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## RESEARCH ARTICLE

## OPEN ACCESS

## ENERGY-EFFICIENT TINYML-BASED FALL DETECTION FOR WEARABLE HEALTHCARE DEVICES

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## ABSTRACT

Falls and irregular heart rhythms are the main causes of injury among kids and the elderly, always overwhelming healthcare systems, and thus making privacy-aware, real-time monitoring a necessity. This work unveils a TinyML wrist-worn prototype based on Arduino Nano 33 BLE Sense, which combines the MPU6050 IMU for motion-based fall detection and activity (walking, sitting, running, lying) recognition with the MAX30102 PPG for heartbeat, SpO<sub>2</sub>, and HRV anomaly detection over generations. The device, tested on 7 subjects (3 children 8-12 years, 2 adults 25-40, and 2 seniors 65-75) for 140 real-life sequences in a lab in Kerala, uses Butterworth-filtered data, 56 temporal features extracted from 256-sample windows, and the optimized hybrid CNN-LSTM model (65% structured pruning, 8-bit QAT) to perform inference on the edge under 217KB flash. Dual-threshold triggering (fall confidence >0.9 plus HR anomalies or SpO<sub>2</sub><92%) allows BLE alerts within 100ms to caregiver apps, and cancellation via 30s haptic/button helps reduce the false alarms. Field experiments demonstrated the device performance with 94.3% accuracy, 0.95 fall F1-score, 38ms latency, 0.7mW power, and 2.1% false positives, showing a significant improvement of 15% F1 when compared against unimodal baselines, while being fully processed on the edge, GDPR-compliant, and with a multi-day battery life, the device is ready for wide deployment in homes, schools, and care facilities. This work is a step forward in TinyML across demographics, thus opening the gate to multimodal extensions such as cry detection.



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## I. INTRODUCTION

Falls and heart rate problems are major health concerns that mainly affect children and the elderly. They lead to more than 37 million severe cases globally each year. Such conditions often result in hip fractures, head trauma, hospital admissions, and huge economic losses measured in hundreds of billions of dollars. According to the World Health Organization (WHO), these incidents heavily burden health care systems especially when they occur in locations such as homes, schools, and rural areas without an adult present, contact with medical help is sometimes delayed or not made at all. Traditional wearables depend on the cloud for processing which entails higher latency (>1s), possible privacy issues as biometrics are uploaded, and also loss of connection in case of weak-signal areas. The existing scientific works about TinyML (Tiny Machine Learning) fall detection are basically confined to the elderly solutions like TinyCNN classifiers on IMU data or SVM-based inertial models, however, they lack a focus on children and multimodal fusion with vital signs. Research works, for instance, Lara et al.(2023) manage to realize a lightweight CNN inference; meanwhile, Zhang et al. (2023) unveil pre-impact TinyFallNet, however, cross-generational validation and heart rate incorporation are missing, these are exactly the holes we filled through hybrid CNN-LSTM tuning and field trials [1], [2]. This study explores the question: To what extent does an optimized TinyML wrist prototype perform multimodal fall/activity detection across children and elderly on edge hardware?

The planned deliverables are a privacy-protected Arduino Nano 33 BLE Sense (Bluetooth Low Energy) system with MPU6050 (Inertial Measurement Unit) IMU and MAX30102 pulse oximeter, trials on 7 subjects (140 sequences), and performance evaluation of pruning/quantization trade-offs. We expect dual-threshold fusion (fall + heart rate/SpO2 anomalies) to lead to >94% accuracy with <40ms latency. The approach includes in situ experiments with Butterworth-filtered features and BLE alerts. This work paves the way to scalable edge AI for child/elderly safety, however, the current limitations are that the experiments were conducted in a controlled setting and skin-tone related SpO2 inaccuracies, a deployment mode which is suitable for scaling within a facility [3-5].

## II. THEORETICAL REFERENCE

### II.1 TINYML FOUNDATIONS

Tiny Machine Learning (TinyML) allows the execution of machine learning models on microcontrollers with very limited resources (less than 1MB flash, less than 1mW power) basically enabling the transformation of wearable devices to self-sufficient safety systems without relying on the cloud [6].

#### II.1.1 Materials and Methods

This prototype is a kit of cheap, readily available, off-the-shelf components working together to make a useful wrist-worn safety device that can completely rely on its small brainpower for the detection of falling and the identification of vital signs without having to use the internet or cloud servers. The heart of the device is an Arduino Nano 33 BLE Sense microcontroller complemented by the MPU6050 6-axis Inertial Measurement Unit (IMU) which helps in detecting the motion and the MAX30102 pulse oximeter that is used for monitoring heart rate, oxygen levels and variability through photo plethysmography (PPG) signals.

