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# A Machine Learning Based System for Fall Detection and Elderly Care

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**Abstract:** Fall detection is vital for the elderly due to the prevalence of fall-related injuries. Implementing such systems can lead to timely interventions, better care, and reduced healthcare costs, improving the overall safety and well-being of older individuals. This paper proposes an innovative fall detection system that combines the Inertial Measurement Unit (IMU) approach with the computer vision approach. The IMU system uses the Random Forest algorithm (RF) for analyzing accelerometer data, distinguishing between normal activities and fall events. Concurrently, a computer vision (CV)-based approach uses Histogram of Oriented Gradients (HOG) feature extraction to train a Random Forest classifier, enabling fall detection based on visual cues. Further, the ensemble model combines predictions from both approaches and uses a voting classifier for final decision-making, leveraging the strengths of both approaches. Experiments were conducted on real-world datasets, demonstrating the high accuracy and sensitivity of detecting falls. The CV-based approach has shown 96% accuracy; the IMU-based approach has shown an accuracy of 98%; and the ensemble approach has shown 97% accuracy for fall detection. The implemented system significantly enhances fall detection, minimizes false alarms, and provides timely assistance for vulnerable individuals. It holds potential for improving fall detection systems, benefiting elderly individuals living independently.

***Keywords:*** *Activity recognition, Fall detection, Residential monitoring, Computer vision.*

## 1. Introduction

Fall detection in the elderly is a significant concern in India, where a large aging population faces a higher risk of falls and related injuries. According to a survey conducted by the Indian Council of Medical Research (ICMR), falls among the elderly in India are a pressing issue with severe consequences. The survey revealed that the number of fall incidences in the elderly has been increasing on a yearly basis. In 2020, there were approximately 4,500 reported cases of falls among older adults, A 15% rise from the previous year. According to WHO, roughly 32-35 percent of adults of age 60 and above suffer from falls on a yearly basis, with the figure expected to rise to 40 percent for senior citizens of age 70 and above. These falls resulted in significant injuries, including fractures, head trauma, and hospitalizations [1]. The survey underscores the urgent need for effective fall detection measures and preventive strategies to safeguard the well-being and independence of the elderly population [2].

This study introduces a cutting-edge fall detection system using ensemble approach that combines data from an Inertial Measurement Unit (IMU)- wearable accelerometer device with advanced computer vision techniques. The wearable accelerometer continuously records acceleration patterns during daily activities, capturing unique motion patterns associated with falls. Random forest algorithm is employed to analyze the accelerometer data, distinguishing between normal activities and fall events with high accuracy. Simultaneously, computer vision techniques based on HOG feature extraction are utilized with the Random Forest algorithm to analyse motion patterns and gradients in the video frames [10]. The ensemble model fuses the predictions from the Random Forest algorithm in both approaches, enhancing the system's accuracy and robustness in detecting fall events. By integrating accelerometer and computer vision data, the system offers comprehensive real-time monitoring and timely assistance for vulnerable individuals, thereby improving fall detection efficacy and reducing the likelihood of false alarms [4].

The research paper presents experimental results obtained from two different diverse datasets of real-world falls and non-fall activities used in accelerometers as well as a computer vision approach, demonstrating the effectiveness of the ensemble approach in detecting fall events with high accuracy and sensitivity. In the next section, insights on participants, procedures, and dataset creation are given.

## 2. Study Design

### 2.1. Participants

The research work involves the participation of five elderly individuals as study participants. Among them, three participants are male, aged between 60 to 65 years, with body mass indexes ranging from 24 to 28 kg/m2, heights between 171.0 to 186 cm, and weights varying from 65.5 to 80 kg. Additionally, two female participants, also aged between 60 to 65 years, are part of the study with body mass indexes ranging from 20 to 24 kg/m2, heights between 160.0

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to 175 cm, and weights varying from 58 to 70 kg. The selection process deliberately included individuals with diverse body shapes and heights to introduce variety in the dataset. It is important to note that individuals who are handicapped or bedridden were excluded from participation in the study. Prior to conducting any experiments, informed consent was obtained from all the participants, ensuring their willingness, and understanding of the research objectives.

