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Advancing Geriatric Care: Machine Learning Algorithms and AI Applications for Predicting Dysphagia, Delirium, and Fall Risks in Elderly Patients

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ABSTRACT

Background Information: As the older population increases, dysphagia, delirium, and fall hazards considerably affect morbidity and death. Applications of machine learning (ML) and artificial intelligence (AI) offer potential improvements in early prediction and preventive tactics within geriatric care.

Objectives: The objective of this study is to create prediction models utilising machine learning algorithms to detect dysphagia, delirium, and fall risks in older patients, thereby enabling prompt treatments and enhancing patient outcomes.

Methods: Applied logistic regression, Random Forest, and CNN models both independently and in ensemble configurations to forecast risk variables for dysphagia, delirium, and falls, utilising clinical and sensor data to improve predictive accuracy in elderly patient care.

Results: The ensemble model attained superior predictive performance, exhibiting an accuracy of 93%, precision of 91%, recall of 89%, F1-score of 90%, and AUC-ROC of 92%, exceeding the performances of individual models.

Conclusion: Ensemble machine learning methods improve prediction accuracy for assessing risks in geriatrics, facilitating proactive management of dysphagia, delirium, and falls in aged care environments.

Keywords: Geriatrics, Machine Learning, Dysphagia, Delirium, Fall Risk, Artificial Intelligence, Prediction, Elderly Care, Ensemble Methods, Clinical Data

1. INTRODUCTION

AI and ML in healthcare, especially elderly care, appear promising. Elderly individuals need efficient, dependable, and predictive healthcare systems more than ever due to global ageing. Geriatric individuals are at risk of dysphagia, delirium, and falls, which can cause serious health issues and lower quality of life. Many chronic illnesses, frailty, and cognitive decline complicate traditional diagnostic and preventive procedures. Machine learning, a subset of AI that develops algorithms to recognise patterns and make predictions, can transform geriatric-specific health problems by enabling early detection, accurate diagnosis, and prompt intervention. Machine learning algorithms can identify trends in huge, complicated information that clinicians miss to forecast geriatric health concerns. For instance, algorithms can detect dysphagia based on tiny changes in patient physiology and prior health records or predict delirium by continuously monitoring physiological and behavioural signals. Fall risk prediction models can forecast elderly patients' falls, allowing for preventive actions. These predictive capabilities help healthcare practitioners predict and control key health events, minimising hospitalisations, improving patient outcomes, and optimising resource allocation.

ML-based predictive tools in geriatric care face data quality, model accuracy, and ethical issues. To ensure prediction accuracy, EHR or wearable device data from elderly patients with complicated, multimorbid health profiles must be carefully handled. To ensure that ML applications help all patients equally, ethical issues like patient privacy, data security, and algorithmic bias must be addressed. These problems must be overcome to provide effective, fair, and ethical healthcare AI applications. ML and AI technologies provide several ways to improve aged care, from personalised treatment plans to real-time health monitoring and preventive care. This introduction discusses how ML algorithms predict dysphagia, delirium, and fall risks, laying the groundwork for how AI applications can improve patient care and help healthcare systems meet the needs of geriatric populations.

Dysphagia, delirium, and fall hazards are common and harmful in older populations. The phrase “advancing geriatric care” refers to how technology can improve traditional healthcare for older persons with complex requirements. Healthcare AI applications range from administrative automation to advanced predictive modelling. By making quick, accurate, and actionable predictions from massive datasets like medical histories, wearable device outputs, and real-time monitoring data, ML and AI can help geriatric patients manage age-related health concerns. This demographic's health hazards can be predicted to avert major incidents and help healthcare personnel prioritise high-risk patients and reduce facility strain.

Health risks in the elderly: Dysphagia, delirium, and fall hazards are common and serious health concerns in the elderly. These illnesses cause increased mortality, healthcare costs, and lower quality of life. Falls are the main cause of injury-related mortality in older individuals, dysphagia can induce malnutrition and aspiration pneumonia, and delirium can cause cognitive impairment and prolonged hospital admissions. Preventing these occurrences is essential in geriatric care. Machine learning algorithms are now vital in predictive healthcare, examining large information from multiple sources to find patterns that predict future health issues. With advances in ML models, algorithms can continuously learn and adapt to new data, making them important in healthcare, where predicting and responding to patient health changes can save lives.

