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Article

A Hybrid Clinical–Machine Learning Framework for Fall Risk Assessment Using Standardized Geriatric Measures

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Abstract: Fall-related injuries, disabilities, imbalance and mortality in elderly adults are serious global public health concerns. Despite the clinical utility of widely used fall risk assessment tools like STRATIFY, the Morse Fall Scale, and the Hendrich II Fall Risk Model, their predictive performance is frequently limited by static scoring mechanisms, limited environmental sensitivity, and decreased compliance across heterogeneous care environments.
The design, validation, and assessment of a Hybrid Fall Risk Assessment and Prediction (HF-RAP) model that combines machine learning-based prediction with standardised clinical scoring are presented in this paper. Five clinically proven and significant predictorssuch as falls in the past, support of ambulatory aids, transfer capacity, Use of potentially inappropriate medicines (PIMs), and mental and emotional factors form the foundation of the suggested evaluation instrument. Over the course of 15 months, information was gathered from 687 older persons in old age home, pain and palliative care homes, hospitals and at homes.
ANOVA, multivariate logistic regression, and chi-square analysis were used to select features.
A variety of supervised ML methods were assessed, such as Random Forest (RF), XGBoost, Logistic Regression(LR), K Nearest Neighbours, Naïve Bayes, LightGBM, and Deep Neural Networks(DNN). With classification accuracy ranging from 86% to 90% and ROC-AUC values ranging from 96% to 98% among models, the HF-RAP model showed significant discriminative capabilities, with ensemble approaches consistently outperforming others.
Optimal risk stratification while balancing sensitivity and specificity was made possible by a theoretically driven threshold (CRS > 8) that was determined using ROC curve analysis. The suggested technique overcomes significant shortcomings of current tools by fusing clinically interpretable scoring with sophisticated predictive analytics. Solution for fall risk assessment in geriatric care that is scalable, comprehensible, and applicable worldwide.
Keywords: Fall risk assessment, Machine Learning, Assessment Tool, Risk Factors, Hybrid Framework, Predictions

1. INTRODUCTION

With the goal of improving older individuals' independence, safety, and quality of life, gerontechnology is an interdisciplinary convergence of gerontology, computer science, healthcare, psychology, and engineering [1–3]. The burden of age-related health concerns, including falls, has increased as the world's population continues to age.For people 60 years of age and older, falls continue to be one of the main causes of injury-related morbidity and mortality. Over 80% of the 684,000 fatal falls that occur worldwide each year take place in low- and middle-income nations, according to the World Health Organisation [4]. Falls often result in long-term functional deterioration, psychological suffering, increasing institutionalisation, and significant healthcare costs in addition to physical harm.

Clinical practice frequently uses several assessment methods, such as the Hendrich Fall Risk Model,STRATIFY, and the Morse Fall Scale model, to reduce fall risk. Although these techniques offer structured riskassessment, there are significant differences in their predictive accuracy between populations and care contexts [6–8]. Static scoring is used by many systems, are not demographically flexible, and do not adequately account for the complex nature of falls, especially those caused by psychological and medication-related factors. Recent advances in machine learning offer exciting ways to improve fall risk prediction by mimicking complex, non-linear interactions between clinical and demographic data [9–11]. Algorithms such as Random Forest, XGBoost, and Support Vector Machines can improve forecast accuracy and customisation by detecting complex, non-linear connections between several risk factors. In comparison to conventional statistical techniques, machine learning-based models have demonstrated superior performance in a range of healthcare prediction tasks through the integration of advanced computer techniques with clinical data. There is an urgent need for fall risk assessment tools that are accurate, data-driven, easy for clinicians to interpret, and flexible enough to be used in different care demographics such as hospitals, long-term care, and community settings. In day-to-day geriatric practice, tools that behave like "black boxes" are difficult to trust and hard to implement, even if they perform well on paper.

This study is designed to close that gap by using a hybrid approach that consciously tries to do two things at once: keep the predictions strong and keep the model easy for clinicians to understand. The main goal is to make fall risk prediction more accurate, while still accounting for differences in age, health status, and care context, so that the same model can be used in acute wards, palliative units, nursing homes, and even in community or home-based care. In practical terms, the intention is to move from reacting to falls after they occur to identifying high-risk patients earlier, supporting targeted prevention and, ultimately, helping to lower fall-related illness and death in older adults.

