

# Proactive Fall Prediction and Integrated Vital Sign Monitoring for Elderly Healthcare

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**Abstract**— Falls are a major cause of injury and reduced independence among elderly individuals, especially those affected by neurological disorders such as Parkinson's disease. Most existing fall detection systems generate alerts only after the fall has occurred, limiting their ability to prevent injuries. This paper presents a wearable system designed to predict fall-risk conditions in advance while simultaneously monitoring vital physiological parameters. The system uses an MPU6050 inertial measurement unit to analyze body motion and a MAX30102 sensor to measure heart rate and blood oxygen levels. A two-stage detection algorithm is implemented, where abnormal motion is first identified using a threshold-based approach, followed by classification using a Support Vector Machine (SVM) model to confirm pre-fall conditions. Simulation analysis and performance evaluation demonstrate reliable detection capability with low response time and efficient power usage suitable for wearable devices. When a fall-risk condition is detected, alert signals are generated and transmitted through Bluetooth Low Energy (BLE) for remote monitoring. The proposed system provides an effective and energy-efficient solution for preventive elderly healthcare monitoring.

## I. INTRODUCTION

Falls are among the most serious health risks affecting elderly individuals and often lead to injuries, hospitalization, and long-term physical limitations. The problem becomes more critical in people suffering from neurological disorders such as Parkinson's disease, where symptoms like postural instability and Freezing of Gait (FOG) significantly increase the likelihood of falling. Detecting early signs of gait disturbance can help reduce fall-related injuries by enabling timely preventive action.

Most existing fall detection systems operate by identifying the fall only after it has occurred. Although these systems can provide emergency alerts, they do not help in preventing the fall itself. Several wearable and mobile-based solutions have been developed using motion sensors and machine learning techniques. However, simple threshold-based methods may produce incorrect alerts, while advanced machine learning

models may require higher processing power and energy, making them less suitable for wearable embedded devices.

To address these limitations, this research proposes a wearable system capable of predicting fall-risk conditions before the actual fall occurs. The system combines motion analysis with physiological monitoring using an embedded microcontroller platform. A dual-stage detection approach is used, where initial abnormal motion is identified using threshold analysis, and further classification is performed using a Support Vector Machine (SVM) model to improve reliability.

The main contributions of this work are summarized as follows:

1. Development of a two-stage fall-risk prediction algorithm using threshold detection and machine learning classification.
2. Integration of motion sensing with vital parameter monitoring including heart rate and oxygen saturation.
3. Implementation of the system on an embedded wearable platform designed for low power consumption and real-time operation.
4. Wireless transmission of alerts and physiological data for remote monitoring and preventive healthcare support.

## II. RELATED WORK

In recent years, wearable fall detection systems have become an important area of research due to the increasing need for continuous health monitoring in elderly populations. Various studies have explored the use of motion sensors, embedded systems, and intelligent algorithms to detect and predict fall events. González-Cañete and Casilari [1] examined the energy requirements of fall detection systems implemented on smartphones using multiple wireless sensors and highlighted the importance of optimising algorithms for low-power operation. Similarly, Wang et al. [2] and Chen et al. [5]

presented review studies that discussed different wearable sensor technologies and classification techniques used for fall detection.

Many fall detection approaches use threshold-based methods, where acceleration magnitude is compared with predefined limits to identify abnormal motion [9]. These techniques are simple and suitable for embedded systems, but they may not always distinguish accurately between normal activities and fall-related motion, which can lead to incorrect alerts.

To improve detection performance, researchers have applied machine learning algorithms such as Support Vector Machines (SVM), decision trees, and other classifiers [10]. These methods analyze patterns in motion data to enhance classification accuracy. Deep learning models have also been investigated for fall detection tasks [8], as they can automatically extract features from sensor data. However, these models typically require higher computational resources, which may not be practical for low-power wearable devices. Although significant progress has been made, most existing systems focus on detecting falls after they occur rather than identifying fall-risk conditions in advance. In addition, limited work has been done on combining motion analysis with physiological monitoring in a single wearable device. Therefore, there is a need for an efficient system that can predict fall-risk conditions while maintaining low power consumption and supporting real-time wearable implementation.

The system proposed in this work addresses these challenges by integrating motion sensing, physiological monitoring, and a dual-stage classification approach to enable proactive fall-risk prediction.