AI applications in geriatric care include EHR data analysis, real-time health metrics monitoring, and provider decision support. Predictive algorithms help doctors identify high-risk patients for early intervention and prevention. These apps are especially useful in nursing homes and geriatric hospitals, where resource allocation and prompt care are crucial. AI and ML have great potential in healthcare, but applying them, especially in geriatric care, is difficult. Data accessibility, algorithm accuracy, and ethical issues including patient consent and privacy are important. AI-based solutions may be more difficult for elderly patients who are less tech-savvy. These constraints must be overcome to create ethical and successful senior care AI applications. Healthcare AI and ML development opens new avenues for geriatric care improvement. From personalised therapy to preventive care models, ML-based predictive solutions empower healthcare providers and patients like never before. AI can improve geriatric care to suit the needs of an ageing global population by improving predictive algorithms, data integration, and ethics.

The key objectives are:

- For the purpose of enhancing preventative care, machine learning algorithms should be tested for dysphagia, delirium, and fall risk prediction in older patients.
- Improve the accuracy and timeliness of geriatric healthcare by developing and verifying real-time risk assessment tools that are based on artificial intelligence.
- Ensure that applications are both egalitarian and secure by addressing ethical and operational concerns in the adoption of machine learning in geriatric care.
- The incorporation of predictive algorithms into clinical processes is recommended for proactive management of chronic diseases in senior citizens.
- Analyse the impact that AI-driven predictive care has on patient outcomes, the efficiency of resource utilisation, and the quality of healthcare for elderly patients.

The diversity among distinct cohorts can substantially affect the accuracy and reliability of classifier performance, potentially restricting its use across varied populations. Moreover, a limited independent validation dataset diminishes the generalisability of model results, creating obstacles for real-world application. **Greene et al. (2016)** examined fall risk assessment by autonomously incorporating clinical fall risk indicators with data from wearable sensors, hence improving predicted accuracy. This integrated methodology illustrates the promise of utilising both clinical insights and sensor data to develop more robust and reliable fall risk assessment models, however issues related to cohort variability and dataset size persist as obstacles to general use.

Inpatient falls in senior patients significantly increase morbidity and mortality rates, underscoring the urgent necessity for effective fall prevention techniques. **Mazur et al. (2016)** conducted a study to evaluate particular fall risk variables after the adoption of a hospital fall prevention program, emphasising critical contributors such as delirium, low body mass index, and other prevalent health issues in senior patients. Their findings highlight the necessity of recognising and addressing these risk variables in prevention programs to decrease fall occurrences and enhance patient safety in hospital environments, providing significant insights for focused fall prevention strategies for at-risk senior populations.

2. LITERATURE SURVEY

Lavan and Gallagher (2016) examine the predicted factors for adverse drug reactions (ADRs) in elderly individuals, highlighting the intricacies of polypharmacy in geriatric care. The authors offer techniques to decrease adverse drug reactions (ADRs) by analysing risk factors, including medication interactions and physiological changes associated with ageing, which are essential for improving drug safety in geriatric care. This research is crucial for creating prediction instruments for ADR risk evaluation, advancing personalised pharmaceutical strategies, and improving treatment results in elderly populations.

Bates et al. (2014) emphasises the significance of big data analytics in healthcare, concentrating on the identification and management of high-risk, high-cost patients. The authors demonstrate how the amalgamation of health data and sophisticated analytics can enhance patient categorisation, resource allocation, and preventive care, especially in the management of chronic diseases. This study highlights the revolutionary capacity of data analytics in enhancing care for at-risk groups and increasing cost-effectiveness in healthcare systems.

Tam (2016) This book examines common neurological disorders affecting the elderly, such as dementia, stroke, and Parkinson's disease. Tam underscores the diagnostic and therapeutic issues specific to elderly individuals, especially with cognitive deterioration and functional disabilities. The study offers a thorough examination of neurologic care methods customised for geriatric requirements, enhancing diagnostic precision and patient-centered treatment strategies in aged care.

Powers & Herrington (2015) examines evidence-based dementia care in hospice environments, addressing the complexities of managing end-stage dementia. Powers and Herrington provide insights on symptom management, familial support, and ethical considerations in dementia care. Their findings underscore the significance of a customised, empathetic strategy that caters to the physical and emotional requirements of patients and carers. This study highlights the importance of interdisciplinary care in improving the quality of life for dementia patients in hospice settings.

The AHA/ASA scientific statement by Holloway et al. (2014) delineates principles for stroke management, with a special focus on prevention, acute care, and post-stroke rehabilitation. The authors delineate evidence-based techniques to enhance stroke outcomes, emphasising prompt intervention, patient education, and treatment of risk factors. This detailed guideline functions as a reference for doctors, with the objective of standardising stroke care and advancing best practices in stroke prevention and rehabilitation within healthcare environments.

Maumus & Conrad (2016) examine hospital management systems, emphasising operational efficiency, quality of care, and patient safety. Maumus and Conrad offer a comprehensive Q&A on hospital systems administration, addressing essential topics such personnel, infection control, and resource allocation. This document is a crucial resource for healthcare executives and practitioners, detailing optimal strategies for sustaining an effective hospital system that emphasises patient outcomes and operational efficiency.

