American Journal of Biomedical Science & Research

www.biomedgrid.com

ISSN: 2642-1747

Review Article

Fall Prediction Using Machine Learning - A Systematic Review

Pankaj Yadav and Vivek Vijay*

Mathematics Department IIT Jodhpur, India

***Corresponding author:** Vivek Vijay, Mathematics Department IIT Jodhpur, India 342037.

To Cite This Article: *Pankaj Yadav and Vivek Vijay. Fall Prediction Using Machine Learning - A Systematic Review. Am J Biomed Sci & Res. 2023 18(6) AJBSR.MS.ID.002537,* DOI: 10.34297/AJBSR.2023.18.002537

Received: May 17, 2023; **Published:** May 25, 2023

Abstract

The primary objective of this study is to conduct a thorough analysis of fall prediction methods that make use of Machine Learning techniques. In this study, a total of 115 articles are analysed using the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) approach out of which 15 articles, published between 2010-2022, have been shortlisted for a detailed analysis. A six-step process of analysis is summarized in the form of a system overview. We discuss some of the advantages and shortcomings of the underlying machine learning algorithms, used for fall prediction by different researchers.

Keywords: Aging, Elderly, Frailty, Physical health

Mathematics Subject Classification (2020): MSC code1, MSC code2, and more.

Abbreviations: ML: Machine Learning; MLA: Machine Learning Algorithm; AUC-ROC: Area Under Curve and Receiver Operating Characteristic; LR: Logistic Regression; DT: Decision Tree; SVM: Support Vector Machine; RF: Random Forest; KNN: K-Nearest Neighbour; NB: Naive Bayes; BN: Baysien Network; ANN: Artificial Neural Network; CHAID: Chi-Squared Automatic Interaction Detector; GBT: Gradient Boosting Tree; MLP: Multilayer Perception

Introduction

The worldwide population of old age people (over 60 years) forcast to reach to 21% by 2050 [1]. The elderly wants to live longer and also maintain quality of life. However, several structural and functional changes occur during the aging process, such as loss of muscle mass, muscle strength, balance, and flexibility [2]. This increases the probability of falls and fall related injuries. Falling is one of the causes of chronic disability [3]. One of the solutions to this problem is timely prediction of fall. Due to increasing availability of data, various machine learning technologies are used to forecast the possibility of fall. It is believed that the implementation of fall prediction technologies has the potential to improve the quality of life for older adults by reducing the incidence of falls and associated injuries [4]. Machine learning algorithms can detect risk factors and predict the probability of fall by examining large databases of patients or Electronic Health Record (EHR) data [5]. This may assist healthcare professionals in creating preventative and treatment approaches that are more successful. In order to detect movement patterns, that can result in falls, machine learning algorithms are used to assess data from a variety of sources, including video cameras, images, motion sensors, and wearable technology [3]. With this data, the algorithms can predict the possibility of a fall and notify carer or emergency personnel in real-time. Gait speed, balance, and the presence of specific medical disorders are among prominent characteristics utilised in these machine learning models.

In order to increase accuracy, machine learning models also include data driven approaches like Electronic Health Record (EHR) data, Time Up and Go (TUG) Assessment, Questionnaire data etc. Thus, machine learning-based fall prediction has the potential to save healthcare expenses related to falls and improve the quality of life for elderly. This article focuses on analyzing fall prediction methods that make use of Machine Learning techniques. A total of 115 articles are analysed using the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) approach. Using the shortlisting criteria, 15 articles published between 2010-2022 have been shortlisted for detailed analysis. A six-step approach, for data analysis, is presented in the form of system overview. Finally, we address advantages and shortcomings of the machine learning models used for fall prediction.

This article is organized as follows-

Introduction along with motivation is given in Section 1. Section 2 discusses the complete methodology and the PRISMA framework. A system overview of analysis is presented in Section 3. Section 4 details the six steps system overview. A table of advantages and shortcomings of underlying machine learning models is presented in Section 5. Finally, the article is concluded in Section 6.

Methodology

This study uses the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework for identifying the articles [6] as represented in Figure 1. It identifies, screens, and selects suitable studies for a systematic review or meta-analysis in a transparent manner [7] (Figure 1).

