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Review

Artificial Intelligence in Fall Risk Assessment: A Systematic Literature Review

Mark Moyer, BS, MS[1] and Farzana Hoque MD, MRCP, FACP, FRCP[2]*

[1]Saint Louis University School of Medicine, St. Louis, MO, USA

[2]Department of Internal Medicine, Saint Louis University School of Medicine, St. Louis, MO, USA

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***Corresponding author:** Dr. Farzana Hoque, MD, MRCP, FACP, FRCP, Associate Professor of Medicine, Saint Louis, University School of Medicine, St. Louis, Missouri, USA, E-mail: farzanahoquemd@gmail.com

ABSTRACT

Several studies have investigated the use of Artificial Intelligence (AI) in fall risk assessment. However, these studies lack a clear systematic evaluation of the optimal Machine Learning (ML) methods for clinicians to model fall risk applications. This study aims to provide a literature review of the advantages, disadvantages, and applications of AI. ML in fall risk assessment within inpatient and outpatient settings. We conducted a systematic review of 15 primary research articles covering both clinical data-driven and sensory data-driven modalities. Here, we report consistent advantages in using clinical Electronic Medical Record (EMR) data for ML algorithms. These studies resulted in the highest quality ML models with superior predictive accuracies and model performance. On the other hand, kinematic sensory data is prone to variable outcomes as ML classifiers are often sensitive to small changes in that sensory data. These data collection methods are more time-intensive and less applicable to the real world. Furthermore, Adaptive Boosting and Random Forest ML classifiers were the most common in producing the highest-performing algorithms. This study suggests that, by using ML, clinicians can reliably streamline and predict fall risk at higher accuracies than current fall risk assessments. Further research may leverage these ML methods to assess variables in fall prevention, bridging the gap between fall risk assessment and prevention strategies.

Keywords: Fall, artificial intelligence, machine learning, fall risk assessment

1. Background

The use of AI in medicine is a novel development that has the potential to improve the practice of healthcare as it provides an opportunity to facilitate the work of physicians through aiding diagnosis or identifying and uncovering predictors of disease. With the many ways healthcare providers have theorized the use of AI, the goal is to leverage these technologies to enhance and improve patient outcomes. Adverse events in hospitals continue to be a focus of healthcare providers to improve clinical outcomes. These have been assessed through predictive risk models that physicians can use to make informed clinical decisions. Falls are not only ubiquitous but are rated among the most preventable complications with an estimated 87.5% of cases being considered preventable.[1] Elderly adults who have suffered falls are likely to suffer from disability and fall-related injury leading to deterioration of personal health and increased burden of healthcare costs.[2] In the United States, it is estimated that each year around $50 billion is spent on medical costs related to falls among older adults, with fatal injuries accounting for $754 million and the remaining cost associated with non-fatal fall injuries.[2] With more than 14 million elderly adults in the United States sustaining a fall each year, falls should be considered among the most important healthcare complications that can be prevented.[3]

Risk predictive models are models using historical data and prospective data to predict probabilities of events occurring. These can be classified as statistical models, including regression models or classification trees, and ML models, which apply models to data to learn over time. While classic statistical models for risk prediction such as the Morse Fall Scale (MFS) have proven helpful over the years, these models do not tell us which risk factors carry more weight and are most significant. AI modalities such as ML can, and although the complexity of ML models may obscure this process, there are methods of increasing interpretability.[4] Among the existing tests clinicians use to assess risk for falls, these can be divided into clinical data-based fall risk assessments and mobility-based fall risk assessments. The MFS is a clinician tool for fall risk assessment that uses patient clinical data to stratify patients into risk levels for falls and is the most common fall risk assessment tool. It is widely used for its simplicity and quickness of use however limitations include low specificity in predicting falls.[5] Mobility-based fall risk assessments such as the Timed Up and Go (TUG) test or the Berg Balance Scale (BBS) analyze a patient's performance in movement activities to indicate or stratify risk for falls. Although useful, limited evidence exists validating the use of the TUG test.[6] As for the BBS, its applicability is limited as the completion of 14 different items on the assessment requires a significant time investment from clinicians.[7] With the advent of ML, the rise of sensory-based fall risk assessment has occurred which entails the use of data from kinematic sensors or camera systems to track body position during movement, which can be used to train ML models for fall risk prediction. AI is a rather broad collection of technologies that can range from physical robots to rule-based expert systems to ML learning. Of all the AI types, ML poses the greatest benefit in risk prediction as this type of AI can learn from prior data and change itself. This field represents algorithms that are developed to better represent a set of data whereby in ML a dataset and output are used to produce an algorithm as opposed to classical programming where a dataset and algorithm produce an output.[8] ML can be further classified into sub-types of algorithms including Support Vector Machine (SVM), Convolutional Neural Network (CNN), Random Forest (RF), and Boosting Decision Tree among many others. Further information regarding the data processing techniques used in these models can be found elsewhere.[8,9] Numerous studies have sought to investigate ML modalities in developing risk predictive models, but questions still arise on the quality of the datasets, determining efficacy versus provider assessments, and what limitations these early modalities have in healthcare.[10] In addition, ML models have often been regarded as black-box algorithms meaning that we cannot understand or explain how those predictions from the ML model came to be.[11] In this study, we provide a literature review exploring ML in the setting of fall risk assessment across healthcare settings. We aim to assess the outcomes of these studies in this field because falls represent one of the most preventable healthcare complications. The findings may prove to inform healthcare providers about new and upcoming AI methods of predicting risk for falls for implementation in the field.

