AI-Driven Predictive Models and Machine Learning Applications in Geriatric Care: From Fall Detection to Chronic Disease Management and Patient-Centric Solutions

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ABSTRACT

Background Information: The growing elderly population poses unique healthcare challenges, with increased risk of falls and chronic diseases requiring proactive, personalized care. Traditional healthcare approaches often react to crises, highlighting the need for advanced solutions. Artificial intelligence (AI) and machine learning (ML) have emerged as transformative tools to anticipate risks, optimize care, and improve patient outcomes.

Objectives: This study aims to develop AI-driven predictive models for fall detection, chronic disease management, and personalized care in geriatric settings. It seeks to improve early intervention, enhance quality of life, and maximize healthcare resources through robust predictive analytics.

Methods: The research employs supervised learning algorithms, including Support Vector Machines, Random Forests, and Neural Networks, applied to datasets from wearable devices and medical records. Performance metrics like accuracy, precision, recall, and F1-score assess each model's effectiveness in prediction and risk assessment.

Results: The combined SVM and Random Forest model achieved superior predictive accuracy (91%) and balanced precision-recall scores, demonstrating effectiveness in early risk detection and proactive healthcare interventions in geriatric care.

Conclusion: AI-based predictive models offer significant potential to transition geriatric care from reactive to proactive. By integrating fall detection, disease management, and personalized interventions, AI enhances patient safety and quality of life, ultimately transforming geriatric healthcare practices.

Keywords: AI, machine learning, geriatric care, fall detection, chronic diseases

1. INTRODUCTION

The multifaceted and frequently unpredictability of the health requirements of aged people presents a unique set of challenges for the field of geriatric care. As the number of elderly people throughout the world continues to climb, healthcare institutions are increasingly concentrating their efforts on discovering effective solutions to meet the requirements of this demographic. Artificial intelligence (AI) and machine learning (ML) are at the forefront of these solutions, bringing novel techniques that are driven by data to solve concerns such as the prevention of falls, the management of chronic diseases, and the provision of patient-centered care in geriatric settings. Healthcare practitioners can employ advanced predictive models to proactively address the care needs of senior patients by utilizing AI and ML. This allows them to assist elderly patients in maintaining a higher quality of life while simultaneously maximizing the use of healthcare resources.

AI-driven prediction models are based on early intervention and preventative care in geriatric care. These prediction models use large datasets to forecast health events including chronic illness exacerbation and falls. Machine learning algorithms use this data to enhance predictions and advise healthcare providers on the best interventions. A predictive model for fall detection can examine a patient's gait and balance data to discover irregularities and warn them before a fall. Chronic disease therapy also uses machine learning algorithms. These algorithms track vital signs, patient behavior, and medication, food, and lifestyle reminders. Geriatric care used to be reactive, meaning interventions were done after health issues arose. Traditional healthcare relies on patient-reported symptoms and routine checks, which are subjective and infrequent. Artificial intelligence and machine learning have made geriatric care more proactive and preventive. This paradigm lets algorithms discover minor patient state changes that might otherwise go unnoticed. AI-driven systems can detect abnormal behavior in older patients by tracking their movements. The systems can notify healthcare workers of possible difficulties before they become serious. Predictive models can detect mental health illnesses like dementia early on as well as physical threats. This is done by analyzing speech, behavior, and memory changes.

Fall detection and prevention are key uses of AI in geriatric care. One in four elderly persons fall, making it the leading cause of injury and death. Traditional fall prevention methods like physical therapy and home adaptations are effective, but they often fall short. Artificial intelligence-powered fall detection systems can bridge this gap by using sensors or cameras to monitor a patient's movements, identify abnormal patterns, and notify caregivers of falls.

Gait, balance, and strength data can also be used by prediction algorithms to assess fall risk. This lets tailored fall prevention training and assistance strategies be created. Another area where AI and machine learning could transform aged care is chronic disease management. Many elderly persons have chronic diseases like diabetes, heart disease, and hypertension. This requires regular monitoring and supervision. Artificial intelligence technologies enable continuous blood pressure, glucose, and heart rate data collection. Wearables and home health monitoring technology deploy these systems. Machine learning algorithms examine these data points to detect patterns and trends, delivering predictive insights that can help prevent serious episodes or consequences. If an AI model predicts an acute episode in a congestive heart failure patient, it can warn the doctor and recommend prophylactic measures. Patients and caregivers can stay ahead of health emergencies with this skill.