### 2.2. Procedures

In the computer vision approach, we recorded video footage of all participants engaging in normal activities such as sitting, standing, lying, and walking, as well as abnormal activities like falling. The recordings were captured using a 12-megapixel web camera from various angles, with a video resolution of 640 x 480 and a frame rate of 30 fps. The distance between the webcam and the participants ranged from 180 cm to 300 cm, while the camera's height varied between 120 cm to 190 cm [5]. One camera is used for each room in the elderly living house to monitor their daily activities and falls. A total of three cameras are used in the implemented system. For participants the fitted clothing that closely follows the body contours is used. Baggy or loose-fitting clothing are avoided as it can obscure important body features and movements, making it harder for the model to accurately recognize activities [7].

In an Inertial Measurement Unit (IMU)-based approach, authors have used accelerometers to assess daily activities and abnormal activity mainly falls that occur in real time, based on acceleration measurements. The electronic system for it consists of an Inertial Measurement Unit (IMU) MPU-6050 used for detecting sudden changes in acceleration and a microcontroller ESP 8266 used for processing the sensor inputs. The IMU used has a pitch and roll resolution of 0.01 degrees and can detect very small changes in orientation found in common exercises. This helps prevent the system from mischaracterizing day-to-day activities as falls. The casing of the wearable device to occupy the electronic system is designed and used to house the sensors and electronic circuitry necessary for the system's functioning. The case was designed in SOLIDWORKS (CAD Software) with extrusions for the wristband and stress- tested in the software to ensure durability and rigidity during falls. Various simulations were run to ensure that the case was rigid and structurally durable enough to sustain the impact of falls. SolidWorks Simulation results indicated that the case could sustain an impact of up to 5g forces. The system was dropped from a height of 200cm. It was also observed that the critical stresses acting on the casing did not cause it to break, and they ensured that it was sturdy enough.

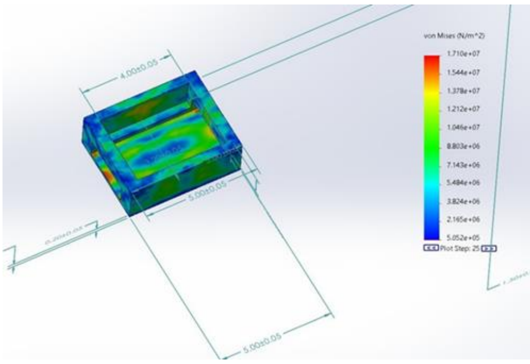



**Fig. 1.** Stress testing of the case in SOLIDWORKS

From Figure 1, we can analyze the equivalent stresses acting on the case. The deformations are minimal, even at falls from an exaggerated height, hence proving the robustness of the casing. It was also structurally reinforced to ensure rigidity.

The extrusions for the casing were designed so that the end user would feel comfortable in wearing the device as a wristwatch, without experiencing any discomfort, since the device was mainly designed for senior citizens.

### 2.3. Dataset creation

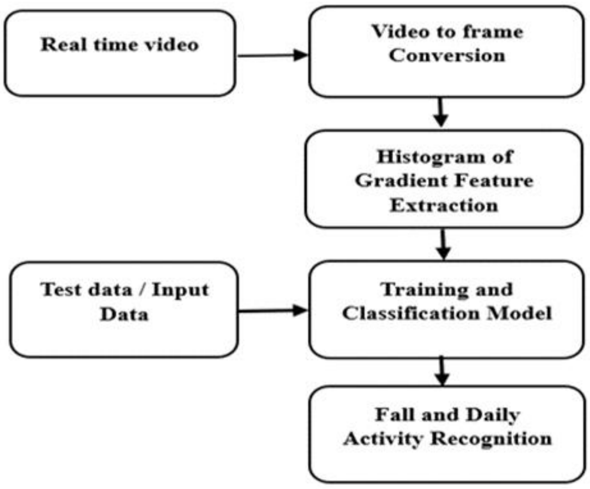
In the computer vision approach to create the dataset, we converted the video recordings of each participant's activities into individual frames. Specifically, we recorded 800 images per person for each activity. The total number of images in the dataset amounted to 20,000. The computer vision approach utilized video recordings from different angles and distances to capture a diverse range of activities performed by the participants. The resulting dataset consisted of 20,000 images, which serves as the foundation for our fall detection research.

