International Journal of Basic and Applied Sciences, 14 (5) (2025) 714-721

International Journal of Basic and Applied Sciences

Website: www.sciencepubco.com/index.php/IJBAS
https://doi.org/10.14419/sdd6fn84
Research paper

Fall Detection for The Elderly People

Ajay Khunteta [1] *, Abhishek Sharma [2]

[1] *Professor, Poornima University, Jaipur, India*
[2] *Research Scholar, Poornima University, Jaipur, India*
**Corresponding author E-mail: Ajay.khunteta@poornima.edu.in*

Received: July 31, 2025, Accepted: September 10, 2025, Published: September 19, 2025

Abstract

Typically, research and industry presented various practical solutions for assisting the elderly and their caregivers against falls via detecting falls and triggering notification alarms calling for help as soon as falls occur to diminish fall consequences. Furthermore, fall likelihood prediction systems have emerged lately based on the manipulation of the medical and behavioral history of elderly patients in order to predict the possibility of falls occurrence. This paper presents an extensive review of the state-of-the-art trends and technologies of fall detection and prevention systems assisting elderly people and their caregivers. Furthermore, this paper discusses the main challenges facing elderly fall prevention, along with a comparison of various machine learning algorithms on the cStick dataset.

Keywords: *Fall Detections; SVM; Fall Predictions; Elderly People, Etc.*

1. Introduction

Nowadays, all around the world, the number of elderly people is increasing due to advanced medical facilities. According to the WHO, the number of elderly people will be more than two billion [1] in 2050. Elderly individuals face a high risk of fall-related injuries, which are a leading cause of mortality in some cases. Fall may happen due to some medical historyor accidentally. It is a serious problem in elderly homes because they live alone in a room and no one is there with them to call emergency services or an ambulance. In the absence of quick medical help, these injuries may increase the chance of death. Falling is one of the major reasons for fatal and non-fatal injuries in elderly people [14]. Once fall occurs, this increases the fear of fall again in the mind of elderly people, and they reduce their daily activities, which can increase the chances of psychological problems [14]. So an accurate fall detection system is required, which can detect a fall and communicate to emergency services.[1] There are many wearable modules available that not only detect falls but also enable calling for help in case of unconsciousness of the patient. For this purpose, the wearable devices have sensors that can detect falls and the body. This paper reviews research work in the field of fall detection. There are many factors or causes for the fall of an elderly person. Generally, unbalancing, sudden slips, unstable moves, bends,turns, and rises are general causes of falls in the case of an elderly person. Broadly, we can divide the different factors into two categories. [8 - 10]. First is personal, and second is the surroundings. Surrounding factors which are natural, sudden, or unknown to the user, like low visual conditions, wet floors, very shiny surfaces, unbalanced floor or road, etc. The personal factors of falling include physiological and neurological functions, medications, many diseases like hypertension, osteoarthritis, diabetes, and sensory impairment, Alzheimer's disease, etc.[11]. [2]

2. Review of Literature

Many approaches and models have been proposed and developed by researchers for fall detection, fall prevention, and communicating with emergency help. The major problem in the research of fall detection is the non-availability of a dataset of true data. A rare data set is available with real falls of elderly people because nobody can predict falls in advance. Almost 94% studies used simulated falls. [20] These falls are recorded in an artificial environment in a lab, performed by young people. So in most cases, the resultant model has a problem of over-fitting, and accuracy in real-time is also an issue. In the absence of this real data, the supervised classification technique is also not giving good results. Broadly, we can divide fall detection systems into two categories:

1) Wearable device
2) Context-aware systems [5].

Each approach has its own pros and cons. In the first approach, a device is worn by a patient or elderly person in the form of a jacket or a cloth. These jackets have many integrated sensors. For the detection of falls, generally, two sensors are important. First is a gyroscope sensor, and the second is an accelerometer sensor. Other sensors, like photo-diodes or barometric pressure sensors, are also important. These sensors are used to sense the acceleration and the angular velocity. These data are used to determine the activity done by the user. Today, many mobile phones are also equipped with these gyroscope and accelerometer sensors. Currently, most of the methods are based on smartphones using machinelearning or fixed threshold techniques [20]. The sensors collect acceleration data in x, y, and z directions, and mathematically it is written as ax(t)=agx (t) + abx (t). Here, ax(t) is the acceleration in the x direction and is the sum of the gravity components of acceleration and the body movement component along the x axis. Similarly, we can represent it in the y and z directions also. By using a high-pass filter on this signal, we can extract the body acceleration. Similarly, using a gyroscope sensor, we can get angular rotation in x, y, and z directions, which are called Pitch (x-direction), roll (Y-direction), and yaw (z-direction). In this technique, a change in orientation of the body from up to down after a negative acceleration represents a fall. Using many methods and classification algorithms on these data, we can predict the fall. These algorithms are based on analysis of body motion, audio signals, posture, proximity, vibrational data, and analysis of spatio-temporal data [20]. The major limitation of smartphones is the processing capabilities of complex machine learning algorithms.

However, the threshold-based techniques have several limitations in terms of generalization, which results in a decrease in performance [21].

