# A comparative Study of Several Machine Learning Algorithms to Identify Fall Detection in Senior Citizens

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**Abstract**.
Falling is a regular incident that occurs in the senior population and may result in severe injuries if not addressed promptly. As a result, early diagnosis of falls in the elderly is critical in order to minimize the critical consequences of a fall in this population. Several fall tracking methods rely on the accelerometer have been presented for the purpose of fall identification in recent years. Most of them, on the other hand, wrongly perceive everyday actions or fall as everyday life engagement as they do. This work proposes a machine learning-based fall detection system that is both efficient and effective in achieving this goal. When based on current state-of-the-art approaches, the suggested methods identify the collapse with high sensitivity, specificity, and precision. To properly identify the fall incidence, a publicly accessible database with a relatively basic and computationally structured collection of attributes is employed in conjunction with machine learning methods. With the Support Vector Machine algorithm, the suggested technique achieves an accuracy of 99.78 percent, according to the results.

**Keywords**. Fall Detection; SisFall Dataset; ML Algorithms; KNN; SVM; WSN; fall detection in seniorcitizens

## 1 INTRODUCTION

The number of persons over the age of 65 who are residing solitary throughout the globe has been steadily growing, particularly in western nations. The elderly are susceptible to a variety of issues, the most common of which is falling. Falling is the most prevalent problem among the senior population under the age of 60. Generally speaking, a fall is described as "unknowingly coming to rest on the ground, the basement, or another lower level, omitting purposeful adjustment of posture to come to rest in furniture, the wall, or other items." One-fourth of adults over the age of 60 experience an average of two falls per year, and two-thirds of them have the chance of collapsing again [1], with the risk of falling increasing as the person becomes older.

According to a research published by the World Health Organization [2], collapses are the second biggest threat of unintended or accidental mortality. When you have a serious fall, it may result in a lengthy hospital stay as well as chronic impairment, difficult rehabilitation, the loss of independence, and even death.

For more than two decades, professionals from both the technology and medical disciplines have been trying to reduce the effects of falls by shortening the reaction time and offering better treatment when a collapse occurs. Collapse are regarded as one of the most dangerous accidents that may occur to an aged people, and they can be fatal.

There has been earlier study on this issue in the emergence and development of various systems connected to Ambient Assisted Living Systems, in which the establishment of a platform for the recognition of Activities of Daily Living and their surroundings has been investigated [3], and this subject is included in that studies.

Falls may have a negative impact on the quality of life of senior individuals by causing a variety of potentially life-threatening health conditions such as tear and central nervous system damage, as well as a decrease in mobility and activity. The "longlie," which is described as being on the floor for longer time following a fall, is a dangerous consequence of falling and may result in death if not treated immediately.

The elderly, defined as anybody over the age of 65, are the group that suffers the largest number of fatal falls. According to estimates, over 646000 people die from falls each year across the world, with more than 80 percent of these deaths occurring in low- and middle-income nations. The number of people who die as a result of inadvertent falls is growing all around the world. Approximately 30,000 senior adults over the age of 65 died in the United States as a result of an unintended fall in the year 2016. In Figure 1, you can see the mortality rates per 100,000 populations for those over the age of 65 from the year 2000 to the year 2015. There has been a continual increase in this rate, with an average annual growth rate of 4.9 percent since the beginning of the period. Furthermore, when comparing senior men to elderly women, the death ratio is greater in males [4] [13].