### III. SYSTEM ARCHITECTURE

The proposed wearable system is designed to continuously monitor user motion and physiological parameters in order to identify fall-risk conditions at an early stage. The architecture combines sensing components, an embedded processing unit, alert modules, and a wireless communication interface to form an integrated wearable platform. The overall structure of the system is illustrated in Fig. 1.

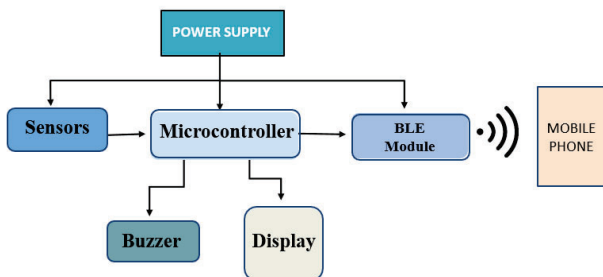


Fig.1. Block diagram of the proposed proactive fall prediction system

The sensing section includes an MPU6050 inertial measurement unit (IMU), a MAX30102 photoplethysmography sensor, and an LM35 temperature sensor. The IMU measures acceleration and angular velocity along three axes, which are used to analyse body movement and detect abnormal gait behaviour. The MAX30102 sensor provides heart rate and blood oxygen saturation values, while the temperature sensor monitors body temperature. These sensors continuously collect motion and physiological data required for fall-risk analysis.

The collected sensor data are processed by the STM32F401 microcontroller, which serves as the central control unit of the system. The microcontroller executes the fall prediction algorithm and manages communication between different system components. A dual-stage detection process is implemented, where abnormal motion is first identified using threshold comparison, and further analysis is performed using a machine learning classifier to confirm fall-risk conditions. This approach improves detection reliability while maintaining efficient use of computational resources.

When a potential fall-risk event is detected, the system generates alerts using a vibration motor and buzzer to notify the user. At the same time, important physiological data and alert information are transmitted to an external device using a Bluetooth Low Energy (BLE) module. This allows caregivers or monitoring systems to receive real-time updates.

The entire system operates using a rechargeable Li-Po battery, making it suitable for portable wearable applications. The architecture is designed to ensure continuous monitoring, low power consumption, and reliable fall-risk detection.

### IV. METHODOLOGY

The proposed system uses a two-stage detection approach to identify fall-risk conditions by analysing motion signals obtained from wearable sensors. The methodology consists of data acquisition, initial threshold-based screening, and machine learning-based classification to improve detection reliability.

#### A. Data Acquisition

The MPU6050 sensor continuously measures acceleration and angular velocity along three orthogonal axes. These motion signals provide information about body movement patterns. In addition, the MAX30102 sensor measures physiological parameters such as heart rate and blood oxygen saturation. All sensor data are collected by the microcontroller using the I2C communication interface and prepared for further processing.

#### B. Stage 1: Threshold-Based Screening

The first stage of the algorithm detects abnormal motion using acceleration and angular velocity magnitude. The overall

acceleration magnitude is calculated using the following equation:

$$A_{res} = \sqrt{a_x^2 + a_y^2 + a_z^2}$$

where  $a_x$ ,  $a_y$ , and  $a_z$  represent acceleration values along the three axes.

- If the calculated acceleration magnitude exceeds a predefined threshold value  $T_a$ , the motion is considered abnormal:

$$A_{res} > T_a$$

where  $T_a$  is the predefined acceleration threshold determined experimentally.

- Similarly, angular velocity magnitude is calculated as:

$$w_{res} = \sqrt{w_x^2 + w_y^2 + w_z^2}$$

- If the angular velocity exceeds the threshold value  $T_\omega$ , abnormal motion is detected:

$$\omega_{res} > T_\omega$$

where  $T_\omega$  is the angular velocity threshold.

This stage allows quick identification of unusual motion while reducing unnecessary processing.

### C. Stage SVM Classification

When abnormal motion is detected in the first stage, motion data are further analysed using a Support Vector Machine (SVM) classifier. The classifier evaluates extracted motion features and determines whether the detected motion corresponds to a fall-risk condition.

The SVM classifier separates motion data into two categories:

- Normal motion
- Fall-risk motion

This additional classification stage improves overall detection reliability and helps reduce incorrect alerts that may occur when using only threshold-based detection.