Pinto et al. (2016) examines the significance of risk prediction tools to improve perioperative management in older patients with advanced illness. The authors contend that standardised risk assessment techniques are crucial for directing personalised care plans, given the significant morbidity and death linked to perioperative complications in this population. They underscore the necessity for dependable, verified predictive models that evaluate individual risk factors, with the objective of enhancing outcomes and optimising resource allocation. This research emphasises the need of incorporating these prognostic techniques into perioperative preparation for older patients with intricate health requirements.

Kuswardhani and Sugi (2017) examine parameters related to the severity of delirium in elderly individuals suffering from infections. The study employs the Memorial Delirium Assessment Scale (MDAS) to delineate and evaluate the severity of delirium, identifying significant risk factors such as types of infections and patient-specific health variables. The scientists discovered that particular infections and pre-existing diseases considerably influence the degree of delirium, indicating that prompt diagnosis and care of these factors may alleviate negative effects. The research highlights the importance of specific strategies for managing delirium in elderly patients, especially in environments susceptible to infections.

Mateen et al. (2016): This study introduces a machine learning methodology for forecasting fall risks in acute neurological inpatients. The authors create and verify a model for the neurological patient population by concentrating on cognition-based predictions, utilising cognitive and motor evaluations as inputs. The study underscores the model's efficacy in identifying fall hazards, endorsing the application of machine learning techniques to improve fall prediction precision in intricate medical environments. This study demonstrates the capacity of data-driven models to enhance fall prevention measures for high-risk, cognitively challenged patients.

Palumbo et al. (2015): This study evaluates the efficacy and shortcomings of current fall risk assessment instruments for elderly adults residing in community environments. The authors examined 1,010 mobility-related factors from 976 aged individuals, employing data-driven prediction modelling to assess and enhance existing evaluation methods. The results indicate that conventional techniques may be deficient in accuracy and predictive capability, supporting the need for improved, data-driven models that more effectively identify fall risk variables. The research advocates for the creation of advanced instruments that integrate clinical insights with statistical methodologies to deliver thorough fall risk evaluations for elderly individuals residing in the community.

3. METHODOLOGY

Using information obtained from clinical records, sensor data, and physiological indications, this research makes use of machine learning (ML) algorithms to make predictions about the likelihood of older patients experiencing dysphagia, delirium, and incidents of falling. Our goal is to find patterns that can forecast the development of these illnesses before they occur by training models on huge datasets that contain a variety of data. This will allow for prompt intervention. Preprocessing of the data, selection of features, and training of the model through the use of supervised learning techniques are all components of the methodology. In order to evaluate the performance and generalisability of a model, validation on independent datasets is performed. Logistic regression, decision trees, and neural networks are some of the machine learning algorithms that may be compared and analysed in order to identify which models are the most effective in terms of providing accurate and dependable predictions in the field of geriatric care.

