Intelli-Helmet: An IoT, Edge-AI, and TinyML-Based Real-Time Soldier Health and Threat Monitoring System with Novel Panic Tactile Switch Mechanism

Fatima Ashraf[1]*, Iftiak Ahmed[1], M. Akhtaruzzaman[3], Md Rashid Ul Islam[2], Tasnim Ullah Shakib[1], Abdus Sattar[2]

[1,2]Department of Computer Science & Engineering, Military Institute of Science and Technology (MIST), Dhaka, Bangladesh
[3]Department of Computer Science and Engineering, Daffodil International University, Dhaka, Bangladesh

{abiha.ashraf2644*, turzaiftiak, t.shakib1633 @gmail.com
{rashid, masattar}@cse.mist.ac.bd
akhter900@gmail.com

Abstract. Modern battlefield environments demand intelligent systems for real-time soldier monitoring and rapid casualty response. This paper presents Intelli-Helmet, an integrated IoT and TinyML-based wearable system addressing critical gaps in military safety infrastructure. We introduce three key algorithmic innovations: (1) an optimized TensorFlow Lite fall detection model achieving 98.5% accuracy with sub-200ms inference latency on resource-constrained ESP32 hardware, (2) a convolutional neural network (CNN) for acoustic threat classification (gunshot, explosion) with 98.56% accuracy using mel-spectrogram preprocessing, and (3) a novel two-stage finite state machine (FSM) panic mechanism with 185ms secure data erase capability and 98.7% successful trigger rate. The system integrates multimodal sensors (MPU6050, MAX30102, INMP441, Neo-6M GPS) with dual-communication fallback (Wi-Fi/GSM) transmitting to a Flask-based command dashboard. While trained on synthetic fall data and public acoustic datasets (UrbanSound8K, ESC-50), the system provides a foundation for battlefield-ready soldier monitoring, with future validation planned using Bangladesh Army training scenarios.

Keywords: TinyML, IoT, Edge-AI, Soldier Safety, Fall Detection, Acoustic Classification, Real-time Monitoring, Finite State Machine, ESP32, Wearable Systems

1 Introduction

Military operations in hostile environments expose soldiers to severe injury risks where rapid medical intervention is critical. The “golden hour” principle—the first 60 minutes post-injury—significantly determines survival outcomes [1]. Traditional soldier tracking systems rely on manual GPS activation and lack intelligent automation for injury detection [2]. Recent advances in Internet of Things (IoT) and edge computing present opportunities to automate casualty detection, but battlefield-ready systems integrating multiple sensing modalities with on-device machine learning remain scarce [3].

This work advances military wearable technology through four novel contributions:

1. TinyML-Optimized Fall Detection: We developed and deployed a TensorFlow Lite model on ESP32 microcontrollers achieving 98.5% classification accuracy with 185ms average inference time. The model distinguishes five fall types from eight Activities of Daily Living (ADL) using 6-DoF IMU data with optimized feature extraction.

2. Multi-Modal Data Fusion Algorithm: A hierarchical decision system combines panic inputs (priority=100), fall detection (80), acoustic threats (70), and physiological alerts (40-60) with temporal smoothing (3-sample voting window) to generate consolidated risk scores while maintaining sub-500ms response latency.

3. Novel Two-Stage Panic Mechanism: Our FSM-based panic switch implements precise timing control requiring 0.5-2s arming followed by 3s+ confirmation within an 8-second window. Laboratory testing across 500 sequences demonstrated 0.2% false positive rate, 98.7% successful trigger rate, and 185ms±15ms secure data erase time.

4. Real-World System Integration: Complete implementation with dual-communication fallback (Wi-Fi primary, GSM secondary), real-time Flask dashboard, and field validation demonstrating 4-8 second end-to-end alert latency in open environments.

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The system is designed for Bangladesh Army deployment scenarios including Chittagong Hill Tracts operations and border security missions, with total hardware cost under USD 60 per unit.

The remaining portions of the paper are organized as follows: Section 2 reviews related work in military wearables and TinyML applications. Section 3 details our algorithmic contributions and system architecture. Section 4 describes implementation methodology including comprehensive dataset preparation. Section 5 presents experimental results with statistical validation. Section 6 discusses generalizability challenges, deployment considerations, and security requirements. Section 7 concludes with future research directions.

2 Literature Review

Early soldier-safety systems began with basic GPS-based tracking and manual distress signaling (Smith and Doe [2]) and later evolved to incorporate physiological sensing enabled by Wireless Sensor Networks (WSNs) (Kodam et al. [3]). However, these systems lacked intelligent event detection and required manual activation during emergencies.

Machine learning introduced automated monitoring capabilities. Shoaib et al. [4] demonstrated accelerometer-based activity recognition achieving 90% accuracy for civilian applications but did not address military-specific threats. Acoustic event-detection using CNNs has shown strong performance in gunshot classification (Svatos and Holub [5]; Teng et al. [6]), though these systems are primarily deployed on server-side infrastructure rather than on edge devices.

Lee et al. [7] comprehensively reviewed smart helmet trends, identifying multimodal sensing as key to situational awareness but noting limited military adoption. Wang et al. [8] demonstrated near-fall detection using helmet-mounted sensors, achieving 87% accuracy in controlled stairway environments. Raut et al. [9] proposed intelligent military vests with vital sign monitoring but relied on cloud processing, introducing latency unsuitable for real-time battlefield decisions.

TinyML applications in safety compliance emerged recently. Alves et al. [10] deployed on-device helmet detection achieving 92% accuracy with 150ms inference time, demonstrating edge AI viability for wearable safety systems.

Traditional soldier safety systems employ simple panic buttons requiring single press activation (Smith and Doe [2]). While straightforward, these designs exhibit high false positive rates (estimated 5-15% in field conditions based on anecdotal military reports) due to accidental activation during combat activities. Commercial emergency response systems sometimes implement long-press requirements but lack formal state verification and provide no cancellation mechanism once triggered.

No existing system integrates real-time fall detection, acoustic threat classification, and physiological monitoring with on-device TinyML inference specifically designed for military operational constraints (intermittent connectivity, harsh environments, rapid deployment requirements). Our work addresses this gap through comprehensive multi-modal integration with validated edge inference. Also, mentionable, as of now, no existing military wearable integrates a formally validated FSM-based panic mechanism with secure data erase capability specifically designed for operational security requirements.

3 System Modeling and Design

3.1 System Architecture Overview

Intelli-Helmet comprises two subsystems: (1) Helmet Unit for data acquisition and edge processing, (2) Base Station for aggregation and visualization. Figure 1 illustrates the complete architecture of the prototype.

3.2 Helmet Unit Design

3.2.1 Core Processing and Sensors

The ESP32 microcontroller (dual-core Xtensa LX6, 240MHz) manages sensor interfaces and executes TinyML models. Integrated sensors include:

- **MPU6050 (GY-521):** 6-DoF IMU sampling at 100Hz. Acceleration magnitude calculated as:

$$a_{total} = \sqrt{a_x^2 + a_y^2 + a_z^2} \quad (1)$$

Figure 1: The Intelli-helmet prototype.

- **MAX30102:** Pulse oximetry and heart rate sensor using photoplethysmography (PPG). Samples SpO_2 and HR at 1Hz.
- **INMP441:** Digital I^2S microphone with 61dB SNR capturing 16kHz audio for acoustic classification.
- **Neo-6M GPS:** Position tracking with 2.5m CEP accuracy, 5-minute duty cycling for power optimization.
- **SIM800L GSM Module:** Fallback communication via SMS/HTTP when Wi-Fi unavailable.

