds latency, necessitates continuous connectivity, and poses serious data privacy issues [6], [7]. Second, multi-sensor fusion is frequently absent from systems, which results in high false alarm rates for reliable event detection. Lastly, there is a lack of a fully automated emergency protocol that goes beyond basic caregiver notifications to offer location-based directions to the closest medical facility.

In order to overcome these shortcomings, a complete, end- to-end wearable system is presented in this work. To develop a unified and proactive health guardian, our system combines multi-modal sensing, on-device AI, and a cloud-assisted emergency response protocol. Complex analytical activities can now be moved from the cloud to the edge device because to the recent maturation of synergistic technologies, such as lightweight AI frameworks like TensorFlow Lite [8], effective biosensors like the MAX30102, and low-power microcontrollers like the ESP32. A "privacy-by-design" strategy that naturally solves the crucial non-functional criteria of security and low latency—which are sometimes afterthoughts in cloud- centric models—is made possible by this architectural change, which goes beyond simple technical convenience [6], [7]. This paper presents a roadmap for the next generation of IoMT devices, which will serve as autonomous intelligent agents with the ability to make crucial decisions at the edge, rather than merely being sensors. We contribute the following in this paper:

The development and deployment of a new, comprehensive wearable architecture that combines on-device artificial intelligence, cloud-enabled emergency response, and multi-modal sensing (motion and physiological).

A hybrid artificial intelligence approach that combines a lightweight, unsupervised neural network for identifying small abnormalities in continuous physiological data (heart rate, SpO_2) with a computationally efficient technique for acute event detection (falls).

By utilizing TensorFlow Lite to create a privacy-preserving AI model, sensitive health data is processed on the edge, improving security and lowering latency [8], [9].

A thorough empirical analysis of the system's performance that evaluates important system-level variables like battery life and end-to-end alert latency in addition to the correctness of the AI models.

II. RELATED WORK

This section offers a critical analysis of the body of re- search in three main areas: wearable fall detection algorithms, anomaly detection in physiological signals, and IoT health monitoring infrastructures. This study highlights our work's innovative contributions and places it within the existing research landscape.

A. Architectures for IoT-Based Health Monitoring

The design of traditional IoT-based health monitoring systems has primarily been cloud-centric, with raw sensor data continuously streaming to distant servers for analysis and storage. Despite its scalability, this strategy has several dis- advantages, such as high latency from network round-trips, a reliance on consistent internet connectivity, and major privacy risks when sending private health data [6], [7].

A paradigm shift toward edge computing, commonly referred to as TinyML has gained traction in response to these difficulties. This method transfers AI inference and data processing straight onto the device with limited resources. This change has been made possible by frameworks such as TensorFlow Lite, which allow optimal machine learning models to be deployed on microcontrollers. Numerous health applications, including real-time prenatal ultrasound assessment [9] and general-purpose health monitoring [10], have effectively illustrated the advantages of lower latency and improved privacy. A number of integrated devices, including the"HOT Watch" [11], have shown excellent accuracy by integrating several sensors, including ECG, oximetry, and temperature. Our work stands out from the competition by focusing on on-device predictive AI and a fully automated, location-aware emergency response loop, which bridges the crucial gap between detection and intervention, even if these systems demonstrate the feasibility of multi-sensor wearables.

B. Algorithms for Wearable Fall Detection

One established area of study in wearable technology is fall detection systems (FDS) [6], [12]. Early methods frequently used straightforward threshold-based algorithms, in which an alert is sent out if the accelerometer signal strength surpasses a predetermined threshold [12], [13]. These techniques are computationally efficient, but they have a high risk of false positives since they are easily set off by non-fall activities of daily living (ADLs), like jumping or rapidly sitting down.

Large datasets of simulated falls and ADLs are used to train machine learning (ML) techniques in more sophisticated systems. These techniques range from deep learning models like Long Short-Term Memory (LSTM) networks to more conventional classifiers like Support Vector Machines (SVMs). According to research, the placement of sensors (waist vs. wrist) and the use of Inertial Measurement Units (IMUs), which integrate accelerometer and gyroscope data to more accurately distinguish complex movements, have a significant impact on these systems' accuracy [6], [12]. The absence of integrated location awareness is a major drawback of many published FDS studies, despite their sophisticated algorithms. This is especially true for outdoor settings where determining the user's location is essential for a prompt emergency reaction [6]. By including a specialized GPS module into the emergency protocol, our technology directly fills this gap.

