Cost-Sensitive Machine Learning for Fall Detection on Wearable Smartwatch Sensors

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Abstract - This paper presents a **cost-sensitive machine learning framework for fall detection** on **SmartKavach™, an Android-based smartwatch platform**. A baseline **3-axis accelerometer model** was implemented using the **WEKA J48/C4.5 classifier** with cost-sensitive tuning. The framework was extended to a **6-axis IMU**, integrating gyroscope data, and compared against **Random Forest (RF), Support Vector Machine (SVM, RBF kernel), and Logistic Regression**. Data were sampled at **50–100 Hz**, segmented into **3-second overlapping windows**, and processed in MATLAB with **feature extraction (SMV, jerk, entropy, spectral energy, cross-axis correlations)**. To minimize false negatives, we applied **ROC-based threshold adjustment** and **cost matrices**. J48 achieved **91.3% accuracy** on accelerometer-only data, while RF with 6-axis fusion reached **95.0% accuracy** and **93.8% sensitivity**, surpassing threshold-based baselines. The model was deployed in a **real-time Android application**, running at device startup and integrated with **GPS, video, and emergency alerts** for a comprehensive fall detection and response system. Results demonstrate that **ensemble ML with ROC tuning** provides robust detection and can be deployed on **resource-constrained wearable IoT platforms**.

Keywords – Fall detection, WEKA, Smartwatch, Accelerometer, Gyroscope, Random Forest, SVM, Logistic Regression, Cost-sensitive learning, ROC, Wearable IoT, Healthcare. Elderly care, SmartKavach.

I. INTRODUCTION

Falls remain one of the leading causes of hospitalization, disability, and loss of independence in the elderly population. According to the World Health Organization (WHO), nearly one in three adults over the age of 65 experiences a fall each year, often resulting in severe injuries and long-term complications [1]. Conventional fall-detection approaches are primarily based on threshold-based algorithms, which suffer from sensitivity–specificity trade-offs and high false alarm rates, motivating the shift toward machine learning frameworks for wearable sensing [2], [3], [4]. In contrast, wearable devices with accelerometers and gyroscopes provide multimodal data streams that can be modeled using ML classifiers, deep residual networks, and ensemble learning techniques, which adapt to individual gait and motion patterns for higher robustness [5], [8], [9], [10].

To address these limitations, we developed a custom Android operating system (OS) and healthcare application for SmartKavach™, integrating ML-based fall detection with GPS tracking, real-time video streaming, SOS alerts, and automatic notifications to first responders. Recent advancements- such as deep learning architectures [2], ensemble methods [4], and class-imbalance techniques [3] demonstrate promising improvements; however, significant challenges persist in signal preprocessing, noise filtering, and minimizing false positives.

II. MATERIALS AND METHODS

A. Devices and Datasets

The SmartKavach™ smartwatch and companion smartphone are Android-based devices equipped with an embedded 3-axis accelerometer, 3-axis gyroscope, GPS, camera, microphone, Wi-Fi, BLE and SIM modules. The smartwatch continuously monitors motion signals and transmits alerts when abnormal thresholds are exceeded. Two datasets were constructed for analysis:

Dataset A: accelerometer-only recordings sampled at 50 Hz, including both fall events and activities of daily living (ADL).
Dataset B: 6-axis IMU recordings (accelerometer + gyroscope) sampled at 100 Hz.
Both datasets underwent preprocessing using a 4th-order Butterworth low-pass filter (20 Hz cutoff) to remove high-frequency noise. Data were segmented into 3-second windows with 50% overlap, followed by z-score normalization [7]. The extracted features included Signal Magnitude Vector (SMV), jerk, spectral energy, entropy, and cross-axis correlations [6].