Hence the study introduces a Hybrid Fall Risk Assessment and Prediction (HF-RAP) model that combines standardised, clinically validated scoring methods with probabilistic machine learning–based prediction. In practice, this means that the model retains the familiar structure and transparency of traditional fall scales, while at the same time drawing on the analytical strength of modern computational methods. This hybrid design aims to offer a scalable, understandable, and globally relevant solution that clinicians can both trust and act on in routine geriatric care.

Objectives

1. To create a fall risk assessment tool which consists of standardised risk elements and medically proven predictive variables
2. To create and implement the detection of modest behavioural anomalies with fall risk outcomes is made possible by **AHybrid clinical–machine learning framework (HF-RAP) model.**
3. To evaluate the clinical utility and prediction performance of the proposed four-layer HF-RAP architecture by comparing numerous supervised machine learning methods.

2. RELATED WORK

Simple bedside checklists have clearly given way to more data-driven, machine-learning methods for predicting falls in older persons, according to recent studies. Newer research integrates data from geriatric exams, gait measurements, and electronic health records to create a more comprehensive picture of each person's risk rather than relying just on traditional scales. According to research published between roughly 2022 and 2025, reported AUROC values typically fall between 0.75 and 0.91. Common risk variables include polypharmacy, total disease load, and gait speed in various settings, including workplaces, hospitals, and long-term care facilities**.**

Chen et al. (2022) used regular electronic health information to create a model for Taiwanese hospitalised older individuals. They tried a number of algorithms, including XGBoost, LightGBM, random forest, and logistic regression, and examined data from more than 1,000 inpatients 65 years of age and older, including age, comorbidities, medication patterns, and mobility scores. With an AUROC of roughly 0.75 and an accuracy of about 73%, XGBoost outperformed more conventional methods like the Morse Fall Scale, demonstrating that meaningful predictions may be achieved with just ordinary EHR data.

Liu et al. (2022) examined long-term care facility residents and once more used EHR data to forecast falls over a three-month period. They reported an AUROC of 0.846 using Extreme Gradient Boosting, indicating a substantial distinction between fallers and non-fallers. The methodology provided a non-invasive method of ranking residents by risk using data already gathered at the institution, and key predictors in their model were factors that clinicians identify in practice, such as several drugs, a high chronic disease burden, and unstable vital signs.

Mishra et al. (2022) addressed the issue of "black-box" models with a particular focus on elderly individuals living in the community. They investigated a number of models, including logistic regression, k-nearest neighbours, SVMs, decision trees, and random forests, and integrated standard geriatric measures (ADL, GDS, MMSE), comprehensive GAIT Rite gait characteristics, and fall history for 92 people. Their best model had an AUC of 0.80 with 82% sensitivity and 72% specificity. They used SHAP values to demonstrate the importance of depressive symptoms, walking speed, and cognitive status, which helped physicians understand why the model flagged patients.

Taking a more comprehensive approach, Smith et al. (2025) conducted a scoping assessment of over fifty machine-learning research on fall prediction that relied mostly on health-record data rather than sensors. They discovered that many models depended on comparable inputs including age, prescription data, and routine lab results, and that tree-based ensemble approaches commonly produced AUROCs above 0.80. In order to keep results understandable for frontline staff, future research should integrate ML models with current clinical tools like STRATIFY and the Hendrich II scale, according to the review, which also highlighted limitations such as a lack of external validation and limited evidence from low-resource settings.

Lee et al. (2025) demonstrated that few inputs are necessary to obtain high performance in occupational health. They used relatively light models like random forest and gradient boosting and only three temporal gait variables gathered from basic walking tests to predict falls in middle-aged and older workers. Their approach demonstrated that tiny, targeted feature sets can be useful and efficient for workplace screening programs, achieving an AUROC of roughly 0.91 with great sensitivity.