### D. Stage : Algorithm Flow

Start

Initialize IMU sensor, physiological sensor, BLE module, and alert system

While monitoring is active:

Read acceleration (ax, ay, az)  
 Read an velocity (wx, wy, wz)

Calculate acceleration magnitude:

$$A_{res} = \sqrt{a_x^2 + a_y^2 + a_z^2}$$

Compute angular velocity magnitude:

$$w_{res} = \sqrt{w_x^2 + w_y^2 + w_z^2}$$

If ( $A_{res} > T_a$ ) OR ( $\omega_{res} > T_\omega$ )

Extract motion features

Apply SVM classifier

If a fall-risk condition is detected:

Activate vibration alert  
 Activate buzzer alert  
 Measure heart rate and SpO<sub>2</sub>  
 Transmit alert and physiological data via BLE

End If

End If

End While

Stop

## V. IMPLEMENTATION

The proposed fall-risk prediction system is developed using an embedded microcontroller platform to enable continuous monitoring of body motion and physiological parameters. The implementation supports real-time signal acquisition, execution of the detection algorithm, generation of alerts, and wireless communication while maintaining efficient energy usage.

### A. Hardware Platform Design:

The system is built around the STM32F401CCU6 microcontroller, selected for its processing capability and suitability for portable embedded applications. Motion data are obtained using the MPU6050 inertial measurement unit, which measures acceleration and angular velocity required for gait analysis and abnormal motion detection. Physiological parameters such as heart rate and oxygen saturation are measured using the MAX30102 sensor, and body temperature is monitored using the LM35 sensor. All sensors are connected to the microcontroller using the I2C communication interface, allowing synchronized acquisition of motion and physiological information required for fall-risk analysis.

**B. Signal Processing Design:**

The microcontroller continuously reads motion sensor data and calculates acceleration and angular velocity magnitudes. These values are compared with predefined threshold limits to identify unusual motion conditions.

If abnormal motion is detected, the system performs additional analysis using a machine learning classifier. This two-stage processing approach improves detection accuracy while minimizing unnecessary computation and reducing processing delay.

Signal filtering techniques are also applied to reduce noise and improve the reliability of motion data.

**C. Alert and User Notification Design:**

When the system identifies a fall-risk condition, alert mechanisms are activated immediately. A vibration motor provides tactile feedback to the user, while a buzzer generates an audible warning signal. These alerts help notify the user about potential fall risk.

**D. Wireless Communication Implementation:**

The system uses a Bluetooth Low Energy (BLE) module to transmit information wirelessly. The transmitted data include:

- Fall-risk alert status
- Heart rate
- Blood oxygen level
- Temperature

This enables remote monitoring by caregivers or external devices.

**E. Power Management:**

The system operates using a rechargeable 3.7 V Li-Po battery with charging and protection circuitry. Power efficiency is achieved through:

- Threshold-based screening to reduce unnecessary processing
- Conditional activation of machine learning classification
- Efficient embedded algorithm execution

This implementation ensures low power consumption and extended battery life during continuous monitoring.

**F. Embedded Operation & System Execution:**

The embedded system is programmed to perform continuous acquisition and processing of sensor data in real time. The STM32 microcontroller reads motion and physiological signals and executes the dual-stage detection algorithm to identify abnormal gait conditions. The system is configured to activate alert mechanisms and transmit data only when abnormal motion is detected, which helps reduce unnecessary processing and improve overall efficiency. This implementation ensures reliable operation and supports continuous wearable monitoring for fall-risk detection.

**VI. RESULTS AND PERFORMANCE ANALYSIS**

The proposed proactive fall-risk prediction system was evaluated using simulated inertial sensor data and machine learning-based classification. The analysis focuses on motion signal behaviour, abnormal motion detection, classification performance, and embedded system efficiency.

**A. Raw Acceleration Signal Analysis:**

The acceleration signals measured along three orthogonal axes provide information about body movement during normal and abnormal conditions. These signals form the primary input for the detection algorithm.

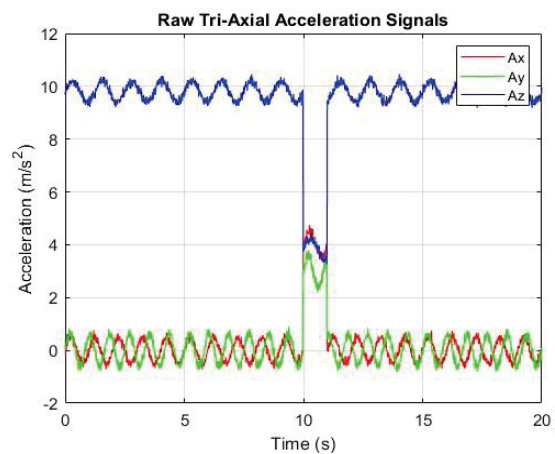


Fig.2. Raw Tri-axial acceleration signals obtained from IMU sensor

A clear disturbance in acceleration values can be observed between 10 and 11 seconds, which represents abnormal movement associated with a potential fall-risk event. This variation confirms the suitability of acceleration data for fall-risk analysis.