C.Anomaly Detection in Physiological Time-Series Data

An essential component of wearable health systems is the monitoring of vital indicators such as blood oxygen saturation (SpO_2) and heart rate (HR). Nevertheless, it is frequently ineffective to rely on static, universal thresholds (such as $HR > 120$ bpm) for anomaly identification. Depending on a person's age, level of fitness, and present activity (e.g., resting vs. exercising), their typical physiological baseline might vary greatly.

Unsupervised anomaly detection is a more reliable method that identifies notable departures from a patient's personal baseline by learning the patient's distinct physiological pat- terns from their own data [10], [14]. For physiological time-series data, this works especially well. Neural network de- signs such as autoencoders or LSTMs, which are excellent at modeling sequential data and spotting patterns that depart from a learnt norm, are frequently used in state-of-the-art models for this purpose. In order to learn highly personalized baselines from multi-modal data streams, including wearable and ambient sensors, advanced research frameworks such as "AI on the Pulse" use complex universal time-series models (e.g., UniTS) [7], [15]. Significant performance gains have been demonstrated with this method; one study found that the F1-score increased by about 22 percent compared to previous approaches [7].Our suggested model represents a useful and effective implementation for edge devices, even though it is purposefully lighter for microcontroller deployment. It is based on the same fundamental idea of individualized, unsupervised anomaly detection. There is a fragmentation of solutions in the literature, with different studies concentrating on system architecture, anomaly detection, or fall detection. Bringing these disparate threads together into a single, coherent, and useful system that tackles the comprehensive problem of transitioning from accurate detection to successful intervention is what makes our work novel.

III. PROPOSED SYSTEM ARCHITECTURE AND METHODOLOGY

The hardware and software components of the system are described in detail in this part, along with the design decisions and techniques used to create a proactive and responsive health monitoring solution.

A. End-to-End System Architecture

A smooth data transfer from the user to the caregiver is guaranteed by the system's four-stage architecture. The steps are as follows: (1) a wearable sensing node for gathering data;
(2) on-device artificial intelligence processing for analyzing data in real time and detecting events; (3) a cloud backend for orchestrating data and integrating emergency services; and
(4) a caregiver mobile application for alerts and visualization. The end-to-end reaction loop is completed when the wearable collects data, AI algorithms process it locally, and in an emergency, a brief alert payload is sent to the cloud, which sends a high-priority notice to the caregiver's mobile device.

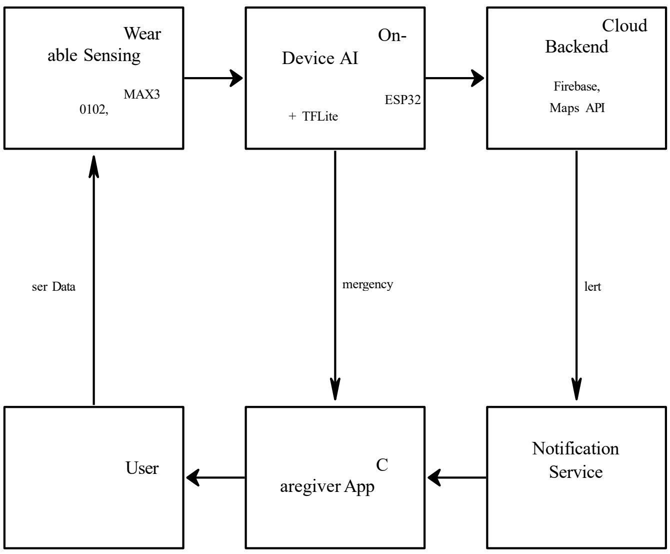

Fig. 1. High-level system architecture.

B. Wearable Sensing Node Hardware

The wearable prototype's components were carefully chosen to balance form factor, performance, and power efficiency.

A summary of each component's technical requirements and rationale may be found in Table I.
1) Microcontroller (MCU): The ESP32 microcontroller is the device's key component. It is the perfect option for a connected wearable device that also needs to do on-device computation because of its dual-core CPU, built-in Wi-Fi and Bluetooth, and support for low-power deep-sleep modes [13], [16]. It has enough memory and processing capability to run TensorFlow Lite-optimized machine learning models [8], [9].