These findings collectively indicate that machine-learning frameworks, like the suggested HF-RAP, can combine interpretable methods (like SHAP) with compact, clinically significant feature sets to enhance prediction while maintaining models that physicians can comprehend. In order to evaluate these technologies across various healthcare systems and ultimately aid in lowering fall rates among older persons, the literature also emphasises the necessity of multi-site studies and real-world implementation efforts.

3. METHODOLOGY

The goal of this research is to develop and validate a novel fall-risk assessment tool for older persons using an analytical, cross-sectional design. The process is simple; first, critical risk variables are determined, and then appropriate information is gathered from various clinical and demographic sources. The evaluation tool is then built using these parameters and integrated into a hybrid prediction model that blends machine learning techniques with clinical rating. In order to assess accuracy and practical utility, a number of algorithms are tested, compared, and their performance is thoroughly assessed using standard metrics.This design ensures that the final tool is simple enough to be used in standard clinical practice and allows for a broad examination of the factors that contribute to fall risk while maintaining the robustness of the approaches.

Data Collection and Study Population

A centralised data gathering technique was used to guarantee diversity and representativeness. Pain and palliative care homes, long-term (old age) care facilities, and assisted living facilities for the elderly. Over 450 days of observations were spent gathering data for the study. This method reflected the diversity of geriatric care in the real world by allowing older adults from both independent and institutionalised controlled situations to be included. 1,200 individuals who were 55 years of age or older were initially registered.When preset inclusion and exclusion criteria centred on relevance to fall risk assessment, completeness of records, and consistency of documentation were applied, a final dataset of 687 participants was found to be suitable for analysis.To preserve data quality and analytical validity, participants with inconsistent assessments or incomplete clinical records were eliminated.

Clinical Variables and Risk Factor Identification

Every participant's baseline demographic, past medical history, current medications, and pertinent functional assessments were all thoroughly recorded during the data collection process. Five fundamental fall risk indicators were then determined to be the most pertinent based on the research and regular clinical practice, and they were methodically recorded for every person.

Figure:1| A novel tool using standardized scales and methods

Periodic vital signs and general clinical data were also gathered in addition to these targeted variables in order to improve data completeness and offer contextual support. Time-stamped clinical evaluations, prescription records, and mobility assessments were all included in each participant's dataset.

Development of the Proposed Assessment Tool

The fall risk assessment tool was developed using an two-stage process. To find frequently validated predictors, well-known fall risk tools including STRATIFY method, Morse Fall Scale, and the Hendrich II model were examined. Second, discussions were held with interdisciplinary clinical specialists, such as nurses, care takers and geriatricians, to guarantee contextual applicability in a variety of care settings.The gathered dataset (n = 687) was then subjected to univariate and multivariate logistic regression analysis for statistical validation. Factors with p-values less than 0.05 that showed statistical significance were kept. Five important predictors were ultimately chosen because of this procedure. Based on clinical severity and statistical impact, each factor was given a weighted score, which is presented in Figure 2. To ensure simplicity and interpretability, a total score of eight or more was considered suggestive of High Fall Risk.

Figure: 2| Fall Risk Assessment Scoring tool

These variables were chosen due to their strong predictive value, clinical relevance, and simplicity of evaluation in a variety of healthcare contexts. An initial Pilot Testing and Preliminary Validation phase [17] was carried out utilising full-scale predictive modelling on the real patient dataset. The purpose of this synthetic dataset is to replicate patient profiles that closely mimic the traits and risk factor distributions found in the real research population. Without jeopardising patient privacy or running the danger of biassed model training on insufficient real-world data, the research was able to test and improve both the evaluation tool and the machine learning workflow by using synthetic data.

Conceptual Architecture of the HF-RAP Model

The Hybrid Fall Risk Assessment and Prediction (HF-RAP) model was designed as a four-layer architecture to balance clinical interpretability with computational rigor.

Layer 1: Clinical Data Acquisition

Standardised clinical inputs routinely available in geriatric care are captured, aligned with existing assessment scales to promote familiarity and ease of adoption.