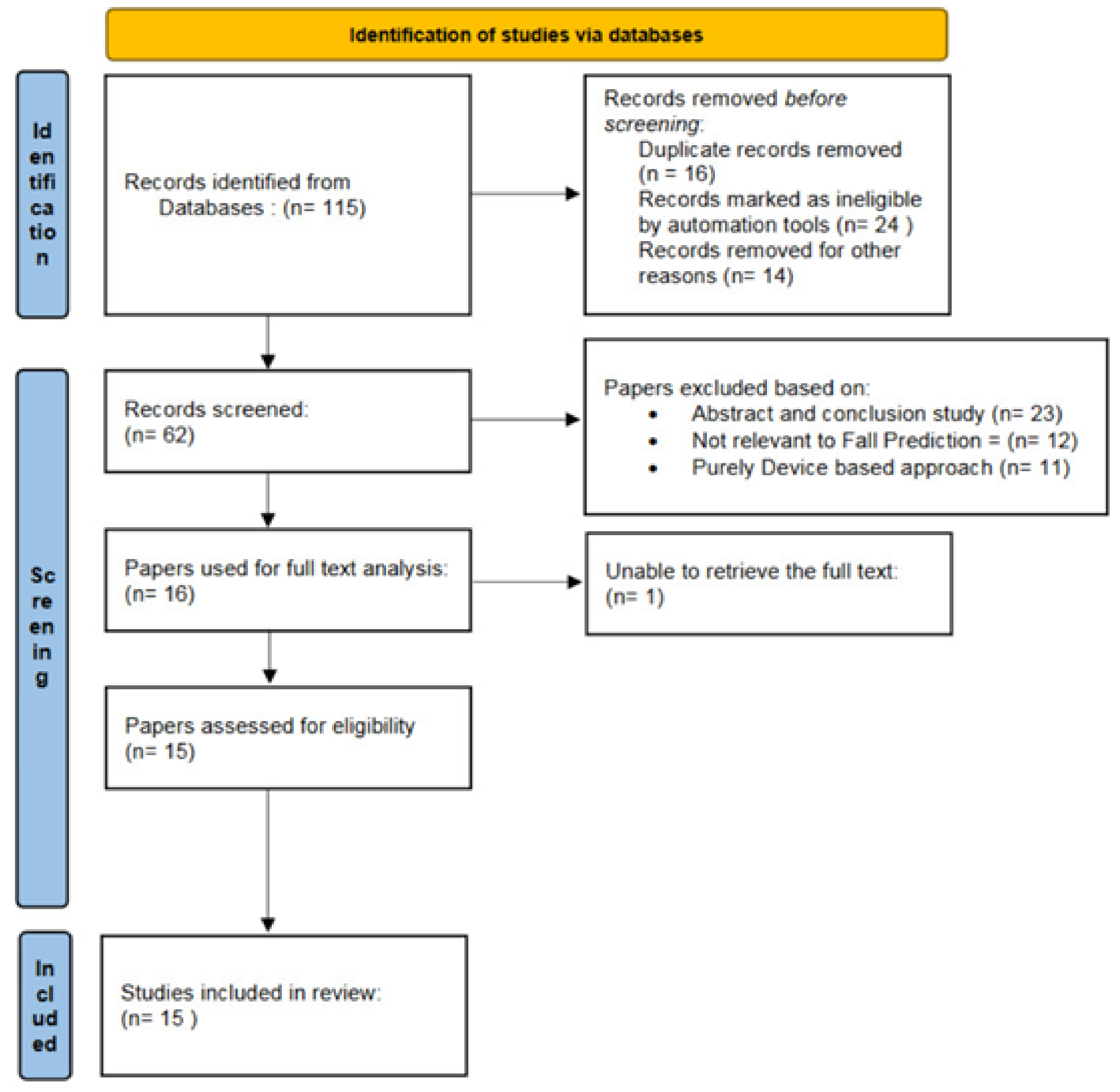

Figure 1: Methodology (PRISMA Framework).

RISMA approach uses following three steps for shortlisting of research articles [6]: Identification The method of locating pertinent research articles using the research questions and a predetermined search strategy. Screening Review of titles and abstracts of identified articles to evaluate their eligibility to be included in the systematic review. Include The process of choosing studies for further analysis in the systematic review that fulfils the established inclusion criteria.

A specific string search is performed to filter the publications based on the PRISMA technique, as presented in Table 1. With these strings, the initial screening procedure yields 1508 results. By using single strings like "Machine Learning" OR "Fall Prediction," we detect some dimensional issues. However, while employing a multi-string dimensionality search engine, the number of results is reduced, and the analysis becomes less complex. The elimination of duplicate records, records flagged as ineligible by automated tools, and records removed for other reasons are all components of the identification process. A total of 115 articles are produced by the identification procedure, and these are utilised for screening in the next phase. In the screening procedure, it entails a number of steps where records based on abstract and conclusions, records unrelated to fall prediction, and records based on using device approaches are all excluded. In another step of the screening procedure, the whole text of the records is examined. We finally selected 15 papers based on this assessment. We present a complete system architecture in the following section (Table 1).

Table 1: Strings shown in table used for searching records on search engines.

Search engines	Strings
Google Scholar	Fall Prediction using Machine Learning
	Fall prediction using Artificial Intelligence
	Fall Prediction using Machine Learning or Artificial Intelligence
	Predicting Falls in elderly using Machine Learning
Scopus	("Fall Prediction") AND ("Machine Learning")
	("Fall Prediction") AND ("Artificial Intelligence") ("Fall Prediction") AND ("Machine Learning") OR
	"Artificial Intelligence")

Table 2:

Ref.	Preferred M.L.A	Advantages	Shortcomings
[13]	PreferredSVM Others- (LR, DT,KNN,RF)	The SVM classifier with linear kernel has an AUC of 0.80, Sensitivity of 0.82, Specificity of 0.72, F1 score of 0.76, and Accuracy (0.75)	Sensitivity to Outliers SVM's is sensitive to outliers in the data, which can lead to poor performance of the model.
			Difficulty with Large Dataset SVM's can be slow and computationally expensive, especially with large datasets.
[18]	Preferred-RF	The RF classifier displays that the AUC obtained a value of 95.6% and that the RF model was trained using 25 ensemble learning cycles with Bootstrap aggregation as the ensamble aggregation technique.	Limited extrapolation: Random Forest models are good at interpolating within the range of the training data, but they may not perform well when extrapolating outside of this range.
[5]	Preferred Xg Boost Others-LR	XgBoost outperformed the other models in achieving a fair balance between the true positive and true negative rates. XgBoost technique uses a large number of features from EHR data to make short term fall predictions with a better performance than conventional fall risk assessment and other machine learning models.	Limited Interpretability: While XgBoost can provide important insights of the relative importance of different features in the dataset, the model itself is not highly interpretable.
			Computationally Expensive: XgBoost can be computationally expensive, especially when dealing with large datasets.
[8]	Preferred-DT Others DT optimized with MinLeaf and Best Level Method	The final depth of the optimized decision tree models was shallow, making the structures too simplistic and leading to underfitting. This may be one of the reasons why the decision tree model performed better than the other two models.	Overfitting: Decision Trees are prone to overfitting, which occurs when the model is too complex.
			Bias: DT can be biased towards features with large number of categories or high cardinality.
[4]	Preferred XgBoost Others-RF	The machine learning methods utilized in prior research (Random Forest) was less powerful, resulting to poorer performance metrics, Consequently, XgBoost approach employed in prediction model for fall risk in community living older persons is more powerful than RF method.	Lack of transparency: XGBoost is a black box model, which means it can be difficult to interpret how it arrived at a particular prediction.
			Parameter tuning: XGBoost has many hyper parameters that need to be tuned, which can be time consuming and require expertise.

[19]	Preferred-DT Others- (LR, SVM, NB, KNN)	The DT model produces good results for the method and is produced with 42 depths of the tree and entropy as criteria.	Lack of robust-ness: Decision trees can be sensitive to small changes in the data and can lead to different trees and predictions for similar datasets. Limited expressiveness: Decision trees are limited in their ability to represent complex relationships between variables and may require many levels of the tree to capture nuanced patterns in the data.
[3]	Preferred-LR Others- (BN, ANN, CHAID)	LR provide the maximum Negative Predictive Value, Sensitivity, AUC, and FMeasure values for fall prediction	Linearity: Logistic regression assumes a linear relationship between the independent variables and the log-odds of the dependent variable. If the relationship is not linear, logistic regression may not perform well. Multicollinearity: Logistic regression can have difficulty handling highly correlated independent variables, which can lead to unstable and unreliable estimates.
[20]	Preferred-GBT Others-DT	DT had inadequate class recalls such as fall occurrence, injury sustenance, and the majority of injury kinds, whereas GBT algorithms performed pretty well. This is a significant result that suggests boosting algorithms may achieve levels of accuracy that are actually reliable even with the small size of the training sample.	Slow training time: Gradient Boosting can be computationally expensive and time-consuming to train, especially on large datasets. Lack of transparency: Gradient Boosting can be difficult to interpret, especially when the model is deep or contains many trees.
[21]	Preferred-KNN Others- (SVM, RF, MLP,LR)	The top 10-fold results for retrospective classification, which demonstrates that KNN attains the highest value in Sensitivity, Positive Predictive Value, Negative Predictive Value, Accuracy, and AUC-ROC, as provided in the article. With an AUC-ROC of 79.21% KNN was considered to be the best model for mapping each individuals' functional parameters to their Final Risk.	Sensitivity to distance metric: The choice of distance metric used to calculate the nearest neighbors can greatly affect the performance of KNN. Slow prediction time: KNN can be slow to make predictions, especially on large datasets, as it requires calculating the distance between the query instance and every training instance.
[22]	Preferred-GBA Others- (LR,AdaBoost, NB,DT, KNN, SVM, RF)	Due to its statistical properties, the Gradient Boosting Algorithm outperformed all other models. Hyper parameters are tuned and used in the model to improve score in order to further increase the accuracy.	Lack of parallelism: Unlike other machine learning algorithms like random forests, gradient boosting cannot be parallelized easily, which can limit its scalability on large datasets. Requires feature scaling: Gradient boosting requires feature scaling to improve its performance. If the features are not scaled, some features may dominate the others, leading to suboptimal performance.
[15]	Preferred-DT Classifier Others-DT Regressor	With a higher accuracy of 81.925%, DT classifier performs better than DT regressor.	Greedy nature: Decision trees are greedy and choose the most informative feature at each node without considering the global optimum. This can lead to suboptimal solutions, especially, when the data has complex interactions between features.
[23]	Preferred-DT (c5.0) OthersLR	The DT model showed a reasonable share of sensitivity, which still qualifies it for usage as a primary fall risk screening tool. Additionally, DT model consists of common and easily measurable fall predictors and thus provides a minimal and personalized combination of predictors to calculate fall probability, ensuring that it can be useful as an efficient tool in various healthcare settings.	Limited handling of continuous variables: The algorithm C5.0 works best with categorical or discrete data and can have difficulty handling continuous variables. Limited handling of missing data: The algorithm does not have a built-in way to handle missing data, and often requires imputation or other data preprocessing techniques.
[24]	Preferred-XgBoost Others- (RF,Lasso, SVM, KNN)	The final prediction model was created using 157 important features that the XgBoost algorithm identified. These predictors largely consisted of demographic characteristics (age and gender), diagnoses of chronic diseases, prescriptions for medications, and clinical utilisation indicators.	Parameter tuning: XGBoost has several hyperparameters that need to be tuned to obtain the best performance. Tuning these hyperparameters can be time-consuming and requires a good understanding of the algorithm.
[25]	KNN,LR, DT,NB, RF,SVM	(N/A) No preferred ML Algorithm	(N/A)
[17]	Preferred-XgBoost	In two different models, the prediction of fallers and recurring fallers was investigated using XgBoost.	Lack of interpretability: The model generated by XGBoost can be difficult to interpret, particularly if a large number of features are used. This can make it challenging to understand how the model is making its predictions.