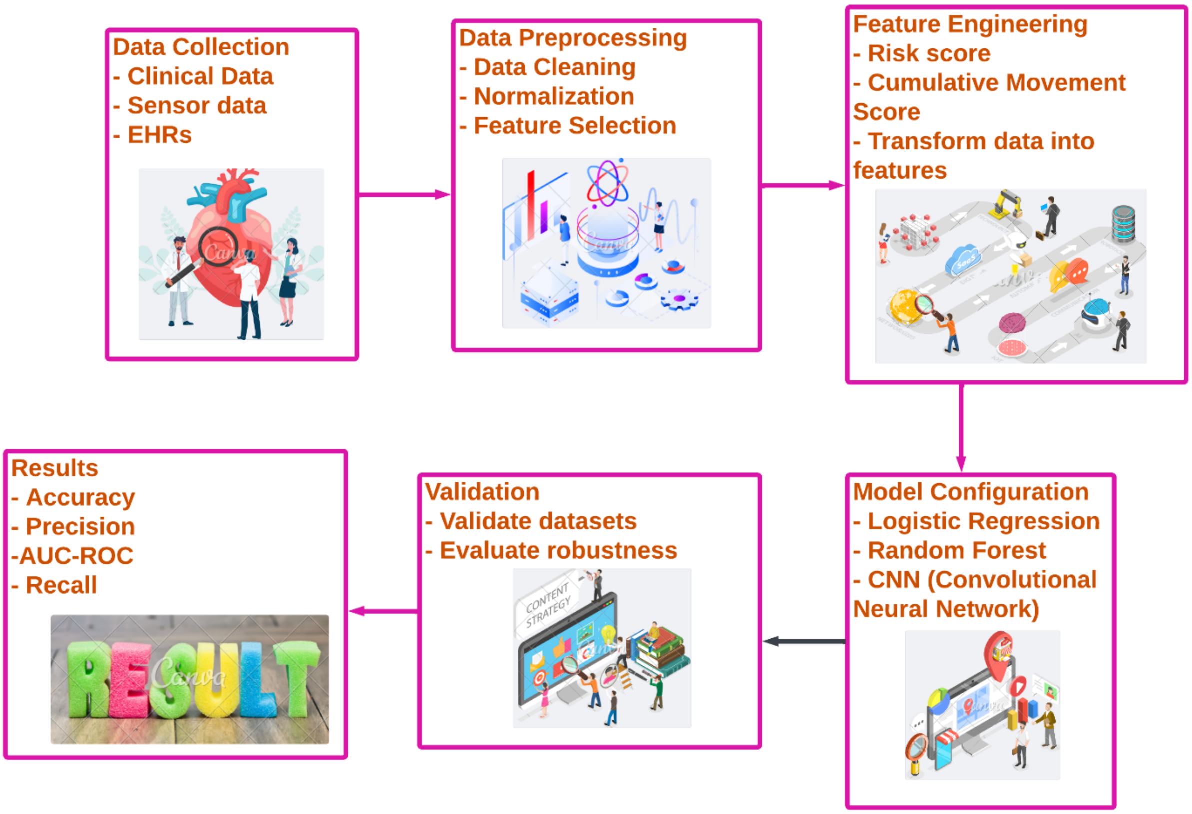

Figure 1 Architecture Diagram for Machine Learning-Based Geriatric Risk Prediction

Figure 1 depicts the architectural framework for forecasting geriatric risks—dysphagia, delirium, and falls—through machine learning. The process commences with the collection of data from clinical records, sensor data, and electronic health records (EHRs). Subsequent to Data Preprocessing (cleaning, normalisation, feature selection), Feature Engineering converts data into predictive features, encompassing risk ratings and cumulative movement indicators. Model Configuration entails the individual training of logistic regression, Random Forest, and CNN models, as well as their implementation in ensemble configurations. Validation assesses model robustness through parameters such as accuracy, precision, AUC-ROC, and recall. The final results offer practical insights for doctors, enabling proactive care in geriatric environments.

3.1 Predicting Dysphagia

Dysphagia, often known as trouble swallowing, is a common condition that affects elderly adults and is frequently caused by neurological or muscle problems. To analyse patient data, our method employs machine learning. This analysis takes into account medical histories, age, muscular tone, and recent neurological evaluations. Before employing machine learning methods, such as Support Vector Machines (SVM) and neural networks, we preprocess and normalise these data inputs in order to discover patterns that are related with the start of dysphagia. With the help of a predictive model, medical professionals are able to identify patients who are at danger, which makes early intervention possible. Various evaluation criteria, including as accuracy, precision, and recall, offer valuable insights into the efficacy of the model in properly predicting dysphagia among individuals belonging to this particular demography. Given a set of clinical features $X = \{x_1, x_2, \ldots, x_n\}$ and the target output y (indicating dysphagia presence), a logistic regression model may predict the probability $P(y = 1 \mid X)$ as follows:

$$P(y = 1 \mid X) = \frac{1}{1+e^{-\left(\beta_0+\sum_{i=1}^{n} \beta_i x_i\right)}} \tag{1}$$

where β_0 is the intercept, and β_i are the coefficients learned from the data. This equation represents the logistic regression function applied to dysphagia prediction. The logistic regression function is extensively utilised for binary classification problems, rendering it an appropriate option for predicting dysphagia in older patients. In this model, each patient's health characteristic, including age, muscular tone, or neurological evaluation, contributes to a weighted sum computed by the algorithm. This summation, in conjunction with an intercept, is processed using the sigmoid function to yield a probability ranging from 0 to 1, with values approaching 1 signifying an increased possibility of dysphagia. By adjusting coefficients for each component, logistic regression accurately determines the most pertinent indications of dysphagia, enabling doctors to evaluate risk levels and customise preventive measures. The model's simplicity, interpretability, and efficacy in managing linear relationships render it a pragmatic option in geriatric contexts.