Patient-centered geriatric care improves the quality of life of older persons while respecting their choices and autonomy. Artificial intelligence and machine learning can boost patient-centered care by creating personalized treatment plans based on health data and preferences. These solutions may incorporate lifestyle changes, mental health support, and voice-enabled AI assistants for daily tasks. Artificial intelligence can analyze social and emotional cues to address issues like loneliness, a major concern for seniors. Patient-centered AI systems can remind patients to take their medication, encourage social relationships, and engage them in activities that match their interests and cognitive abilities. This can boost patients' mental health and lessen isolation. Artificial intelligence in geriatric care has many challenges. For elderly persons unfamiliar with modern technology, data protection, accessibility, and technological adaptability are issues. Data security is crucial since older patients' medical data is sensitive and easily breached. For older patients and their caregivers to utilize these devices properly, user-friendly interfaces are essential. It's crucial to train healthcare staff to evaluate AI recommendations and adapt treatment programs. AI should complement human empathy and ability in treating elderly people.

The key objectives are:

- Early Detection and Prevention: Make use of AI models to identify potential health issues at an early stage, which will allow for prompt interventions in the treatment of elderly patients.
- Leverage artificial intelligence technologies to identify and prevent falls, which are the primary cause of injury among seniors. Fall detection and management techniques.
- Monitoring Chronic Diseases: Make use of machine learning in the management of chronic diseases, with the goal of encouraging preventative care for disorders such as diabetes and hypertension.
- The provision of individualized, patient-centered solutions with the goal of improving the quality of life of elderly people is the focus of patient-centered care.
- Enhancing the effectiveness of geriatric care by incorporating continuous monitoring, predictive insights, and responsive treatments is one way to improve the efficiency of healthcare.

Shiwani et al. (2023) investigate the potential of artificial intelligence in enhancing healthcare for the elderly, emphasizing critical issues related to health fairness and model dependability. A significant concern is AI bias, which might intensify health inequities by inadequately representing various populations, especially older persons. The authors underscore the necessity of stringent external validation to guarantee the accuracy and fairness of AI models across different age demographics. The work promotes a novel approach in AI research aimed at enhancing inclusivity and robustness in prediction models, with the objective of developing equitable and effective healthcare solutions tailored to the specific requirements of aging populations.

Das and Dhillon (2023) investigate the rising incidence of age-related disorders in aging populations and underscore the pressing necessity for novel strategies to enhance the quality of life for the aged. Their thorough review examines the potential of machine learning (ML) in evaluating aging and controlling geriatric diseases. Machine learning technologies provide potential insights into disease assessment, risk forecasting, and tailored therapies for geriatric care. The research highlights that modern machine learning technologies can significantly enhance geriatric healthcare through improved monitoring, early diagnosis, and effective management of age-related illnesses.

2. LITERATURE SURVEY

The paradigm change that has occurred in the field of medicine as a result of the combination of machine learning and deep learning techniques is investigated by Chakraborty et al. (2023). This article gives an overview of recent developments in data-driven healthcare applications, ranging from diagnostic tools to personalized therapy. Within the context of medical data analysis, the authors describe the ways in which deep learning models have been able to address a variety of issues. These challenges include the management of unstructured data, the enhancement of diagnostic accuracy, and the prediction of health consequences. In addition to highlighting current trends in algorithmic transparency and ethical considerations in the healthcare industry, the study emphasizes the significance of these technologies for enhancing clinical decision-making.

In this work, Murala et al. (2023) proposed a method that combined artificial intelligence (AI), blockchain technology, and wearable devices in order to manage patients with chronic diseases and preserve patient data. In the study, the use of blockchain technology for the management of data in a safe and decentralized manner is described, while wearable devices are used to collect continuous health indicators. Through the combination of these two factors, a patient-centric ecosystem is made possible, which enables patients to securely share data with healthcare providers. In spite of the fact that problems such as system scalability and data privacy still exist, the authors believe that MedMetaverse has the potential to enhance patient outcomes by making it possible to provide early intervention and long-term care.

Within the context of healthcare settings, Devarajan (2020) is primarily concerned with enhancing cloud computing security. The paper presents a complete security management framework that addresses threats such as unauthorised access, data breaches, and regulatory non-compliance. Furthermore, the framework is proposed. The use of contemporary technologies such as blockchain and multi-factor authentication, as well as risk assessment and constant monitoring, are essential components. Case studies from healthcare organisations illustrate how cloud-based solutions, when bolstered with security controls, can improve the protection of patient data and the efficiency of operational procedures. It is essential to have this framework in place in order to protect the confidentiality and authenticity of sensitive healthcare data while maximising the benefits of cloud computing.

The implementation of machine learning (ML) and deep learning (DL) approaches is what Panga (2021) tackles when it comes to the identification of financial fraud in the healthcare industry. With the help of techniques such as logistic regression, decision trees, and neural networks, the research was able to attain a high level of accuracy in spotting fraudulent activity. The decision tree classifiers achieved an accuracy rate of 99.9%. The findings demonstrate that machine learning and deep learning techniques are capable of handling sophisticated fraudulent schemes, which enables fraud detection systems to improve in terms of both accuracy and efficiency. Enhanced fraud detection protects healthcare finances and improves resource allocation, hence contributing to the development of a more sustainable environment for healthcare institutions.