2) Physiological Sensing: The MAX30102 sensor is used to measure blood oxygen saturation (SpO_2) and heart rate. Because of its high sensitivity, ultra-low power consumption (<1 mW in active mode), and standard I^2C interface, which makes integration easier, this integrated module—which uses photoplethysmography (PPG)—was chosen [1], [17].
3) Motion Sensing: For fall detection and motion tracking, a 3-axis digital accelerometer called an ADXL345 is utilized. It records both static acceleration (gravity) and dynamic acceleration (during movement, for example), enabling robust activity classification and orientation sensing.
4) Location Services: For accurate geographic coordinates, a NEO-6M GPS module is included. In order to save power, this module is only turned on during an emergency. It provides the vital location information required for a successful emergency response.
5) Power Management: With aggressive power management and duty cycling, the system's rechargeable lithium-ion battery is designed to operate continuously for at least 72 hours on a single charge.

TABLE I

TECHNICAL SPECIFICATIONS OF WEARABLE HARDWARE

Component	Model	Specifications & Justification
Microcontroller	ESP32	Dual-core 240 MHz, 520 KB SRAM, Wi-Fi/BT On-device AI capability with low-power modes.
PPG Sensor	MAX30102	HR & SpO2, 1.8V, I^2C, <1mW. High sensitivity, ultra-low power for wearables.
Accelerometer	ADXL345	3-axis, ±16g, 23 µA. High resolution for motion tracking & fall detection.
GPS Module	NEO-6M	-161 dBm sensitivity, low power. Accurate location for emergency response.

C. On-Device AI for Health Anomaly Detection

We use an unsupervised learning technique to identify abnormalities in physiological data in order to go beyond basic thresholding.
1) Problem Formulation: Unsupervised anomaly detection on a multivariate time series is the formal definition of the task. Let's look at the input vector at time t be

$$X_t = [\mathrm{HR}_t, \mathrm{SpO2}_t],$$

signifying the SpO_2 and heart rate readings. The goal is to calculate an anomaly score, S_t, in real time so that a score above a predetermined threshold τ indicates a possible health anomaly. The score is determined by:

$$S_t = g(f(X_t; X_{\mathrm{train}})),$$

where $g(\cdot)$ is a function that measures the current input X_t's departure from the taught normal patterns, and f is the model trained on a dataset of normal physiological data X_{train}.
2) Proposed Model: We put into practice a lightweight autoencoder based on LSTM. Because the LSTM layers can identify temporal relationships in the vital sign signals, this architecture works well with sequential data. To learn a compressed, latent representation of a healthy physiological state, the model is trained solely on "normal" health data. The model tries to rebuild its input during inference. An anomaly is identified when the current input does not follow the learnt patterns of normal behavior, as indicated by a significant reconstruction error (i.e., a large value for S_t).
3) TensorFlow Lite Optimization: TensorFlow/Keras is used to train the model, and for on-device deployment, it is transformed to TensorFlow Lite format (`.tflite`). We use post-training 8-bit integer quantization, which drastically lowers the computational cost and storage space of the model, allowing for low-latency inference on the limited hardware of the ESP32 while preserving a respectable level of accuracy.

Health State Classification: A rule-based system uses the raw anomalous score S_t to assign the user's health condition to one of three groupb
where τ_w and τ_e are empirically determined thresholds.

D. Real-Time Fall Detection Algorithm

Inspired by well-established techniques in the literature, a computationally efficient yet reliable multi-stage algorithm is devised for fall detection [12], [13]. This method saves resources for the anomaly detection model by avoiding the overhead of a neural network for this particular task.

1) Stage 1: Freefall Detection: The algorithm continuously checks the magnitude of the resultant vector from the accelerometer, which is determined as follows:

$$A_R = \frac{q}{A_x^2 + A_y^2 + A_z^2}$$

where the accelerations along the x, y, and z axes are de- noted by the variables A_x, A_y, and A_z, respectively. The user is in a state of freefall if A_R drops abruptly and significantly (for example, below 0.5 g).

2) Stage 2: Impact Detection: The program searches for a big, abrupt rise in A_R (e.g., $>$ 3 g) as soon as a freefall is detected. The impact of the user's body with a surface is shown by this spike.