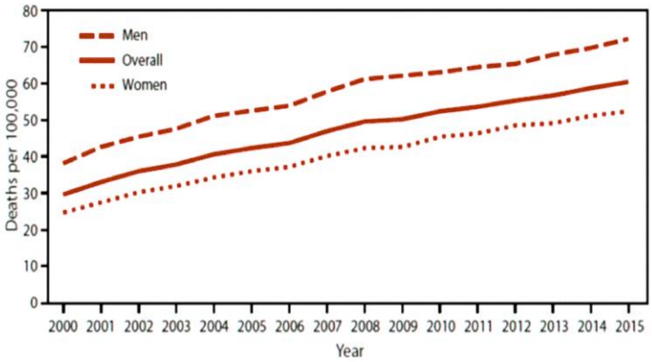


Figure 1: Fall-related death toll in the United States, 2000-2015

The repercussions of a fall are not just limited to serious bodily injuries, but may also include psychological distressing effects. A few of the symptoms people with this illness experience include worry, movement disorder, depression, hyperbolic activity restriction, and a lack of self-confidence over. Fear of collapse is one of the most common psychological difficulties that affect senior individuals, and it significantly limits their ability to carry out their everyday duties. Because of their fear of falling, about 60% of the older population restricts their daily life activities [5]. It is possible that this activity limitation will result in poor gait balance and muscular weakening, which will eventually impair the mobility and independence of the elderly, and as a consequence, the incidence of falling will recur. Figure 3 depicts the fall cycle that may occur repeatedly as a result of a fear of collapse.

Because the human body grows weaker with age and as a result of the ageing process, the likelihood of a fall rises. Every year, around 35 to 60 percent of persons residing in long-term care facilities are injured in a fall, with 40 percent of those injured falling again. Falls become exponentially more common as a result of age-related physiologic changes. During the previous three decades, the frequency of various fall-related injuries, such as breakage and spinal cord damage, has grown significantly, by a factor of 131 percent. On average, one or more persons in each team of five people will be 65 years or older by the year 2050, according to projections. As a result, if preventative assess are not implemented in the coming days, the amount of casualties caused by collapse is expected to rise dramatically.

A fall occurrence happens anytime an individual lacks his or her equilibrium and is unable to maintain their balance and remain upright. When a youngster loses his or her equilibrium, he or she has the ability to regain it; but, when an old person loses his or her stability, it is exceptionally hard for him or her to recoup since he or she is relatively feeble at that stage of their lives. There are a variety of variables that might contribute to a fall. All of the elements that have the potential to cause falls are together referred to as risk factors for falls. In reality, the incidence of a fall is the consequence of a complicated interplay between a variety of circumstances. Specifically, there is a relationship between the risk of dropping and the number of variables, with the chance of falling increasing as the number of factors grows. As seen in Figure 2, the risk factors may be divided into three categories: behavioural, environmental, and biological risk variables. Behavioral risk factors are the most common form of risk factor.

Risk factors associated with human behaviors, emotions, and routines of everyday living are referred to as behavioral risk factors. By implementing a strategic intervention, these elements may be brought under control. For example, if a person suffers a fall as a result of excessive drug or alcohol use, this habit or behavior may be changed via strategic therapy. People are exposed to environmental risk factors because they live in an area that is hazardous to them. Floors that are too slippery, inadequate illumination, and damaged paths are just a few of the serious ecological risks to be aware of.

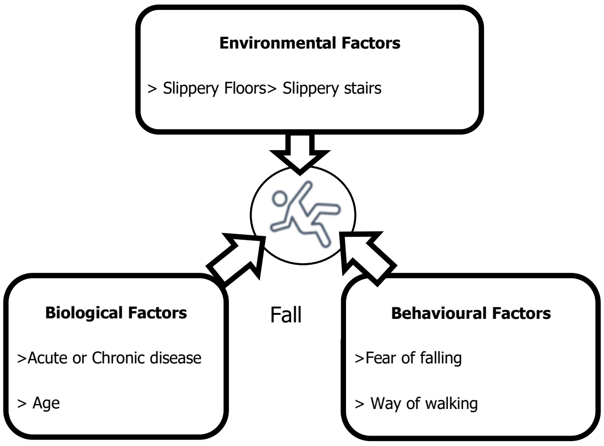


Figure 2: Risk Factors During Collapse

Genetic risk factors are associated with a person's age, gender, and physical well-being. Biological risk factors include chronic diseases, insulin, heart disease, eyesight abnormalities, blood pressure, movement and equilibrium issues, and other conditions. Although biological characteristics such as age and gender are unchangeable, illnesses may be relieved or managed by effective therapy, and physical health can be enhanced as a result of proper treatment.