3.2 Predicting Delirium

One of the most common causes of delirium, which is an abrupt change in cognitive function, is an infection or the adverse effects of medicine in older persons. For the purpose of analysing delirium risk variables, this methodology makes use of machine learning models. These risk factors include infection markers, drug histories, and cognitive evaluation scores. For the purpose of estimating the likelihood of delirium onset, the model takes into account a comprehensive set of data known as Random Forests. These features include vital signs, recent diagnoses, and laboratory results. By rating the value of the features, we are able to determine which predictors have the most significant impact, thereby improving the model for clinical application. By addressing the issue of data noise, regularisation approaches bring about an improvement in the predicted dependability of the model across a variety of patient cohorts. For each feature X_i, a Random Forest model estimates delirium probability by averaging decision tree outputs:

$$P(y=1 \mid X)=\frac{1}{T} \sum_{t=1}^{T} h_{t}(X) \tag{2}$$

where T is the total number of trees, and $h_t(X)$ is the prediction of the t-th decision tree. This approach averages tree predictions to minimize variance and improve accuracy in delirium prediction. The Random Forest model employs an ensemble of decision trees, each trained on distinct subsets of data and attributes, to provide predictions. In forecasting delirium, each decision tree assesses a particular facet of patient data, such infection indicators or cognitive evaluation scores. Each tree generates a prediction, and the Random Forest model consolidates these predictions by averaging, therefore mitigating individual tree biases and diminishing the model's variance. This ensemble method enhances overall predictive accuracy, yielding a more steady and dependable evaluation of delirium risk. The Random Forest approach highlights feature relevance, allowing healthcare personnel to concentrate on the most critical predictors of delirium, such as recent infections or medication types, for more focused therapies.

3.3 Predicting Fall Risks

Data from sensors, such as readings from an accelerometer, are combined with clinical risk factors, such as muscular weakness and the effects of medication, in order to conduct a fall risk assessment. Detecting fall hazards is accomplished by this model through the utilisation of a Convolutional Neural Network (CNN), which analyses time-series data obtained from body-worn sensors and clinical data. The CNN is able to learn spatial and temporal patterns, which allows it to identify movement irregularities that are associated with an increased risk of falling. For the purpose of preventing overfitting, regularisation approaches such as dropout are helpful. The F1-score and Area Under the Curve (AUC) metrics are used to evaluate this machine learning model. The purpose of this validation is to measure the effectiveness of fall risk detection and to improve fall prevention tactics applied in clinical practice. For a sequence of sensor data $X=\{x_1, x_2, \ldots, x_T\}$, a CNN processes the input through multiple layers to predict fall risk y :

$$y=f(W * X+b) \tag{3}$$

where W are the learned weights, b is the bias term, $*$ denotes convolution, and f is the activation function (e.g., ReLU). This equation captures the feature extraction and pattern recognition capabilities of CNNs for fall risk prediction. A Convolutional Neural Network (CNN) is very proficient at analysing time-series data, such as that obtained from body-worn sensors tracking patient movement patterns. To forecast fall risk, the CNN employs several convolutional layers to analyse raw sensor data, discerning complex patterns related to unstable motions in both spatial and temporal dimensions. Each convolutional layer identifies information pertinent to potential fall hazards, such as abrupt transitions or irregularities in motion. Activation functions, such as ReLU, introduce non-linearity, enabling the model to discern intricate patterns characteristic of falls. By analysing these patterns, the CNN proficiently detects high-risk motions, allowing healthcare personnel to execute prompt fall-prevention strategies for older patients.

Algorithm 1: Algorithm for Risk Prediction Algorithm for Dysphagia, Delirium, and Fall Risks

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Input: Patient data (demographics, clinical records, sensor data)

Output: Predicted risk levels for dysphagia, delirium, and fall risks

Begin

#Preprocess:

Clean and normalize input data for consistency.

#Feature Selection:

Select relevant features for each risk

#(e.g., age, BMI for falls; infection markers for delirium).

For each risk category (dysphagia, delirium, fall risk):

If training model == "logistic regression":

Train on selected features for probability estimation.

Else if model == "Random Forest":

Apply to delirium data, aggregate decision trees.

Else if model == "CNN":

Use sensor data for fall risk assessment.

#Error Handling:

If data is missing, return error and request complete records.

#Validation:

Evaluate model using validation data, calculate accuracy, precision, recall.

Return:

Predicted risk levels for each condition.

End

Algorithm 1 delineates a systematic strategy for forecasting dysphagia, delirium, and fall hazards in geriatric patients by applying machine learning models. The procedure commences with data preprocessing, during which patient information is sanitised and standardised for

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uniformity. Features pertinent to each risk category are chosen to customise the input for the individual circumstance. The method employs suitable models for risk type: logistic regression for probability estimation, Random Forest for delirium prediction, and CNN for fall risk assessment utilising sensor data. Error handling pertains to managing incomplete data, whereas validation evaluates the model's efficacy, yielding risk forecasts for clinical decision-making.