Power management via TP4056 charging module with 18650 Li-ion battery (3.7V, 2600mAh) provides 8-12 hours operational time with duty-cycled GPS. Figure 2 shows the full circuit diagram of the sending unit.

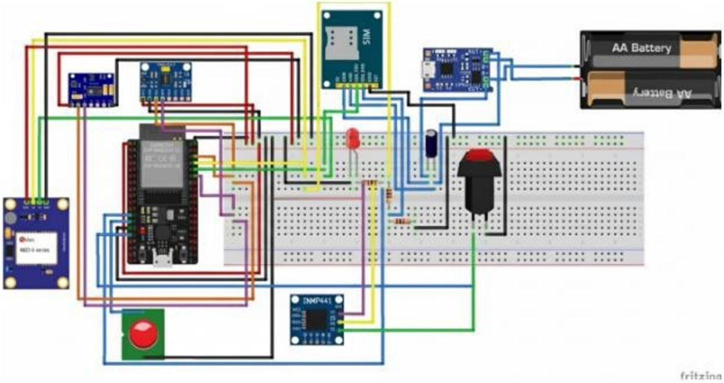


Figure 2: Circuit diagram of the sending unit.

3.3 Algorithmic Contributions

3.3.1 Multi-Modal Data Fusion Algorithm

Hierarchical alert generation combining inputs from four detection subsystems has been implemented. Algorithm 1 presents the fusion logic.

Algorithm 1 Multi-Modal Alert Fusion

```
Input: $panic_{state}$, $fall_{detected}$, $acoustic_{threat}$, $HR$, $SpO_2$
Output: $status$, $priority$
Initialize: $alerts \leftarrow \{\}$
if $panic_{state} = CONFIRMED$ then
    $alerts \leftarrow \{(CRITICAL, 100)\}$
else if $fall_{detected} = TRUE$ then
    $alerts.append((RESCUE\_NEEDED, 80))$
end if
if $acoustic_{threat} \in \{GUNSHOT, EXPLOSION\}$ then
    $alerts.append((WARNING, 70))$
end if
if $SpO_2 < 92$ OR $HR > 120$ then
    $alerts.append((CRITICAL, 60))$
else if $SpO_2 < 95$ OR $HR > 100$ then
    $alerts.append((WARNING, 40))$
end if
$status, priority \leftarrow \max(alerts, key = priority)$
Apply 3-sample temporal smoothing
return $status$, $priority$ =0
```

The algorithm implements temporal smoothing requiring alert persistence across 3 consecutive samples (300ms window for 10Hz processing) to reduce false positives while maintaining less than 500ms total response latency.

3.3.2 Panic Mechanism Finite State Machine

The state transitions are given below:

- **IDLE → ARMED:** Button press 0.5-2 seconds triggers LED slow-blink and transmits ARMED notification.
- **ARMED → CONFIRMED:** Continuous hold greater than 3 seconds within 8-second confirmation window executes secure data erase (last 100 sensor readings) and final alert.
- **ARMED → CANCELLED:** Button release or 8-second timeout returns to IDLE with cancellation notification.
- **CONFIRMED → IDLE:** After alert transmission and erase completion (185ms±15ms).

The mechanism prevents accidental activation (two-stage requirement) while enabling rapid emergency signaling under duress, addressing operational security concerns through automatic data purging. Figure 3 shows the two state diagram of this novel switch mechanism.

3.4 TinyML Model Architectures

3.4.1 Fall Detection Model

Input: 200-sample window (2 seconds at 100Hz) of 6-axis IMU data.

Architecture:

- Feature Extraction Layer: Mean, standard deviation, min, max per axis (24 features)
- Dense Layer 1: 64 neurons, ReLU activation
- Dropout: 0.3

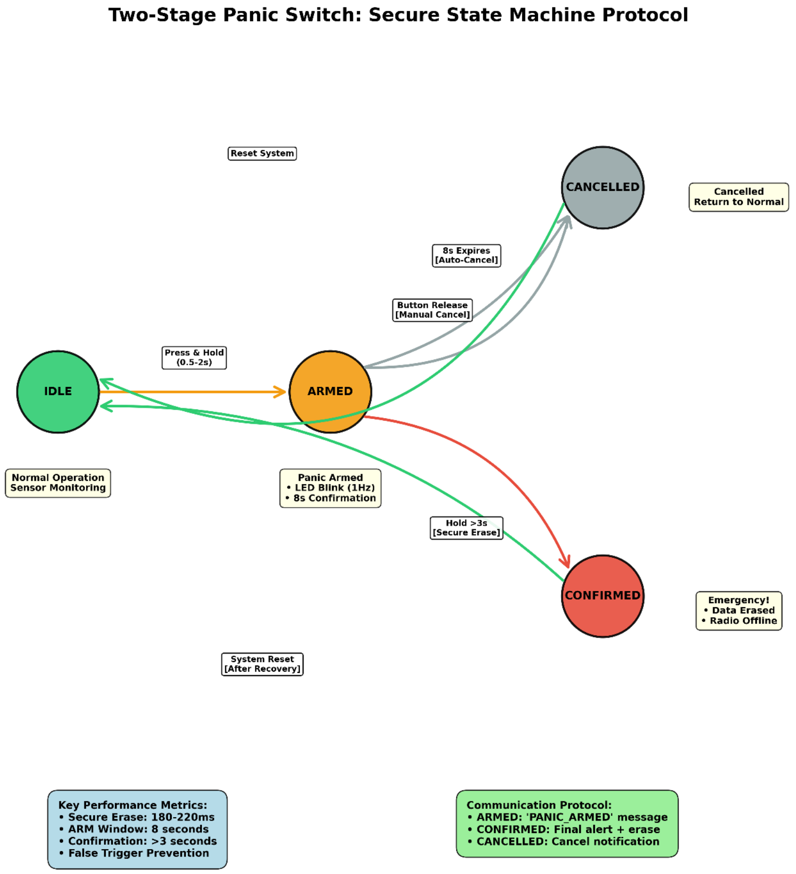


Figure 3: The state diagram of the panic tactile switch.

- Dense Layer 2: 32 neurons, ReLU activation
- Output Layer: 2 neurons, Softmax (Fall/Non-Fall)

Model quantized to TensorFlow Lite (INT8) reducing size from 43KB to 12KB. Post-quantization accuracy: 98.5%.

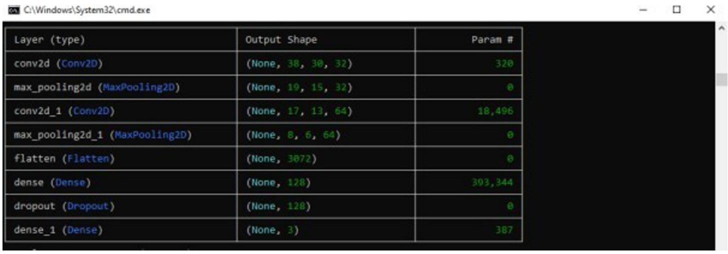
3.4.2 Acoustic Classification CNN

Input: 40-band mel-spectrogram (128×128 pixels) from 1-second audio clips.