Figure 3: Falling Life Span

The acute and lengthy consequences of falling may be mitigated by recognizing the fall as soon as possible and seeking medical attention as soon as possible. Fall surveillance systems may thus assist in reducing these issues by sending out an emergency notice in the event that a fall incidence occurs. Many systems for collapse identification have been presented in order to achieve this goal. It has also been recommended for fall detection that several fall tracking model based on accelerometer and gyroscope be implemented. This work proposes a machine learning-based fall detection system that is both efficient and effective in achieving this goal. In the human fall-related arena, there are two study tracks: falling identification and prevention of Collapsing. The primary goal in the falling detection area is to minimize the amount of time it takes to rescue someone once a fall has happened. The primary emphasis of the falling prevention domain is the prediction of falls using gait and balance analyses.

In the event of a falling occurrence, fall detection systems may be quite useful in shortening the reaction time. Fall prevention devices may be very effective in both preventing and delaying future falls. It is possible to categories people fall-related devices into three groups: camera systems, environmental systems, and wearable systems. Camera- and ambient-based gadgets are seldom utilized because of the elevated amount of the technologies. Wearable gadgets that employ inertial measuring units such as accelerometers and gyroscopes are becoming more popular. As a result of the development of micro-electro-mechanical systems, wearable gadgets that are both compact and lightweight may be deployed. In fall detection systems, a variety of data processing methods are utilized to detect falls. These strategies are reliant on the parameters that have been obtained from the sensors. In FDS, there are primarily two kinds of data processing techniques that are used: analytical approaches and machine learning methods.

### *1.1. Analytical Approach*

Fall prediction and prevention are accomplished via the use of analytical approaches that use statistical methodologies. These strategies for data categorization are based on techniques that have been around for a long time. Thresh-Holding, HMM [12], and BF are some of the most well-known data-processing analytical approaches available. All of these strategies are used to differentiate between collapse and non-collapse. The Thresh-Holding method is the most often utilized of these approaches. When maxima or certain form characteristics are recognized in the transmitted data, the fall is recorded or anticipated using this approach. This strategy is primarily employed in wearable technology-based systems. Environment-based systems used to track vibration signals,while camera-built device employ image analysis methods to predict and track falling objects.

### *1.2. ML Techniques*

Machine learning approaches use complicated system to determine or identify the occurrence of falls. These complicated methods are utilized to get a detailed understanding of data in order to anticipate the occurrence of falls. In machine learning approaches, the technique is first trained on a set of features collected from the database, and then it is applied to real-time data to see how well it works [14] [15]. Well-known machine learning techniques are utilized for the identification or forecasting of falls. In order to identify and even anticipate future falls, these strategies are employed to acquire insight into the data collected.

The remainder of this work is arranged in the following manner. Section II discusses the work that is associated with it. The methods used are described in Section III. Section IV discusses the outcomes of the experiment. Final section of this article, which includes an acknowledgment, brings the article to a close.

## 2. RELATED STUDY

The frequency of fall sensing devices has expanded dramatically as the world's older population has grown at an alarming rate. With sophisticated detection and monitoring, it is possible to guarantee that medical assistance is provided as soon as possible. The past decade has seen the development of a number of technologies that can properly detect falls and alert caretakers when they occur. However, the majority of systems were designed on the basis of sensor data from specialized quality detectors. As a consequence, the model performed worst on machines that had various qualities of the same sensors in different locations. On the [6, the author offers Fall Guardian, a system for fall identification and tracking that can be deployed in Mobile devices with a variety of detector characteristics. In this system, acquired sensor data was transferred to a cloud server, which was equipped with a Random Forest model. Then, using a post-fall motion identification algorithm, the system determined the severity of the fall injury and informed the career of the senior user, who was also given the elderly person's GPS position.