3. Methods

This study is a systematic literature review covering the exploring ML in the setting of fall risk assessment in according with PRISMA guidelines.[12] Inclusion criteria included peer-reviewed, full-text, English language primary research articles studying ML methods in fall risk assessment. Exclusion criteria included assessment of fall detection, lack of reporting both model performance and predictive accuracy of the ML algorithm, less than 20 fallers, and study population with a mean age of < 55 years old. Studies were identified via the PubMed database in 2023 resulting in 181 unique articles identified. Keywords used in the article search process included: Machine Learning, ML, fall risk, fall risk assessment, prediction, and classification. During screening 86 records were excluded based on abstract and conclusion lacking relevance, 8 articles were review articles that were removed. An additional 22 articles were not retrieved due to paywalls. Of the 69 remaining articles advanced to full-length review, 28 were excluded based on: not including measures of both model performance and predictive accuracy, not meeting the desired age criteria, having too small a sample size, assessing fall detection, or not utilizing a machine learning model. Of the 37 eligible articles, 15 were included in the study and evaluated in two categories: those involving clinical data on fall risk and those involving sensory data on fall risk. Given the nature of the articles being either retrospective or prospective prediction studies with differing methods of population selection and feature importance extraction, selection bias and confounding variables were discussed. Screening, data collection, and bias assessment were performed by one reviewer and independently reviewed by a second reviewer.

4. Results

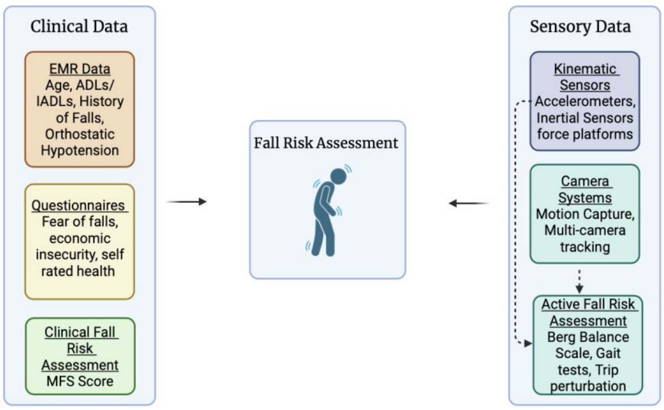

Figure 1: An Overview of the Use of Clinical and Sensory Data in Fall Risk Assessment.

4.1. Clinical data-driven machine learning models

In Lindberg, et al., Lo, et al., Chu, et al., and Ye, et al., clinical and EHR data were utilized for ML-based fall risk models which produced AUC values of 0.90, 0.67, 0.72, and 0.81 respectively.[4,13-15] These performances were superior to control models based on the Morse Fall Scale or the Missouri Alliance for Home Care fall risk assessment.[4,13] Unstructured clinical notes from EHR systems were utilized predict 1 year fall outcomes yielding a ML model with an AUC of 0.718.[16] In Lathouwers, et al., an ML model using census socioeconomic information has accuracy of 73% in predicting falls within the next year.[17] Ikeda, et al., ML models based on community questionnaire data produced an AUC of 0.88 (SD = 0.02).[18] In Patterson, et al., several ML algorithms were used to stratify recently discharged ED for fall risk to predict fall re-visit within the next 6 months which produced an AUC of 0.78.[19] They estimated that an intervention consisting of fall clinic referrals had a number needed to treat (NNT) of 12.4 referrals to a fall clinic to reduce the number of ED re-visits by 1.