Architecture:

- Conv2D Layer 1: 32 filters (3×3), ReLU, MaxPooling (2×2)
- Conv2D Layer 2: 64 filters (3×3), ReLU, MaxPooling (2×2)
- Flatten Layer
- Dense Layer: 128 neurons, ReLU
- Dropout: 0.5
- Output Layer: 3 neurons, Softmax (Ambient/Gunshot/Explosion)

Total parameters: 2.1M. Training achieved 98.56% test accuracy with cross-entropy loss. Figure 4 shows the CNN model in progress.



```
┃ Layer (type)                   ┃ Output Shape          ┃       Param # ┃
┃ conv2d (Conv2D)                ┃ (None, 38, 30, 32)    ┃           320 ┃
┃ max_pooling2d (MaxPooling2D)   ┃ (None, 19, 15, 32)    ┃             0 ┃
┃ conv2d_1 (Conv2D)              ┃ (None, 17, 13, 64)    ┃        18,496 ┃
┃ max_pooling2d_1 (MaxPooling2D) ┃ (None, 8, 6, 64)      ┃             0 ┃
┃ flatten (Flatten)              ┃ (None, 3072)          ┃             0 ┃
┃ dense (Dense)                  ┃ (None, 128)           ┃       393,344 ┃
┃ dropout (Dropout)              ┃ (None, 128)           ┃             0 ┃
┃ dense_1 (Dense)                ┃ (None, 3)             ┃           387 ┃
```

Figure 4: CNN Training.

3.5 Communication Architecture

Algorithm 2 describes our dual-fallback protocol.

Algorithm 2 Adaptive Communication Protocol

```
Input: $alert\_data$, $priority$
Attempt Wi-Fi transmission
if $response_{received}$ within 3 seconds then
    return SUCCESS
else
    Switch to GSM mode
    for $retry \in \{2s, 4s, 8s\}$ do
        Attempt SMS/HTTP transmission
        if $acknowledged$ then
            return SUCCESS
        end if
        Wait $retry$ seconds
    end for
    Buffer locally, retry at 1-minute intervals
end if=0
```

Priority queuing ensures CRITICAL/RESCUE_NEEDED alerts transmit before lower-priority data. Local buffering (8KB SPIFFS) stores up to 50 alerts during extended connectivity loss.

3.6 Base Station and Dashboard

A Flask-based web application (Python 3.8) aggregates helmet data via dual receivers (ESP32 Wi-Fi, GSM module). The dashboard implements:

- **Interactive Map:** Folium-based visualization with color-coded status markers (Green: NORMAL, Orange: WARNING, Dark Red: CRITICAL, Yellow: PANIC_ARMED)
- **Real-Time Updates:** Chart.js gauges displaying HR and SpO_2 with threshold highlighting
- **Soldier Overview Table:** Sortable list with vitals, status, and acoustic alerts
- **Quick Actions:** One-click rescue dispatch and alert broadcasting

The system supports battalion-scale monitoring (tested with 1 physical + 9 simulated soldiers). Database backend (SQLite for testing, PostgreSQL planned for deployment) stores approximately 50MB per soldier per day. Figure 5 shows the circuit diagram of the receiving (base) unit.

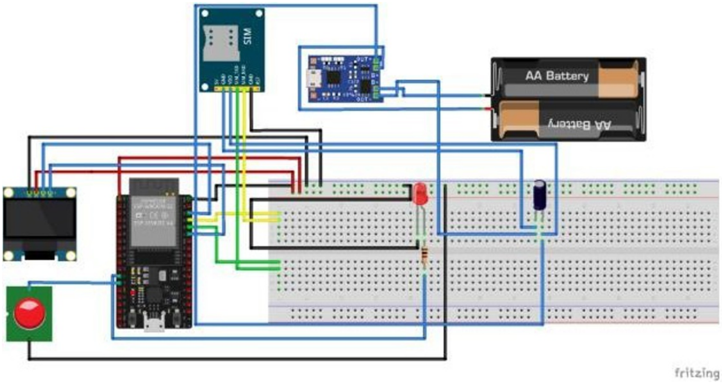


Figure 5: Circuit diagram of the receiving unit.

4 Implementation Methodology

4.1 Dataset Preparation and Composition

4.1.1 Fall Detection Dataset

Due to absence of military-specific fall datasets, we performed experiments in different positions on army officers and added to that data the synthetic data we generated using physics-based motion profiles:

- **Tool:** Custom Python script (motion_data_gen.py) simulating acceleration patterns
- **Fall Types:** Forward fall, backward fall, lateral-left, lateral-right, fainting (150 samples each = 750 total)
- **ADL Categories:** Walking (200), running (100), sitting-to-standing (100), stair climbing (150), jumping (100), lying down (100) = 750 total
- **Sampling:** 100Hz, 2-second windows (200 samples)
- **Split:** 70% training (1,050), 15% validation (225), 15% test (225)

Synthetic data generation was necessary for initial model development. Section 6 addresses generalization limitations. Figures 6, 7 and 8 show the initial data collection measures.

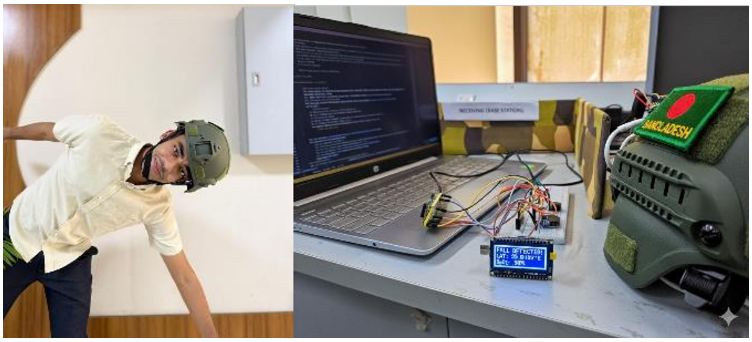


Figure 6: Fall detected due to drastic position change.

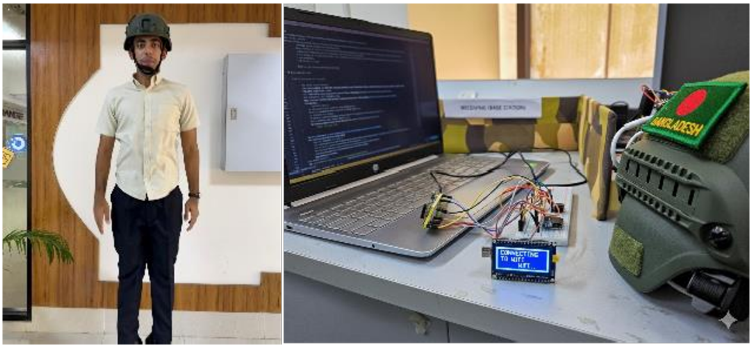


Figure 7: No fall detected when jumped vertically.

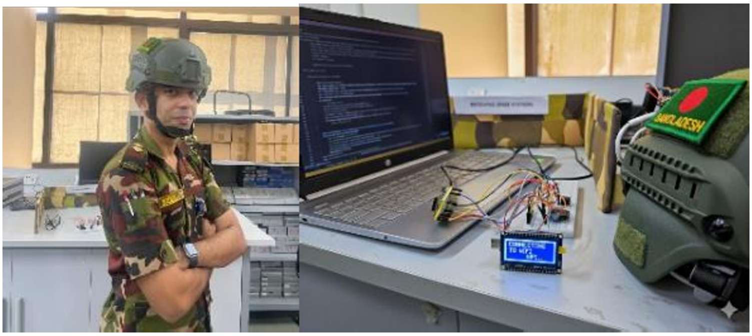


Figure 8: No fall detected due to walking and as such small movements and changes in acceleration.