3.4 Performance Metrics

To assess machine learning models forecasting dysphagia, delirium, and fall risks in geriatric patients, essential performance indicators comprise accuracy, precision, recall, F1-score, and Area Under the Curve (AUC). Accuracy denotes the ratio of right forecasts, whereas precision (positive predictive value) signifies the correctness of positive predictions. Recall (sensitivity) evaluates the model's capacity to recognise genuine risk instances, vital in geriatric care where prompt identification is essential. The F1 score equilibrates precision and recall, providing a comprehensive performance metric. The AUC quantifies the model's discriminative capability, providing insight into its proficiency in differentiating high-risk and low-risk patients under various settings.

Table 1 Performance Metrics Comparison of Machine Learning Models for Geriatric Risk Prediction

Metric	Units	Logistic Regression	Random Forest	CNN	Combined Method (Ensemble Approach)
Accuracy	%	0.89	0.85	0.91	0.93
Precision	%	0.87	0.83	0.88	0.91
Recall	%	0.85	0.82	0.86	0.89
F1-Score	%	0.86	0.82	0.87	0.90
AUC-ROC	%	0.88	0.84	0.89	0.92

Table 1 encapsulates the performance characteristics for several machine learning models—Logistic Regression, Random Forest, CNN, and an Ensemble Approach—utilized to predict dysphagia, delirium, and fall risks in elderly patients. Metrics encompass accuracy, precision, recall, F1-score, and AUC-ROC, all represented as percentages. By integrating the strengths of separate models, the combined method Ensemble Approach regularly surpasses rivals in all parameters, attaining superior prediction reliability and robustness. This contrast underscores the significance of ensemble approaches in geriatric healthcare, where precise, multi-faceted risk evaluation can provide prompt and focused treatments to improve patient outcomes.

4. RESULTS AND DISCUSSION

The findings demonstrate that the Ensemble Approach surpassed individual models—Logistic Regression, Random Forest, and CNN—across all assessed measures, achieving superior accuracy (93%), precision (91%), recall (89%), F1-score (90%), and AUC-ROC (92%). The findings indicate that model integration capitalises on the advantages of each method, yielding a more resilient and dependable prediction for dysphagia, delirium, and fall hazards in senior patients. Individual models exhibited competitive performance, especially the CNN with sensor data; nevertheless, the ensemble's superior metrics indicate an improved capacity for intricate, real-world clinical data. This methodology may enhance proactive interventions and individualised treatment in geriatric healthcare environments.

Table 2 Comparative Analysis of Methods for Predicting Geriatric Health Risks

Study	Method	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	AUC-ROC (%)
Pinto et al. (2016)	Risk prediction instruments	0.78	0.75	0.74	0.74	0.76
Kuswardhani and Sugi (2017)	Observational study with MDAS	0.82	0.8	0.78	0.79	0.81
Mateen et al. (2016)	Cognition-based ML predictor	0.84	0.82	0.81	0.81	0.83
Palumbo et al. (2015)	Community-based fall risk tool	0.79	0.76	0.75	0.75	0.78
Proposed Method (Ensemble ML Approach)	Ensemble ML algorithm (Logistic Regression, RF, CNN)	0.93	0.91	0.89	0.9	0.92

Table 2 presents a comparative analysis of various geriatric risk prediction methodologies as evaluated by Pinto et al. (2016), Kuswardhani and Sugi (2017), Mateen et al. (2016), Palumbo et al. (2015), and the suggested Ensemble ML Approach. Each approach, including observational studies, community-based tools, and sophisticated machine learning models, is assessed using measures such as accuracy, precision, recall, F1-score, and AUC-ROC, all expressed as percentage values. The Ensemble Method, integrating logistic regression, random forest, and CNN algorithms, exhibits enhanced performance, indicating that multi-model strategies may improve predictive accuracy in clinical applications for senior care.