System Overview

The six processes that make up our system's overall Fall Prediction are depicted in Figure 2. Data collection, which has two components-primary data and secondary data-is the system's first stage. These are classifed based on the set up of underlying experiments. EHRs, TUG assessments, and survey data are all included in the primary dataset. In contrast, secondary data comes from organisations, and contains studies that were conducted in the past. The obtained datasets are mostly incomplete, in the sense of using them as direct inputs. So, we require some preprocessing methods to remove these clustered and incomplete data. The techniques accomplish this via preprocessing filters like the Datawig [8] and Random Forest-based Boruta algorithm [4]. Imbalanced data is the third phase. Imbalanced data means the dataset having the number of positive instances (falls) significantly fewer than the number of negative instances or vice-versa. Handling imbalanced data is an important step since it might produce biased models that underperform for the minority class(fall) and favour the majority class(non-falls). Imbalance nature is one of the important issues in any healthcare data analysis, especially in fall prediction [9]. Various resampling techniques, such as, SMOTE [10] are utilised to balance these classes. Training of the model using ML algorithms is used in the fourth phase to classify irregular falls. The data is often divided into a specific proportion for training and testing. This division is based on how various studies have set up their experiments. The ML algorithm is used in this stage to identify fall prediction using training data. The performance of these classifiers is assessed using test data, once the classifiers are trained.

This step analyses the overall performance of the system using multiple performance metrics, including AUC-ROC, accuracy, sensitivity, and specificity [11]. The predictive model is used for the prescriptive analysis in the last stage.

We detail all the six steps in the following section (Figure 2).