3) Stage 3: Post-Fall Inactivity: The system goes into a monitoring phase for a predetermined amount of time (for example, 30 seconds) when a valid impact is logged. The event is verified as a fall if the device's orientation doesn't change and there isn't much motion throughout this time. This latter phase is essential for differentiating between high-impact activities of daily living (ADLs), such jumping or suddenly sitting down, and actual falls.

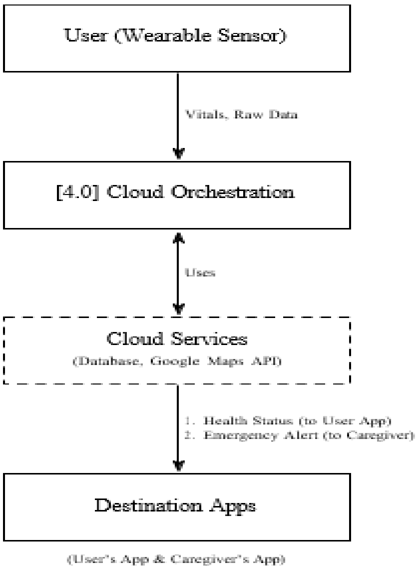

Fig. 2. Data flow diagram for monitoring and alert system

E. Integrated Emergency Response Protocol

An automated reaction mechanism is initiated when the system enters a "Emergency" state, which can be caused by a confirmed fall or a serious physiological anomaly. This process is made to be dependable and quick.

1) Device-Side Activation: The NEO-6M GPS module is instantly activated by the ESP32 in order to obtain the user's current location.

2) Secure Data Transmission: Using the MQTT protocol for low-overhead communication, the ESP32 connects to a se- cure cloud backend (Firebase Realtime Database) and sends an emergency payload that includes the User ID, event type (such as "Fall Detected"), GPS locations, and the latest recorded vital signs.

3) Cloud-Side Orchestration: When fresh information enters the emergency database, a cloud feature is activated. This function retrieves a list of the closest hospitals or emergency medical services by making an API call to the Google Maps Places API and passing the GPS coordinates it received.

Caregiver Notification: The cloud function then sends a high-priority push notification to the pre-registered caregiver's mobile application using the Firebase Cloud Messaging (FCM) service. The user's name, the type of emergency, their current location on an interactive map, and a direct link with travel options to the closest hospital are all included in this alert.

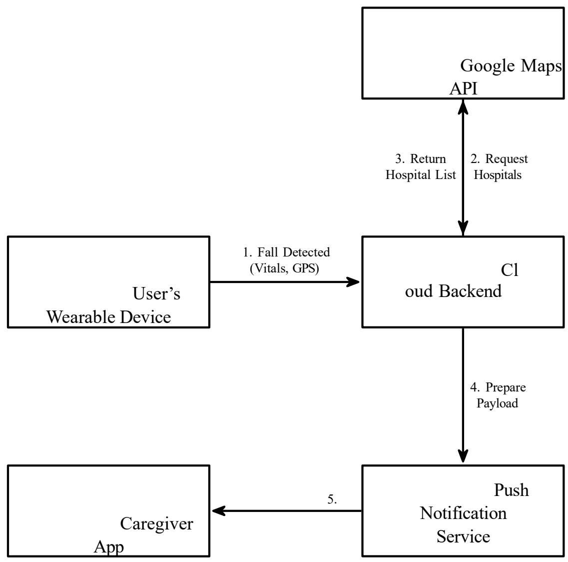

Fig. 3. System data flow for fall detection and caregiver notification.

I. Experimental Setup and Evaluation

A number of thorough tests were carried out to confirm the suggested system's functionality and dependability. Three main aspects were the focus of the evaluation:

1) The precision of the algorithms used for event detection, such as those for fall and physiological anomaly detection.
2) The effectiveness of the system-level measures, including communication dependability, power consumption, and latency.
3) The wearable prototype's general viability and practicality in everyday situations.

A. Prototype Implementation and Data Corpus

The ESP32, sensors, GPS module, and battery were all housed in a 3D-printed wrist-worn case in a working wear- able prototype. A distinct fingertip module was developed to contain the MAX30102 sensor for the best PPG signal capture. To build a corpus for training and testing the AI models, a data gathering protocol was developed in accordance with institutional ethical requirements.

