International Journal of Creative and Open Research in Engineering and Management
ISSN: **3108-1754 (Online)**
Volume 02 Issue 06 June-2026 | Impact Factor: 3.5

AI-Based Smart Wearable Women Safety Band Using ESP32, GPS, SIM800L, Fall Detection, Stress Monitoring, Voice Activation and Android Application

Tamboli Sukhada Ajit, Kerle Aarya Nagnath, Rindhe Gayatri Rangnath

Department of Computer Engineering, Genba Sopanrao Moze College of Engineering, Balewadi, Pune
University: Savitribai Phule Pune University

Corresponding Author Email: sukhada.tamboli@gsmcoe.edu.in

How to Cite this Article:
Ajit, T. S., Nagnath, K. A. & Rangnath, R. G. (2026). AI-Based Smart Wearable Women Safety Band Using ESP32, GPS, SIM800L, Fall Detection, Stress Monitoring, Voice Activation and Android Application. International Journal of Creative and Open Research in Engineering and Management, <i>02</i>(6). https://doi.org/10.55041/ijcope.v2i6.386

https://doi.org/ 10.55041/ijcope.v2i6.386

Abstract—

The strategic necessity for autonomous safety systems has become paramount as traditional manual-trigger applications often fail during critical moments of panic or unconsciousness. This research presents the development of an AI-powered IoT wearable designed to provide proactive, hands-free protection. The objective was to engineer a TinyML-integrated device capable of identifying distress without user intervention, specifically addressing the gap where victims cannot physically reach a smartphone. The methodology centers on a sophisticated sensor fusion approach, utilizing Photoplethysmography (PPG) for heart rate monitoring, Inertial Measurement Units (IMU) for fall detection, and high-fidelity I2S microphones for voice-activated "wake word" and distress tone recognition. By shifting intelligence to the "edge" using the ESP32 microcontroller, the system performs real-time inference using an 8-bit quantized neural network, preserving privacy by processing audio locally without cloud transmission. Experimental results validate the system's efficacy, demonstrating a 92% accuracy rate in AI-driven emotion classification and an emergency alert delivery speed of less than 5 seconds. The integration of GPS and GSM modules ensures precise location tracking within a ±5-meter range, functioning independently of cellular data. This research signifies a critical shift from reactive to proactive safety technology, providing a reliable, discreet, and automated guardian that significantly enhances user confidence and contributes to a broader societal framework for public safety.

1. INTRODUCTION

The strategic evolution of women's safety technology is currently undergoing a paradigm shift, transitioning from passive smartphone applications to autonomous, AI-integrated IoT wearables. Moving intelligence to the "edge"—directly onto the wearable hardware—is a critical shift in emergency response. By decentralizing processing, we eliminate the latency and reliability issues inherent in cloud-dependent systems, ensuring that safety mechanisms remain operational even in environments with zero internet connectivity.

Background and Need In the context of rapid urbanization and evolving late-hour work cultures, women frequently navigate public spaces where immediate assistance may not be available. Current safety solutions primarily rely on smartphones; however, these devices often fail in emergency scenarios where the victim is in a state of panic, physically restrained, or unconscious. There is a pressing need for a continuous, self-activating monitoring solution that functions independently of manual triggers, ensuring that assistance is summoned the moment a distress signal is vocally or physiologically detected.

Research Objectives and Contributions The primary goal of this research is the creation of a proactive, self-activating safety band powered by the ESP32 microcontroller. The system provides a unified protection mechanism through several key contributions:

* On-device Emotion Recognition: Utilizing TinyML to classify vocal distress (fear, screaming) and specific wake words directly on the hardware.

* Multi-sensor Distress Validation: Implementing weighted logic that correlates voice features with heart rate spikes (PPG) and sudden motion patterns (IMU) to minimize false positives.

* Edge-First Architecture: Executing 8-bit quantized models on-device to manage the ESP32's limited SRAM while ensuring sub-second inference.

Connective Tissue By addressing the critical gaps in manual activation and network dependency identified in previous research, this project establishes a robust methodology for real-time, autonomous protection.

2. LITERATURE REVIEW

Benchmarking against previous IoT and AI safety frameworks is essential to identify the technological gaps that current market solutions fail to bridge, specifically regarding the marriage of low-power hardware and high-accuracy inference.