Another category of fall detection technique is Context-aware systems. This includes ambience device-based and vision-based analysis. In this method, one or more sensors like floor sensors, infrared sensors, microphones, and cameras like RGB cameras or depth cameras are deployed in areas where we want to monitor the elderly person, like the bedroom, toilet, kitchen, etc. This system takes video from the camera and converts it into a series of frames. Then, by applying many image processing techniques and classification algorithms, falls have been detected [11] [12] [17]. The main components of analysis are the change of shape, head position, and posture.

Many machine learning algorithms and classification algorithms are commonly used by researchers, such as Decision Trees, Naive Bayes, K-Nearest Neighbour, and SVM. These techniques work with good accuracy based on feature selection [22]. The Main challenges in the design of these techniques are the privacy of the user, the appropriate threshold value, reliability, robustness, computational complexity and cost, energy backup and consumption in wearable devices, noise in sensing data, de-noising technique, aging, and many more. The comparison of various methodologies is given in Table I.

Table 1: Summary of Various Published Research Works

Study	Methodology	Results	Disadvantages
Jinxi Zhang, Zhen Li, Yu Liu, Jian Li (2024)[18]	dual-stream convolutional neural network self-attention (DSCS) model	Apply on the Sisfall and Mobifall dataset and achieve 96.41% accuracy	The proposed work did not encompass all possible fall poses
Thilo et al. (2019)[19]	Real field testing with older adults	Positive user feedback, easy to use	Small sample size, limited testing with only 10 participants
Alam et al. (2023)[20]	Used MoveNet and a threshold-based classifier	84.38% accuracy	Used only 96 video samples, which is not sufficient
Lin B-S, Yu T, Peng C-W (2022)[23]	real-time fall detection system based on the AI chip	91.1% accuracy	Complex and high cost
Kausar, F., Mesbah, M., Iqbal(2023)[24]	analyzing the effect of sliding window size on system performance	96.34% accuracy with a window size of 3 sec with the SisFall dataset	processing time and detection performance are not good if the window size is more than 3 seconds
Yue Wang, Tiantai Deng (2024)[25]	Body key points identified by BlazePose were used as input to a random forest for classification	89.99% accuracy	Used only a single webcam and limited to a short area
Ganesha, H.S., Gupta, R., Gupta (2024)[26]	few-shot transfer learning algorithm	Worked on HAR dataset, 74.6% accuracy	Low accuracy
Khan IU, Lee JW. (2024)[27]	convolutional neural networks (CNNs) and echo state networks (ESNs), followed by a self-attention mechanism for optimal feature selection	Worked with two datasets, PAR and PER	Less accurate at longer frames
HYUNMOK SON , JAE WOON LIM (2022)[28]	Three-axis inertial sensors (SHIMMER3, ShimmerTM, Ireland) were used to capture the acceleration and angular velocity for falls and Ag_ADL_M_E.	ANN classifier shows better results, 64% compared to others	Only 10 activities were proposed in the own dataset
Jalal Alizadeh (2021)[29]	Support Vector Machine (SVM), k-Nearest Neighbors (kNN), and Random Forest (RF)	SVM is good with 93% accuracy	False alarm rate is more than .1 to .5 per hour

In this paper, we have applied a Machine learning algorithm using the cStick Data set freely available on the internet. The cStick Data Set: The cStick (Calm Stick) system was developed to address these needs through a state-of-the-art, IoT-enabled walking aid. cStick operates within the Internet of Medical Things (IoMT) framework, providing real-time data collection and edge computing capabilities. Its unique value lies in not only detecting falls but also predicting them, thus enabling proactive intervention. The device integrates multiple physiological and environmental sensors, is suitable for visually and hearing-impaired users, and is designed for comfort and reliability.

Dataset Features and Labels Sensor:

- Heart Rate Variability (HRV): Sudden changes may indicate impending loss of balance or stress.
- Accelerometer (linear acceleration, 3-axis): Detects movement patterns, spikes, and potential falls.
- Grip Pressure: Measures the squeezing force exerted on the stick, often increasing before or during a fall.
- Blood Sugar Level: Hypoglycemia increases fall risk; monitored for health status.
- Blood Oxygen Level (SpO2): Low levels can precede fainting or weakness.
- Distance from Nearest Object: Proximity to objects, obstacles, or the ground.
- Gyroscope: Orientation data (direction and angle of fall).
- Location Data (optional in dataset): To provide contextual awareness and enable location-based alerts.

Target Labels:

- No Fall: Normal activity, stable walking.
- Fall Predicted: System warns user to act (e.g., “Take a break, you tripped!”) before an actual fall occurs.
- Fall Detected: System detects a fall event and triggers emergency protocols.

Each data record represents a snapshot of these sensor readings, mapped to one of the three target classes for supervised ML model training.

3. Methodology

The primary objective is to build robust, interpretable models that can distinguish between three classes: "No Fall", "Fall Predicted (Slipped)", and "Definite Fall", using multi-sensor physiological and environmental features recorded by the cStick device. The process also addresses data imbalances and validates the generalizability of results through rigorous testing. The data is captured via IoMT-enabled cStick prototypes under controlled and semi-naturalistic scenarios to maximize ecological validity. The dataset is loaded into a pandas DataFrame and subjected to initial inspection to ensure integrity: Initial EDA ensures the absence of missing values and inspects the range, mean, and distribution of each feature. This is critical for subsequent scaling and modeling.