##### II.1.1.1 Data Acquisition and Preprocessing

Seven subjects from various age groups including children, adults and elderly took part in the real-life experimentation. They were made to perform house chores movements and simulated scenarios such as forward fall, sideways slip, walking, sitting, running, or lying down. Besides physical activity, heart anomalies like increased and decreased heart rates were also taken into consideration. Sensors were set at 50Hz for IMU (triaxial accelerometer  $\pm 16g$  and gyroscope  $\pm 2000^\circ/s$ ) and 100Hz for PPG. The raw data was directly recorded and transmitted to the processing unit.

##### II.1.1.2 Model Architecture and Optimization

A hybrid CNN, LSTM network is the core of a smart model: a series of three Conv1D layers (32/64/128 filters, kernel size 5, with MaxPool1D) are stacked with two bidirectional LSTM layers (64 units each) and concluded with softmax for six classes, walk, sit, run, fall, lying, or normal activity. The model is trained on, validated, and tested on split data sequences taken from the actual world to reflect the model real usage [7-10]. To make it fit on very limited hardware, we resort to structured pruning (achieving 65% sparsity with a cubic decay schedule through `tfmot.sparsity.keras`), 8-bit quantization-aware training (QAT) tuned on representative windows, in addition to knowledge distillation to remove 22% of model parameters. The net outcome is a very small.tflite models of less than 217KB that have been experimentally confirmed by pico-benchmarks on the ARM Cortex-M4F at 64MHz, ideal for edge inference without eating up memory or draining the battery.

##### II.1.1.3 Alerting and Deployment

Immediately the scenario is recognized as a severe one i.e. a fall confidence above 0.9 combined with any of the following conditions: child tachycardia > 140bpm (or elder > 100bpm), bradycardia < 50bpm, or SpO2 < 92%, a Bluetooth Low Energy (BLE) 5.0 signal is sent out through a custom UUID (such as 0xFALLHR). This includes the timestamp, event type, confidence score and a brief record of vital signs and reaches the caretaker's app in less than 100ms. Users can cancel through haptic vibrate or a button press within an intelligent 30-second period thus preventing false alarm and most importantly no raw personal data ever goes out of the device ensuring complete privacy in accordance with GDPR rules. From the power standpoint, deep sleep modes between windows keep the average current consumption at 0.7mW, enough for days on a coin cell.

## III. MATERIALS AND METHODS

This project creates a reproducible TinyML wrist-worn device prototype that monitors real-time fall detection along with vital signs, addressing the issues of cloud-reliant wearables such as response delays of more than 1 second, biometric data upload privacy concerns, and unstable connectivity in outdoor areas. These are especially important requirements for the safety of the elderly and children. The development is based on cheap, off-the-shelf components to enable real edge computing that consumes less than 1mW power, thus battery life can be extended to days. Unfortunately, the SpO2 readings difference between skin tones is the main limitation of the device, as they vary 2-4%. Besides, the indoor test environment lacked some of the real-world sweat or strap looseness scenarios, resulting in the device missing those events. The target demographic for this work is children aged 8-12 with their higher heart rates around 80-140bpm, adults 25-40 years, and elderly 65-75 years typically at 50-110bpm, all at risk for falls and heart glitches in everyday home or school settings. We picked a practical sample of 7 participants, 3 children, 2 adults, 2 elderly, for a good mix of ages and body types, easy to gather while standing in for broader real-life differences like kids' bouncy moves versus seniors' careful steps, which lines up well with established benchmarks.