[7] The author offers a real-time, high-accuracy, deep learning-based collapse detection approach with automated human recognition and tracking that is both accurate and quick to implement. To be more specific, the proposed technique first enhances the YOLOv3 network in order to more effectively recognize people and extract feature maps from the item under consideration. YOLOv3 feature maps are fed into a multi-target monitoring system, which is constructed as a Deep SORT technique, for cascade matching and IOU matching. Following that, it enhances the YOLOv5 network's ability to identify postural irregularities. Finally, it refines the posture abnormalities that have been discovered in order to achieve the final fall detection result. The experimental findings demonstrate that the suggested strategy enhances both the accuracy and the efficiency of fall detection at the same time.

Deep learning-based collapse identification is one of the most important jobs for smart video monitoring systems, which attempts to identify accidental collapse of people and alert users to potentially hazardous circumstances when they occur. The author of [8] presents a simple and efficient method for detecting falls using a convolutional neural network to detect falls. In order to do this, we first offer a novel image synthesis approach that can accurately capture human motion in a single frame of video. As an image classification problem, the fall detection task is made simpler as a result of this. Furthermore, the suggested synthetic data creation approach allows for the development of a substantial quantity of training database, which results in good efficiency even with a tiny model. As part of the inference process, they also portray genuine human movement in a single picture by calculating a mean of the initial frames from the images.

In healthcare monitoring, movement detection is critical since it helps to identify when someone is doing anything. Most of our vital measures, such as heart rate and BP, are influenced by the activity we are engaged in at the moment, and without understanding this, it is difficult to identify irregularities in these values. Apart from that, activity detection may assist us in identifying emergency scenarios such as falls or even heart attacks. Taking into consideration the significance of distinguishing between abnormal activities and normal activities, this research has identifying the possibility of detecting falls using three important frequencies of wrist accelerations in each axis and their amplitudes in order to detect falls and ADLs. The use of an IMU in a wearable device has been shown in this context [9], which can detect moving, running, being still, and falling. With the help of ANN, we may compute the decision function (statistical model). In order to train the algorithm, 674 samples from almost 30 persons were collected. The results demonstrate that 94.8 percent of the time, continuing activity may be detected.

Author [10] has proposed a rapid and robust technique that can instantly identify falls and notify careers by SMS so that they may offer prompt aid, hence decreasing the amount of damage and treatment expenses. As a result, author [10] has highlighted the critical need of establishing an intelligent surveillance system to detect fall occurrences and notify the family or the caregivers. Two networks are used in their technique, a posture estimation network and an MLP classifier. First, they obtained a database that comprises features of the body in 500 postures, including lying and non-lying postures with varying lighting conditions, and then they utilized an MLP net to identify the poses using the information from the database. With regard to the validation dataset, the accuracy and loss were 92.5 percent and 0.3 percent, respectively.

According to [11], the author recommends an Internet of Things-based collapse detection and mitigation system for such persons in order to encourage living alone without relying on others or the need to be continuously watched, therefore boosting their quality of life. Our prototype of the system identifies the fall using a threshold-based accelerometer technique and prevents a fall by deploying Bluetooth Low Energy modules at key areas around the building. When a fall occurs, the system informs parents, caregivers, and medical personnel in charge by email and SMS so that they may take the necessary steps to prevent additional harm from occurring.

## 3. METHODOLOGY

For the purpose of detecting falls, the suggested technique makes use of a machine learning approach. Using the SisFall database, which are freely accessible, researchers were able to train and test the suggested method on a variety of activities that included falling or not falling.

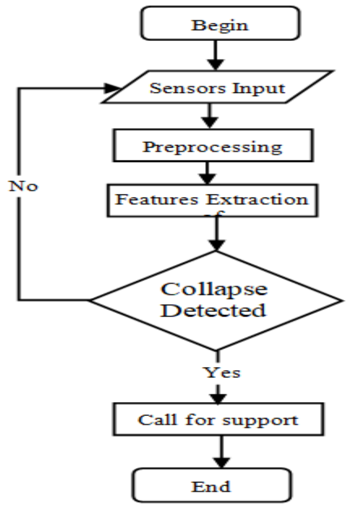


Figure 4: Proposed Methodology Flowchart

Figure 4 depicts the four important processes of the proposed technique, which are collection of data, preprocessing, extraction of features, and fall detection. Figure 4 depicts the four phases of the suggested method.