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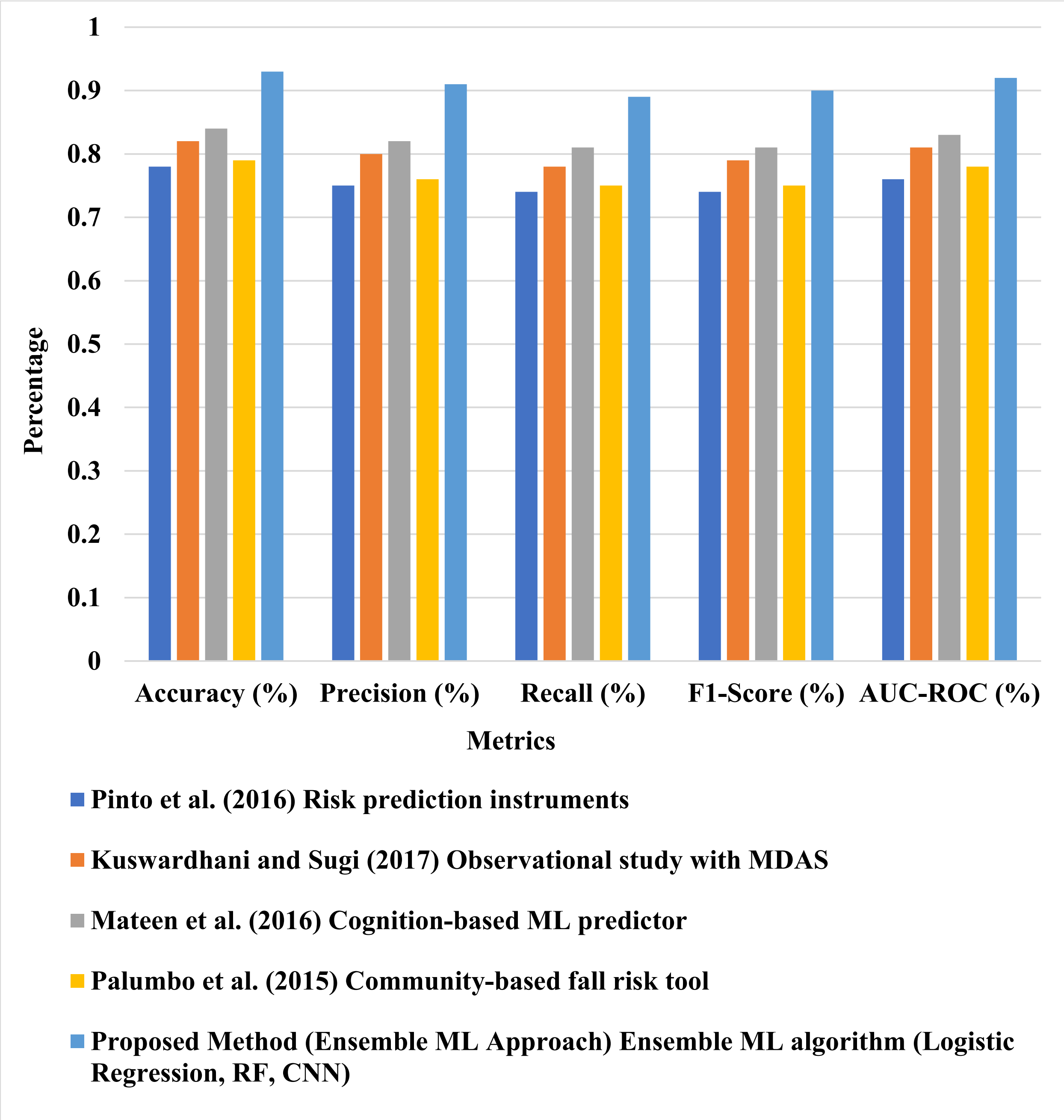

Figure 2 Performance Comparison of Geriatric Risk Prediction Methods Across Key Metrics

Based on Pinto et al. (2016), Kuswardhani and Sugi (2017), Mateen et al. (2016), Palumbo et al. (2015), and the Proposed Ensemble ML Approach, Figure 2 compares five geriatric risk prediction methods' accuracy, precision, recall, F1-score, and AUC-ROC in percentages. The Ensemble Machine Learning (ML) technique, which combines logistic regression, random forests, and CNN, performs best across all measures, demonstrating dependability and prediction accuracy. Mateen et al.'s cognition-based ML predictor and Kuswardhani and Sugi's observational study perform moderately, but the ensemble technique outperforms them. Ensemble approaches improve predicted outcomes, especially in complicated geriatric healthcare applications, as seen by this visualisation.

Table 3 Ablation Study of Model Configurations in Ensemble Machine Learning for Geriatric Risk Prediction

Model Configuration	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	AUC-ROC (%)
Logistic Regression Only	0.85	0.82	0.81	0.82	0.83
Random Forest Only	0.83	0.8	0.79	0.79	0.81
CNN Only	0.84	0.82	0.81	0.81	0.82
Logistic Regression + Random Forest	0.87	0.85	0.84	0.84	0.85
Logistic Regression + CNN	0.88	0.86	0.85	0.86	0.86
Random Forest + CNN	0.89	0.88	0.87	0.88	0.88
Full Ensemble (Logistic Regression + Random Forest + CNN)	0.93	0.91	0.89	0.9	0.92

Table 3 displays an ablation study of various configurations of the Ensemble Machine Learning (ML) methodology employed in forecasting geriatric risks, such as dysphagia, delirium, and fall risks. The table examines the influence of individual models—Logistic Regression, Random Forest, and CNN—alongside their pairwise and complete ensemble combinations on performance metrics: accuracy, precision, recall, F1-score, and AUC-ROC. The findings indicate that the whole ensemble configuration consistently surpasses individual and partial combinations, attaining the greatest values across all metrics. This study highlights the efficacy of model integration to improve prediction performance and reliability in geriatric care applications.