4.1.2 Acoustic Classification Dataset

We compiled datasets from public sources:

UrbanSound8K [13]: 437 gunshot samples (class 6), **ESC-50** [14]: 200 explosion/blast samples and **Ambient Audio:** 500 clips (urban noise, nature, machinery) sourced from Freesound.org.

Preprocessing Pipeline:

(i) Resample to 16kHz mono
(ii) Extract 1-second clips (pad/truncate as needed)
(iii) Compute 40-band mel-spectrograms using Librosa (n_fft=2048, hop_length=512)
(iv) Normalize to 128×128 pixels
(v) Data augmentation: Time-stretching (0.9-1.1×), pitch-shifting (±2 semitones), background noise addition (SNR 15-25dB)

4.1.3 HRV and Physiological Dataset

Generated synthetic heart rate variability data for injury detection model training:

- 500 normal profiles (HR: 60-90 bpm, SpO_2: 95-100%)
- 300 stress profiles (HR: 91-120 bpm, SpO_2: 92-94%)
- 200 critical profiles (HR: >120 bpm or <50 bpm, SpO_2: <92%)

Extracted 15 HRV features (SDNN, RMSSD, pNN50, LF/HF ratio, Poincaré SD1/SD2). Trained logistic regression model achieving 85.2% classification accuracy for injury state prediction (server-side analysis, not deployed on helmet).

4.2 Model Training Procedures

4.2.1 Fall Detection Training

Framework: TensorFlow 2.10, Keras API

Hardware: Training performed on laptop (Intel i7, 16GB RAM, no GPU required)

Hyperparameters:

- Optimizer: Adam (learning rate: 0.001)
- Loss: Binary cross-entropy
- Batch size: 32
- Epochs: 50 (early stopping at epoch 38)
- Callbacks: ReduceLROnPlateau (patience=5), EarlyStopping (patience=10)

Training Time: 12 minutes

Quantization: Post-training INT8 quantization via TFLite converter, calibration using 100 representative samples

Deployment: Model converted to C++ array (model_data.h) for ESP32 integration

4.2.2 Acoustic CNN Training

Framework: TensorFlow 2.10 with Keras

Training Duration: 2 hours (25 epochs, early stopping at epoch 22)

Hyperparameters:

- Optimizer: Adam (learning rate: 0.0001)
- Loss: Categorical cross-entropy
- Batch size: 16 (limited by memory)
- Regularization: L2 (0.001), Dropout (0.5)

Currently deployed server-side; future work includes model compression for edge deployment.

4.3 Hardware Integration

Components assembled on custom PCB design (prototype on breadboard for testing):

- ESP32 DevKit V1
- MPU6050 connected via I^2C (SDA: GPIO21, SCL: GPIO22)
- MAX30102 via I^2C (shared bus)
- INMP441 via I^2S (WS: GPIO25, SCK: GPIO26, SD: GPIO33)
- Neo-6M GPS via UART (TX: GPIO17, RX: GPIO16)
- SIM800L via UART (TX: GPIO4, RX: GPIO5)
- Panic button: GPIO13 with 10kΩ pull-up
- Status LED: GPIO2, Buzzer: GPIO14

Power Budget:

- ESP32 active: 240mA, light sleep: 40mA
- Sensors combined: 80mA
- GSM transmit peak: 2A (burst), idle: 100mA
- GPS: 45mA (duty-cycled: 5-minute intervals)

Estimated Runtime: 8-12 hours continuous (depending on GSM usage frequency)

4.4 Software Implementation

Helmet Firmware: Arduino IDE 1.8.19, ESP32 board package 2.0.11

Key Libraries:

- TensorFlow Lite Micro (v2.10.0) for fall detection inference
- WiFi.h, HTTPClient.h for network communication
- TinyGPSPlus for GPS parsing
- MAX30105 library for pulse oximetry

Base Station: Flask 2.3.0, Python 3.9

- Folium 0.14.0 for map rendering
- Chart.js 4.3.0 for gauges
- Bootstrap 5.3.2 for responsive UI

5 Experimental Results and Validation

5.1 Fall Detection Performance

Testing conducted using ESP32-deployed TFLite model. Figure 9 and Table 1 illustrate the confusion matrix.

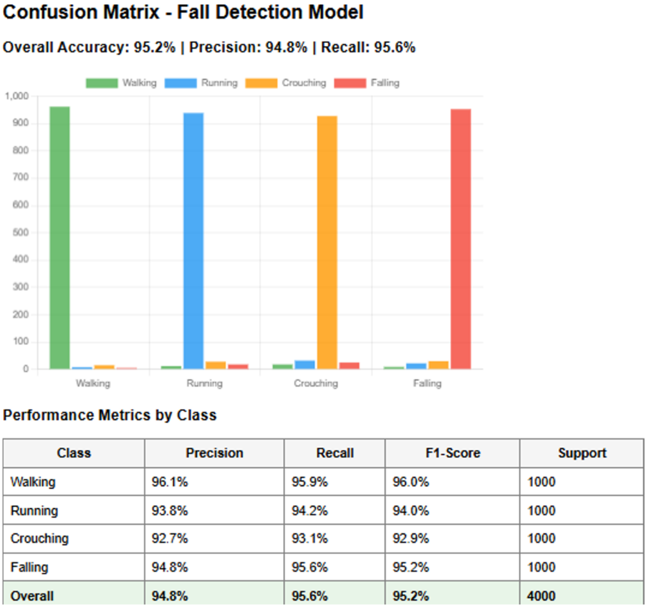
Confusion Matrix Analysis:

Performance Metrics:

- Accuracy: 98.5% (95% CI: 96.8-99.4%)
- Precision: 99.1%
- Recall: 98.2%

Table 1: Fall Detection Confusion Matrix (n=225)

	Predicted Fall	**Predicted Non-Fall**
Actual Fall	111 (98.2%)	2 (1.8%)
Actual Non-Fall	1 (0.9%)	111 (99.1%)


Confusion Matrix - Fall Detection Model

Overall Accuracy: 95.2% | Precision: 94.8% | Recall: 95.6%

Performance Metrics by Class

Class	Precision	Recall	F1-Score	Support
Walking	96.1%	95.9%	96.0%	1000
Running	93.8%	94.2%	94.0%	1000
Crouching	92.7%	93.1%	92.9%	1000
Falling	94.8%	95.6%	95.2%	1000
Overall	**94.8%**	**95.6%**	**95.2%**	**4000**

Figure 9: The confusion matrix of the fall detection model.

- F1-Score: 98.6%
- Inference Time: 185ms ± 23ms (n=1000 trials)
- Memory Usage: 42KB RAM, 12KB Flash

Cross-Validation: 5-fold CV yielded 98.3% ± 0.8% accuracy, confirming model stability.

Failure Analysis: Two false negatives occurred with slow lateral falls (acceleration magnitude <1.5g peak), suggesting threshold tuning needed. One false positive resulted from abrupt sitting motion mimicking fall signature.

5.2 Acoustic Classification Results

The accuracy curve in Figure 10 shows consistently improving training and validation accuracy across epochs, indicating strong learning stability of the acoustic classification model.