3.1. Feature Engineering and Selection: Feature Cleaning

- Column Name Stripping: Ensures all columns have consistent names (e.g., removing trailing spaces from 'Decision ').
- Categorical Encoding: If any feature is categorical (e.g., pressure as levels), encode as numeric.

Correlation Analysis

A correlation matrix heatmap is generated to visualize linear relationships among features. Highly correlated features (correlation coefficient > 0.4 and < 1) are candidates for removal to reduce multicollinearity, thereby improving model generalizability. The methodology is designed to address several real-world constraints:

- Multimodal Sensing: By leveraging multiple sensor streams, the approach accounts for physiological, environmental, and behavioral factors in falls, yielding more robust models than single-sensor solutions.
- Class Imbalance: Real-world datasets are naturally imbalanced; the use of SMOTE ensures that all classes, especially dangerous “Definite Fall” events, are represented in training.
- Model Transparency: Logistic regression’s coefficients provide actionable insights for clinical experts—highlighting which sensor data is most predictive of each fall status.
- Generalizability: Stratified splits and rigorous validation ensure that performance is not inflated by over-fitting.

The overarching objective is to accurately classify fall risk into three categories: Safe (Class 0), Moderate Risk (Class 1), and High Risk (Class 2). Each record in the dataset encapsulates multiple physiological and biomechanical indicators collected in real-time. These include mobility-related, metabolic, and respiratory measurements.

3.2. Logistic Regression-Based Classification Framework for Fall Risk Prediction

Logistic Regression (LR) is one of the foundational classification techniques in the machine learning domain and is particularly well-suited for problems where the target variable represents categorical outcomes. In the context of this research, the target variable (decision) captures the fall risk classification of elderly individuals into three classes: Class 0 (No risk), Class 1 (Moderate risk), and Class 2 (High risk). Although logistic regression is traditionally associated with binary classification, it can be extended to multi-class problems using strategies such as One-vs-Rest (OvR) and Multinomial Logistic Regression, both of which are explored in this methodology.

The logistic regression framework for fall risk prediction involves transforming the physiological and movement-related sensor data into a structured feature matrix, normalizing inputs, and fitting a multinomial logistic model using the One-vs-Rest strategy. The model is trained using regularized optimization to ensure generalization, and the decision boundary for each class is constructed in the feature space based on the linear combination of weighted inputs. Logistic regression provides a balance between performance and interpretability, making it a suitable candidate for early-stage model evaluation in health monitoring applications. The features and their units used in the dataset are given in Table II below:

Table 2: List of Features with Units

Feature	Description	Unit
Distance	Distance moved by the individual	cm
Pressure	Pressure measured by sensors	kPa (approx.)
HRV	Heart Rate Variability	ms
Sugar Level	Blood glucose concentration	mg/dL
SpO_2	Blood oxygen saturation	%
Accelerometer	Motion level (simplified acceleration)	m/s^2

3.3. Support Vector Machine-Based Classification Framework for Fall Risk Prediction

Support Vector Machines (SVMs) are among the most powerful and widely used supervised learning algorithms for classification tasks, particularly in cases where data exhibits non-linear separation or high dimensionality. In the context of fall risk prediction for elderly individuals, SVMs provide a robust and mathematically grounded framework that constructs decision boundaries with maximal margin, ensuring strong generalization and resistance to over-fitting.

In this study, the One-vs-Rest strategy is used for simplicity and efficiency, resulting in three binary classifiers:

1) Class 0 vs. Classes 1 and 2
2) Class 1 vs. Classes 0 and 2
3) Class 2 vs. Classes 0 and 1

In this study, the RBF kernel is selected as it effectively captures localized relationships and accommodates non-linear spectral ability common in human biometric data. Tuning hyperparameters is critical to achieving good generalization. For SVM with RBF kernel, the main parameters are shown in Table III, given below:

Table 3: Parameters with Default Values

Parameter	Description	Default Value Used
CCC	Regularization strength	1.0
γ	Kernel coefficient in RBF	‘scale’ (1/n_features)
Kernel	Type of kernel to use	'rbf'
Decision Function	One-vs-Rest for multi-class problems	OvR

Hyper-parameter optimization is performed via grid search with cross-validation, although in the base methodology, defaults are retained to demonstrate conceptual effectiveness.

Training Procedure

1) Data Normalization Features are standardized using Z-score normalization to a zero mean and unit variance. This prevents any feature from dominating the distance computations used in the RBF kernel.
2) Train-Test Splitting The dataset is split into 80% training and 20% test data using stratified sampling to ensure class balance across splits.
3) Model Fitting. For each of the three binary classifiers under the OvR strategy, SVM optimizes the decision boundary using support vectors and the selected kernel.
4) Prediction: Given a new instance xxx, each binary classifier returns a decision score. The class with the highest score is chosen as the predicted label.