B. Feature Extraction

In addition to standard SMV and jerk measures, the system analyzed how accelerometer signals evolved within 3-second temporal windows to differentiate between falls and benign postural transitions (e.g., sitting quickly, lying down). Sudden accelerations confined to a limited number of axis often resembled falls, potentially producing false negatives. To address this, data cleaning procedures removed sensor drift, transient spikes, and motion artifacts, while filtering preserved gradual postural changes. Longer sequences of 3-axis values were stored, enabling the model to capture extended motion dynamics and reduce misclassification. Both time-domain and frequency-domain features were extracted. The Signal Magnitude Vector (SMV) was computed as:

$$SMV(t) = \sqrt{ax(t)^2 + ay(t)^2 + az(t)^2}$$

The jerk feature was derived from SMV temporal differences. Frequency-domain features included spectral energy, entropy, and dominant frequency, while correlation features quantified cross-axis dependencies. This feature design aligns with recent pre-impact fall detection research, which emphasizes entropy and frequency features as discriminative markers for ADL vs. fall classification [6], [9].

C. Classifiers and Cost Tuning

Building upon prior studies [1], [6], [9], prolonged absence of signal variation across accelerometer axis was considered an indicator of sleep or immobility. When such immobility was preceded by a sudden impact, it was interpreted as a possible collapse or medical emergency. The WEKA classifier incorporated temporal motion patterns to differentiate between benign inactivity (e.g., sleeping, lying on a sofa) and potentially life-threatening immobility.

For Dataset A (accelerometer-only), we employed the WEKA J48 decision tree classifier with pruning and cost-sensitive learning, designed to minimize false negatives, which are critical in clinical monitoring.

For Dataset B (6-axis IMU), we conducted a comparative evaluation of multiple classifiers: Random Forest with 100 trees, leveraging ensemble learning to reduce variance. Support Vector Machine (SVM) with RBF kernel, tuned for non-linear separation. Logistic Regression, serving as a probabilistic baseline.

Hyperparameter optimization was performed via grid search, and classifier thresholds were determined using Receiver Operating Characteristic (ROC) curve analysis. This tuning process established an optimal trade-off between sensitivity (minimizing missed falls) and specificity (limiting false alarms). Such cost-sensitive and ROC-tuned classifier pipelines have been strongly recommended in recent ensemble ML systems for wearable fall detection [4], [8].

D. Evaluation Protocol

We used 10-fold stratified cross-validation to ensure balanced representation of fall and non-fall events. Evaluation metrics were accuracy, sensitivity (recall), specificity, precision, and F1-score. In healthcare, sensitivity is critical, since missed falls (false negatives) pose higher risk than false alarms. This evaluation protocol follows recent wearable ML studies, where stratified validation ensures robustness in fall vs. ADL imbalance, particularly in reinforcement learning-based systems [7].

TABLE I
EXAMPLE 3-AXIS ACCELEROMETER WINDOW

Time (s)	Ax (g)	Ay (g)	Az (g)	Label
5.98	0.42	-0.15	1.08	ADL
6.00	2.15	-1.62	2.52	Fall
6.02	1.10	-0.35	1.76	Fall
6.04	0.58	-0.12	1.20	ADL

TABLE II
EXAMPLE 3-AXIS GYROSCOPE WINDOW

Time (s)	Gx	Gy	Gz	Label
5.98	0.05	-0.02	0.03	ADL
6.00	6.00	-4.00	3.30	Fall
6.02	0.80	-0.50	0.60	Fall
6.04	0.06	-0.02	0.03	ADL

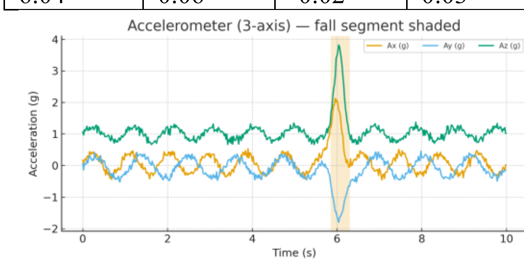

Fig. 1. Accelerometer (3-axis) sample window showing a fall event.