Layer 2: Rule-Based Scoring and Feature Encoding

Each risk factor is encoded using the validated scoring framework. Let $xi \in \{0,1\}$ denote the presence or absence of the i-th factor, and wirepresent its Odds Ratio–based weight. The Cumulative Risk Score (CRS) is computed

asbelow where w_i= Weight assigned to the ith factorX_i = Binary presence/absence of the ith factor.

$$\text{CRS}= \sum_{i-1}^{5} \omega_i \times X_i \tag{1}$$

This layer make sure transparency, evidence-based reasoning, and reduced cognitive burden for clinicians.

Layer 3: Machine Learning Prediction

The CRS together with the encoded input features is then passed through seven supervised machine learning models. In this stage, ensemble-based methods show the best overall performance, largely because they can capture non-linear relationships, cope with multicollinearity between predictors, and reduce the risk of overfitting. The output from this layer is a probabilistic fall risk estimate, expressed as $P(\text{Fall}) \in [0,1]$, which represents the predicted likelihood that an individual will experience a fall.

Layer 4: Threshold-Based Risk Stratification

Probabilistic outputs are converted into actionable risk categories using ROC-optimised thresholds:

If $CRS \geq 8 \Rightarrow$ High Fall Risk

Else $\Rightarrow$ Low / Moderate Risk

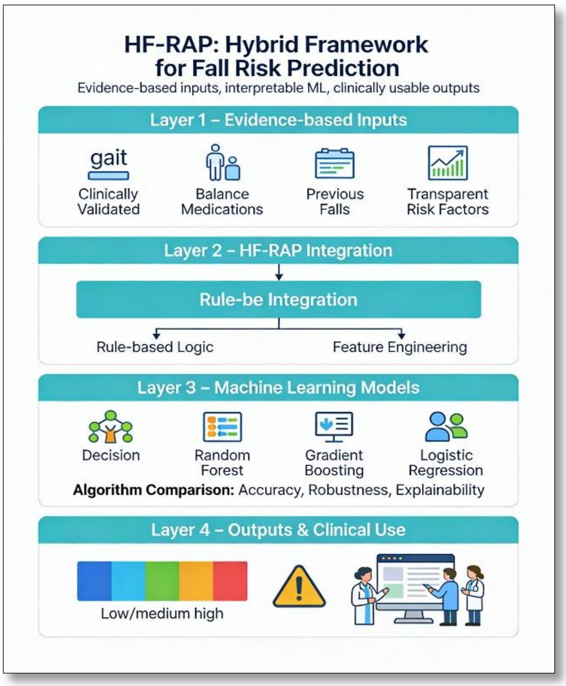


Figure: 3|A 4-Layered Conceptual Architecture of the HF-RAP Model

Formal HF-RAP Algorithm

Algorithm: Hybrid Fall Risk Assessment and Prediction (HF-RAP)

Input: Clinical dataset $D = \{x1,2,x3,x4,x5\}$

Output: Fall Risk Category $\in$ {Low, Moderate, High}

1. Collect standardized clinical inputs
2. Encode risk factors using validated scoring
3. Compute cumulative risk score (CRS)
4. Input features into trained ML classifier
5. Generate fall probability $P(Fall)$
6. Apply ROC-derived threshold $T = 8$
7. Assign fall risk category
8. Output risk category and probability score