3.4. A K-Nearest Neighbors (KNN) Based Classification Framework for Fall Risk Prediction

The K-Nearest Neighbors (KNN) algorithm is a fundamental instance-based learning technique used for classification and regression. Unlike parametric models such as logistic regression and SVM, KNN does not explicitly learn a decision function. Instead, it stores the entire training dataset and classifies new observations by examining the 'k' most similar training examples in the feature space. This simplicity makes KNN easy to implement and interpret, yet powerful in various pattern recognition problems, including biomedical signal classification and fall detection.

In the context of fall risk prediction in elderly individuals, KNN can utilize the similarity of physiological attributes like HRV, blood glucose levels, SpO, and activity metrics (distance, pressure, accelerometer values) to classify a new instance into one of the three risk classes: Class 0 (Safe), Class 1 (Moderate Risk), and Class 2 (High Risk). KNN is a non-parametric, lazy learning algorithm. Lazy learning implies that there is no explicit training phase; the model performs computation only when a query (test point) is made. Choosing an appropriate value for k is crucial. A small k may lead to over-fitting (noise-sensitive), while a large k could cause under-fitting (smoothing out useful distinctions). Typical strategies to choose optimal k include:

- Empirical tuning via cross-validation
- Use of the elbow method on the accuracy vs. k plot
- Grid search optimization

In this study, an initial value of k=5k = 5k=5 is used, and further tuning is considered via grid search if needed.

KNN Classification Workflow

The operational pipeline for fall risk prediction using KNN is as follows:

1) Data preparation
- Input: Raw dataset with 6 features and 1 target label (decision)
- Cleaning: Check for nulls, outliers (none found in dataset)
- Scaling: Standardized all features using Z-score normalization
2) Splitting
- Data split into 80% training and 20% testing using stratified sampling
3) Distance Calculation
- Euclidean distance calculated between the test instance and all training samples
4) Neighbor Selection
- Top K neighbors with the lowest distance identified
5) Voting
- Count labels of the K neighbors and assign the majority label to the test point
6) Prediction Output
- Final predicted class label is returned for each test instance

KNN generates non-linear and local decision boundaries. Unlike global decision surfaces (as in SVM), the boundary around a class changes dynamically based on the sample density and local feature space. This is particularly useful for heterogeneous biomedical data, where similar risk cases cluster together.

The decision boundary is affected by:

- Value of k
- Distribution and density of samples in the feature space
- Feature scaling and noise

The use of KNN for fall risk classification has several theoretical benefits:

- No Assumptions: KNN does not assume linearity, normality, or feature independence, making it suitable for diverse sensor data.
- Naturally Multi-Class: Unlike logistic regression or SVM (which need modification), KNN supports multi-class classification by default.
- Localized Modeling: Predictions are based on local neighborhoods, which can adapt to subtle changes in physiological conditions.
- Interpretable Behavior: The logic of voting based on nearest samples is intuitive and easily understood.

4. Results

Overall, the analysis highlights the potential of these machine learning methods in improving fall detection and prediction for older adults using the cStick dataset. These methods offer different strengths and can be selected based on the specific requirements of the application. It's essential to carefully choose the appropriate algorithm, perform feature engineering, and fine-tune the model to achieve accurate and reliable results in fall prevention systems. Additionally, the interpretability and transparency offered by Decision Trees can be particularly useful in healthcare settings where understanding the reasoning behind predictions is crucial for decision-making. The analyses of parameters are listed in Table IV with 2039 rows × 7 columns.

Table 4: Analysis of Features from Dataset

Distance	Pressure	HRV	Sugar level	SpO2	Accelerometer	Decision
0	25.540	1.0	101.396	61.080	87.770	1.0
1	2.595	2.0	110.190	20.207	65.190	1.0
2	68.067	0.0	87.412	79.345	99.345	0.0
3	13.090	1.0	92.266	36.180	81.545	1.0
4	69.430	0.0	89.480	80.000	99.990	0.0
...	...	...	...	...	...	...
2034	5.655	2.0	116.310	162.242	71.310	1.0
2035	9.660	2.0	124.320	177.995	79.320	1.0
2036	15.220	1.0	93.828	40.440	82.610	1.0
2037	9.120	2.0	123.240	175.871	78.240	1.0
2038	62.441	0.0	78.876	76.435	96.435	0.0

We have classified the dataset into three classes, as shown in Figure I. We have defined three classes: Class 0 belongs to safe, Class 1 belongs to Moderate Risk, and Class 3 is defined as High Risk. The distribution of these three classes is approximately the same in the dataset, as shown in Figure 1.

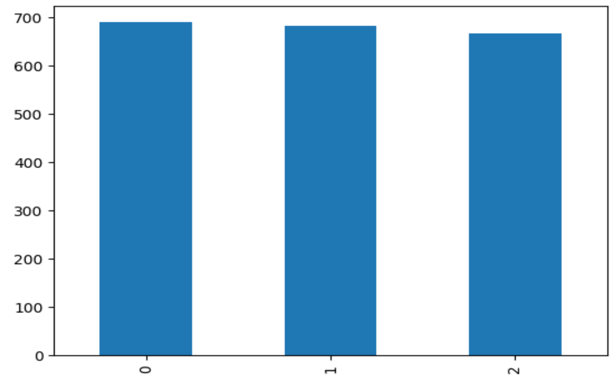

Fig. 1: Analysis of Dataset with Respect to Fall Instances (Class 0 (Safe), Class 1 (Moderate Risk), and Class 2 (High Risk)).