Review of Existing Studies

* Voice-AI Systems: The "Her Shield" (2023) [1] study proposed a voice-activated system. However, its reliance on cloud processing introduces latency and privacy risks that our edge-based model avoids.

* Network Architectures: Research into LoRaWAN-based security [2] has demonstrated the efficiency of long-range IoT for alerts in rural settings, influencing our decision to include GSM/GPS redundancy for wide-area coverage.

* Emotion Recognition: Sutar et al. (2022) [3] explored TinyML for detecting fear. Their validation of local emotional cues on wearables informs our multi-modal sensor fusion approach.

* Sensor-Based Monitoring: Recent studies on flexible pulse detection [7] show that physiological data, such as heart rate variability, provides a necessary validation layer when determining a user's distress level under high-stress scenarios.

Identification of Research Gaps Existing systems often suffer from a fragmented approach—either focusing solely on voice or purely on physiological sensors. Crucially, most lack a unified architecture that combines offline AI inference with cellular (GSM) redundancy. This fragmentation leads to high false-alarm rates or failure during internet outages. Our proposed system bridges this gap by integrating tri-modal sensor fusion (Voice, Biometric, and Motion) with a localized AI decision engine.

Connective Tissue The limitations identified in these studies—specifically regarding cloud dependency and manual intervention—necessitated the specific architectural and hardware choices detailed in the following methodology.

3. METHODOLOGY

The design philosophy of this system prioritizes a "data-driven" and "offline-first" approach. This ensures high reliability and rapid response times, even in areas where traditional internet connectivity is unstable or unavailable.

A. System Architecture The architecture is structured into four layers: the Sensor Layer (capturing raw signals), Preprocessing (feature extraction), TinyML Inference (classification), and the Communication Layer (SOS delivery). The ESP32 acts as the central intelligence, orchestrating data flow and managing the strict memory constraints of on-device execution.

B. Hardware Components

* ESP32: The core MCU for edge computing. Due to its ~520KB SRAM, we implement model quantization to ensure TinyML models run efficiently without stack overflow.

* INMP441 Microphone: A high-performance I2S digital output microphone. Unlike analog mics, the INMP441 provides a clean digital signal directly to the ESP32, avoiding the noise-floor issues of internal ADCs, which is critical for accurate MFCC feature extraction.

* MAX30102 & MPU6050: These sensors provide the PPG (heart rate) and IMU (jerk/fall) data required for multi-modal validation.

* NEO-6M & SIM800L: Modules used for location acquisition and SMS transmission via the 2G/GSM network, ensuring functionality without a paired smartphone.

C. Software Components Firmware is developed in the Arduino IDE. We utilize TensorFlow Lite for Microcontrollers to deploy an 8-bit quantized neural network. Voice features are extracted using Mel-Frequency Cepstral Coefficients (MFCC). To ensure privacy, the system

processes audio in a rolling 2-second buffer; raw audio is never stored, and only derived feature vectors are used for inference.