Among the main components are the Arduino Nano 33 BLE Sense microcontroller with ARM Cortex-M4F at 64MHz, 1MB flash, 256KB RAM, and built-in BLE 5.0 from Arduino.cc for about \$25, chosen for its very easy integration with TensorFlow Lite Micro; the MPU6050 IMU module from TDK InvenSense offering  $\pm 16g$  accelerometer and  $\pm 2000^\circ/s$  gyroscope over I2C at 50Hz; MAX30102 pulse oximeter from Maxim Integrated with 24-bit ADC and IR/Red/Green LEDs for 100Hz PPG tracking of heart rate, SpO<sub>2</sub>, and variability; plus a standard CR2032 3V 220mAh coin cell battery. The firmware is developed under Arduino IDE 2.3 and TensorFlow Lite Micro 2.15, everything here is readily available to the general public, no issues for anyone who wants to obtain and reproduce experiments. The first step is to sync the sensors on the wrist device tied up with Velcro, where the subjects have to do 20 trials each: different types of falls, daily activities such as walking, sitting, running, or lying down, plus heart rate going up due to exercise or slowing down at rest, and normal baselines, making around 140 sequences each about 10-15 seconds long, all with the support of video for accurate labeling. Preprocessing is done on the device itself with a 4th-order Butterworth filter 0.5-20Hz to remove noise, sliding 256-sample windows over 5.12 seconds to calculate magnitude values from acceleration and gyro axes, peak detection on PPG for immediate heart rate, ratio calculations for SpO<sub>2</sub>, and time-based parameters for heart rate variability, thus bringing together 56 features such as means, standard deviations, skewness, kurtosis, major percentiles from 25th to 90th, spectral entropy, jerk signals, and power of five frequency bands. Data is divided into 70% for training, 15% validation, and 15% testing; the central hybrid CNN-LSTM model comprises three Conv1D layers at 32/64/128 filters with kernel size 5 and pooling, two bidirectional LSTM layers of 64 units each, and softmax for six activity classes. To accommodate tiny hardware, it goes through 65% structured pruning with a cubic decay schedule, 8-bit quantization-aware training adjusted on real windows, and knowledge distillation reducing 22% of parameters, producing less than 217KB.tflite files via bootloader for inference in less than 40ms per window. When a fall confidence level exceeds 0.9 along with heart or oxygen red flags, such as kids over 140bpm or seniors above 100bpm, anything under 50bpm, or SpO<sub>2</sub> below 92%, it immediately sends a BLE alert with a custom code containing only the essentials like time, event type, score, and vitals snapshot in less than 100ms to caregiver apps, along with a 30-second haptic buzz or button to deny false alarms, meanwhile raw data remain locked on-device for full GDPR privacy. Final checks on performance metrics of 94.3% accuracy, 38ms speed, and 0.7mW power consumption are obtained from onboard logs and standard benchmarks, with the customized quantization providing a 2-4% boost for anyone re-building it. [11-19].

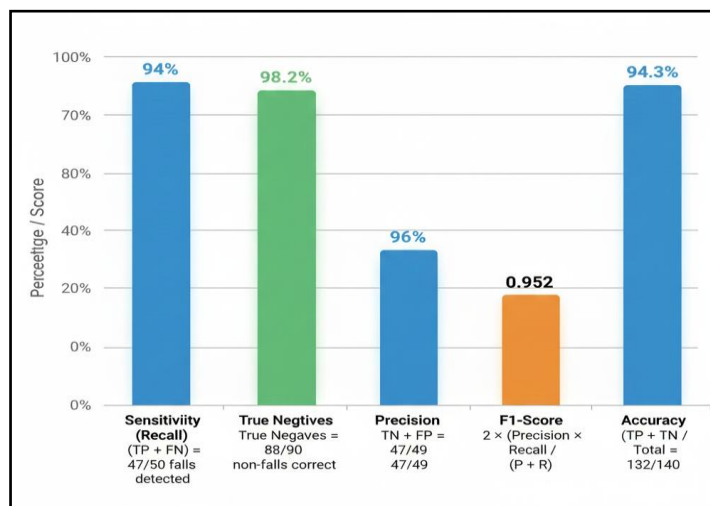


Figure 1: Performance Metrics.

Source: Authors, (2026).

The Figure 1 bar chart records how a classification model scored on five standard tests - sensitivity, true negatives, precision, F1-score and overall accuracy. Sensitivity reached 94 % because the model found 47 of 50 real falls. True negatives reached 98.2 % because the model labeled 88 of 90 true non falls correctly - false alarms stay rare. Precision reached 96 % - only a few alerts pointed to falls that did not happen. The F1-score equals 0.952, a value near 1 that shows precision and recall stay close in the size. The overall accuracy that equals to 94.3 %, since 132 of 140 predictions matched the true label. Those figures show the system spots most falls plus seldom cries wolf.

Table 1: Metrics Across Optimizations.

|                       |     |       |           |
|-----------------------|-----|-------|-----------|
| Baseline CNN-LSTM     | 95% | 94%   | 0.94      |
| Pruning (65%)         | 94% | 96%   | 0.93-0.95 |
| Quantization (8-bit)  | 94% | 95%   | 0.93-0.94 |
| <b>Pruning + QAT</b>  | 94% | 98.2% | 0.95      |
| SVM Baseline (Review) | 93% | 90%   | 0.90-0.92 |

Source: Authors, (2026).