**B. Signal Magnitude Vector Analysis:**

To obtain a single parameter representing overall body motion, the Signal Magnitude Vector (SMV) was calculated using acceleration components.

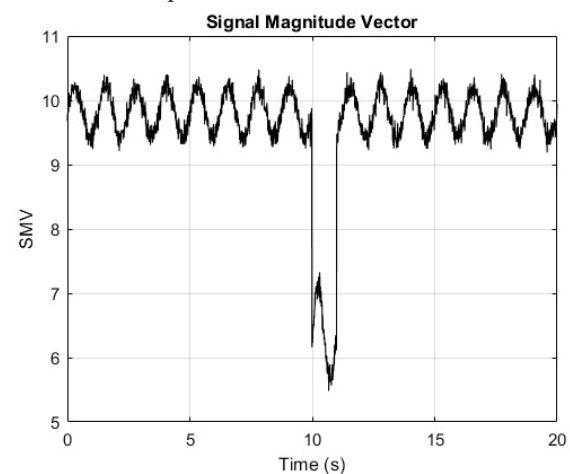


Fig.3. Signal magnitude vector of motion data

The SMV plot shows a significant deviation during the abnormal motion period, indicating instability in body movement. This parameter simplifies detection by combining information from all three axes.

**C. Threshold-Based Detection:**

The SMV values were compared with a predefined threshold to identify abnormal motion events.

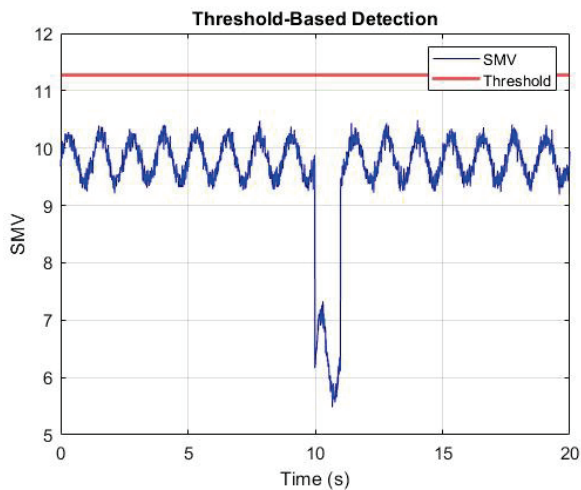


Fig.4. Threshold-based abnormal motion detection

The figure shows that the SMV crosses the threshold during abnormal motion, triggering the fall-risk detection process. This confirms the effectiveness of the threshold-based screening stage.

**D. Machine Learning Classification:**

The Support Vector Machine classifier was used to categorize motion data into normal and fall-risk conditions.

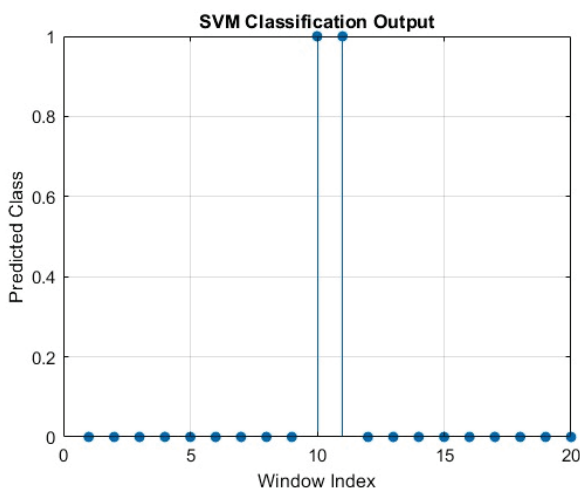


Fig.5. SVM classification output

The classifier successfully detected abnormal motion at specific time intervals while maintaining correct identification of

normal movement. This demonstrates the ability of the machine learning model to improve detection reliability.

**E. Confusion Matrix and Performance Evaluation:**

The classification results were evaluated using a confusion matrix, which summarizes prediction accuracy.