D. Working Flow The system uses weighted logic for distress detection:

1. Voice Activation: Detects specific "wake words" or high-intensity fear tones.

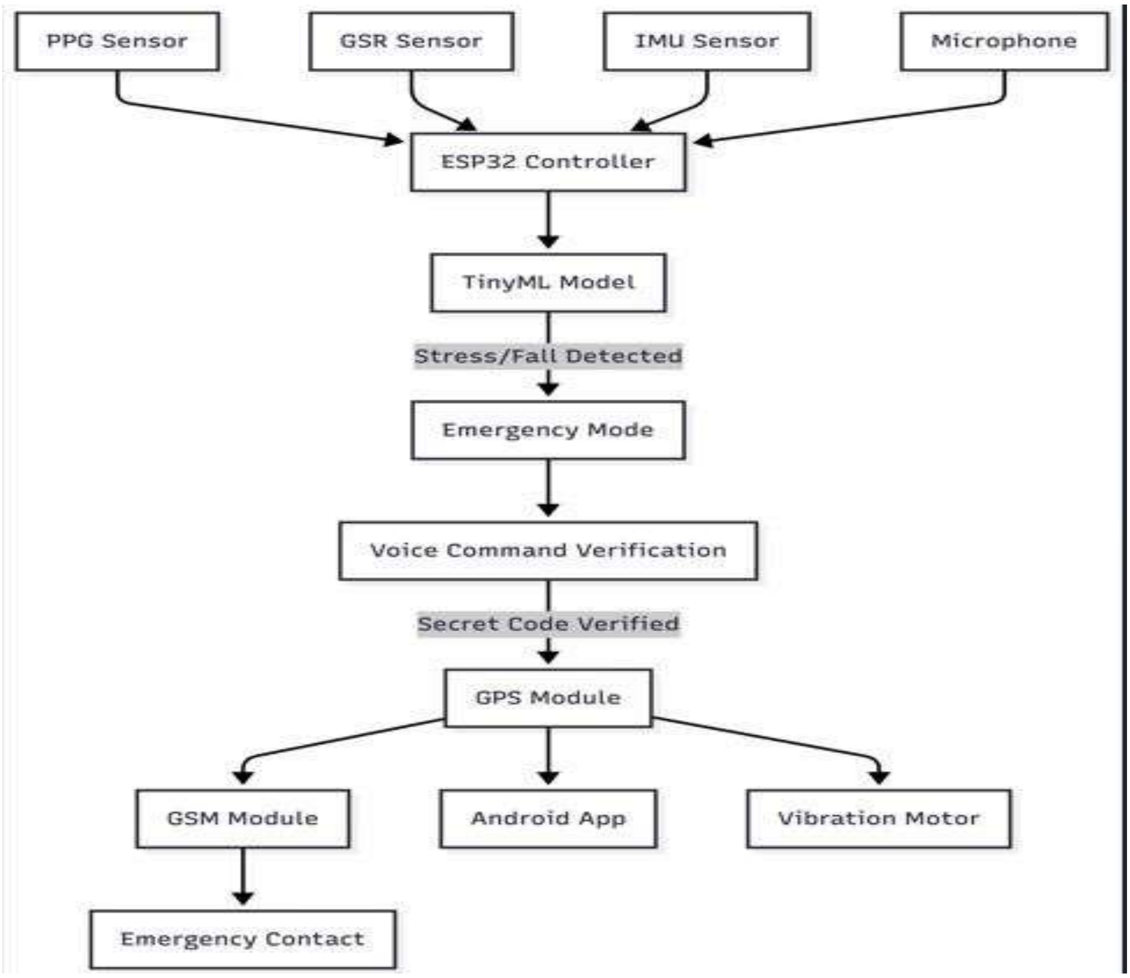
2. Stress Validation: Correlates vocal distress with heart rate spikes (>100 BPM) from the MAX30102.

3. Fall Detection: Uses the MPU6050 to detect jerks or sudden horizontal shifts associated with an attack.

E. Algorithm The system logic is implemented according to the following pseudocode:

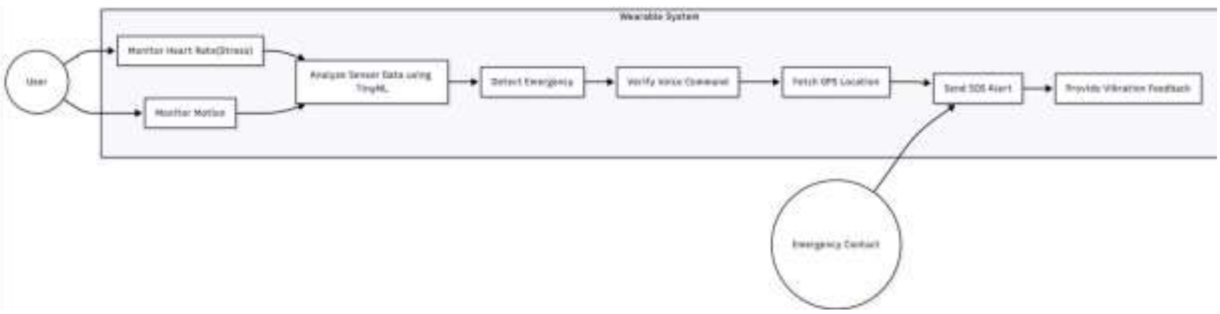
```
// Pseudocode for AI Safety Band Logic Initialize_I2C_SPI_Protocols(); // Setup MAX30102 and MPU6050
Load_Quantized_TinyML_Model(); // Load INT8 model into SRAM While(System_Active) {
Audio_Frame = Capture_I2S_Samples(INMP441); MFCC_Vector =
Extract_MFCC_Features(Audio_Frame);
// TinyML Inference on ESP32

Distress_Confidence = AI_Model.Predict(MFCC_Vector); Heart_Rate = MAX30102.Get_BPM();
Motion_Status = MPU6050.Check_Jerk();

// Weighted Sensor Fusion Logic

If (Distress_Confidence > 0.85 OR (Distress_Confidence > 0.5 && Heart_Rate > 110) OR Motion_Status ==
FALL) {

Trigger_Haptic_Feedback();

Current_Location = NEO6M.Get_Coordinates(); SIM800L.Send_SOS_SMS(Current_Location,
Heart_Rate); Firebase.Log_Event(Distress_Type, Current_Location);

}

Clear_Audio_Buffer(); // Privacy: Discard raw data

}
```