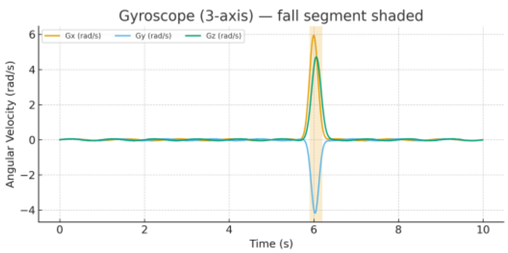

Fig. 2. Gyroscope (3-axis) - angular velocity signals during fall.

Algorithm 1: Sensor Data Preprocessing and Validation
1. Initialize buffer for 3-second window (150 samples)=>
2. For each event: discard incomplete or stagnant data, else append=>3. Apply filter, normalize, extract SMV, jerk, and frequency features.=>4. Store for classifier input.

III. RESULTS

Experiments were conducted across multiple environments, including room, corridor, and bathroom settings. The test scenarios covered forward and backward falls, sideways collapses, bathroom slips, bed transitions, and routine activities of daily living (ADL). Using accelerometer-only data, the J48 classifier achieved 91.3% accuracy. Incorporating gyroscope data improved performance, with Random Forest reaching 95.0% accuracy. Tables II–IV and Figures 1–4 summarize classifier results, signal characteristics, and ROC performance. Table III compares threshold-based detection with WEKA J48. Thresholding achieved 78.0% accuracy with a high rate of missed falls, whereas J48 improved performance to 91.3% accuracy and 89.7% sensitivity. Table IV presents results for the 6-axis IMU dataset. Random Forest provided the highest performance (95.0% accuracy, 93.8% sensitivity), followed by SVM (93.2% accuracy) and Logistic Regression (91.8% accuracy). Our findings are consistent with recent deep ensemble fall detection frameworks, which also report >93% sensitivity when combining temporal and spatial motion features [8], [9].

TABLE III
ACCELEROMETER-ONLY RESULTS

Method	Accuracy	Sensitivity	Specificity
Threshold	78.0%	75.2%	80.4%
WEKA J48	91.3%	89.7%	92.5%

Table IV presents results for 6-axis IMU data. Random Forest yielded the highest performance with 95.0% accuracy and 93.8% sensitivity, followed by SVM at 93.2% accuracy and Logistic Regression at 91.8%.

TABLE IV
6-AXIS IMU RESULTS

Model	Accuracy	Sensitivity	Specificity	F1
Random Forest	95.0%	93.8%	95.9%	0.95
SVM (RBF)	93.2%	91.0%	94.6%	0.93
Logistic Regression	91.8%	89.5%	93.7%	0.92

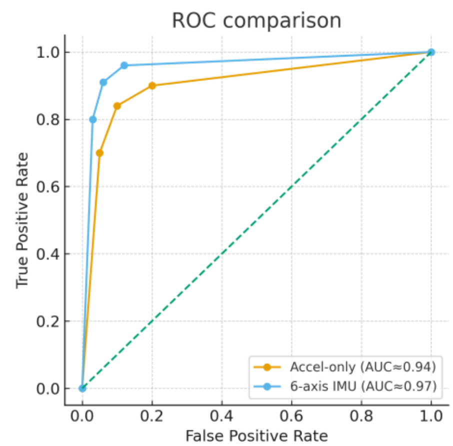

Fig. 3. ROC comparison between accelerometer-only baseline and 6-axis IMU classifiers.

