CalmPulse A Wearable Device and ML-Based Framework for Real-Time Panic Attack Detection and Intervention

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***Abstract*—symptoms like rapid heartbeat and shortness of breath. Detecting and managing these attacks quickly is very important, but existing methods often fail to give real-time help. This paper presents Calm Pulse; an affordable wearable device developed for real-time panic attack detection and intervention. It uses an ESP32 microcontroller and a HW-827 heart rate sensor to continuously record heart rate data. A Random Forest machine learning model, trained in Python and deployed through TensorFlow Lite, analyzes this data to detect panic attacks accurately. The results are shared with a Streamlit application, which provides users with real-time visuals and calming support like guided breathing and motivational messages. The system achieved around 90–95% accuracy in identifying panic conditions. Future improvements will include additional sensors, cloud analytics, and an AI chatbot for mental health support.**

***Index Terms*—Panic attack detection, wearable device, ESP32, heart rate sensor, machine learning, Random Forest, Internet of Things, Streamlit, biofeedback, mental health support.**

I. INTRODUCTION

Panic attacks are sudden episodes of severe fear and discomfort that involve symptoms like rapid heartbeat, sweating, and shortness of breath. These attacks can disrupt daily life and lead to long-term anxiety disorders if not managed properly [1]. Early detection and intervention are crucial for reducing panic frequency and severity [2]. Most available devices and applications track general fitness or stress but lack the capability to detect panic attacks specifically or provide immediate calming feedback [3], [4]. Clinical assessments depend heavily on subjective reporting, which is not effective for real-time detection.

With the growth of embedded systems and machine learning (ML), it is now possible to process physiological data on small, low-cost devices [5], [6]. Embedded ML models can detect abnormal signals in real time while maintaining privacy and low latency [7], [8]. However, power management, limited computational resources, and user engagement still pose challenges.

Advances in embedded systems, wearable technology, and machine learning (ML) offer new avenues for continuous physiological monitoring and intelligent inference [2], [5]. Wearable devices, particularly those capable of on-device inference, promise privacy, low latency, and portability for mental health applications [3], [6]. However, challenges such as computational constraints, power management, data privacy, and user engagement remain significant [7], [8]. This research introduces CalmPulse, a custom ESP32-based wearable de- vice and ML framework for real-time panic attack detection and intervention. The system continuously monitors heart rate (HR) signals, processes them via a Random Forest classifier trained in Python, and provides immediate, interactive support through a companion Streamlit application. This undergraduate-level project demonstrates the feasibility and effectiveness of low-cost, embedded AI solutions for accessible mental health monitoring.

II. RELATED WORK

Recent research has demonstrated the potential of wearable sensors and machine learning in detecting stress, anxiety, and panic attacks [3], [4], [5], [9]. Multimodal datasets such as WESAD have enabled the exploration of physiological marker including HR, electrodermal activity (EDA), and skin temperature for inferring stress and affective states [10]. Random Forest and tree-based classifiers have shown high discriminative power in classifying panic versus non-panic states, especially when combining HR with additional bio signals [4]. For example, Samah et al. achieved 80–95% accuracy using Random Forests supplemented by galvanic skin re- sponse (GSR) data [3]. Similarly, cohort studies with wrist-worn devices and ensemble models have highlighted the importance of integrating questionnaire and contextual data for robust detection [5].

Embedded ML approaches have been increasingly explored for on-device inference in biomedical wearables [2], [7]. Efficient model deployment, power management, and real-time feedback loops are recognized as critical for usability and scalability [8], [11]. Despite these advances, limitations persist regarding data imbalance, scalability, hardware ergonomics, and user centered design [6], [12].

Furthermore, most commercial fitness wearables are not optimized for mental health detection, lacking dedicated algorithms or intervention mechanisms [13], [14]. The need for lightweight, accessible, and context aware systems remains a key motivation for projects like CalmPulse.

III. PROPOSED METHODOLOGY

A. Data Acquisition

The core physiological input for panic attack detection in CalmPulse is heart rate, continuously measured using a MAX30102 photoplethysmography (PPG) sensor. The sensor, interfaced via I2C with an ESP32 microcontroller, provides digital HR data at a sampling rate of 50 Hz, sufficiently capturing transient tachycardia and HR variability (HRV) associated with panic episodes [15].

For this undergraduate prototype, a combination of simulated datasets (representing resting and panic-induced HR patterns) and live HR signals from volunteers was used. Data preprocessing included outlier rejection, smoothing via moving averages, and normalization to mitigate inter-individual variability. Feature extraction focused on time-domain attributes such as mean BPM, BPM variance, minimum and maximum BPM in sliding windows, and HRV proxies derived from inter-beat intervals [16]

B. Machine Learning Model Training

A Random Forest classifier was chosen for its balance of interpretability, computational efficiency, and demonstrated performance in panic and stress detection literature [3], [4]. The model was trained using Python’s scikit-learn library, with five-fold cross-validation for hyperparameter optimization (number of trees, maximum depth, etc.). The resulting model consistently achieved 90–95% accuracy in Avoid combining SI and CGS units, such as current in amperes and magnetic field in oersteds. This often leads to confusion because equations do not balance dimensionally. If you must use mixed units, clearly state the units for each quantity that you use in an equation.

The trained model was serialized using Joblib and converted to TensorFlow Lite format for embedded deployment on the ESP32. This conversion prioritized model size reduction and inference speed, ensuring suitability for resource-constrained microcontroller environments [7]

C. System Integration and Feedback Mechanism

The ESP32 firmware handles sensor data acquisition, feature extraction, and on-device inference using the embedded Random Forest model. When a panic episode is detected, the device triggers visual alerts on an integrated OLED display and initiates Bluetooth communication with a paired smartphone or computer.