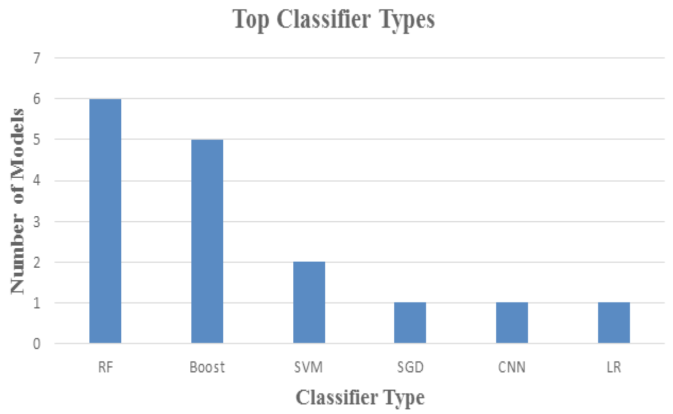

Figure 2: Bar Graph Demonstrating the Distribution of Data Types and Top Performing Machine Learning Classifiers. Patterson, et al. had two equally top performing classifiers (RF and AB) accounting for a total ML model number of 16.

4.2. Sensory data-driven machine learning models

In Eichler, et al., a ML fall risk assessment was developed using motion tracking systems while capturing patients performing the Berg Balance Scale (BBS) with a final fall risk prediction accuracy of 75.5% and an "Efficient BBS" of 3-6 tasks resulting in improved accuracy (76-77%).[7] Roshdibenam, et al., Noh, et al., Sun, et al., Kelly, et al., and Lockhart, et al., all utilized kinematic inertial, postural, or accelerometer data with varying results. Each of these studies were limited in their own way such as lack of direct or objective measurement of fall risk or model performance that was no better than guessing.[20-24] Mishra, et al., utilized model based on temporal spatial gait analyses with geriatric assessment to predict 6 month fall outcome producing an AUC 0.80.[25]

5. Discussion

The previous section provided the results of 15 studies and this section provides a discussion and evaluation of those results. Of the 15 papers, 8 described ML algorithms driven by clinical data, while 7 were driven by sensory data. Three papers[7,17,22] do not provide an AUC (Area Under the Curve) which is a measure of predictive model performance and instead accuracy was provided which has limitations. Accuracy measures the ratio of true predictions to the total number of samples meaning it is ideal for uniformly distributed data, where there is an equal number of fallers to non-fallers. In the 3 papers[7,17,22] that reported Accuracy but not AUC, data is imbalanced which can lead to cases where true negatives contribute to a larger portion of the sample while the ratio of true positives to false positives is relatively less and the ML algorithm cannot reliably predict positive fallers. In addition, 4 studies do not include a 95% CI for the AUC meaning the 95% CI could theoretically include an AUC of 0.5, which is no better than guessing.[15,18,23,24]

Table 1: Overview of 15 research articles assessing Fall Risk Assessment through Machine Learning. Either AUC or Accuracy when available in the paper is provided with regards to their top-performing ML algorithm. The top 3-5 predictive variables isolated in each paper are also provided indicating which factors had the highest importance in feature selection.