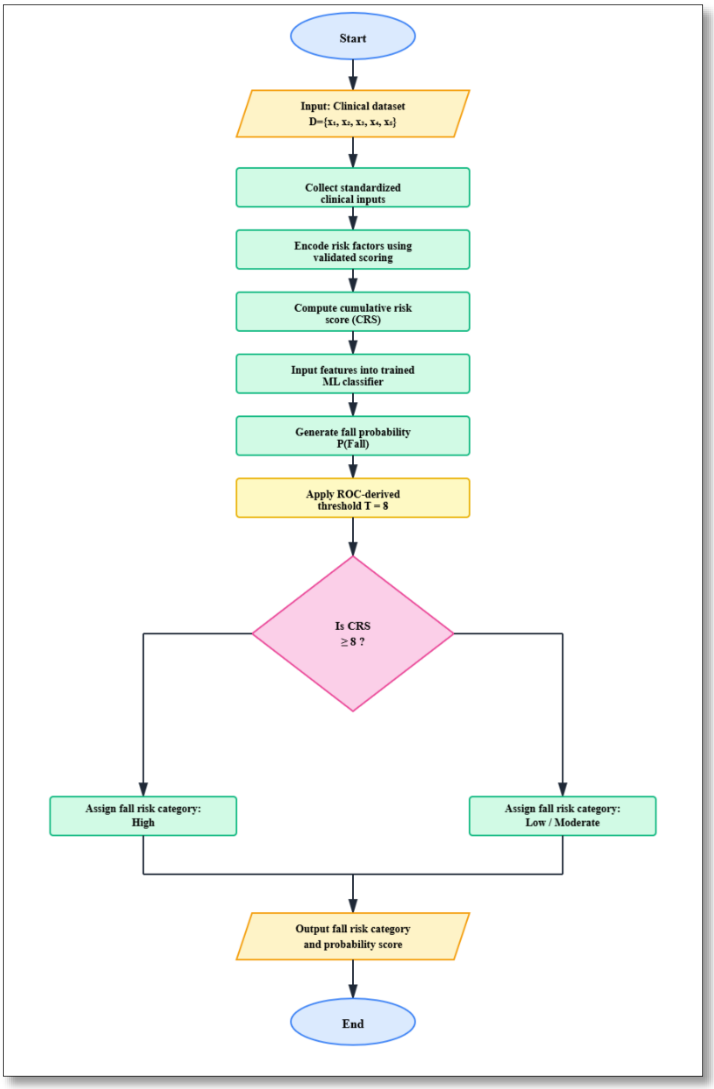
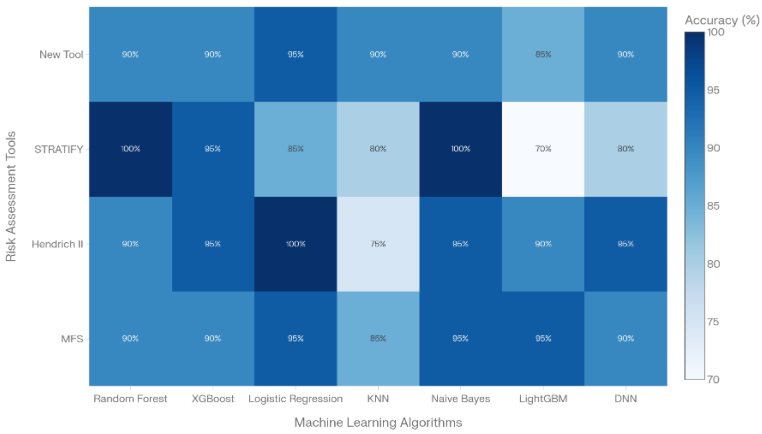


Figure: 4| Hybrid Fall Risk Assessment and Prediction (HF-RAP) Algorithm

Pilot testing using synthetic data

Pilot testing using synthetic data was conducted prior to full-scale modelling to validate workflows and debug algorithms without patient data exposure. Datasets mirrored real demographic and fall prevalence distributions, enabling comparison of the ML algorithms and across the New Tool, STRATIFY, Hendrich II, and Morse Fall Scale.

Table:1| Comparative Accuracy of ML Algorithms on Synthetic Data



High synthetic accuracies (e.g., XGBoost 90–95%, Random Forest 90–100%) indicated unrealistic separability due to absent clinical noise, confirming synthetic data's utility for pipeline testing only.

Risk Stratification and Threshold Optimization

A weighted Cumulative Risk Score (CRS) was derived from multivariate logistic regression odds ratios for the five factors (history of falls, ambulatory aids, transfer ability, PIMs, psychological factors). ROC analysis across CRS 2–15 identified optimal threshold at CRS ≥8, balancing sensitivity/specificity while prioritizing missed faller minimization:

Low Risk: CRS < Threshold Level 1

Moderate Risk: CRS between Thresholds 1–2

High Risk: CRS ≥8 (Threshold Level 2)

Metrics converged at T=8 (peak Accuracy, Precision, Recall, F1), with declines in Recall/F1 beyond (false negatives ↑) and Precision compromised below (false positives ↑).