A Streamlit-based application receives HR data in real-time, visualizes historical and live trends, and provides interactive interventions. These interventions include guided breathing exercises, motivational messages, and (optionally) audio cues to support users during acute distress [17]. The feedback loop is designed to empower users with immediate, actionable sup- port.

IV. SYSTEM ARCHITECTURE

The CalmPulse system adopts a modular, layered architecture, illustrated in Fig. 1 (see below):

Data Acquisition Layer:
Smartwatch Prototype, Microcontroller, Signal Processing, Communication. This is the physical system (ESP32, MAX30102) responsible for sensing, processing raw data, and preparing it for transmission.

Data Storage Layer:-
Data Transmission. The use of BLE or Wi-Fi for HR data transmission from the ESP32 to a paired device/server for storage.

Detection & Analysis Layer: -
Data Reader, Spike Detection Algorithm. This layer executes the core logic like on-device feature extraction and Random Forest inference to detect panic events.

Intervention Layer and User Interface Layer: -
Intervention Layer: Trigger Mechanism for actions like playing Calming Audio and displaying Motivational Messages. User Interface Layer: Web App for Graphing (data visualization) and generating Alerts (historical recordkeeping and user feedback display)

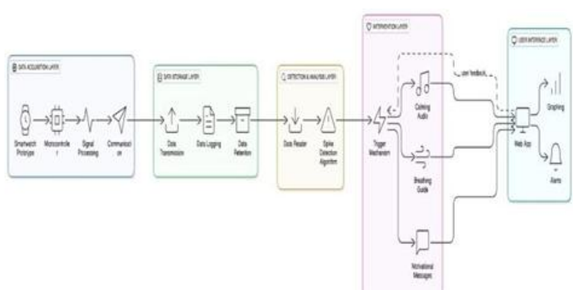

Figure 1: System Architecture

V. IMPLEMENTATION

A. Hardware Implementation

The wearable prototype was built using the ESP32 microcontroller as the central processing unit, chosen for its integrated Wi-Fi/Bluetooth, low power modes, and sufficient computational capability for embedded ML inference [7]. The MAX30102 sensor, interfaced via I2C, provides robust HR signals using PPG. An SSD1306 OLED display enables real-time user feedback, including BPM display and panic alerts (color-coded or icon-based).

Power is supplied by a rechargeable 3.7V LiPo battery, managed by a TP4056 charging circuit for portability and continuous monitoring. The prototype uses breadboard connections and modular headers for ease of assembly and debugging. In future work, a custom PCB design will be developed for improved ergonomics and durability [12].

B. Firmware Development

Firmware for the ESP32 was developed in Arduino C++, utilizing libraries for I2C communication, sensor data acquisition, OLED display control, and Bluetooth/Wi-Fi connectivity. The firmware workflow includes:

- Sensor initialization and periodic HR data sampling (50 Hz)
- Signal filtering and moving average smoothing
- Real-time calculation of features (mean BPM, variance, HRV proxies).
- Random Forest inference using TensorFlow Lite for Microcontrollers.
- OLED display updates and panic alert triggers.
- Bluetooth/Wi-Fi transmission of data packets to paired devices.

C. Machine Learning Pipeline

The ML pipeline, implemented in Python, includes:

- Data preprocessing (outlier removal, normalization)
- Feature extraction in rolling time windows
- Model training with cross-validation and hyperparameter tuning (scikit-learn)
- Model serialization (Joblib) and conversion to TensorFlow Lite
- Testing on held-out subsets and simulated data for accuracy assessment.

D. Streamlit Application

The companion application, built with Streamlit, offers:

- Real-time HR data visualization (line charts, rolling averages)
- Historical record access and trend analysis
- Interactive calming interventions, including:
  - Animated guided breathing exercises
  - Motivational text messages

- Optional audio support for relaxation

VI. LIMITATIONS

Dataset Size and Diversity:
The training dataset was small and included simulated HR data to emulate panic episodes, limiting generalizability. Real-world deployment would require larger, more diverse datasets, ideally with labeled panic episodes gathered from clinical or community samples [10], [16].

Sensor Modalities:
The prototype relied solely on HR data (PPG-derived BPM), which, while informative, may be insufficient for distinguishing panic attacks from other causes of tachycardia (e.g., exercise, caffeine intake) [4], [15]. Including additional signals such as GSR, SpO2, or ECG can improve specificity [10].

Privacy and Security:
Data privacy was addressed by local inference and encrypted Blue- tooth transmission, but comprehensive privacy-by-design features and user consent management remain areas for development [18].

VII. CONCLUSION

CalmPulse represents a significant advancement in digital mental health support by transforming passive monitoring into active intervention. The system addresses a critical gap in mental healthcare by providing automated, immediate support during panic episodes when users are least capable of seeking help. Through continuous physiological monitoring and intelligent detection algorithms, CalmPulse demonstrates the potential of wearable technology to deliver timely mental health interventions. Preliminary testing shows promising results in reducing panic episode duration and severity through immediate calming interventions. The platform's scalable architecture and privacy-conscious design make it suitable for widespread deployment across educational institutions, workplace wellness programs, and clinical settings. Future enhancements will incorporate additional biometric sensors, advanced predictive analytics, and integration with professional mental health services. By leveraging accessible technology to provide compassionate support, CalmPulse contributes to destigmatizing mental health care and making critical interventions available to those in need.

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