The IMU-based wearable device worn by participants in their hands continuously monitors their daily activities as well as falls. For dataset creation, acceleration values in all three axes for five elderly participants' daily activities of sitting, standing, walking, and lying were recorded. As a fall is a rare case, it is simulated and recorded in a real-time environment. A total of 2,40,000 values of acceleration were recorded for all daily activities and falls to create the dataset. These acceleration values are used to differentiate between falls and other daily activities.

## 3. Methodology

Fall detection is a critical application where the accuracy and robustness of the system are paramount. An ensemble technique can help improve accuracy by combining the outputs of multiple classifiers or models. By leveraging different sources of information and handling diverse data characteristics, ensemble methods can provide a more reliable and robust fall detection system. An IMU-based fall detection captures motion patterns and acceleration data, while computer vision-based approaches analyze visual cues and body movements. These two sources of data are complementary and combining them in an ensemble allows the system to benefit from the strengths of each approach, leading to a more comprehensive fall detection system.

**Fig. 2.** Computer vision-based approach for the fall detection




Firstly, As shown in figure 2 the authors have implemented a computer vision-based approach. Activity recognition using Histogram of Oriented Gradients (HOG) for feature extraction and the Random Forest algorithm for classification is a popular approach in computer vision. The HOG feature descriptor is a widely used technique to represent the local gradient or edge information in an image. It captures the shape and appearance of objects, making it suitable for detecting human bodies and their movements.


**Fig. 3.** (a) Falling (b) Standing (c)Walking

The HOG algorithm involves the following steps:

1. Image Preprocessing: Convert the input image to grayscale and apply normalization or contrast equalization if required.

2. Gradient Computation: Calculate the gradients (magnitude and orientation) for each pixel in the image. The magnitude represents the strength of the edge, while the orientation indicates the direction of the edge. Gradient Magnitude (M) at pixel (x, y) is,

$$M(x, y) = \mathrm{sqrt}(Gx^2(x, y) + Gy^2(x, y)) \quad (1)$$

Gradient Orientation (θ) at pixel (x, y) is,

$$\theta(x, y) = \mathrm{atan2}(Gy(x, y), Gx(x, y)) \quad (2)$$

3. Cell Formation: Divide the image into small cells. Each cell typically covers a square region of pixels (e.g., 8x8 pixels).

4. Histogram Calculation: For each cell, create a histogram of orientations by accumulating gradient magnitudes into orientation bins. The number of bins can be predefined (e.g., 9 bins representing 20 degrees per bin). The histogram bin index is given by:

$$\text{Bin index}(x, y) = \mathrm{floor}(\theta(x, y) / (360° / B)) \quad (3)$$

4. Block Normalization: Combine neighboring cells into larger blocks (e.g., 2x2 cells) and normalize the histograms within each block to enhance the descriptor's robustness to lighting variations and contrast changes. After feature extraction, a random forest classifier is used for activity

classification [8].

Let X be the feature matrix obtained from the HOG descriptors of the training data. Each row in X represents a sample, and each column represents a feature. Let y be the corresponding class labels for the training samples. Training the Random Forest involves constructing multiple decision trees using bootstrapped subsets of the data and random feature subsets. The prediction for a new sample x is obtained by aggregating the predictions from each decision tree. Mathematically, the prediction for a given sample x can be represented as follows:

$$RF(x) = mode(T\_1(x), T\_2(x), ..., T\_n(x)) \quad (4)$$

Where RF(x) is the final prediction, T_i(x) is the prediction of the i-th decision tree, and mode () returns the most frequent prediction among all the decision trees. The number of decision trees, n, is a hyperparameter specified before training the Random Forest classifier.

Overall, the HOG feature extraction technique provides meaningful representations of human body features, and the Random Forest classifier is capable of learning complex decision boundaries for activity recognition based on these features. The combination of these two methods has been successfully used in this system for fall detection.

Figure. 3 shows identified activities using a computer vision approach.