### *3.1 Data acquisition*

Using the suggested technique, the first step is to gather data that will be utilized in the subsequent phases once it has been preprocessed and organized. Collection of data in real time by individuals, particularly those conducting activities, is a highly difficult process, especially for senior individuals. A large number of scholars have gathered information on autumn activities as well as activities of everyday living. There are a variety of available data, although the majority of them include actions done by only very young children. For a senior fall detection system to be effective, the dataset should include not only the falls but also the everyday living activities conducted by the old persons themselves. As a result, we discovered the SisFall dataset, which has people who are both young and old.

A tumble and motion database, SisFall, was employed in this work to gather data. In the SisFall dataset, there are 4505 files, including 1798 files containing 15 kinds of falls and 2700+ files containing nineteen types of Daily life activities done by 20+ young adults between the ages of 19 and 30 years and 15 older persons between the ages of 60 and 75 years. In this study, all actions are collected using a wearable device positioned at the waist of the subject and equipped with three motion sensors, namely two accelerometers and one gyroscope, at a sampling rate of Fs = 200 Hz.

### *3.2 Data Preprocessing*

Once the information has been analyzed, the following step is to retouch it in order to eliminate any unpleasant noise from the signal, which will allow the machine learning algorithms to do a better categorization job. Many various filters are employed, but in this research, we chose a 4th order lowpass filter infinite impulse response (IIR) Butterworth filter with a cut-off frequency of 5 Hertz since it is small and requires little processing power.

### *3.3 Extraction of Feature*

| **Features** | **Equation** |
|---|---|
| Maximum Amplitude | max $(a[k])$ |
| Minimum Amplitude | min $(a[k])$ |
| Mean Amplitude | $\mu = \frac{1}{N}\sum a[k]$ |
| Variance | $\sigma^2 = \frac{1}{N}\sum (a[k] = \mu)^2$ |
| Kurtosis | $K = \frac{m_4}{(m_3)^2}$ |
| Skewness | $S = \frac{m_3}{(m_3)^{\frac{2}{3}}}$ |

Table I: Collection of Details Used in Identification of A Fall

After the raw signal has been prepared, the next objective is to remove the attributes that will be used in the classification method. From the preprocessed data, we were able to extract six characteristics. The maximum amplitude, minimum amplitude and average amplitude are some of the characteristics of the signal. Table I contains a list of these characteristics, as well as some mathematical expressions. In this study, each feature is extracted from three sensors' data, which includes two accelerometers and one gyroscope, along three axes: we get a final feature vector of size [1 x 54] for all three sensors along all three axes for a single sample for all three sensors.

### *3.4 Collapse Identification*

Following the extraction of features, the next phase is to determine if the task is a collapse or not by classifying it as such. When it comes to fall detection, it's a binary classification issue, which means we have to decide whether an action is fall-related or non-fall-related. As a result, we separated the entire database into two categories, namely, Class-1 for collapse activity and Class-2 for non-Collapse activities. Every one of the extracted features that were obtained from the samples acquired in the database by doing falls was labeled as Class-1, while every one of the extracted features that were derived from the specimens collected by conducting ADL was marked as Class-2, and so on. As a result, the total amount of data in Class-1 for falls is 1748, whereas the total amount of data in Class-2 for ADL is 2737.

Following the labelling of the feature vector of data, we employed the 10-fold cross-validation procedure in order to improve the prediction model and reduce the bias of the machine learning classifier. Finally, in order to test the performance of the proposed approach, we employed four machine learning classifiers. In this group include decision tree algorithms, logistic regression methods, the K-Nearest Neighbour (KNN), and the Support Vector Machine classifier. Section IV contains a summary of the findings.