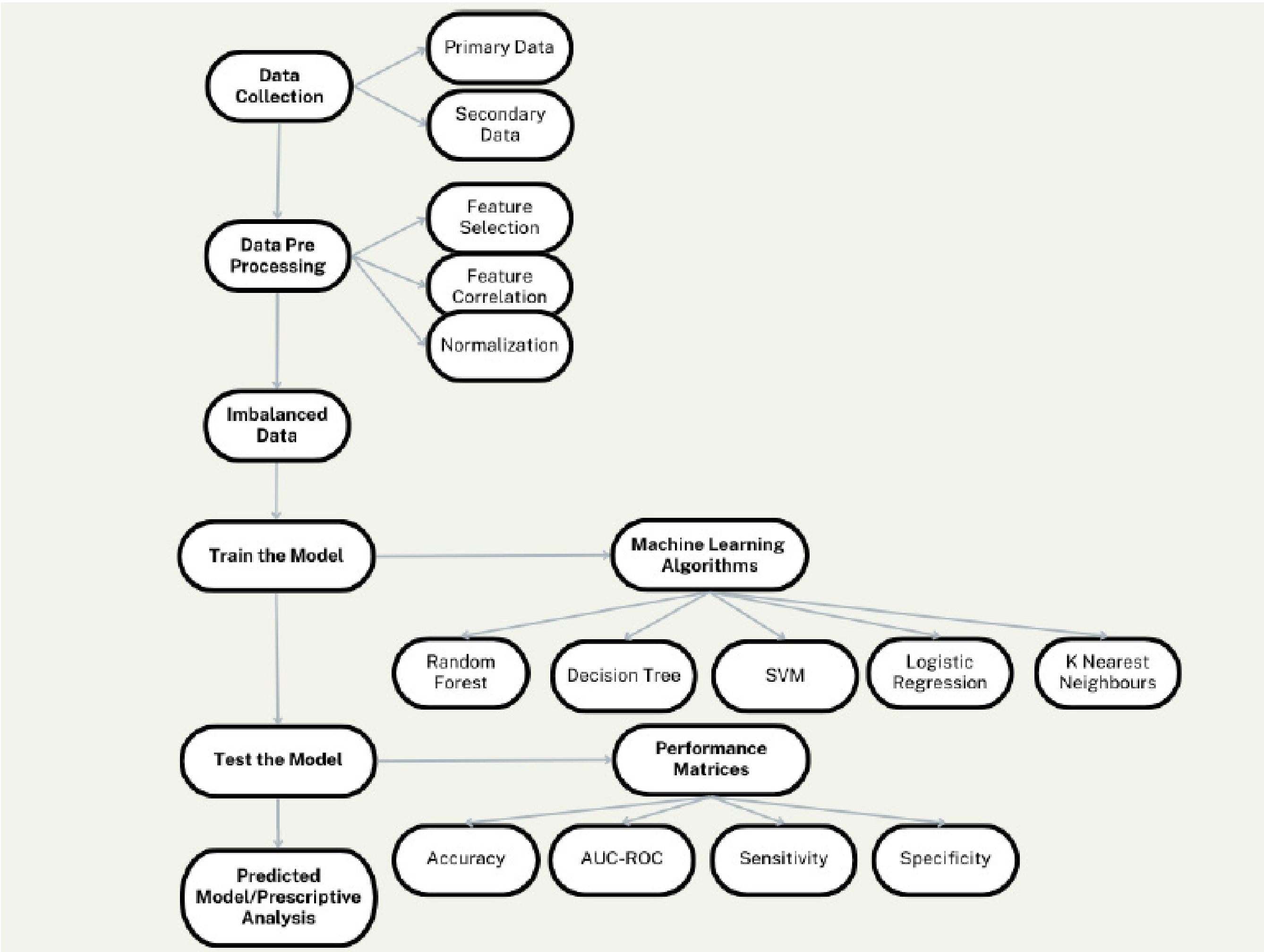

Figure 2: System Overview.

Review of Fall Prediction

As mentioned in section 2, we have shortlisted 15 research articles on fall prediction. This section details the overall analysis of the 15 articles that are selected.

Data Collection

Models must be trained with accurate and representative data to effectively identify fall hazards and avoid falls. Data on a person's medical background, physical condition, lifestyle characteristics, and environmental factors are all needed for fall prediction algorithms. We can pinpoint the variables that raise the risk of falls and develop models that can precisely forecast an individual's risk of falling by collecting and evaluating data. With this data, one may create individualised preventative plan for each person that may include focused interventions like fitness regimens, balancing, training, and environmental changes.

We categorize the collected data, for our analysis of Fall Prediction, into primary data and secondary data. Primary data is gathered directly from a source or by means of an investigation. For example, survey results, medical records, observational data, and experimental data. Secondary data, on the other hand, refers to dataset that have already been gathered and examined by some organisations or individuals [12]. According to our analysis, most of the data utilised to predict fall are primary data that were gathered via electronic health records (EHR), questionnaires, assessments of hospital admissions, Time Up and Go (TUG) assessments, Sit to Stand (STS) movements and surveys. Using online resources and some earlier studies, secondary data is gathered. Approximately 73% of the underlying studies are using primary datasets to produce the results. In contrast, as seen in Figure 3, only 27% of the studies have used secondary data sources (Figures 3,4).

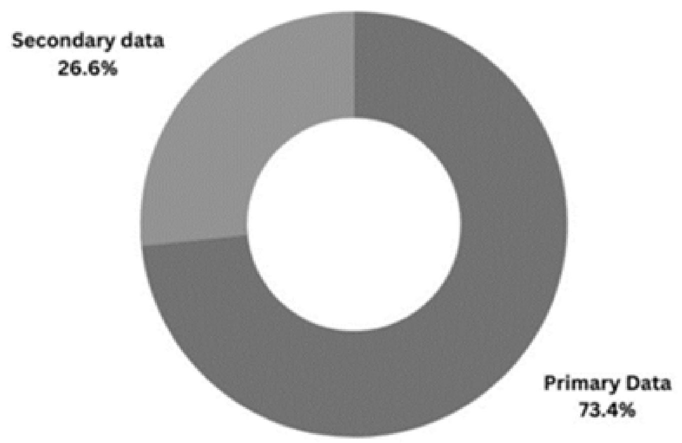

Figure 3: Data Collection.

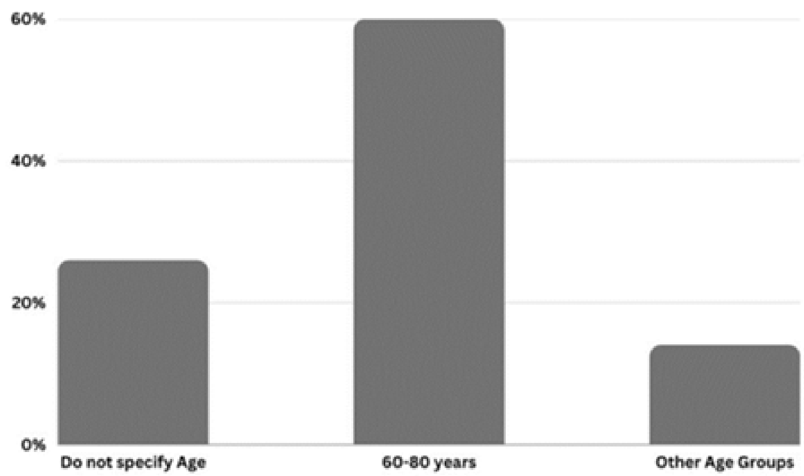

Figure 4: Age of Participants.

In the dataets that we have, roughly 60% of the subjects have participants aged above 60 years, which is the majority, as shown in Figure 4. Participants in some cases are also between the age of 80 and 90 years [13]. Also, 26% of the articles do not specify the participant's actual age. As a result, it is challenging to divide the participants into a definite age range.

Data Preprocessing

Data preprocessing is a crucial stage in this process. Preprocessing helps to clean, transform, and normalize the data to enable efficient analysis and modelling because healthcare data, in general, is complicated, varied, and noisy [14]. Data cleaning, feature selection, data normalization, handling categorical data, and handling missing values are just a few steps of data preprocessing. Finding and fixing errors, missing numbers, and outliers [15] in the data is known as data cleaning (Figure 5).