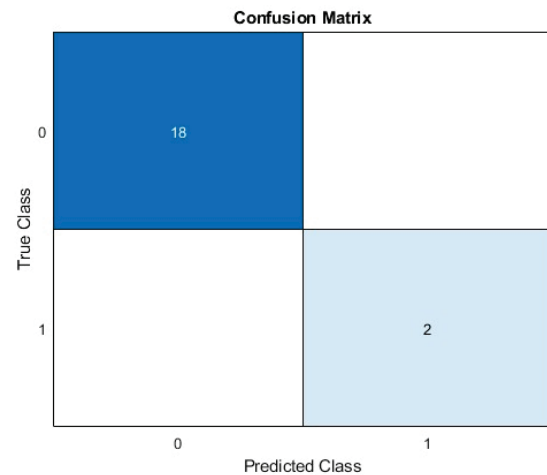


Fig.6. Confusion matrix for fall-risk classification

From the confusion matrix, the obtained results are:

- True Negative (TN) = 18
- True Positive (TP) = 2
- False Positive (FP) = 0
- False Negative (FN) = 0

**F. Performance Parameter Calculation:**

The classification performance parameters were calculated as follows:

Accuracy:

$$\text{Accuracy} = (\text{TP} + \text{TN}) / \text{Total}$$

$$\text{Accuracy} = (2 + 18) / 20$$

$$\text{Accuracy} = 100\%$$

Precision:

$$\text{Precision} = \text{TP} / (\text{TP} + \text{FP})$$

$$\text{Precision} = 2 / 2$$

$$\text{Precision} = 100\%$$

Recall:

$$\text{Recall} = \text{TP} / (\text{TP} + \text{FN})$$

$$\text{Recall} = 2 / 2$$

$$\text{Recall} = 100\%$$

F1-Score:

$$\text{F1 Score} = 1.0$$

These results indicate accurate classification of fall-risk conditions in the simulation environment.

#### G. Latency Analysis:

The response time of the system includes sensor data acquisition and algorithm execution. The measured detection delay was less than **100 milliseconds**, which confirms that the system can operate in real-time conditions.

#### H. Power Consumption Analysis:

Power usage was estimated based on embedded system operation. The implementation reduces energy consumption by activating advanced processing only when abnormal motion is detected.

Battery performance observations:

- 10–12 hours continuous monitoring
- 4–5 hours frequent alert conditions

This demonstrates the suitability of the system for wearable applications.

### VII. DISCUSSION

The simulation and classification results demonstrate that the proposed fall-risk prediction system can effectively identify abnormal gait conditions using motion sensor data. The acceleration and signal magnitude vector plots clearly show noticeable deviations during abnormal movement, which confirms that inertial sensor signals can be used to detect instability associated with potential fall events. The threshold-based screening stage provides fast detection of unusual motion and ensures that only relevant data are processed in the next stage.

The addition of the Support Vector Machine classifier improves the reliability of detection by distinguishing between normal and fall-risk motion patterns. The confusion matrix results indicate that the classifier correctly identified all motion samples in the simulated dataset. This confirms that the combination of threshold screening and machine learning classification can improve fall-risk prediction performance compared to using a single detection method.

The analysis also shows that the system is capable of operating with low detection delay, which is essential for real-time wearable healthcare applications. Early identification of fall-risk conditions allows timely alert generation, which may help reduce fall-related injuries. In addition, the embedded implementation and selective activation of processing stages help reduce power consumption, making the system suitable for battery-powered operation.

However, the current evaluation was performed using simulated motion data with a limited number of samples. In practical situations, sensor noise, variations in walking patterns, and different user conditions may affect system performance. Therefore, further testing using real-time hardware implementation and larger datasets is necessary to validate the system under real-world conditions.

Overall, the proposed system provides a promising approach for proactive fall-risk prediction and continuous monitoring using a wearable embedded platform.

### VIII. CONCLUSION

This paper presented a wearable system for early fall-risk prediction using motion and physiological monitoring. The proposed dual-stage method, combining threshold detection and Support Vector Machine classification, enables reliable identification of abnormal gait conditions. Simulation results show accurate detection with low response time and efficient power usage.

The embedded STM32 implementation supports continuous wearable operation and wireless alert transmission for remote monitoring. Future work will focus on real-time hardware validation and testing with larger datasets to further improve system performance and reliability.

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