## 4. RESULTS AND DISCUSSIONS

The suggested algorithm's effectiveness is evaluated using three generally used performance measures, namely, sensitivity, specificity, and precision, which are all presented in this paper. These are the ones that are defined as follows:

### *4.1 Sensitivity (SE)*

A fall detection system's ability to detect falls will be measured by this test. In other words, it is the relationship between true positives and the overall amount of collapse.

$$SE = \frac{TP}{TP + FN} \times 100 \qquad (1)$$

### *4.2 Specificity (SP)*

It refers to the system's ability to sense collapse only when they really happen.

$$SP = \frac{TN}{TN + FP} \times 100 \qquad (2)$$

### *4.3* ***Accuracy***

It refers to the system's capacity to distinguish between collapse and non-collapse situations.

$$Accuracy = \frac{TP + TN}{TP + FN + TN + FP} \times 100 \qquad (3)$$

Where TP is an abbreviation for True Positive, which means that a fall happens and the algorithm finds it. TN stands for True Negative, which means that a fall does not occur and the algorithm does not identify a fall. False Positive (FP) refers to a situation in which a collapse does not happen but the method claims that it did, while False Negative (FN) refers to a situation in which a collapse does happen but the method does not identify it.

The tests are carried out with the help of MATLAB R2018a. In order to assess the retrieved features, we employed four ML models for fall detection, each of which was assessed in terms of the variables stated above. As seen in Figure 5, the classification confusion matrices of various Models are displayed.

| Confusion Matrix - DT | | |
|---|---|---|
| **DT** | **Predicted** | |
| **Actual** | ***Fall*** | ***ADL*** |
| ***Fall*** | 1776 | 22 |
| ***ADL*** | 22 | 2685 |

| Confusion Matrix - LR | | |
|---|---|---|
| **LR** | **Predicted** | |
| **Actual** | ***Fall*** | ***ADL*** |
| ***Fall*** | 1778 | 20 |
| ***ADL*** | 8 | 2699 |

| Confusion Matrix - KNN | | |
|---|---|---|
| **KNN** | **Predicted** | |
| **Actual** | ***Fall*** | ***ADL*** |
| ***Fall*** | 1794 | 4 |
| ***ADL*** | 0 | 2707 |

| Confusion Matrix - SVM | | |
|---|---|---|
| **SVM** | **Predicted** | |
| **Actual** | ***Fall*** | ***ADL*** |
| ***Fall*** | 1797 | 1 |
| ***ADL*** | 0 | 2707 |

Figure 5: Confusion Matrix of DT, LR, KNN, and SVM Models

Training and testing are carried out with the use of the 10-fold cross-validation technique, which means that the database is arbitrarily split into 10-folds, with 9-folds utilized for training and 1 fold used for testing on each occasion. The findings of the four ML techniques are shown in Table II. These characteristics are computed by the use of confusion matrices, as seen in Figure 5.

| **Model** | **Sensitivity** | **Specificity** | **Precision** |
|---|---|---|---|
| Decision Tree | 97.68% | 98.91% | 98.69% |
| Linear Regression | 97.92% | 98.99% | 98.78% |
| K-Nearest Neighbor | 98.98% | 98.78% | 98.89% |
| Support Vector Machine | 99.56% | 99.95% | 99.78% |

Table II: Detection Results from the Suggested Method.

It can be shown in Table II that based on collected number of characteristics; SVM outperforms the other three machine learning algorithms in terms of sensitivity, specificity, and accuracy when compared to the other three classifiers.

## 5. CONCLUSION AND FUTURE SCOPE

In this work, a basic and computationally efficient collection of characteristics taken from a publically accessible dataset was used to develop an efficient fall detection system, which was shown to be effective. The collected features are used to train and evaluate four machine learning classifiers, with the results being presented in this paper. Out of all of these classifiers, SVM has the greatest accuracy, with a 99.99 percent rate of success, which is better than the current best practices, as seen in Table III. The suggested method is effective for application in a real-time fall detection system because of its efficiency. The suggested fall detection algorithm will be implemented in hardware in the future, which would allow older persons to maintain their independence for longer periods of time.

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