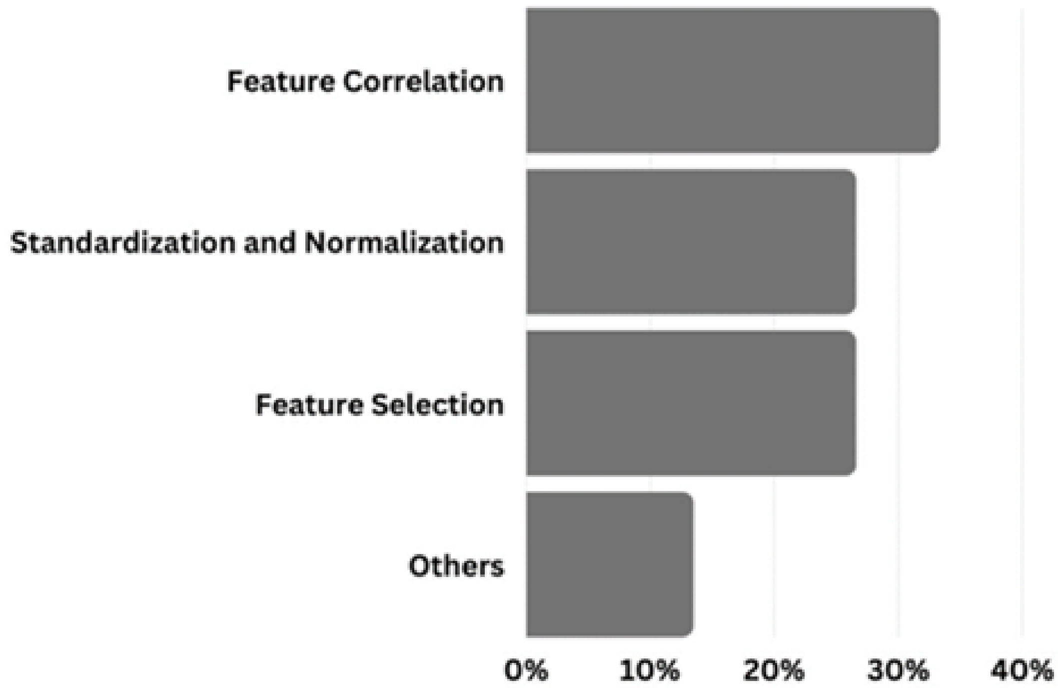

Figure 5: Data Preprocessing Techniques.

In feature selection, the most significant features are chosen from the raw data and converted into a modeling-friendly format. Data normalization entails converting the input data to a common range, which helps to resolve problems caused by varying measurement scales and units [16]. For machine learning algorithms to handle categorical data, it is first converted into a numerical representation. Replacing missing values [8] or deleting data points with missing values are two common approaches for handling the missing entries.

According to our analysis, 33.3% of the underlying studies focus on standardizing and normalizing the data. Nonetheless, several papers employed methods based on the removal of outliers [15], data duplication [17], and imputed missing values [8]. A total of 13.5% of the articles utilised this form of analysis is marked as others. The crucial processes in data preprocessing are feature correlation and feature selection. These methods are employed as the data preprocessing steps in about 26.6% of the total publications. There are many distinct phases in preprocessing, but the most common ones feature correlation, feature selection, standardization and normalization, as shown in Figure 5.

Imbalanced Data

In healthcare, data imbalance is a frequent problem, particularly in fall prediction, where the frequency of fallers is much lower than the number of non-fallers [5]. As a result, machine learning algorithms may produce models that are inaccurate, having bias towards forecasting the majority class [9]. To overcome the problem of imbalanced nature and enhance the precision of fall prediction models in healthcare, data resampling techniques such as SMOTE, Tomek Link, etc., are applied (Figures 6,7).