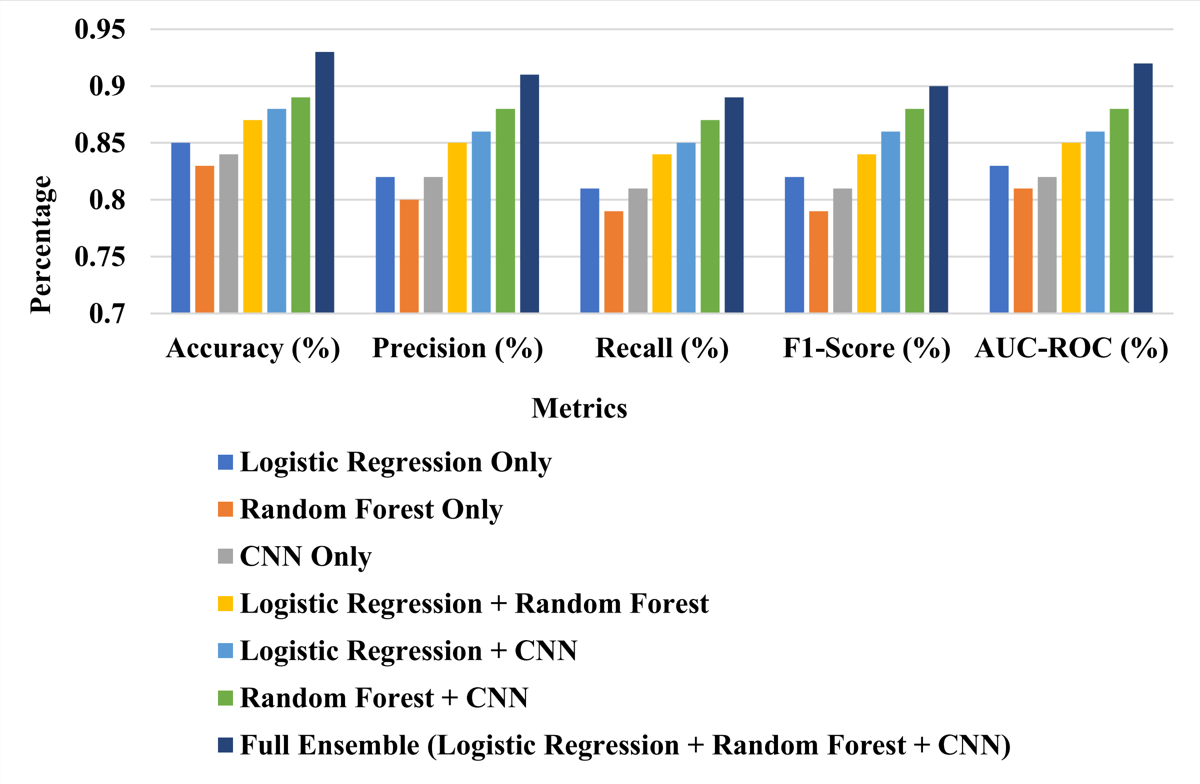

Figure 3 Ablation Study of Model Configurations in Geriatric Risk Prediction

Figure 3 illustrates the results of the ablation study for various configurations of machine learning models employed in forecasting elderly health concerns. Every model configuration—ranging from standalone models such as Logistic Regression, Random Forest, and CNN to pairwise and comprehensive ensemble combinations—is assessed using five metrics: accuracy, precision, recall, F1-score, and AUC-ROC. The Full Ensemble, which integrates Logistic Regression, Random Forest, and CNN, consistently attains superior performance, validating the advantages of amalgamating different models to capture varied patterns and improve prediction accuracy. This study demonstrates that ensemble approaches, especially when integrating complementary algorithms, yield enhanced outcomes in geriatric risk assessment.

5. CONCLUSION

The suggested ensemble methodology for forecasting geriatric hazards, which integrates Logistic Regression, Random Forest, and CNN models, shows substantial enhancements in accuracy, precision, recall, F1-score, and AUC-ROC relative to individual models. This method efficiently utilises the advantages of each algorithm, improving predicted accuracy and reliability in evaluating hazards such as dysphagia, delirium, and falls in older patients. The ablation investigation verifies that the integration of these models encompasses a wider range of clinical patterns and enhances robustness in practical applications. This ensemble model is a valuable resource for proactive geriatric care, facilitating prompt interventions and perhaps enhancing patient outcomes in healthcare environments.

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