The analysis of the correlation of features for Regression is shown in Figure 2.

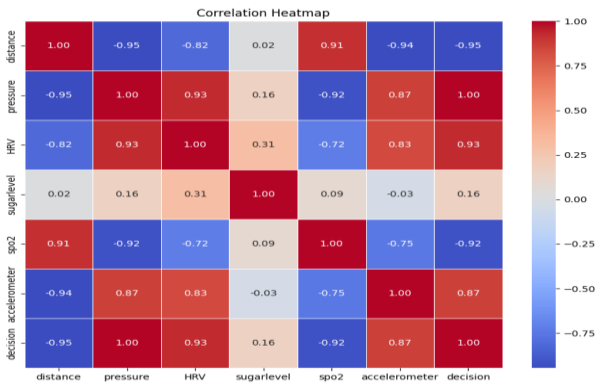

Fig. 2: Analysis of Correlation of Features for Regression-Based Analysis.

In Figure 2, it is visible that the variables Pressure, HRV, and Accelerometer are the major contributors to the Decision variable. The variables Distance and SpO2 are negatively related to the Decision variable, acting as inverse predictors. It concludes that the Decision outcome depends on the value of physiological and the reading of the sensors.

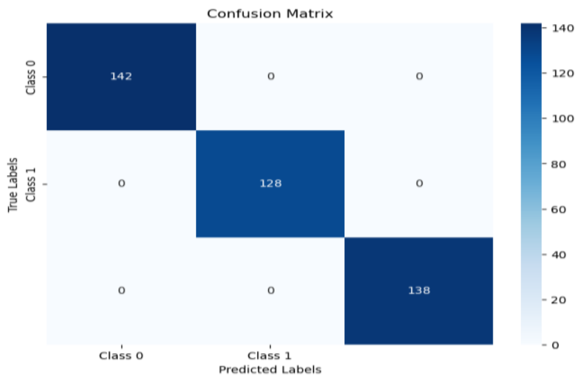

Fig. 3: Analysis of the Confusion Matrix for Regression-Based Analysis.

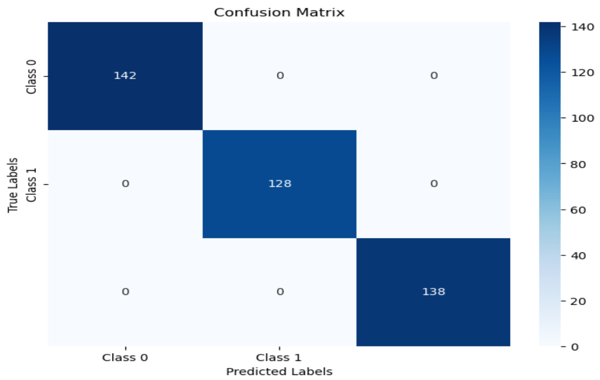

Fig. 4: Analysis of the Confusion Matrix for SVM-Based Analysis.

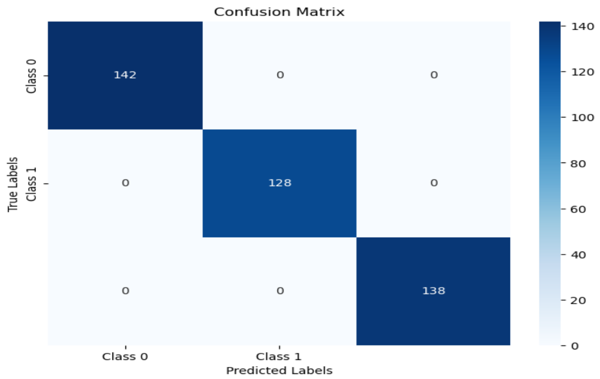

Fig. 5: Analysis of the Confusion Matrix for the KNN-Based Classifier.

In Figures 3, 4, and 5, the confusion matrices for regression, SVM, and KNN are shown. It is very clear that in all three algorithms, 142 samples of class 0, 128 samples of class 1, and 138 samples of class 2 are matched accordingly. We have applied the Random forest and decision tree algorithms, and the analysis is shown in Figures 6 and 7.

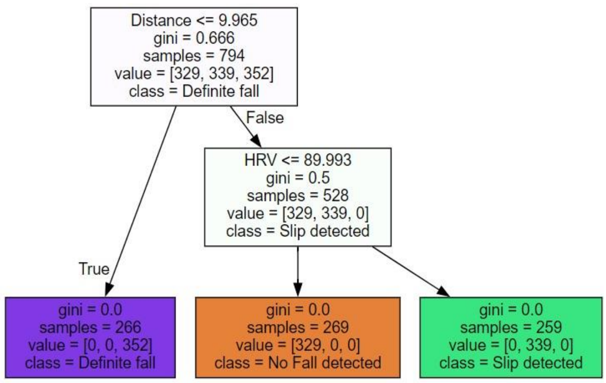

Fig. 6: Analysis of Feature Importance and Fall Detection Using Random Forest.