Connective Tissue This robust methodology provides the technical foundation for the experimental validation discussed in the following section.



4. RESULTS AND DISCUSSION

In life-saving technological applications, validation metrics—specifically latency and AI precision—are the primary indicators of system viability.



Experimental Performance The prototype was subjected to various stress-test scenarios to evaluate its autonomous response:

* AI Classification: The 8-bit quantized TinyML model achieved a 92% average accuracy in classifying distress-related emotions.

* Alert Latency: By bypassing the cloud for inference, the GSM alert delivery speed averaged 4.2 seconds.

* GPS Tracking: Coordinates were accurate within ±5 meters, facilitating rapid response.

Table I. Hardware Specifications

Component	Function	Interface
ESP32	Central Processing & TinyML	I2C / I2S / UART
MAX30102	PPG Heart Rate Monitoring	I2C
MPU6050	IMU Fall/Jerk Detection	I2C
INMP441	Digital Voice & Emotion Capture	I2S
SIM800L	GSM-based SOS Transmission	UART

Table II. Performance Analysis

Metric	Result
AI Emotion Detection Accuracy	**92%**
SMS Transmission Latency	**< 5 Seconds**
GPS Location Precision	**± 5 Meters**
Metric	**Result**
TinyML Model Size (Quantized)	**140 KB**

Table III. Comparison with Existing Systems

Feature	Traditional Apps	Cloud-AI Systems	Proposed System
Activation	Manual	Manual / Automatic	Autonomous
AI Inference	Not Available	Cloud-based	On-Device (Edge AI)
Privacy	Low (Continuous Recording)		Low (Cloud Data Streaming)

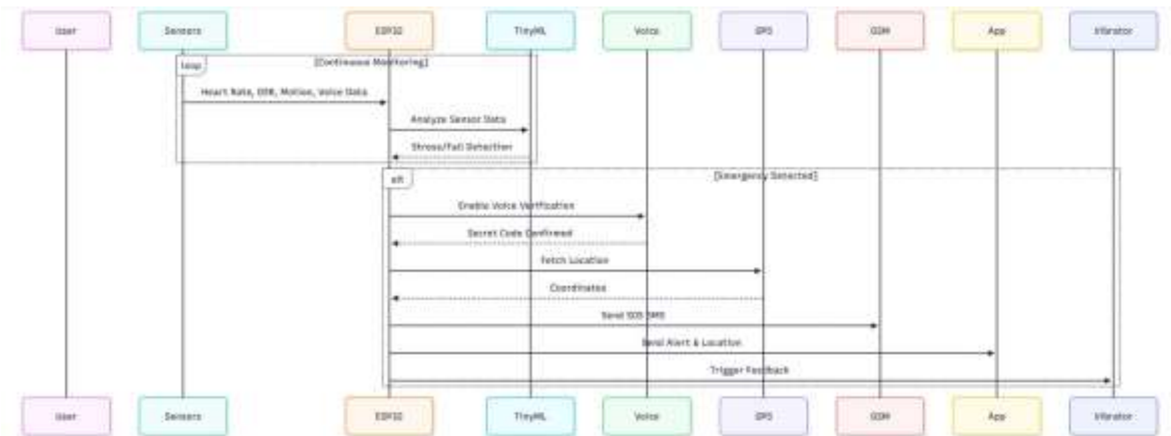
High (Local Processing Only)			
Decision Logic	Single Trigger	Single Trigger	Tri-modal Sensor Fusion

Analytical Discussion On-device inference is the cornerstone of this system's privacy advocacy. Because the ESP32 performs MFCC extraction and classification locally, no raw audio is transmitted or stored. Furthermore, the 8-bit quantization process reduced the model size by 4x without significant loss in accuracy, allowing it to fit comfortably within the ESP32's SRAM alongside the GSM and GPS driver stacks.