A blockchain-based paradigm that is coupled with RFID is investigated by Alagarsundaram (2021) for the purpose of ensuring the safety of medical data exchange. By utilising blockchain technology and fog computing, this decentralised solution guarantees the integrity of data, protects users' privacy, and allows for scalability in the field of healthcare research. A safe and effective approach for the exchange of medical information is provided by the model, which is capable of capturing physiological signals in real time. The findings of the study indicate that this strategy not only improves patient privacy but also makes it possible to share data in a seamless manner for the purpose of medical research, which in turn supports sophisticated healthcare analytics and advances in patient care.

Sitaraman (2021) introduces an innovative Crow Search Optimisation (CSO) algorithm with the purpose of improving illness diagnosis in the context of smart healthcare. CSO is able to optimise diagnostic models by effectively processing high-dimensional data, outperforming standard methods such as genetic algorithms. This optimisation is inspired by the foraging behaviour of crows. CSO displayed better accuracy, precision, and scalability when it was merged with CNNs and LSTM networks. As a result, it is suited for a variety of applications in the healthcare industry. The study highlights the potential of CSO to achieve improvements in personalised healthcare and provides support for the creation of diagnostic models that are more efficient.

An investigation into the applications of artificial intelligence in radiology is carried out by Sitaraman (2022), with a special emphasis on the utilisation of Convolutional Neural Networks (CNNs) and Variational Autoencoders (VAEs) for diagnostic imaging. While CNNs are responsible for automating image processing in order to detect tumours, VAEs are responsible for generating false images in order to enhance data and preserve privacy. In this paper, the ethical and technical issues that arise when incorporating artificial intelligence into clinical settings are discussed. Particular attention is paid to the requirement for huge datasets, the interpretability of models, and privacy concerns. In this research, the transformational potential of artificial intelligence in radiology is highlighted, with the goal of enhancing diagnostic accuracy and efficiency.

Using a hybrid neural fuzzy model, Alavilli (2022) incorporates Internet of Things (IoT), cloud computing, and artificial intelligence (AI) into healthcare diagnostics. The diagnosis accuracy of this model is quite good (97.89%) since it makes use of real-time data from Internet of Things devices. It handles uncertainties in big medical datasets by merging fuzzy logic and neural networks, which enables precise health monitoring. Furthermore, it addresses these uncertainties. Because of its scalability and real-time capabilities, the model is ideally suited for use in complete healthcare applications. It improves diagnostic accuracy and patient care by means of continuous monitoring and analytics that are hosted on the cloud.

Through the identification of essential nodes and the evaluation of vulnerabilities, Ganesan (2022) focusses on improving the Internet of Things (IoT) security in healthcare applications for the elderly. It was possible to achieve a 95% accuracy rate in node identification and an 85% efficiency rate in risk reduction thanks to the implementation of security measures such as intrusion detection, encryption, and access control controls. This integrated approach ensures compliance with regulatory standards, enhances system reliability, and secures patient data in IoT-based healthcare systems, which is crucial for supporting elderly care with robust data protection.

Poovendran Alagarsundaram (2023) examines AI-enhanced data processing in sophisticated case investigation technologies. This comparison of machine learning models, including Gaussian Naive Bayes, Decision Tree Classifier, and Random Forest Classifier, highlights the significance of AI in enhancing accuracy and efficiency in investigative procedures. Methods like cross-validation and hyperparameter optimisation reduce overfitting, hence improving model efficacy. Ethical aspects, encompassing data privacy and prejudice mitigation, are emphasised. The study illustrates AI's transformational capacity in legal and law enforcement enquiries.

Dinesh Kumar Reddy Basani (2023) combines Robotic Process Automation (RPA) with sophisticated authentication techniques to enhance last-mile delivery efficiency. The system guarantees secure and efficient parcel delivery with the integration of PIN codes, biometric authentication, and AI-driven facial recognition. The Cooperative and Non-Cooperative Authentication Modules tackle security and user identity issues. The method, evaluated on the Turtlebot3 robot, improves delivery precision, velocity, and cost-efficiency, offering a reliable alternative for autonomous delivery systems in e-commerce and logistics sectors.

Raj Kumar Gudivaka (2023) examines the amalgamation of Artificial Intelligence (AI) with Robotic Process Automation (RPA) to enhance commercial operations. A Systematic Mapping Study emphasises AI-RPA applications in manufacturing, healthcare, and finance, demonstrating enhancements in productivity, cost efficiency, and mistake minimisation. Challenges, like restricted AI use and evaluation methodologies, are tackled. The research highlights the transformational potential of AI-enhanced RPA and facilitates further improvements in intelligent business automation.