The feature importance analysis in Figure 6 indicated that Distance and HRV are sufficient discriminative features for classifying fall-related events in the dataset. In this Figure, the dataset is highly separable, and the Random Forest will likely achieve near-perfect classification accuracy.

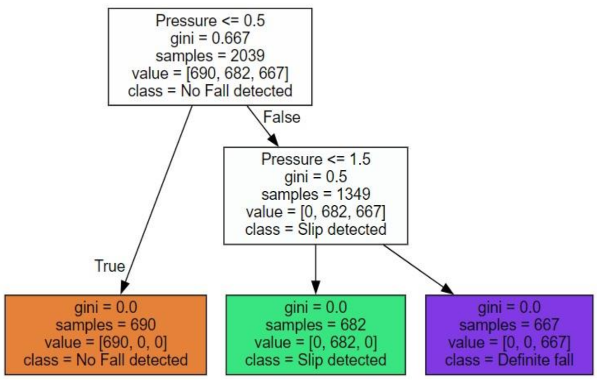

Fig. 7: Analysis of Feature Importance and Fall Detection Using a Decision Tree.

The feature importance in the decision tree is shown in Figure 7. The variable Pressure is the most discriminative feature for the dataset, which perfectly classifies all instances into "No Fall," "Slip Detected," and "Definite Fall" with thresholds at 0.5 and 1.5. The accuracy, Precision, and F-measure are shown in Table VI. Random forest is working well in our case.
We have compared the proposed algorithm with the existing work shown in Table VII. It is found that our algorithm is working well with an accuracy of 97.472% in the case of the Random Forest algorithm. In case of [30], the accuracy was 95% with the cStick dataset. This reflects that the proposed algorithm is working fine with the cStick dataset. In [26], the authors use an advanced version of the cStick dataset and use a secure and fast pipeline for communication. They reported an accuracy of 97.4%. They used the cStick dataset with blockchain and were able to get higher accuracy. In our algorithm, we used a baseline dataset of cStick and got the same higher accuracy of 97.4%.

Table 5: Metrics of Algorithms

Metrics	SVM	KNN	RF
Accuracy	88%	90%	95%
Precision	84%	86%	94%
F-Measure	85%	87%	97.47%

Table 6: Comparison of Proposed Work

Reference	Sensing & modalities	Labels/dataset & split	Reported performance	Contribution
Proposed Work	IMU (acc, gyro, lin) + physiology (HRV, SpO_2, sugar) + grip pressure & distance + 14-var clinical risk table	Binary IMU: 1,428 trains / 356 test (balanced, subject-wise split). Tri-class cStick-like: 2,039 samples (0/1/2).	RF test 97.472% (9/356 errors); 95% CI 95.27–98.66%; macro-F1 ≈ 97.47%., 100% accuracy/precision/recall/F1 (claim) with cstick	Ensemble of RF, SVM, KNN, NB, LR, cost-sensitive thresholds, feature fusion, latency/FAR framing.
cStick (Rachakonda et al., 2022)[30]	IoMT walking stick with motion & physiological sensing; device can predict and detect falls and trigger controls	Tri-phase concept (predict/detect/control); evaluation summary in paper	~95% accuracy	Introduces calm-stick hardware + DL model
IoT-Blockchain TriNet (Frontiers, 2023)[32]	DL (LSTM+CNN+RNN) with IoT; adds blockchain for integrity	Compared against cStick on a shared dataset	97.40% accuracy (vs cStick 96.67%)	Focus on a secure pipeline + higher accuracy than cStick baseline.

5. Discussion

This study demonstrates the effectiveness of machine learning in fall detection, particularly for high-risk populations like the elderly and chemotherapy patients. By leveraging sensor data and clinical features, these models can significantly enhance patient safety. However, further refinement and real-world testing are essential before widespread clinical adoption. Machine learning models, particularly Random Forest and KNN, show exceptional promise in fall detection. However, continued research, larger datasets, and real-world validation are essential for clinical implementation. This study lays a strong foundation for AI-driven Patient safety solutions, potentially reducing fall-related injuries in high-risk populations. Each classifier successfully exploited the high feature-class separation ability and clean dataset characteristics. From a deployment and design standpoint, Logistic Regression is the most efficient and interpretable.

6. Ethical Issues

The fall detection systems generally rely on wearable devices, sensor readings, and cameras to record the data for analysis of the fall. In this process, there are many ethical issues, such as highly sensitive personal information, such as location, activity level, and heart rate, being recorded. In cases of cameras, we have a risk of exposing daily activities that are not part of the fall. In the case of IoT devices used, they are vulnerable to cyberattacks and hackers gaining access to fall detection data.

7. Future Scope

Future studies in this area should address the gaps by focusing on larger and more diverse datasets, including many ADL activities and fall detection scenarios. The multimodal data set, like video analytics, pressure sensors, or contextual information, can improve the accuracy and reduce false alarms. To improve the predictions, we may deploy a hybrid model using hyperparameters. We can also use Random Search and Grid Search for the selection of the best hyperparameters. Transfer learning and domain adaptation are also helpful to overcome scarcity and enable models trained and applied in different scenarios. Moreover, we can develop a new model to ensure low latency and minimal energy consumption.