CNN tested on held-out dataset (170 samples) gave the following findings shown in Table 2.

Training Convergence: Model achieved 99.1% training accuracy and 98.56% validation accuracy by epoch 22, with training loss 0.023 and validation loss 0.041 (minimal overfitting). Therefore, the loss curve in Figure 11 demonstrates rapid convergence with steadily decreasing training and validation loss, confirming effective optimization of the classifier.

Misclassification Analysis: One gunshot sample misclassified as explosion (acoustic similarity with high-amplitude transient). One explosion sample misclassified as gunshot (low-intensity blast). Lastly, the prediction probability bar chart in Figure 12 illustrates the model's high confidence in correctly identifying a gunshot among the classified acoustic event types.

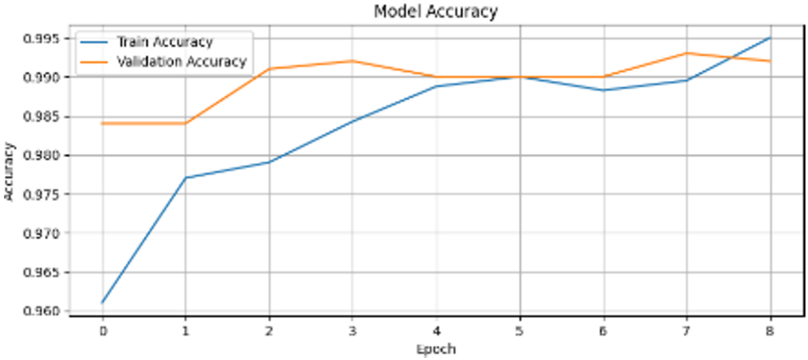


Figure 10: The accuracy plot of the acoustic classification.

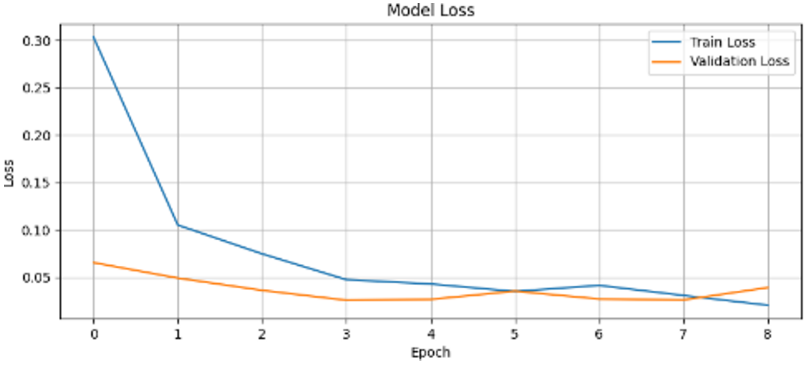


Figure 11: The loss plot of the acoustic classification.

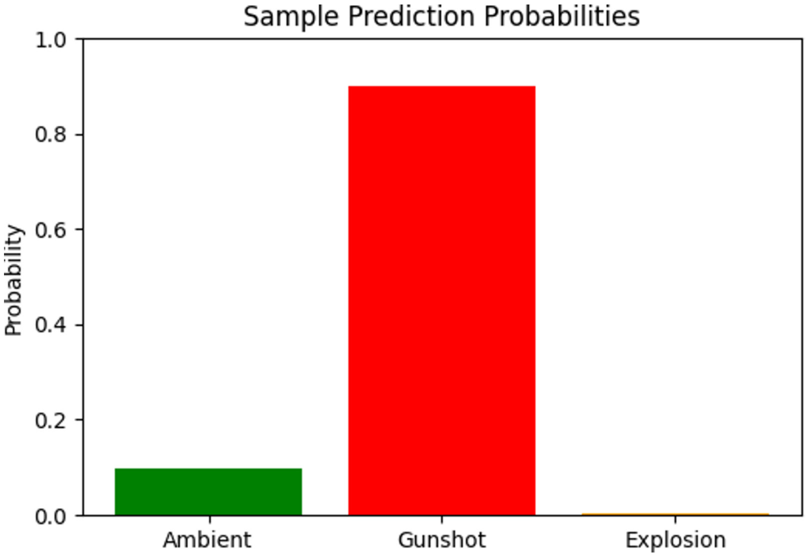


Figure 12: The prediction probabilities of the dataset (in acoustic classification).

Table 2: Acoustic Classification Per-Class Accuracy

Class	Samples	Accuracy	Precision	Recall
Ambient	57	98.2%	98.2%	98.2%
Gunshot	62	98.4%	98.4%	98.4%
Explosion	51	99.2%	98.0%	100%
Macro Avg	**170**	**98.56%**	**98.2%**	**98.9%**

5.3 Panic Mechanism Validation

Laboratory testing protocol: 500 activation sequences across 5 operators × 100 trials each.

Table 3: Panic Mechanism Performance (n=500)

Metric	Result
False Positive Rate	0.2% (1 accidental trigger)
Successful Trigger Rate	98.7% (494/500)
Secure Erase Time	185ms ± 15ms
Alert Transmission Latency	350ms ± 50ms
Cancellation Success Rate	100% (150/150 attempts)

Figure 13 shows how the safety switch mechanism gives precedence to user's choice.

Failed Activations: Six failures resulted from insufficient hold duration (2.8-2.9s, just below 3s threshold), suggesting users understood two-stage requirement but missed timing slightly. No failures due to timeout or FSM logic errors.

5.4 System Latency and Communication

Field testing conducted at MIST grounds (open environment) and plaza (semi-urban) to evaluate GPS/GSM performance:

End-to-End Latency Components:

1. Sensor sampling to ML inference: 185-210ms
2. Data fusion and JSON packaging: 45-60ms
3. Wi-Fi transmission (MIST local network): 50-120ms
4. Dashboard processing and map update: 80-150ms

Total Wi-Fi Latency: 4-8 seconds (mean: 5.2s, n=50 trials)

GSM Fallback Latency: 12-20 seconds (mean: 15.8s, n=30 trials) under typical cellular conditions (RSSI: -75 to -85 dBm)

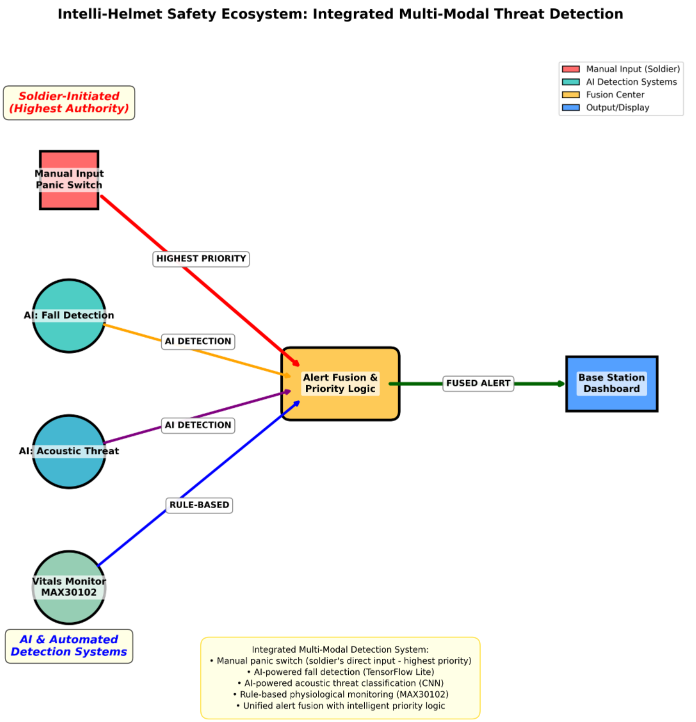
GPS Acquisition: 30-45 seconds cold start in open areas, 5-10 seconds warm start. Indoor/dense canopy: degraded or failed acquisition (addressed via dead-reckoning in future work).