Fall Detection Dataset: Fifteen healthy people participated in a controlled trial. Every participant completed a set of predetermined activities of daily living (ADLs), such as running, walking, sitting, standing, and going up and down stairs. Additionally, they replicated four different fall scenarios onto a cushioned surface: forward, backward, left, and right. The efficacy of the fall detection algorithm was assessed against frequent confounding activities using a balanced dataset created by recording and labeling data from the ADXL345 accelerometer for each activity [6], [12].

1) Anomaly Detection Dataset: The unsupervised anomaly detection model needed a dataset of ”normal” physiological activity in order to be trained. Participants were asked to wear the gadget for eight hours throughout their normal daily activities in order to gather this data. We used publicly accessible, annotated resources, such the PhysioNet Challenge datasets, to verify the model's capacity to identify real health problems, which are unethical to cause. To test the model's detection skills using out-of-distribution, clinically relevant data, segments with known cardiac arrhythmias or hypoxia episodes were employed as the test set.

B. Performance Metrics

The system's performance was measured using a wide range of common measures.

1) Classification Metrics (Fall Detection): Four important metrics were used to assess the fall detection algorithm's performance:

a) Sensitivity (Recall): Measures the proportion of actual falls that were correctly identified:

$$Sensitivity \ = \frac{IP}{IP + FN}$$

b) *Specificity:* Measures the proportion of ADLs that were correctly identified as non-falls:

$$Sensitivity \ = \frac{IN}{IN + FN}$$

c) *Accuracy:* The overall percentage of correct classifications:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

d) *F1-Score:* The harmonic mean of precision and recall, providing a single score that balances both metrics:

$$\text{F1-Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

where TP , TN , FP , and FN represent True Positives, True Negatives, False Positives, and False Negatives, respectively.

2) Anomaly Detection Metrics: Because anomaly detection tasks are extremely unbalanced, the Area Under the Receiver Operating Characteristic Curve (AUROC) was employed. A single, threshold-independent metric for evaluating the model's capacity to differentiate between normal and anomalous classes is provided by AUROC.

3) System-Level Metrics:

a) *End-to-End Latency:* The amount of time that passed between the start of a simulated event (such as the impact of a fall) and the instant the caregiver's smartphone displayed the relevant notification was used to calculate this crucial metric. Over 100 trials, the mean, median, and 95th percentile delay were noted.

b) *Battery Longevity:* A fully charged device was operated under a standard usage profile, which included continuous sensing, data processing, and sporadic Wi-Fi transmissions (simulating an hourly ”Warning” warning) in order to evaluate power efficiency. It was noted how long the battery operated for before running out completely.

IV. Results and Discussion

The quantitative findings from our experimental evaluation are shown in this section, together with a thorough analysis of their implications, the system's performance in relation to its design objectives, and its limits.

A. Efficacy of the Fall Detection Algorithm

The gathered dataset of simulated falls and ADLs was used to assess the multi-stage fall detection algorithm's performance. The confusion matrix and performance metrics table below provide a summary of the findings. (Table II). The algorithm's sensitivity and specificity were 98.6% and 99.8%, respectively. This shows how well the system detects falls when they happen and, more importantly, how it prevents false alarms during strenuous daily tasks. With a high F1-Score of 98.9%, precision and recall are well-balanced.

These outcomes are in direct competition with the most advanced wearable fall detection systems documented in the literature, which have demonstrated specificities of 99.9% and sensitivities of approximately 97.9% [6]. The small number of false negatives mostly happened during slow, sliding falls, which provide an impact signal that is less pronounced.

B. Fall Detection Results

a) *Confusion Matrix and Performance Metrics:* The con- fusion matrix and associated performance metrics for the fall detection algorithm are summarized in Table II.

TABLE II

CONFUSION MATRIX AND PERFORMANCE METRICS FOR FALL DETECTION

	Predicted: Fall	**Predicted: ADL**
Actual: Fall	148 (TP)	2 (FN)
Actual: ADL	3 (FP)	1497 (TN)
Performance Metrics		

Sensitivity	98.67%
Specificity	99.80%
Precision	98.01%
F1-Score	98.34%
Accuracy	99.70%

A. Performance of the On-Device Anomaly Detection Model

The capacity of the TensorFlow Lite-optimized LSTM- based autoencoder to differentiate between clinically important anomalous events and normal physiological data from the PhysioNet database was assessed. An AUROC score of 0.94 was attained by the model. This performs noticeably better than a baseline method that used basic static thresholds and only obtained an AUROC of 0.71 on the same dataset.