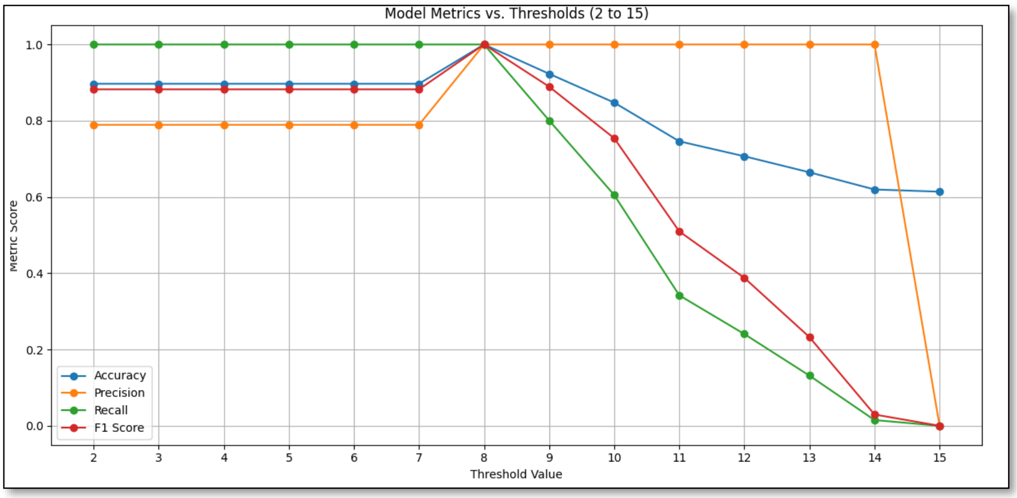


Figure:5| Model Performance Metrics Across Threshold Values

Data Preprocessing and Feature Selection

A comprehensive preprocessing approach was first used to assure that the dataset was consistent and suitable for modelling. After trying to identify missing values, suitable imputation techniques were employed when information was inaccessible. In order for the ML algorithms to handle qualitative data such as fall history and the use of ambulatory aids they were first converted into numerical codes using label encoding. When necessary, the feature values were scaled or normalised to place them on a same scale. For models that are prone to changes in magnitude, this is crucial. Because there were fewer fallers than non-fallers, the imbalance in class posed another challenge. The Synthetic Minority Over-Sampling Technique was used to lower the bias in the models' data-driven processing and to rebalance the target age groups.

Table: 2| Machine Learning Algorithms used for testing

Algorithm	**Description**	**Core Formula**
Logistic Regression (LR)	Foundational statistical model for binary classification; applies sigmoid function to linear feature combination for fall probability (0-1). Highly interpretable with low computational cost.	$\boldsymbol{P\left(y=\frac{1}{X}\right) = \frac{1}{1+e^{-(\beta_0+\beta_1X_1+}\beta_2X_2+\ldots\ldots\ldots\ldots+\beta_nX_n)}}$

Decision Tree (DT)	Rule-based tree structure using Gini/Information Gain to recursively split on most predictive features until pure leaf nodes. No scaling needed.	$\boldsymbol{InformationGain = H(S) - \sum_{i=1}^{k} \frac{\lvert Si \rvert}{\lvert S \rvert} H(Si)}$
Random Forest (RF)	Ensemble of decision trees trained on random data subsets; majority vote determines final class. Reduces overfitting via bagging.	$\boldsymbol{RF = \sum_{k-1}^{K} Pk(1 - Pk) = 1 - \sum_{k-1}^{K} Pk^2}$
XGBoost	Sequential tree boosting with L1/L2 regularization; each tree corrects prior errors. Handles missing data efficiently.	$\boldsymbol{XGBoost = \sum_{i=1}^{n} l(y_i, y_{i^2}) + \sum_{i=1}^{t} \Omega(f_i)}$
K-Nearest Neighbors (KNN)	Non-parametric; classifies based on majority vote of k nearest training instances using Euclidean distance.	$\boldsymbol{d(x,y) = \sqrt{\sum_{i=1}^{n} (x_i - y_i)^2}}$
Naïve Bayes (NB)	Probabilistic classifier assuming feature independence; uses Bayes' theorem for posterior class probability.	$\boldsymbol{P(C \mid X) = \frac{P(X \mid C) \times P(C)}{P(X)}}$
LightGBM	Leaf-wise gradient boosting with GOSS/EFB for speed; excels on large/sparse datasets with GPU support.	$F(x)=F_0(x)+\sum_{i=1}^{T} f_0(x)$
Deep Neural Network (DNN)	Multi-layer networks learning hierarchical feature representations from raw geriatric data.	$\boldsymbol{z = \sum (w.x) + b}$ $\mathbf{a = g(z)}$