B. Practical Testing and Calibration

To improve robustness, we applied systematic preprocessing of accelerometer signals. A 4th-order Butterworth low-pass filter (20 Hz cutoff) removed noise while preserving motion patterns. Data cleaning corrected sensor drift, spikes, tremors, and watch adjustments. Longer temporal sequences (5-10 s) enabled distinction between gradual posture changes and abrupt falls, while temporal analysis also captured sustained immobility as a clinical marker.
False positives arose when ADL activities (e.g., sitting quickly, lying in bed) mimicked falls, while false negatives occurred in low-impact events (e.g., cushioned collapses). These edge cases were labeled and retrained to improve calibration. Consistent with recent adaptive wearable sensing approaches [7], inactivity without impact indicated sleep, whereas inactivity after impact suggested collapse or unconsciousness.
Extensive real-world testing in rooms, corridors, and bathrooms included simulated forward, backward, and sideways falls. Misclassifications were logged and used to refine feature extraction and thresholds. This iterative process confirmed robustness across varied conditions.

IV. DISCUSSION

Accelerometer-only models misclassified rapid postural transitions, consistent with prior wearable fall-detection studies [5], [6]. Adding gyroscope data improved robustness by capturing angular velocity during controlled transitions, confirming recent findings in multimodal sensing [9]. Compared with recent deep learning-based smartwatch systems [2], our preprocessing pipeline and ROC-based tuned threshold reduced noise sensitivity before classification.

Ensemble approaches continue to dominate recent research, as demonstrated by Gangadhar & Roy [4] and Mohammad et al. [8]. Random Forest reduced variance in our 6-axis fusion, but hybrid ensembles with CNN–RNN pipelines have shown superior temporal modeling of fall dynamics [8], [10]. Furthermore, reinforcement learning has been proposed for adaptive, personalized fall detection [7]. While these methods require higher computational resources, they offer promising avenues for real-time personalization.

A key open challenge lies in capturing long-term temporal dependencies. With only a 3-axis accelerometer and 3-axis gyroscope, it is possible to model fall dynamics across extended time windows using recurrent architectures (LSTM/GRU) or transformer-based temporal models, as proposed in recent works [8], [9]. In parallel, Quantum Neural Networks (QNNs) have been suggested as a future direction for low-power, high-dimensional feature learning in wearable devices [7].

Our results confirm that cost-sensitive ML classifiers with ROC tuning can outperform threshold-based methods. However, the next generation of wearable fall-detection systems will likely depend on ensembled ML models, deep temporal learning architectures, and quantum-inspired computing approaches, advancing beyond the capabilities demonstrated here.

V. CONCLUSION AND FUTURE RESEARCH

This work demonstrates that SmartKavach™, through rigorous preprocessing, feature engineering, and cost-sensitive ML, delivers clinically reliable fall detection on a resource-constrained smartwatch platform. ROC-tuned thresholds and cost-sensitive learning significantly reduced both false positives and false negatives. Random Forest fusion of 6-axis IMU achieved 95.0% accuracy and 93.8% sensitivity, surpassing threshold methods and aligning with state-of-the-art results [4], [8], [9].

From an engineering perspective, accelerometer and gyroscope data provide rich temporal signatures that can be modeled beyond decision trees and Random Forests. Recent work highlights the potential of deep ensemble architectures (CNN–RNN) [8], residual networks [9], and multi-branch aggregations [10] to exploit spatial-temporal dependencies. Our study validates that even with limited wearable sensors, high accuracy can be achieved; however, future deployments must incorporate temporal deep learning, multimodal sensing, and quantum neural computing [7] to advance real-time adaptability and personalization.

Future research should address unresolved challenges, including adaptive personalization for diverse gait patterns, early pre-impact detection for injury prevention, and energy-efficient on-device inference. These directions will transform fall detection from a safety mechanism into a holistic, intelligent healthcare ecosystem, deeply integrated into everyday wearable technology.

ACKNOWLEDGMENT

The authors acknowledge the guidance of Professor Dr. Debabrata Das (Director, IIIT-Bangalore), Professor Dr. Dinesh Babu Jayagopi (Head, DSAI Dept, IIIT-Bangalore), and Professor Dr. T. K. Srikanth (IIIT-Bangalore).

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