References

[1] S. C. Mukhopadhyay and S. Chandra, "Wearable sensors for human activity monitoring: a review," *IEEE Sensors Journal*, vol. 15, no. 3, pp. 1321–1330, 2015. https://doi.org/10.1109/JSEN.2014.2370945.

[2] L. S. Hu, S. Z. Wang, Y. Q. Chen et al., "Fall detection algorithms based on wearable device: a review," *Journal of Zhejiang University (Engineering Science)*, vol. 52, no. 9, pp. 92–103, 2018.

[3] R. Broadley, J. Klenk, S. Thies, L. Kenney, and M. Granat, "Methods for the real-world evaluation of fall detection technology: a scoping review," *Sensors*, vol. 18, no. 7, p. 2060, 2018. https://doi.org/10.3390/s18072060.

[4] E. Boutellaa, O. Kerdjidj, and K. Ghanem, "Covariance matrix-based fall detection from multiple wearable sensors," *Journal of Biomedical Informatics*, vol. 94, pp. 103–189, 2019. https://doi.org/10.1016/j.jbi.2019.103189.

[5] J. K. Lee and E. J. Park, "3D spinal motion analysis during staircase walking using an ambulatory inertial and magnetic sensing system," *Medical & Biological Engineering & Computing*, vol. 49, no. 7, pp. 755–764, 2011. https://doi.org/10.1007/s11517-011-0738-y.

[6] D. Litvak, Y. Zigel, and I. Gannot, "Fall detection of elderly through floor vibrations and sound," in *Proceedings of the 2008 Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, pp. 4632–4635, IEEE, Vancouver, Canada, August 2008. https://doi.org/10.1109/IEMBS.2008.4650245.

[7] Y. Zigel, D. Litvak, and I. Gannot, "A method for automatic fall detection of elderly people using floor vibrations and sound-proof of concept on human mimicking doll falls," *IEEE Transactions on Biomedical Engineering*, vol. 56, no. 12, pp. 2858–2867, 2009. https://doi.org/10.1109/TBME.2009.2030171.

[8] A Edgcomb and F. Vahid, "Automated fall detection on privacy-enhanced video," in *Proceedings of the 2012 Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, pp. 252–255, IEEE, San Diego, CA, USA, August 2012. https://doi.org/10.1109/EMBC.2012.6345917.

[9] B. Z. Dai, D. Q. Yang, L. G. Ai et al., "A novel video-surveillance-based algorithm of fall detection," in *Proceedings of the 2018 International Congress on Image and Signal Processing, BioMedical Engineering and Informatics (CISP-BMEI)*, pp. 1–6, Beijing, China, January 2018. https://doi.org/10.1109/CISP-BMEI.2018.8633160.

[10] A L. Liu, M. Popescu, M. Skubic et al., "Automatic fall detection based on Doppler radar motion signature," in *Proceedings of the 5th International Conference on Pervasive Computing Technologies for Healthcare (PervasiveHealth) and Workshops*, pp. 222–225, Dublin, Ireland, 2011.

[11] Nag, S. C. Mukhopadhyay, and J. Kosel, "Wearable flexible sensors: a review," *IEEE Sensors Journal*, vol. 17, no. 13, pp. 3949–3960, 2017. https://doi.org/10.1109/JSEN.2017.2705700.

[12] L. Chen, R. Li, H. Zhang, L. Tian, and N. Chen, "Intelligent fall detection method based on accelerometer data from a wrist-worn smart watch," *Measurement*, vol. 140, pp. 215–226, 2019. https://doi.org/10.1016/j.measurement.2019.03.079.

[13] S. A. Waheed and P. S. A. Khader, "A novel approach for smart and cost effective IoT based elderly fall detection system using Pi camera," in *Proceedings of the 2017 IEEE International Conference on Computational Intelligence and Computing Research (ICCIC)*, pp. 1–4, Beijing, China, September 2017. https://doi.org/10.1109/ICCIC.2017.8524486.

[14] Senthamarai, S., Mala , D. R. ., & Palanisamy , D. V. . (2025). Revolutionizing Healthcare Analytics with A Robust Model for Secure Data Management and Superior Disease Prediction. *International Journal of Basic and Applied Sciences*, *14*(SI-1), 122-130. https://doi.org/10.14419/mr62y398.

[15] Nalande, N. V., Patil, S. M., Shivdas , R. K. ., & Nalande, V. V. (2025). Deep Learning for Vibration Signature Analysis in CNC Turning: A Review of Modern Techniques and Future Directions. *International Journal of Basic and Applied Sciences*, *14*(4), 578-590. https://doi.org/10.14419/cmf93x48.

[16] S. M. Adnan, A. Irtaza, S. Aziz, M. O. Ullah, A. Javed, and M. T. Mahmood, "Fall detection through acoustic local ternary patterns," *Applied Acoustics*, vol. 140, pp. 296–300, 2018. https://doi.org/10.1016/j.apacoust.2018.06.013.

[17] Jinxi Zhang, Zhen Li, Yu Liu, Jian Li, Hualong Qiu, Mohan Li, Guohui Hou, Zhixiong Zhou, "An Effective Deep Learning Framework for Fall Detection: Model Development and Study Design", Published in Journal of Medical Internet Research, Vol 26, 2024 https://doi.org/10.2196/56750.