This study used several metrics for assessment to accurately and independently evaluate the models' performance. Both the models' overall accuracy rate and how well they handled errors like false positives and false negatives have been evaluated by these measures. The metrics used were Accuracy, Sensitivity (Recall), Specificity, Precision, F1-Score, and the Area Under the ROC Curve (ROC-AUC).

To reduce bias caused by splitting of the data, a five-fold cross-validation approach was used. The dataset was divided into five equal parts for each round, four of which were used for model training and the remaining half for testing. During the five repetitions of this process, each component of the data was utilised as a test set once. The outcome results were generated by averaging the five successive runs.

In addition, thirty percent of the original dataset was reserved as a hold-out collection. After the algorithms were trained, this unique set was utilised to evaluate the resilience and modify parameter sets, which was crucial for advanced approaches like ensemble tree models and deep neural networks. Together, these evaluation techniques helped ensure that the fall-risk prediction models were both highly accurate and strong enough to be considered for real-world clinical use.

4. RESULTS AND DISCUSSION

The HF-RAP framework was evaluated using seven distinct supervised ML algorithms using the new assessment tool. The performance of each model was subjected to a five-fold stratified cross-validation, in which the data were split into five sections and each section was used once for testing. The findings were finally verified using another 30% hold-out test set to assess how well the models performed on data they had never seen previously.

Comparative Performance Metrics

All algorithms performed well when the new assessment tool was utilised as input. Even simpler models may still produce accurate predictions, as evidenced by the classification accuracy ranging from 86% for Logistic Regression to 90% for Naïve Bayes and the DNN with just these five parameters. With ROC-AUC values ranging from 0.96 to 0.98, the models were likewise excellent at distinguishing between fallers and non-fallers; XGBoost, Logistic Regression, LightGBM, and DNN all achieved an AUC of 0.98. When taken as a whole, these five factorsfall history, use of ambulatory aids, transfer ability, potentially inappropriate medications, and psychological factorsform a highly informative and clinically significant set of inputs for identifying older adults who are more likely to fall.

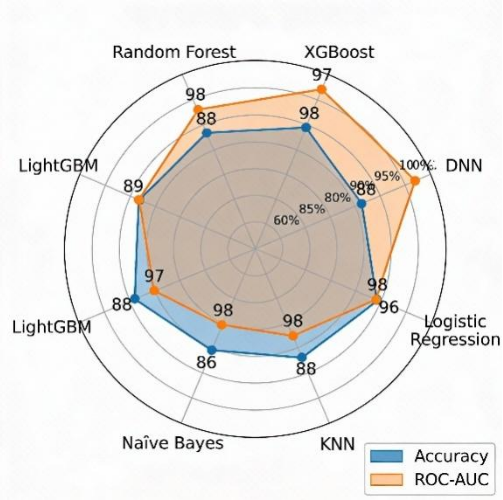


Figure: 6|Enhanced Efficiency of MLAlgorithms for Predicting Fall Risk in Senior Citizens

Further, the precision was frequently excellent, with values spanning 0.92 to 0.98, meaning that barely any individuals had been incorrectly identified as high risk. This is a significant consideration in real-world healthcare settings, where unnecessary actions could add tension and strain. For both DNN and Naïve Bayes, the F1-Score, which quantifies how well Precision and Recall are integrated, was greater than 0.87 and reached 0.91. The results obtained simpler approaches such as Naïve Bayes and Logistic Regression can perform almost as well as more complex collective models, and that the five selected criteria are highly effective in identifying between those who fall and those who do not fall.