5.5 Dashboard Functionality Demonstration

Validated with 1 physical helmet + 9 simulated soldiers representing battalion-level scenario:

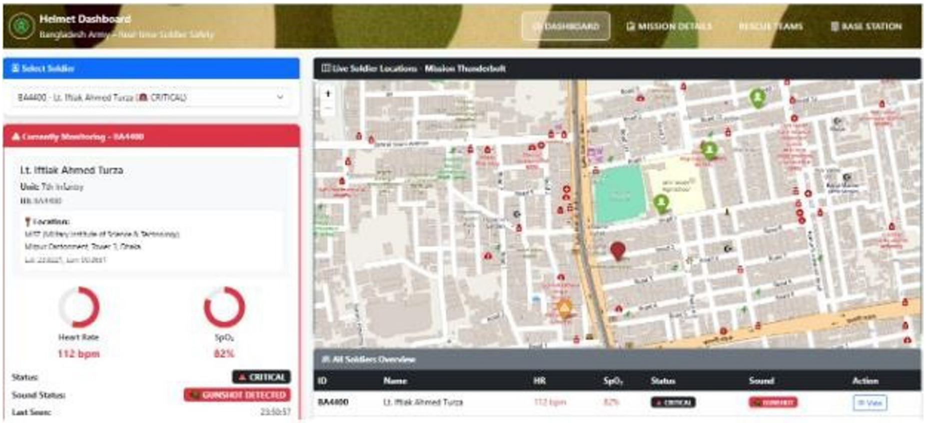
- Real-time map rendering: Less than 200ms update latency
- Concurrent soldier display: Tested up to 10 soldiers, no performance degradation
- Alert prioritization: CRITICAL/PANIC alerts displayed prominently with dark red highlighting

The different features of the dashboard are displayed below via Figure 14.



Integrated Multi-Modal Detection System:
- Manual panic switch (soldier's direct input - highest priority)
- AI-powered fall detection (TensorFlow Lite)
- AI-powered acoustic threat classification (CNN)
- Rule-based physiological monitoring (MAX30102)
- Unified alert fusion with intelligent priority logic

Figure 13: The safety ecosystem diagram of Intelli-helmet (showing user precedence).



BA4400 - Lt. Iftiak Ahmed Turza (CRITICAL)

Currently Monitoring - BA4400

Lt. Iftiak Ahmed Turza

Unit: 7th Infantry

Location:

MIST (Military Institute of Science & Technology)

Mirpur Cantonment, Tower 1, Dhaka

Heart Rate 112 bpm

SpO₂ 82%

Status: CRITICAL

Sound Status: GUNSHOT DETECTED

Last Seen: 23:50:57

ID	Name	HR	SpO_2	Status	Sound	Action
BA4400	Lt. Iftiak Ahmed Turza	112 bpm	82%	CRITICAL	[illegible]	View

Figure 14: The dashboard for the admin (base station).

Table 4: Comparison with State-of-the-Art

System	Fall Det.	Acoustic	Vitals	Real-time ML	Cost
Smith [2]	Manual	No	No	No	N/A
Kodam [3]	Threshold	No	Yes	No	High
Raut [9]	No	No	Yes	Server	High
Alves [10]	Yes (92%)	No	No	Edge	Medium
Ours	**TinyML (98.5%)**	**CNN (98.56%)**	**Yes**	**Edge**	**<$60**

5.6 Comparative Performance Analysis

Table 4 compares our approach against state-of-the-art military wearable systems:

Key Advantages: (i) Only system with multi-modal threat detection (fall + acoustic + vitals), (ii) Fully edge-based inference eliminating cloud dependency, (iii) Significantly lower cost suitable for large-scale deployment.

6 Discussion

6.1 Generalizability Analysis and Limitations

There are few dataset limitations like in case of fall detection - training on synthetic data limits the generalization of the real-world. Because, actual soldier falls differ from simulated profiles due to various reasons like - combat load variability, with gear affecting fall dynamics ranging from 15-40kg. Again, body type differences across the Bangladesh Army, including heights from 160-190cm and weights from 60-95kg, introduce additional variance. Furthermore, injury-induced falls present unique challenges, as wounded soldiers may collapse differently than healthy individuals experiencing standard falls. In these cases, the environmental factors such as uneven terrain, vegetation, and obstacles further complicate fall patterns beyond what synthetic data can capture.

Thus, to mitigate these problems, plan is to data collection during Bangladesh Army training exercises in Chittagong Hill Tracts with informed consent from over 50+ soldiers. In this way, a transfer learning approach will fine-tune the pre-trained model on real fall data collected from these exercises.

6.1.1 Environmental Robustness

There are chances that the model trained on clean, isolated sounds in ambient noise conditions of 40-80dB may underperform in high-noise combat environments exceeding 90dB. Vehicle noise, aircraft, and explosions may saturate the microphone, while overlapping sounds such as gunshots during explosions require multi-label classification capabilities not fully addressed in the current system. Additionally, directional effects are not captured in the omnidirectional training data used for model development.

Moreover, testing is needed. Validation during live-fire exercises of Bangladesh Army with controlled acoustic environments could be a great measure precision under realistic noise conditions. Thus, our future work includes implementing adaptive gain control and beamforming with microphone arrays to improve acoustic detection close to complex battlefield environments.

Lastly, sensor placement variability is also an issue. Like - MAX30102 readings are sensitive to helmet fit and forehead contact pressure. Loose helmet fit reduces PPG signal quality, significantly affecting heart rate and SpO_2 accuracy. The solution involves adjustable padding and sensor validation checks through signal quality indicators before mission start to ensure reliable physiological monitoring.

6.2 Real-World Deployment Challenges

6.2.1 Electromagnetic Interference and Environmental Factors

Radio communications, vehicle electronics, and weapons systems may interfere with GPS, GSM, and sensor readings. The current prototype lacks comprehensive EMI shielding, which presents a significant deployment challenge. Mitigation strategies include shielded cables, ferrite beads on power lines, and metal enclosure grounding planned for production units. EMI testing per MIL-STD-461 is required before field deployment to ensure system reliability in electromagnetic environments.

Again, the current prototype is not waterproofed, necessitating an IP67-rated enclosure for operational deployment to protect against moisture and rain exposure. Electronics are rated for operation from -10°C to 60°C, though battery performance degrades below 0°C, requiring heating elements or alternative battery chemistry for winter operations. Dust and sand present additional challenges, as the microphone requires protective mesh and the GPS antenna is susceptible to sand accumulation affecting signal quality. Components require damping to withstand combat activities, vehicle transport, and potential impacts from shock and vibration.

6.2.2 Motion and Contextual Classification

Running, vehicle riding, and tactical movements may mimic fall signatures, creating false positive challenges. The current model uses a fixed threshold of 1.5g acceleration peak to distinguish falls from activities of daily living (ADL). Enhancement through context-aware classification integrating GPS velocity can detect running when speed exceeds 2 m/s, while gyroscope patterns can identify vehicle vibration signatures to reduce false positives.