[18] Ganesha, H.S., Gupta, R., Gupta, S.H. *et al.* Few-shot transfer learning for wearable IMU-based human activity recognition. *Neural Comput & Applic* 36, 10811–10823 (2024). https://doi.org/10.1007/s00521-024-09645-7.

[19] Khan IU, Lee JW. PAR-Net: an enhanced dual-stream CNN-ESN architecture for human physical activity recognition. Sensors. 2024;24(6):1908. https://doi.org/10.3390/s24061908.

[20] HYUNMOK SON1 , JAE WOON LIM, A Machine Learning Approach for the Classification of Falls and Activities of Daily Living in Agricultural Workers, IEEE Access 2022.

[21] Hassan F., Mehmood M.H., Younis B., Mehmood N., Imran T., Zafar U. Comparative Analysis of Machine Learning Algorithms for Classification of Environmental Sounds and Fall Detection. Sci. Technol. 2022;4:163–174. https://doi.org/10.33411/IJIST/2022040112.

[22] Wang, X., Ellul, J., and Azzopardi, G. "Elderly fall detection systems: A literature survey", Front. Robot. AI, 23 June 2020, Sec. Smart Sensor Networks and Autonomy, Volume 7 - 2020 | https://doi.org/10.3389/frobt.2020.00071.

[23] Ya Wang, Peiman Alipour Sarvari and Djamel Khadraoui, "Fusion of Machine Learning and Threshold-Based Approaches for Fall Detection in Healthcare Using Inertial Sensors", In Proceedings of the 17th International Joint Conference on Biomedical Engineering Systems and Technologies (BIOSTEC 2024) - Volume 1, pages 573-582, https://doi.org/10.5220/0012250500003657.

[24] Liu H., Xue T., Schultz T. On a Real Real-Time Wearable Human Activity Recognition System; Proceedings of the 16th International Joint Conference on Biomedical Engineering Systems and Technologies-WHC. INSTICC, SciTePress; Lisbon, Portugal. 16–18 February 2023; pp. 711–720. https://doi.org/10.5220/0011927700003414.

[25] Kausar, F., Mesbah, M., Iqbal, W. *et al.* Fall Detection in the Elderly using Different Machine Learning Algorithms with Optimal Window Size. *Mobile Netw Appl* 29, 413–423 (2024). https://doi.org/10.1007/s11036-023-02215-6.

[26] Yue Wang, Tiantai Deng, Enhancing elderly care: Efficient and reliable real-time fall detection algorithm, Published in Digit Health 2024 Feb 20;10:20552076241233690. https://doi.org/10.1177/20552076241233690.

[27] Alam E, Sufian A, Dutta P, et al. Real-Time human fall detection using a lightweight pose estimation technique. Computational intelligence in communications and business analytics. Switzerland: Springer Nature, 2023, pp.30–40. https://doi.org/10.1007/978-3-031-48879-5_3.

[28] Lin B-S, Yu T, Peng C-W, et al. Fall detection system with artificial intelligence-based edge computing. IEEE Access 2022; 10: 4328–4339. https://doi.org/10.1109/ACCESS.2021.3140164.

[29] Zheng,D.Zhang,L.Yang,Z.Zhou, " Fall detection and recognition based ongcn and 2 dpose ,in the International Conference on Systems and Informatics(ICSAI), IEEE, 2019, pp.558–562. https://doi.org/10.1109/ICSAI48974.2019.9010197.

[30] R.Espinosa,H.Ponce,S.Guti´errez,L.Mart´ınez-Villasen˜or, J.Brieva,E.Moya-Albor, 'Application of convolutional neural networks for fall detection using multiple cameras", Published in Challenges and Trends in Multimodal Fall Detection for Healthcare, Springer,2020,pp.97–120 https://doi.org/10.1007/978-3-030-38748-8_5.

[31] Rachakonda, Laavanya, Saraju P. Mohanty, and Elias Kougianos. 2022. "cStick: A Calm Stick for Fall Prediction, Detection and Control in the IoMT Framework." In Internet of Things. Technology and Applications: 4th IFIP International Cross-Domain Conference, IFIPIoT 2021, Virtual Event, November 4–5, 2021, https://doi.org/10.1007/978-3-030-96466-5_9.

[32] Divya Priya, R., and J. Bagyamani. 2024. "An Early Detection of Fall Using Knowledge Distillation Ensemble Prediction Using Classification." In Advanced Computing: 13th International Conference, IACC 2023, Kolhapur, India, December 15–16, 2023, Revised Selected Papers, Part II, edited by Deepak Garg, Joel J. P. C. Rodrigues, Suneet Kumar Gupta, Xiaochun Cheng, Pushpender Sarao, and Govind Singh Patel, 26–38. Cham: Springer. https://doi.org/10.1007/978-3-031-56703-2_3.

[33] Alfayez, Fayez, and Surbhi Bhatia Khan. 2023. "IoT-Blockchain Empowered Trinet: Optimized Fall Detection System for Elderly Safety." Frontiers in Bioengineering and Biotechnology 11: 1257676. https://doi.org/10.3389/fbioe.2023.1257676.