The authors have implemented the second approach of an accelerometer-based wearable device for fall detection. The accelerometer-based wearable device for fall detection is designed to detect sudden changes in acceleration that occur during a fall. The device uses an MPU 6050 sensor to measure the acceleration in three axes (X, Y, and Z) and an ESP8266 microcontroller for data processing and communication. An accelerometer-based fall detection system is shown in figure 4.

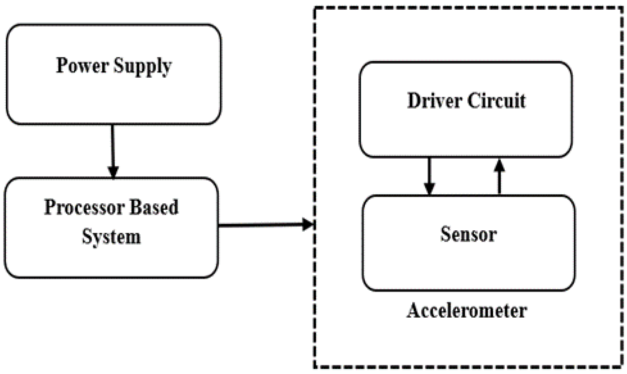



**Fig. 4.** Accelerometer-based fall detection system

Machine learning techniques, specifically the Random Forest classifier, are used to distinguish between normal activities and fall events based on the accelerometer data. The MPU 6050 sensor measures acceleration along the three axes (X, Y, and Z) relative to the device's orientation. These acceleration values are sampled at regular intervals, generating a time series of acceleration data. To apply machine learning algorithms, meaningful features are extracted from the raw accelerometer data. The authors have calculated the mean acceleration along each axis from the acceleration time series.

$$mean\_X = (1/N) * \Sigma(a\_X[i]), \text{ for } i=1 \text{ to } N \quad (5)$$

$$mean\_Y = (1/N) * \Sigma(a\_Y[i]), \text{ for } i=1 \text{ to } N \quad (6)$$

$$mean\_Z = (1/N) * \Sigma(a\_Z[i]), \text{ for } i=1 \text{ to } N \quad (7)$$

where a_X[i], a_Y[i], and a_Z[i] are the acceleration values along X, Y, and Z axes at time i, respectively, and N is the total number of samples. The collected accelerometer data needs to be labelled with the corresponding activity type, i.e., fall or non-fall (normal activities) [16] This labelling is done using human annotation. The labelled accelerometer data is divided into two sets: a training set and a testing/validation set. The training set is used to train the Random Forest classifier. The classifier is an ensemble of decision trees, where each tree is built on a random subset of the training data and features. Once the RF classifier is trained, it can be used to predict whether a new input acceleration data corresponds to a fall event or not. The trained classifier takes the extracted features from the new data and returns the predicted class (fall or non-fall). During the training phase, each decision tree in the ensemble is built using a subset of the training data and a random subset of features. The decision trees learn to partition the feature space based on the labelled data, creating multiple hypotheses for predicting fall or non-fall events. By averaging the predictions of multiple decision trees, the Random Forest classifier can improve the overall accuracy, robustness, and generalization capabilities of the fall detection system based on accelerometer data [18].

As shown in figure 5, by combining the above mentioned two approaches using a voting classifier, the authors have created a more reliable, accurate, and robust fall detection system suitable for real-world scenarios. In the ensemble approach, authors have used soft voting.

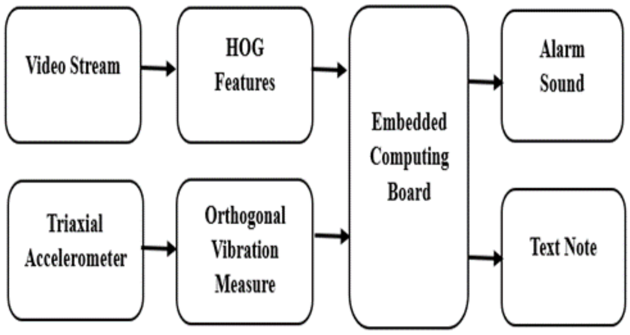



**Fig .5.** Ensemble approach for fall detection

It considers the confidence levels or probabilities associated with the base classifiers' predictions. Soft voting combines the probabilities of each base classifier from computer vision and accelerometer-based techniques and produces a final prediction based on the highest average or weighted probability.