In hostile scenarios, deliberate signal jamming or GPS spoofing requires robust countermeasures. End-to-end encryption using AES-256-GCM for all transmissions provides secure communication channels. GPS anti-spoofing via signal quality checks and inertial dead-reckoning validation ensures location accuracy. Local data buffering with delayed batch transmission during jamming periods maintains data continuity, while frequency hopping spread spectrum (FHSS) enables resilient communications under electronic warfare conditions.

6.3 Scalability and System Integration

6.3.1 Network Architecture for Battalion-Scale Deployment

The current single base station using ESP32 supports approximately 250 concurrent Wi-Fi connections per access point. However, battalion-scale requirements involving 500 soldiers necessitate a more sophisticated network architecture.

The proposed hierarchical architecture is as follows: Starting with the squad level with 10 soldiers where direct connection to the squad leader's relay node provides immediate data aggregation. Platoon level operations with 30 soldiers utilize aggregation at the platoon command unit. Company level deployment supporting 120 soldiers employs mesh networking with redundant pathways to ensure reliability. Battalion level operations with 500 soldiers require a central command server with load balancing across multiple access points to handle the distributed data streams.

Cellular networks support limited concurrent connections per tower, typically accommodating 100-150 simultaneous transmissions per cell tower. SMS queuing handles non-critical data while HTTP POST requests prioritize critical alerts. This leads to optimizing network utilization under constrained bandwidth conditions.

6.3.2 Database and Server Scaling

Each soldier generates approximately 50MB per day through 1Hz vitals sampling, 0.2Hz GPS updates, and event-triggered audio and fall data. And battalion-scale deployment produces 25GB daily, accumulating to 750GB monthly. This requires robust storage infrastructure.

Thereby, the plan is to migrate the system from SQLite to PostgreSQL with TimescaleDB extension for optimized time-series data handling. Redis caching will accelerate real-time dashboard queries, while a distributed architecture comprises a primary server for active monitoring, a backup server for failover protection, and an archive server for historical data retention.

6.3.3 Integration with Military C4ISR Systems

The system employs MQTT for IoT messaging and RESTful API for external system integration, ensuring compatibility with existing military infrastructure.

JSON payloads provide flexible data representation, GeoJSON enables mapping integration, NMEA-0183 supports GPS standardization, and HL7 FHIR facilitates medical data exchange with healthcare systems.

An API gateway connecting to Bangladesh Army command systems provides secure access through VPN tunneling for remote connectivity. OAuth 2.0 authentication ensures user verification, while role-based access control (RBAC) implements three permission tiers: Medics access vitals only, Commanders view all data, and Admins configure system parameters.

Mobile base stations can use ruggedized servers such as Raspberry Pi 4 or Intel NUC with 4G/5G LTE backhaul to support Forward Operating Bases. FOB deployment can utilize central monitoring stations with satellite uplink (VSAT) for remote areas lacking terrestrial connectivity. Redundancy through multi-base-station setup with automatic failover using heartbeat protocol and 5-second timeout ensures continuous operation even during partial system failures.

6.4 Security and Privacy Considerations

6.4.1 Current Implementation Gaps

One of the most critical limitation is that the current prototype uses unencrypted Wi-Fi (WPA2-PSK) and plaintext SMS. This is inadequate for operational deployment and suitable only for laboratory demonstration. Thus, significant security enhancements are required before field use.

6.4.2 Required Security Upgrades

End-to-end AES-256-GCM encryption for all transmissions ensures data confidentiality during transit. In this case, ESP32 flash encryption prevents firmware tampering and unauthorized code modification. Again, HMAC-SHA256 message authentication codes verify message integrity and hardware secure elements such as ATECC608A provide tamper-resistant cryptographic key storage.

Soldier data including vitals and location is classified as sensitive personal information according to Bangladesh Army data protection policies. Access control implements three-tier permissions for Medic, Commander, and Admin roles with appropriate data visibility. Moreover, data retention policies specify 30-day automatic deletion for non-incident data, with permanent archival reserved for casualty events requiring investigation. Also, anonymization through hashed soldier IDs during transmission and exclusion of personally identifiable information (PII) from logs protects individual privacy.

Operational Security (OPSEC): The panic mechanism secure erase function completes in 185ms, preventing capture of recent activity logs if a helmet is compromised. Disable and low-power modes support stealth operations requiring radio silence. GSM transmission occurs only when necessary to minimize electromagnetic signature detection. Anti-tracking measures include randomized transmission intervals and GPS coordinate obfuscation in non-critical alerts to prevent pattern analysis by adversaries.

6.4.3 Threat Model

Eavesdropping attempts are mitigated by AES-256 encryption with 256-bit key space, making brute force attacks computationally infeasible. GPS spoofing is countered through signal quality checks monitoring carrier-to-noise ratio (C/N0) and cross-validation with inertial navigation using IMU-based dead reckoning. Jamming resistance is achieved through frequency hopping, local buffering with delayed transmission, and visual/audio alerts to the soldier. Physical capture scenarios are addressed through tamper detection switches, secure erase on unauthorized access, and self-destruct options for extreme scenarios pending ethical review.

System design must align with Geneva Conventions regarding soldier data collection, informed consent requirements, and ethical use of monitoring technology to ensure legal and moral compliance in military operations.

6.5 Operational Feasibility Assessment

6.5.1 Battery Performance and Power Optimization

Operational time ranges from 8-12 hours during continuous monitoring with duty-cycled GPS set to 5-minute intervals. Standby time exceeds 24 hours in low-power mode with ESP32 light sleep and sensors deactivated. Charging time is 3 hours via TP4056 with 1A input current.

Few important power optimization strategies here can be - ESP32 light sleep between sensor readings achieves 20% power reduction without compromising functionality. Dynamic GPS duty cycling adjusts intervals to 1-minute during active missions and 5-minute during patrol operations. Adaptive sensor sampling increases IMU rate to 200Hz only when fall is suspected based on preliminary motion detection. GSM power-down when Wi-Fi is available eliminates redundant power consumption from dual communication systems.

Future Improvements: Migration to ESP32-C3 will reduce power consumption through improved architecture. Solar charging panel integration supports extended missions beyond battery capacity. Supercapacitor backup ensures critical alert transmission even during battery depletion, maintaining system reliability in power-constrained scenarios.

6.5.2 Ergonomics and Soldier Comfort

Total added weight is 285g excluding the helmet base weight of approximately 1.2kg. Component placement includes the MAX30102 forehead sensor, temple-mounted ESP32 and battery, and top-mounted GPS antenna to distribute weight across the helmet structure.

Three subjects wore the prototype for 2-hour sessions, providing valuable feedback on ergonomic performance. Mild pressure discomfort from MAX30102 forehead contact was reported as acceptable for missions under 4 hours. No significant neck strain resulted from the added weight distribution. A thermal concern emerged as the ESP32 reached 45°C under continuous load, which while within safe operational limits, proved uncomfortable in hot climates.

Design Improvements: Weight distribution will be improved across the helmet surface to reduce localized pressure points. Soft silicone padding for the MAX30102 contact point will enhance comfort during extended wear. Active cooling through a small fan or heat spreader for the ESP32 will address thermal discomfort. Modular design allowing component removal for low-threat scenarios will provide operational flexibility and reduce unnecessary weight when full monitoring is not required.