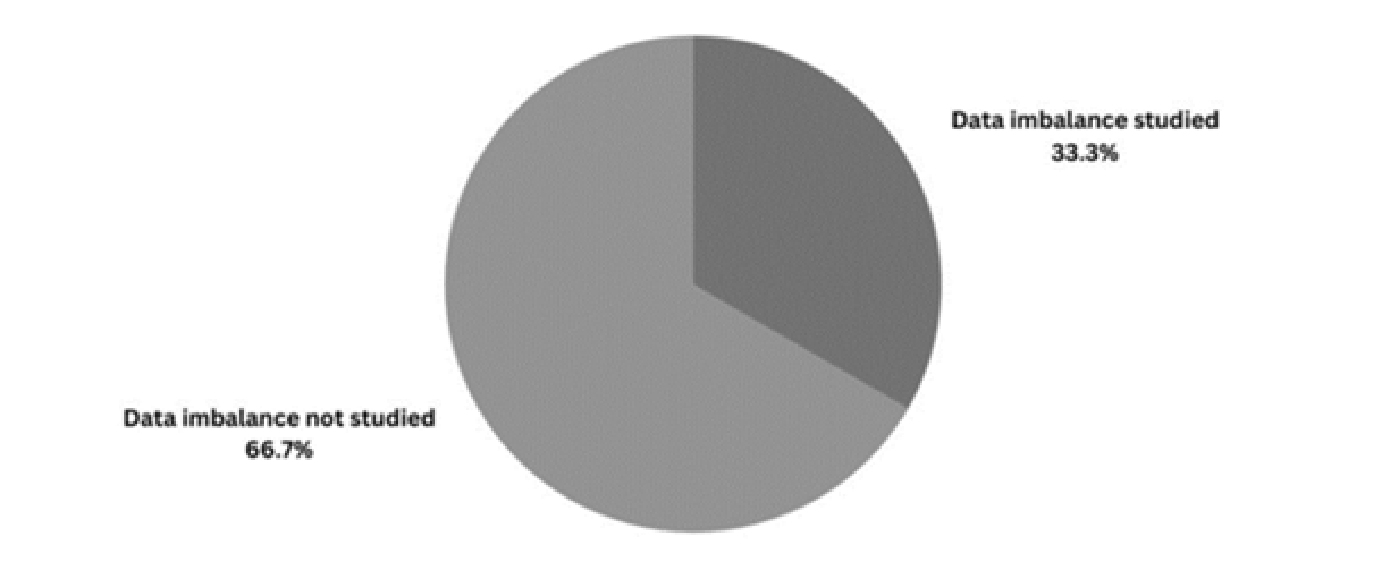

Figure 6: Imbalanced Data.

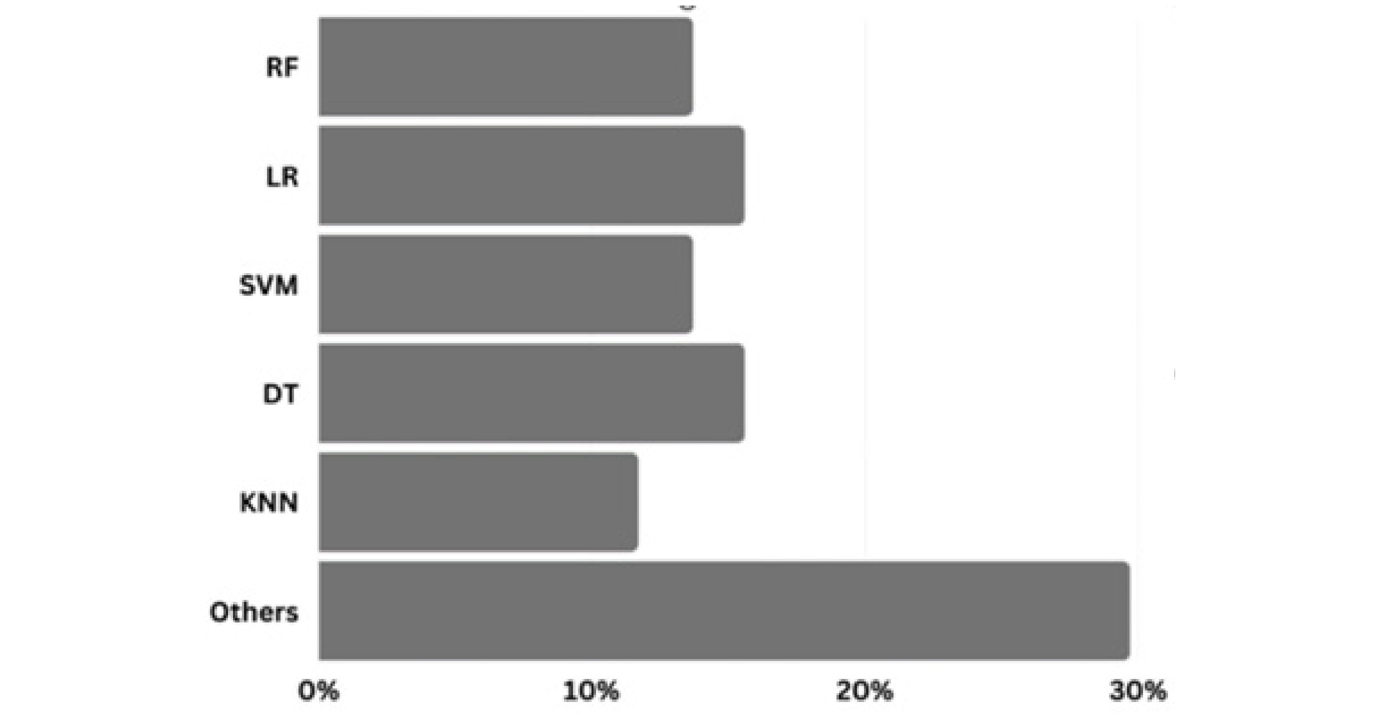

Figure 7: Machine Learning Algorithms.

We observe that 33.3% of the total articles discuss data handling strategies or employ them to address the problems of data imbalance. In 66.6% of articles, no imbalanced data approaches are employed or referred to in the course of their study, as shown Figure 6.

Machine Learning Algorithms

The choice of Machine Learning algorithms is the most crucial step. These algorithms are applied in accordance with the prediction model or methodology specified by the authors in respective articles. In some studies, authors employ just one algorithm, while in others, they use multiple. When there are multiple algorithms, the authors decide which algorithm performs the best for the underlying data. Figure 7 clearly shows that the most frequent machine learning algorithms are Logistic Regression (LR), Decision Tree (DT) followed by Support Vector Machine (SVM), Random Forest (RF) and K-Nearest Neighbour (KNN) (Figure 8).