For all implemented models, the authors utilized the cross-validation approach to evaluate the machine learning model's performance on unseen data. The data was divided into multiple subsets or folds, with one serving as the validation set and the others used for training the model. They employed a ten-fold cross-validation technique, which effectively addressed the issue of overfitting.

All approaches are implemented and tested on local machines first. Then, for a real-time environment, the Jetson Nano computing board is used as a stand-alone system. Among the two approaches, the first is a computer vision system ported completely to the Jetson Nano. The required 12-megapixel camera is configured with the Jetson Nano. In the second approach, the IMU-based wearable device is worn by elderly people. The acceleration data generated by the IMU-based system is continuously sent to the Jetson Nano through Wi-Fi. The random forest classifier model of the IMU-based system ported to the Jetson Nano predicts the result. And finally, the ensemble approach ported to the Jetson Nano makes the final decision through the voting classifier.

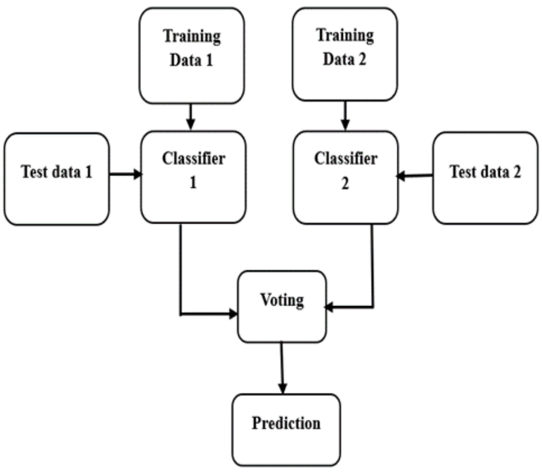



**Fig. 6.** Alert system for fall detection

Figure 6 shows the alert system for fall detection. At Fall event detection, an alarm sound is enabled, and a text note is sent to the caretaker.

In the result analysis section, the authors thoroughly discussed the outcomes of their implemented system.

## 4. Results and Discussion

In this section, the authors have discussed the performance metrics, methods, and performance analysis of all three implemented systems.

### 4.1. Performance metrics and methods

The system's validation was conducted using the confusion matrix, which is an effective method to evaluate the classification algorithm. The confusion matrix represents the comparison between correct and incorrect predictions. The authors employed two distinct approaches for fall detection in the implemented system, each using its own dataset. Both datasets were split into training and testing subsets. The system's efficacy was assessed by evaluating its performance on these testing and training datasets. Based on these evaluations, the authors calculated metrics such as "Accuracy, Recall, Precision, and F1 scores" to represent the implemented system's performance.

At the same time, all implemented systems were tested in a real-time scenario; all three implemented systems were tested 200 times randomly on all participants. During testing, daily activities like sitting, standing, walking, and lying were captured 150 times, and fall events were captured 50 times. In real-time scenarios, all individual systems have performed exceptionally well. The fall event was efficiently differentiated from other daily activities.

### 4.2. Performance analysis of the computer vision approach using the RF algorithm

The Random Forest algorithm performance analysis is done by varying the number of estimators. At 50 number of estimators, an algorithm got highest accuracy. As shown in table.1 For a computer vision-based approach, on all the mentioned daily living activities, the implemented system had an average accuracy of 95.6%, precision of 94.6%, recall of 92%, and an F1 score of 94.8%.

**Table.1** Performance analysis of the computer vision approach using the RF algorithm.

| Activity | Accuracy | Precision | Recall | F1 |
|---|---|---|---|---|
| Fall | 0.96 ± 0.1 | 0.96 | 0.91 | 0.96 |
| Lying | 0.95 ± 0.1 | 0.94 | 0.89 | 0.95 |
| Sit | 0.98 ± 0.2 | 0.98 | 0.97 | 0.98 |
| Stand | 0.95 ± 0.1 | 0.94 | 0.90 | 0.93 |
| Walk | 0.94 ± 0.3 | 0.91 | 0.93 | 0.92 |

In this approach, fall detection is clearly differentiated from all other activities. It has shown 96% accuracy. The response time was also recorded. A computer vision-based approach takes 1.2 seconds for decision making of normal and abnormal activity recognition.