Table: 3| Comparative Performance Metrics of Machine Learning Algorithms for Fall Risk Prediction

Algorithm	Dataset Size	Accuracy (%)	Precision (%)	Recall (Sensitivity) (%)	F1-Score (%)
Random Forest	100	90	88	100	93
XGBoost	100	90	88	100	93
Logistic Regression	100	95	93	100	97
Deep Neural Network (DNN)	100	90	88	100	93
LightGBM	100	85	87	93	90
Naïve Bayes	100	90	93	93	93
K-Nearest Neighbors (KNN)	100	90	88	100	93

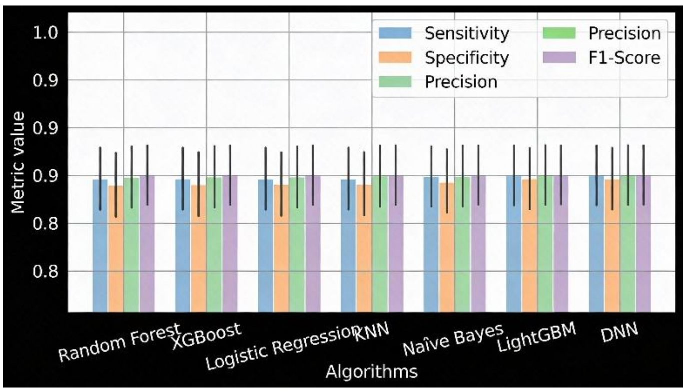


Figure: 7| Comparative Performance Metrics of Machine Learning Algorithms for Fall Risk Prediction

5. CONCLUSION

The HF-RAP framework exhibits outstanding performance in all seven algorithms, with AUC values greater than 0.96 and F1-scores of at least 0.87. This shows that the new evaluation tool outperformed several earlier models, such as the long-term health care model by Liu et al. (AUC 0.846) and the hospital-based XGBoost model by Chen et al. (AUC around 0.75), in predicting falls in the elderly.

The hybrid tool's success is largely due to its five-factor design. It focusses on looking at fall incidents, mobility or transfer skills, the use of ambulatory aids, being exposed to potentially dangerous medicines, and psychological factors. They are all combined into an individual cumulative risk score (CRS) after being weighted using odds ratios. This specific cut-off of CRS = 8 seems to capture key relationships between factors, such as how using a walking aid could make limited mobility even more dangerous, when compared to more extensive standard instruments like the Morse Fall Scale or STRATIFY.

One of the most positive outcomes is that basic algorithms like Naïve Bayes and Logistic Regression achieved nearly the same AUC (around 0.98) as more complex ensemble methods like XGBoost and LightGBM. This aids in attaining the goal of keeping the model's prediction ability while making it accessible to medical professionals. Well-established geriatric study suggests that fall history and transfer ability are likely the most significant contributors to the risk score. It is possible to show how each component influences the predicted outcome for a particular patient using methods such as SHAP.

The high precision (around 0.95) is especially useful from a clinical perspective since it indicates that the majority of patients identified as high risk actually require treatment, which minimises needless workload and alarm fatigue. This enables clinicians to concentrate on the group of older adults who are most likely to benefit from targeted interventions, such as customised exercise regimens, balance training, home or ward modifications, and careful medication review. Many of these individuals would otherwise be among the 20–30% of people who suffer major fall-related consequences, such as fractures or head injuries.

There are some significant limitations to this study. As noted by Smith et al. in their analysis of gaps in external validation, all data were gathered from a single hospital site in Bengaluru, hence the results must be verified in other locations. SMOTE was used to address class imbalance during the model's development, but in actual use, the system should also take changes in risk over time into account, perhaps by adding serial or recurring evaluations.

The HF-RAP framework has the advantage of not depending on sensors when compared to gait-based methods like the model of Lee et al., which achieved an AUC of 0.91 utilising three gait features. This makes it more feasible and scalable in Indian geriatric settings with limited resources. In the future, an electronic health record-embedded dashboard will be linked to the final "Layer 4" outputs, and the system will be tested prospectively to see if its use is linked to a quantifiable decrease in fall rates among older persons.

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