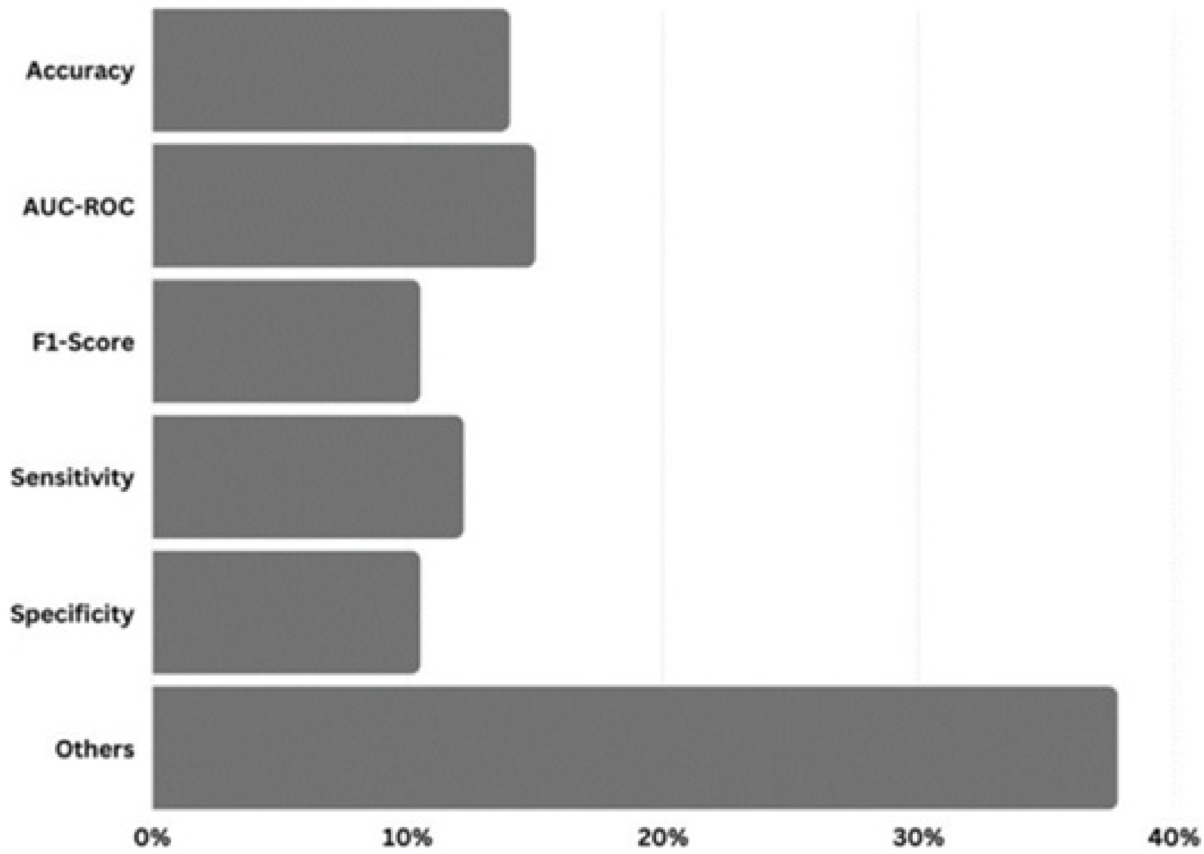

Figure 8: Use of Performance Metrices.

Performance Metrices

Performance metrics are useful for assessing the performance of machine learning models. Our analysis reveals that several studies have utilised various metrics to assess the effectiveness of the models. There could be several reasons for it, including different datasets, imbalance nature of dataset, participants, environment, and underlying machine learning methods utilized in these studies. For the articles under discussion, AUC-ROC is the most frequent measure followed by accuracy as shown in Figure 8.

Discussions

Advantages of using various Machine Learning techniques is the focus point of our analysis. Depending on the algorithms, the author determines which algorithm performs the best and why have they selected the same for the purpose of analysis. The following table presents some of the advantages and shortcomings of preferred machine learning algorithms that the authors have used.

Conclusions

The physical and cognitive abilities of older individuals are directly affected by aging, making it challenging for them to carry out daily activities. This decrease in functionality also increases the risk of falls, which can have severe consequences. To prevent such incidents, it is crucial to develop fall prediction models. This study scrutinizes several aspects of these systems, such as the datasets used, the age of participants, data preprocessing methods, machine learning algorithms, and common performance metrics employed for fall prediction.

In addition, the analysis highlights the significance of studying imbalanced data when creating a fall prediction model. One of the most important contributions of this article is to present the advantages and shortcomings of different machine learning algorithms used in the 15 selected articles.

Competing interests

The authors declare that they have no conflict of interest.

Authors Contributions

Mr Pankaj Yadav collected the articles and read the appropriate articles as per PRISMA approach. Dr Vivek Vijay analyzed the articles for figuring out the advantages and shortcomings of machine learning methods. Both prepared the manuscript according to their contributions.

Funding

Not Applicable.

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