### 4.3. Performance analysis of accelerometer-based approach using RF algorithm

The Random Forest method's performance is also evaluated in this approach by adjusting the number of estimators. A method with 10 estimators achieved the maximum accuracy.

**Table.2** Performance analysis of IMU-based approach using RF algorithm.

| Activity | Accuracy | Precision | Recall | F1 |
|---|---|---|---|---|
| Fall | 0.98 ± 0.2 | 0.97 | 0.95 | 0.96 |
| Lying | 0.97 ± 0.1 | 0.98 | 0.92 | 0.97 |
| Sit | 0.98 ± 0.3 | 0.98 | 0.96 | 0.98 |
| Stand | 0.95± 0.1 | 0.97 | 0.95 | 0.96 |
| Walk | 0.96 ± 0.2 | 0.94 | 0.96 | 0.93 |

According to Table 2, the IMU-based approach of the implemented system achieved impressive results across all mentioned daily living activities. The system demonstrated an average accuracy of 96.8%, precision of 96.8%, recall of 94.8%, and an F1 score of 96%. Notably, the fall detection in this approach showed exceptional performance with 98% accuracy, effectively distinguishing it from all other activities.

The response time was also recorded. Accelerometer based approach has taken 400 milliseconds for decision making of normal and abnormal activity recognition.

### 4.4 Performance analysis of ensemble technique

As shown in Table 3, The ensemble approach demonstrates excellent performance with an accuracy of 0.97, indicating that 97% of the predictions made by the system are correct. The high precision score of 0.96 suggests that the system has a low false-positive rate, meaning it accurately identifies true fall events and minimizes false alarms. The recall score of 0.96 indicates that the system correctly detects 96% of actual fall events, showing good sensitivity. The F1 score of 97%, which is the harmonic mean of precision and recall, confirms the overall effectiveness of the ensemble approach in accurately detecting falls while maintaining a balanced trade-off between precision and recall.

**Table 3.** Performance analysis of ensemble technique for fall detection

| Approach | Accuracy | Precision | Recall | F1 |
|---|---|---|---|---|
| Computer vision Approach | 0.96 | 0.96 | 0.91 | 0.96 |
| IMU-based Approach | 0.98 | 0.97 | 0.95 | 0.96 |
| Ensemble technique | 0.97 | 0.96 | 0.96 | 0.97 |

The response time was also recorded. Ensemble approach takes 1.5 seconds for decision making of normal and abnormal activity recognition.

## 5. Conclusion

The implemented system presents an innovative fall detection system with an ensemble approach. This ensemble method effectively leveraged the strengths of the accelerometer-based and computer vision-based approaches, resulting in a highly accurate and sensitive fall detection system. Experiments conducted on real-world datasets demonstrated the ensemble's impressive accuracy of 97% in detecting falls. These results highlight the ensemble approach's success in achieving reliable fall detection with minimal false alarms, which is crucial for providing timely assistance to vulnerable individuals, particularly the elderly. The system's high accuracy and sensitivity make it a valuable tool for enhancing emergency response and safeguarding the well-being of elderly populations or individuals with mobility limitations. This novel approach offers comprehensive real-time monitoring, supporting carers and healthcare professionals in ensuring the safety and well-being of the elderly population. However, it's essential to continue evaluating the system's performance on diverse datasets and real-world scenarios to ensure its effectiveness in various environments and use cases. This paper contributes to the advancement of healthcare technologies by addressing the critical need for reliable fall detection systems.

### Author contributions

The study was designed by **Sudhir Gaikwad** and **Shripad Bhatlawande**. Sudhir Gaikwad undertook the study, contributing to the drafting of the manuscript. **Anjali Solanke** provided support in terms of analysis, literature review. All authors participated in the review and approval process of the final manuscript version.

### Conflicts of interest

The authors state that there are no conflicts of interest to disclose.

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