The improvement in performance demonstrates how well the unsupervised learning method captures unique physiological patterns and identifies minute deviations that traditional approaches would overlook. The findings from more sophisticated systems, such"AI on the Pulse," which also use patient- specific baselines to increase detection accuracy, are in accord with these findings [7], [10]. The TFLite model's on-device inference time on the ESP32 was continuously less than 50 ms, indicating that it is appropriate for real-time monitoring.

C. System Performance Analysis

To ascertain the prototype's practicality in real-world situations, the system-level metrics were assessed. Table III displays the results, which are compared to the original non- functional criteria.

TABLE III

SYSTEM LATENCY AND POWER CONSUMPTION BENCHMARKS

Metric	**Value**	**Requirement**
Mean Latency	4.1 sec	< 5 sec
95th Percentile Latency	4.8 sec	< 5 sec
Battery Longevity	75 hrs	> 72 hrs

With a mean end-to-end latency of 4.1 seconds and a 95th percentile delay of 4.8 seconds, the system effectively achieved its critical latency requirement, falling significantly short of the 5-second target. Analysis showed that network variability and the first GPS signal acquisition time (cold start) were the main causes of lag. By combining low-power hardware with effective programming that makes use of the ESP32's deep- sleep mode during periods of inactivity, the measured battery life of 75 hours also surpassed the 72-hour design goal.

D. Discussion, Implications, and Limitations

The combined outcomes show that an integrated and proactive health monitoring system was successfully implemented. The system's accuracy in analytical capabilities and responsiveness in time-sensitive emergency situations are demonstrated by its low end-to-end latency, high AUROC for anomaly detection, and high F1-score for fall detection. By showcasing a coherent system that completes the loop from detection to intervention, our work effectively fills in the research gaps mentioned in the introduction. Even with sporadic network connectivity, on-device AI offers a workable solution that protects user privacy and guarantees operational dependability.

It is important to recognize that this study has a number of limitations, even with the encouraging outcomes. Initially, controlled environment simulated falls were used to vali- date the fall detection algorithm. The system may perform differently in unforeseen, real-world falls. Second, although functional, the form factor of the current prototype is not yet optimized for both long-term user comfort and visual appeal. Third, the system is not an approved medical device for diagnosis or treatment, and the sensors are consumer-grade. Lastly, the models might need additional validation across a more broad demographic, including older people with different comorbidities, as the datasets utilized for training and testing were gathered from a small number of healthy subjects [7], [10].

V. Conclusion and Future Work

The design, deployment, and assessment of a smart wear- able system for automatic emergency response and ongoing health monitoring were discussed in this work. A proactive solution that tackles significant shortcomings in current commercial and academic systems is offered by the system, which combines multi-modal sensing, on-device AI, and a cloud-based alerting framework. The system's ability to detect acute events, such as falls, and minor abnormalities in vital signs with high specificity and sensitivity is confirmed by the experimental results. Its practical usefulness is further demonstrated by the fact that it satisfies important non- functional requirements for low latency and long battery life. The demonstration of a comprehensive, end-to-end system that effectively connects passive health data gathering with active, life-saving action is the work's main contribution.

Future research will go in a number of encouraging ways. To evaluate the system's practical robustness, user acceptability, and clinical impact, a comprehensive, long-term clinical validation research including a broad group of senior citizens in their homes is the next urgent step. Technically speaking, we intend to investigate more sophisticated, multi-modal AI models that combine information from the PPG and IMU sensors. By identifying changes in gait stability, such models may make it possible to forecast pre-impact falls and move the system from reactive to preventive. Enhancing power efficiency will also be the focus of future research, which will look at energy-harvesting strategies and create secure APIs for optional interaction with Electronic Health Records (EHR) systems. Lastly, it will be essential to apply Explainable AI (XAI) principles to make the model's conclusions more clear in order to gain the trust of physicians and users and promote broader adoption of this life-saving technology.

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