Data Type	Reference, Country	Sample Size	Best Performing ML Classifier	AUC (95% CI)	Accuracy ((95% CI	Predictive Variables Isolated by ML Algorithm	Setting
Clinical (EMR)	Lindberg, et al., U.S.	814 (272 fallers, 542 non-fallers)	Random Forest	0.9 (0.87, 0.92)	*NA*	*History of Falls, Total Morse Score, Age, Mental Status, Unit Type*	Inpatient Hospital
Clinical (EMR)	Lo, et al., U.S.	59006 (5.14% fallers)	Random Forest	0.67 (0.66, 0.68)	*NA*	*Age, Severity of Home Care Diagnoses, Frequency of Therapy Visits, Pain Affecting Function*	Home Health Care
Clinical (EMR)	Chu, et al., China	1,101 (349 fallers, 752 non-fallers)	XGBoost	0.57 (0.559, 0.603); 0.72 (*AUC analyzing top 5 variables*)	*73.2% ,71.8%) (76.1%*	*IADLs, Brade Score, ADLs, Age, Systolic BP*	Inpatient Hospital
Clinical (EMR)	Ye, et al., U.S.	265,225 (1.64% fall rate)	XGBoost	0.807	*NA*	*Cognitive Disease, Abnormalities of Gait and Balance, Orthostatic Hypotension, Parkinson's Disease, Muscle Disorders*	Inpatient Hospital and FQHC
Clinical (Social Determinants Questionnaire)	Lauthowers, et al., Belgium	82,580	Random Forest	NA	*73%*	*Number of grandchildren, Insecurity, Number of Children, Housing Change, Mental Activity*	Community Dwelling
Clinical (Community Questionnaire)	Ikeda, et al., Japan	61,883 (5.43% multiple falls rate)	XGBoost	0.88	*88%*	*Prior experience of falls, self rated poor health, older age, fear of falling, inability to stand up from chairs*	Community Dwelling
Clinical (EMR)	Patterson, et al., U.S.	9,687 (8.85% fall rate)	Random Forest, AdaBoost	0.78 (0.74, 0.81)	*NA*	*Not Applicable*	Inpatient Hospital and Clinic
Clinical (EHR)	Dormosh, et al., Netherlands	36,470 (4,778 fallers, 31,692 non-fallers)	Logistic Regression	0.718 (0.708-0.727)	*NA*	*Residential Care, Cognitive Impairment, Fractures, Head Trauma, Info exchange between providers & CVRM lab measurements*	Clinic

Sensory (Spatiotemporal tracking, Clinical Fall assessment)	Mishra, et al., U.S.	92 total (31 fallers, 61 non-fallers)	SVM	0.80 (0.76-0.85)	*75% ,72%) (79%*	*IADL, ADL, Gait speed, FAP score, MMSE*	Inpatient (Intermediate Care Facility)
Sensory (Kinematic Sensors)	Roshdibenam, et al., U.S.	100 (54 fallers, 46 non-fallers)	CNN	0.56 (0.33, 0.74)	*60.6% ,44.4%) (72.2%*	*None identified*	Inpatient Hospital and Clinic
Sensory (Multi Camera Tracking)	Eichler, et al., Israel	130 (30 low risk fallers)	SVM	NA	*,75.5% E-BBS) Accuracy (97%*	*BBS Scale Tasks 9, 7, 6, 11, 8*	Inpatient Hospital and Healthy Visitors
Sensory (Intertial Sensors)	Noh, et al., South Korea	746 (456 low risk, 290 high risk)	XGBoost	0.72 (0.66-0.79)	*NA*	*Walking Speed, Stride Length, BMI, Physical Activity, Age*	Clinic
Sensory (Postural Sway Mechanics)	Sun, et al., U.S.	153 (103 MS cases, 50 controls)	Random Forest	NA	*92.3%*	*Sample Entropy, Sway Range, Sway Area*	Clinic
Sensory (Kinematic Sensors)	Kelly, et al., Sweden	1705 (15% fall rate)	SGD	0.544	*NA*	*Free Living Accelerometer Data across all ML classifiers*	Community Dwelling
Sensory (Inertial sensor)	Lockhart, et al., U.S.	171 total (34 fallers, 137 non-fallers)	Random Forest	0.78	*NA*	*Recurrence-Medial Lateral signal, Complexity- Medial Lateral Signal Entropy, Determinism-Vertical Signal, Recurrence-Vertical Signal, Overall Walking Time Series Complexity*	Community-Dwelling

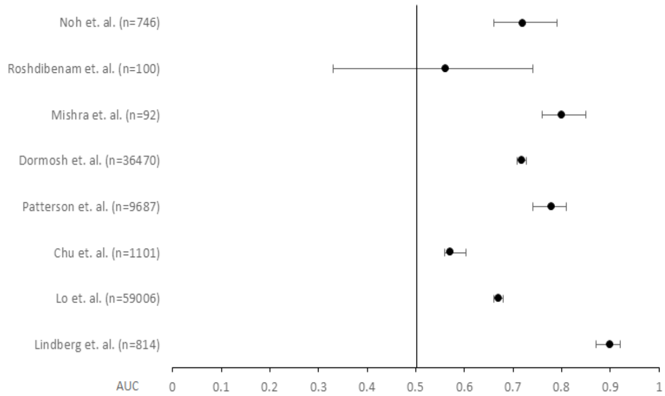

Figure 3: A Forest Plot Comparing AUC with 95% CI. These papers were selected based on papers providing both AUC and 95% CI. The X-axis corresponds to AUC with 0.50 representing a model that is no better than randomly guessing.