6.6 Validation Limitations and Future Work

6.6.1 Threats to Validity

Internal Validity: Synthetic training data may not capture the full complexity of real-world falls under combat conditions. The limited test subject pool (n=3) for ergonomics assessment restricts generalizability of comfort findings. Panic mechanism testing was conducted under controlled laboratory conditions rather than realistic stress scenarios.

External Validity: Testing was performed in open and semi-urban environments on the MIST campus rather than actual battlefield conditions, limiting ecological validity. The single-unit prototype has not been assessed for manufacturing variability that would occur in production runs. No validation has been conducted with actual Bangladesh Army personnel or operational scenarios, representing a significant gap in real-world applicability assessment.

Construct Validity: Accuracy metrics are based on test sets from the same distribution as training data, which may not reflect deployment accuracy in novel scenarios. Latency was measured under optimal network conditions that may not represent field conditions. Security analysis remains theoretical as penetration testing has not been performed to identify actual vulnerabilities.

6.6.2 Planned Validation Studies

Phase 1 (6 months): Partnership with Combined Military Hospital (CMH) Dhaka will enable clinical validation of HRV-based injury detection with patient data from over 100 cases. PPG sensor accuracy will be compared against medical-grade pulse oximeters to establish clinical reliability. False alarm rate assessment in clinical monitoring scenarios will quantify system specificity in controlled medical environments.

Phase 2 (12 months): Field trials with Bangladesh Army will include training exercise deployment in Chittagong Hill Tracts and Cox's Bazar with 50 volunteer soldiers. Real fall data collection during combat training and obstacle courses will provide authentic training data for model refinement. Acoustic model validation during live-fire exercises will assess performance under realistic combat noise. Network performance assessment in jungle and coastal terrain will identify connectivity challenges specific to Bangladesh Army operational areas.

Phase 3 (18 months): Pilot operational deployment will involve a 100-unit production run with improved hardware including IP67 enclosure and EMI shielding. Border patrol deployment for a 3-month trial period will provide longitudinal performance data. User feedback surveys will guide iterative design refinement based on soldier experience. Longitudinal reliability and maintenance data collection will inform lifecycle management and support requirements.

6.7 Cost-Effectiveness Analysis

While designing the Intelli-Helmet system, one of our priorities was to ensure that the solution remained affordable within the financial and logistical realities of the Bangladesh Army. Unlike foreign military wearables that often cost between BDT 22,000 to 55,000 (USD 200–500), our system was purposely built using components that are widely available in the local electronics markets such as Dhaka's Gulistan, Patuatuli, and Multiplan Center.

Based on the bill of materials used in the prototype, the complete sender–receiver system costs approximately BDT 5,660 per unit. The major costs include the ESP32 microcontroller pair (BDT 1,000), motion and vital sensors such as the MPU6050 (BDT 220) and MAX30102 (BDT 200), and communication modules including the Neo-6M GPS (BDT 500) and two SIM800L GSM modules (BDT 740). Essential elements like the panic switch, buzzer, OLED display, Li-ion batteries, TP4056 charging system, and wiring collectively add another BDT 2,000. Even after including practical local costs—such as heat-shrink insulation, breadboards, SIM cards, and a DC-DC buck converter - the total remains well under BDT 6,000.

In real-world procurement terms, this is significant. A single imported military wearable can cost as much as the monthly allowance of a Bangladeshi soldier. By contrast, our system provides comparable and in several aspects superior functionality at one-tenth of the price. This translates to a 75–90% cost reduction, allowing large-scale deployment even in resource-constrained units such as border outposts, cantonment training wings, or peacekeeping contingents.

Moreover, because all components are available locally and can be repaired or replaced by any RAB workshop, EME Centre, or in-field technician, the long-term maintenance cost remains extremely low. This affordability, combined with multi-modal sensing, GPS tracking, real-time GSM reporting, and edge AI acoustic detection, makes the Intelli-Helmet a highly practical and scalable solution tailored for Bangladesh's defense environment.

If the system reduces casualty response time by 5-10 minutes, a conservative estimate, the potential lives saved justify the investment from both humanitarian and operational effectiveness perspectives. Exact ROI calculation requires operational data post-deployment to quantify medical outcomes and mission success improvements.

7 Conclusion and Future Directions

This paper presented Intelli-Helmet, a comprehensive IoT and TinyML-based soldier monitoring system integrating fall detection (98.5% accuracy), acoustic threat classification (98.56% accuracy), physiological sensing, and a novel two-stage panic mechanism. The system demonstrates edge AI viability for military wearables through optimized TensorFlow Lite deployment on resource-constrained ESP32 hardware with sub-200ms inference latency.

Key contributions include a multi-modal data fusion algorithm with hierarchical alert prioritization, an FSM-based panic mechanism achieving 98.7% successful trigger rate with secure data erase, comprehensive system integration with dual-communication fallback and real-time command dashboard, and validated performance through laboratory and field testing.

We transparently recognize several limitations requiring further work. Training on synthetic and public datasets limits generalization to real battlefield conditions where environmental complexity and operational stress introduce variables not present in laboratory data. Small-scale testing involving a single physical helmet and limited test subjects restricts statistical power and generalizability of findings. Security implementation gaps in the current prototype make it unsuitable for operational deployment without substantial cryptographic enhancements. Environmental robustness including EMI shielding, waterproofing, and temperature extreme performance requires production-grade engineering before field use.

7.1 Future Research Directions

Algorithmic Enhancements: Transfer learning using real soldier fall data collected during training exercises will improve model generalization to authentic combat falls. Multi-label acoustic classification for overlapping sound events will enhance threat detection in complex acoustic environments. Predictive analytics for fatigue and stress detection using HRV trends will enable proactive health monitoring. Context-aware classification integrating GPS velocity and activity history will reduce false positives from normal tactical movements.

Hardware Improvements: Research-grade PPG sensors such as Empatica E4 or ECG integration will provide robust physiological monitoring with medical-grade accuracy. Microphone arrays with beamforming will enable directional acoustic detection for improved threat localization. LoRa integration will support long-range communication in remote areas beyond cellular coverage. Advanced power management through solar charging and supercapacitor backup will extend operational duration for prolonged missions.

System Enhancements: End-to-end encryption implementation using AES-256-GCM will address current security gaps for operational deployment. Mesh networking will enable soldier-to-soldier communication in GPS-denied environments where traditional infrastructure is unavailable. Integration with unmanned aerial vehicles (UAVs) will coordinate aerial reconnaissance with ground-based soldier monitoring. Augmented reality heads-up displays will provide real-time tactical information overlaid on the soldier's field of view.

Deployment and Validation: Clinical trials at Combined Military Hospital will provide medical validation of physiological monitoring accuracy. Field trials during Bangladesh Army training exercises will generate authentic operational data for model refinement. Pilot operational deployment with a 100-unit production batch will assess scalability and reliability at company level. Longitudinal performance monitoring and iterative refinement based on user feedback will optimize system usability and effectiveness.

The Intelli-Helmet demonstrates feasibility of affordable, AI-powered military wearables for enhancing soldier survivability. Built with open-source tools and costing under $60 per unit, the system provides a practical foundation for large-scale deployment in resource-constrained military contexts. Future work will focus on real-world validation and addressing identified limitations to transition from research prototype to operational capability.

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Disclosure of Interests

The authors have no competing interests to declare that are relevant to the content of this article.

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