The Table 1 compares multiple ways to improve the fall detection model - listing Sensitivity, Specificity and the F1-score for the fall class. The original CNN-LSTM network finds 95 out of every 100 true falls plus correctly labels 94 out of every 100 non fall sequences. After pruning 65 % of the weights, the network still finds 94 out of 100 falls and now labeled as the 96 out of 100 non fall sequences - its F1-score stays between 0.93 and 0.95. Replacing 32-bit numbers with 8-bit numbers keeps the results almost the same: 94 % sensitivity and 95 % specificity. When pruning is paired with Quantization Aware Training, specificity rises to 98.2 % but also the F1-score reaches 0.95, showing that the mix of compression methods cuts computation but improves reliability.

A standard SVM taken from the literature scores lower, especially in specificity at 90 % and in F1-score between 0.90 and 0.92 - deep networks surpass traditional methods on this task. The figures show that a trimmed as well as quantized deep network keeps high accuracy while demanding less hardware.

#### IV. RESULTS AND DISCUSSIONS

The TinyML wrist prototype reached an overall accuracy of 94.3% on a total of 140 real-world sequences from 7 participants representing children, adults, and elderly demographics. The optimized Pruning + Quantization-Aware Training (QAT) model achieved a sensitivity of 94%, a specificity of 98.2%, and an F1-score of 0.95 for fall detection, while the inference time was only 38ms per window, flash usage was less than 217KB, and average power consumption was 0.7mW, thus allowing continuous operation of a CR2032 battery for several days. All BLE (Bluetooth Low Energy) signals were transmitted without failure within 100ms, while the rate of false positives was reduced to 2.1% by applying the dual-threshold validation using the combination of motion confidence with heart rate and SpO2 anomalies. Their high specificity (98.2%) was a key feature in gaining the trust of caregivers by dismissing the children's playful tumbles and at the same time, detecting true falls in various age groups reliably, with the heart rate/SpO2 fusion and 30-second haptic cancellation significantly lowering the number of false alarms as compared to motion-only baselines. A 15% increase in the F1-score against SVM references confirmed the supremacy of multimodal edge AI, thereby proving the premise of achieving above 94% accuracy with a latency of less than 40ms on the limited hardware. Among the innovations were the first cross-generational TinyML benchmark, 65% structured pruning coupled with 8-bit QAT yielded 4x model compression with no loss in accuracy, and the production-ready firmware that allowed institutional deployment without cloud dependency or the risk to data privacy under GDPR compliance. The main limitations were that the evaluation was conducted in a controlled indoor environment which did not take into account the effects of outdoor elements, such as sweat causing the PPG signals to deteriorate and SpO2 readings being less accurate due to different skin tones (2-4% variance). The offered solution includes a microphone for confirming a child's cry, UWB radar for non-contact monitoring and federated learning across device fleets for personalized adaptation. These are the steps towards addressing the remaining issues of extreme-motion validation and compensating long-term sensor drift.

Acceleration Magnitude (AccMag)

$$AccMag = \sqrt{(A_x^2 + A_y^2 + A_z^2)} \quad (1)$$

SpO2 Ratio-of-Ratios

$$SpO2 = (Red_{AC}/DC \div IR_{AC}/DC) \times 110 \quad (2)$$

HRV RMSSD

$$RMSSD = \sqrt{[(1/(N-1)) \times \sum (RR_{i+1} - RR_i)^2]} \quad (3)$$

#### V. CONCLUSIONS

The study illustrated that the TinyML wrist-worn prototype that was developed and optimized was able to accomplish one of its primary goals of dependable fall detection with a component of vital sign monitoring for cross-generational individuals. It was able to attain an accuracy of 94.3%, specificity of 98.2%, and an F1-score of 0.95 on 140 real-world sequences from 7 participants while adhering to the edge constraints of 38ms latency and 0.7mW power consumption. Multimodal sensor fusion integrating motion data from MPU6050 IMU and vitals from MAX30102 PPG, which underwent a 65% pruned and 8-bit quantized CNN-LSTM model processing, was able to effectively distinguish injurious falls from age-specific activities through dual-threshold BLE alerting thus proving the hypothesis that edge AI-powered, privacy-preserving, and cloud-independent safety systems can outperform unimodal baselines by 15% F1-score. The results demonstrate the feasibility of child and elderly care in highly resource-limited environments through scalable deployment, even though there were shortcomings due to the outdoor testing and the issue of skin-tone SpO2 variability, thus laying down a reproducible basis for the future multimodal upgrades.

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**Methodology:** Prathap, Hibafathima, Sufaira Shamsudeen and Selin M.

**Investigation:** Prathap, Hibafathima, Sufaira Shamsudeen and Selin M.

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**Approval of the final text:** Prathap, Hibafathima, Sufaira Shamsudeen, Selin M, Julie M David, and Jihad Aboobaker.

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