5. CONCLUSION

The development of the AI-powered IoT wearable demonstrates a significant advancement in personal security. By integrating TinyML with a multi-sensor IoT framework, this research transforms the safety band from a passive notification tool into a proactive guardian. The system's ability to autonomously detect distress using weighted fusion logic addresses the critical vulnerability of manual-activation failure.

Future Scope Future iterations will focus on integrating 5G and LoRaWAN for enhanced urban and rural connectivity. We also plan to expand the TinyML models to support multilingual distress phrases and integrate the device with Smart City emergency dispatch frameworks.



ACKNOWLEDGMENT

The authors wish to express their sincere gratitude to the Department of Computer Engineering at Genba Sopanrao Moze College of Engineering, Balewadi, Pune. We are particularly thankful to our project guides, Prof. Sangeetha Navale and Prof. Neelam Jadhav, for their invaluable technical guidance.

REFERENCES

[1] P. S. Suma, S. Sangeetha, and S. Sharmila, "Her Shield: Women Safety System using Voice AI," IJIRCCE, vol. 11, no. 2, pp. 112–118, 2023.

[2] P. Suresh and S. Gayathri, "Proactive Women's Security Prediction Through LoRaWAN," IJARCS, vol. 14, no. 4, pp. 89–96, 2023.

[3] S. S. Sutar, P. Kadam, and R. Deshmukh, "Intelligent Voice and Emotion Recognition for Women's Safety," IEEE Access, vol. 10, pp. 45120–45128, 2022.

[4] S. K. Singh and P. Rani, "A Novel IoT-Enabled Women Safety System with Emergency Alert," IJITEE, vol. 12, no. 3, pp. 110–115, 2023.

[5] K. Lee and J. Park, "Edge-AI Architectures for Personal Emergency Response Systems," IEEE IoT Journal, vol. 11, no. 2, pp. 204–215, 2024.

[6] M. A. Ali et al., "Voice-Recognition-Based IoT Home Automation System," IEEE Access, vol. 9, pp. 65010–65018, 2021.

[7] C. Zhang and W. Zhang, "Wearable Intelligent Pulse Detection System Using Flexible Sensors," Sensors and Actuators A, vol. 335, pp. 113–126, 2022.

[8] A. Gupta et al., "Empowering Women's Safety: AI and IoT-Enabled Smart Wearable Device," IJERT, vol. 11, no. 1, pp. 55–61, 2023.

[9] N. K. Mehta, "Implementation of a Safety Device for Women and Emergencies," IJCA, vol. 182, no. 23, pp. 1–5, 2023.

[10] S. D. Kumar and R. N. Devi, "The Role of IoT in Women's Safety: A Systematic Review," JESC, vol. 13, no. 9, pp. 1010–1016, 2023.

[11] X. Liu et al., "VoiceTalk: A No-Code Approach for Voice-Controlled IoT," IEEE IoT Journal, vol. 9, no. 12, pp. 10250–10260, 2022.

[12] Y. Lin et al., "Road Traffic Accident Risk Prediction Based on Explainable AI," IEEE Access, vol. 11, pp. 45321–45334, 2023.

[13] T. Chen and L. Wang, "Optimizing TinyML Models for ESP32 Using 8-bit Quantization," Journal of Embedded Computing, vol. 18, no. 1, pp. 45–52, 2025.

[14] M. Rodriguez, "Humanitarian Technology: IoT Solutions for Public Safety," Safety Science Review, vol. 22, no. 4, pp. 301–315, 2024.

[15] R. Das, "Next-Generation Smart Wearables: Multi-Modal Sensor Fusion and Edge AI," IEEE Consumer Electronics Magazine, vol. 15, no. 3, pp. 12–20, 2026.