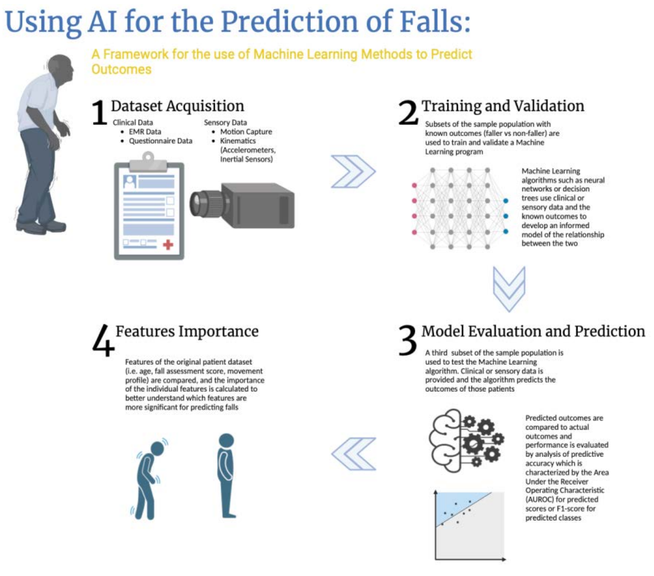

Figure 4: Infographic Depicting the Framework Machine Learning Studies Use in Assessing Fall Risk.

When assessing selection bias, randomization of populations are not explicitly described. Clinical data papers, save for two[13,17], consistently report baseline population data that would allow analysis of the significant differences between the faller and non-faller demographics. On the other hand sensory data papers, save for two[20,25], do not report baseline characteristics and completely rely on sensory data leading to potential selection biases.

Datasets were gathered in a plethora of settings including inpatient hospital in 8 of the papers, outpatient settings in 6 of the papers, or community settings as in 4 of the papers. We see this as reflecting the importance of fall risk detection in all settings, with promising results in each unique setting. In papers where EMR data was used as a dataset, sample populations are quite large ranging up to the hundreds of thousands of analyzed patients which prompts concerns about those studies being overpowered. Indeed, in Lo, et al. 137 EHR-derived patient features or variables had miniscule effect sizes, many of which were not statistically significant.[13] The interpretation of these variables and their effect sizes is limited by the inability of ML model output to determine the presence of interactions (multiple variables influencing the effect of a dependent variable) or collinearity (multiple variables highly correlated in a linear manner) and thus confounding variables arise. This introduces difficulty in assessing the true importance of a variable as interactions may make it unpredictable how changing one variable may affect prediction, and collinearity may result in redundancy or lack of validity for a given variable. Feature extraction differs between each article including use of Lasso regression[15,16], SHAP[18,25], ReliefF[13], or scores provided by the chosen ML models such as XGBoost[14,21]. While the former methods may address some amount of collinearity, other articles directly attempt to address the issue by analysis with Pearson correlation coefficient[25] or clustering methods[17]. Six articles remain as not detailing any methods of addressing these issues. One additional issue is that there is a notable amount of ambiguity provided in the papers reporting whether the outcomes are based on training or testing datasets, however, all except 4 articles[7,16,22,25] report separation of training and testing data and describe testing data before reporting outcomes. In terms of generalizability, populations are the desired age of 55 or older, and are represented across multiple continents including North America, Europe, and Asia, however these tend to focus on developed countries. Lack of clear randomization, especially in the sensory data studies also reduces generalizability, while the larger populations seen in clinical data studies enhances generalizability.[24] Among the ML classifiers used, 6 of the most common ones included conventional techniques such as SVM and SGD, deep learning techniques such as CNN, and decision tree techniques including RF and Boosting Decision Trees (i.e. XGBoost, AdaBoost). Two classifier types rose above the rest and appeared to produce the highest model performance and prediction accuracies, those being RF and Boosting Tree. Conventional wisdom in the field of ML tells us that the advantage of RF is that it is fast and effective with large amounts of data and tends to avoid problems of overfitting, but is sensitive to small changes in training data such as what we would see in studies on gait and kinematics which are dynamic.[9] This was consistent with our results as the RF classifiers were predominant in the clinical EMR studies but not the sensory studies. As for Boosting Tree models, it is expected that their predictive accuracy is generally higher compared to other models, but drawbacks include computational intensiveness and difficulty in interpreting the final models.

There is a high degree of variability in the model performance and predictive accuracy of the provided papers. For example, the use of worn accelerometers in daily living provided no ability to predict future falls with AUCs indicating that they were no better than randomly guessing.[20,23] The better performing sensory models seen in Sun, et al. and Lockhart, et al. may be an indication of the need to measure nonlinear gait variables to produce more accurate predictions. Beyond the fact that dynamic gait measurements can widely alter sensitive ML algorithms, the AUCs of these algorithms do not often exceed the 0.80 threshold.[22,24] The performance of the ML algorithms is dependent upon the measuring devices, data acquisition settings, obtained datasets, ML classifiers, and resultant ML algorithms, all of which are very different among the sensory data articles meaning they are not easily comparable. On the other hand, the clinical EMR data-driven studies have more consistent outcomes despite differences. The 3 top ML classifiers with AUCs > 0.80 are clinical data driven, and similar predictive features including age, history of falls, and mental status appear across clinical data papers.[5,15,18] Even in the case of unstructured EMR data, the ML model performance was acceptable indicating that there is often ignored value in those notes that can be integrated into other clinical-data models.[16] It can be safely concluded that the use of EMR data can be more consistently relied upon to reflect the parameters predictive of falls and can be easily collected as opposed to the time-intensive nature of measuring physical movement.

Underlying several of the ML algorithms used in the papers covered in this review, were several fall risk assessments such as the MFS, TUG, and BBS that were incorporated into the datasets. The MFS was not only incorporated into ML datasets producing excellent AUCs, but was also solely incorporated into a ML logistic regression model that performed relatively similarly to the other ML algorithms.[4] The TUG was incorporated into two papers with varying results in the ML classifiers.[20-25] Lastly, the BBS was also a reliable test contributing to an ML classifier with 75.5% prediction accuracy of fall risk, with the Efficient-BBS produced by Eichler, et al., which included 4-6 of the most important BBS tasks, produced predictive accuracies of around 97%.[7] Imbalance of the dataset while utilizing accuracy however casts doubt upon the ML model performance.[7] Realistic adoption of these ML techniques and the underlying data is dependent upon the efficiency and applicability of these methods. One can see the ease of use in collecting standardized EMR data and its advantages over wearable kinematic sensors or motion capture for several reasons including less time investment from clinicians in data collection, easier interpretability of variables, and ability to be implemented across a wider range of healthcare settings who don't have access to sensory equipment.

While the 15 articles addressed in this review address the topic of fall risk assessment, there still exists the gap between fall risk prediction and using that information to prevent falls. One study sought to explore this where they used their ML model to estimate the number of predicted fallers that would be enrolled in a multidisciplinary fall clinic.[19] They assumed a relative risk reduction (RRR) for fall clinic referral (in reducing incidence of falls) based on a prior study and multiplied this RRR with the absolute risk from their ML model data to calculate a NNT.[19] If there were no constraints on the number of referrals that could be made to the theoretical fall clinic, they estimated the NNT to be 2.6, but when considering a limit of 10 referrals per week, the NNT was 12.4.[19] Referral of 12.4 patients to a fall clinic in order to prevent 1 fall may seem costly, but this should also be compared to the healthcare costs if that 1 patient did fall, which is estimated to be up to $62,521 in inpatient settings.[26,27]

As of now, the current state of ML in fall prevention literature equates fall detection studies with fall prevention studies implying that detection will automatically lead to prevention.[9] This is not what we are implying, because if the fall is detected the fall has happened. Instead, we are suggesting that the interventions used to prevent falls would be investigated using ML. The collection of these interventions as dataset variables among patients identified with high fall risk could provide insight into the significance of which variables help prevent falls in those patients. Therefore, ML can close this gap between fall risk assessment and fall prevention.

6. Conclusion

Overall, we identified promising results with regards to the use of ML techniques in fall risk assessment, with advantages in using clinical EMR data producing ML models with higher model performance and predictive accuracy. On the other hand, there is more variation within the realm of sensory data, as ML classifiers are often sensitive to small changes in data, and these data collection methods are more time-intensive and less applicable to the real world. Nevertheless, this study found that ML models have been proven to not only reliably predict fall risk across healthcare settings and clinicians could benefit from the use of these technologies.

7. Financial support and sponsorship

None

8. Conflicts of interest

None, consent for publication was obtained from all authors.

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