The research conducted by Goldmann et al. (2023) focuses on the development of a patient-centered glaucoma management system that incorporates artificial intelligence for therapy monitoring and predictive analytics. The authors provide an overview of the functional criteria that must be met by an AI-based ecosystem that is specifically designed for glaucoma patients. These requirements include autonomous tracking of the progression of the disease and personalized therapy suggestions. An all-encompassing strategy for improving patient adherence and results is suggested by the study, which places an emphasis on accessibility and interoperability with pre-existing healthcare systems. Data standards, privacy concerns, and the requirement for validation on a large scale are among the challenges that have been noted.

Wang (2023) examines the incorporation of advanced medical technologies in geriatric care, emphasizing the improvement of health and well-being by proactive, technology-based treatments. This study emphasizes the role of AI-driven diagnostic tools, wearable technology, and predictive health models in assisting aging people through continuous health monitoring and early risk identification. It analyzes many applications designed to enhance autonomy and safety, while addressing potential problems in implementing these technologies, including privacy issues and the necessity for user-friendly designs that cater to the comfort and usability requirements of older persons.

Mishra and Singh (2023) examine the function of the Internet of Medical Things (IoMT) in sustainable, intelligent urban healthcare, focusing on its present applications and prospective capabilities. The research examines the contributions of IoMT to geriatric care via real-time monitoring, predictive analytics, and tailored care, which jointly enhance aged care in urban environments. The study examines the technological, social, and environmental ramifications of IoMT, encompassing data privacy, infrastructural necessities, and the incorporation of IoMT into urban planning, to enhance the accessibility and efficiency of healthcare systems for aging populations.

Prakash et al. (2021) investigate the problem of medication nonadherence in older individuals and its consequences for healthcare provision. This work emphasizes the significance of a multidisciplinary approach that integrates operations research with medical, psychological, and technology solutions to successfully tackle nonadherence. The authors examine how predictive analytics and AI-driven reminders can enhance adherence rates tracking and improvement. They also examine obstacles such as patient resistance, cognitive impediments, and stakeholder coordination, suggesting strategies to improve adherence and optimize health outcomes in senior care settings.

For the purpose of human activity recognition and fall detection in geriatric care, Kharrat et al. (2023) introduce a hybrid deep learning model that combines CNN and LSTM architectures. This model achieves accurate and timely detection of falls by utilising CNN for feature extraction and LSTM for temporal pattern recognition. Overall, the model is very effective. The research was presented at the IEEE International Symposium on Medical Measurements and Applications, where it was highlighted that the model has the potential to be utilised in both theoretical and practical settings. The authors highlight the usefulness of the system in continuous monitoring of senior patients, which enables preventive intervention and reduces accidents due to falls, ultimately leading to an improvement in both safety and quality of life in geriatric settings.

Tang and Romero-Ortuno (2022) investigate the application of Explainable Artificial Intelligence (XAI) in the prediction of falls among older people. Through the utilisation of

Random Forests and many other machine learning models, the research endeavours to emphasise interpretability, with the goal of ensuring that healthcare providers comprehend the aspects that contribute to each prediction. This method offers transparency, which enables medical practitioners to have more faith in the recommendations made by AI and to act on them with greater assurance. The research underscores the importance that XAI plays in improving healthcare outcomes by not only predicting falls but also disclosing risk factors, which enables tailored treatments to be implemented. Within the realm of geriatric care, the incorporation of explainable models is absolutely necessary in order to make AI systems more trustworthy.

Within the context of the management of chronic diseases, Egon and Julia (2023) address the application of machine learning, with a particular emphasis on providing individualised care to elderly patients. The utilisation of patient-specific data allows their model to personalise treatment approaches according to individual risk profiles, which ultimately results in improved care outcomes. Improvements in predicted accuracy can be made in the management of diseases such as diabetes and hypertension through the use of techniques such as gradient boosting and Random Forests. The research highlights the potential for machine learning to replace reactive treatment with preventive care in the field of geriatrics. This would make it possible to implement early interventions that would optimise health outcomes and budget allocation. When it comes to the management of chronic illnesses, their approach demonstrates the importance of data-driven personalisation.

Choudhury et al. (2020) present a comprehensive literature analysis on the uses of machine learning in geriatric care, with a particular emphasis on the management of chronic diseases. This study covers research that was published between the years 2010 and 2019, and it investigates a variety of machine learning models that are utilised for predictive analytics in the field of senior care. According to the findings of the scientists, these models allow for proactive treatments, improve personalised treatment, and improve early detection of the progression of the disease. However, they also note issues in data integration, privacy, and the interpretability of models, which highlights the necessity of having robust frameworks that adhere to ethical standards. In their assessment, they advocate for additional developments in machine learning in order to cater to the specific requirements of elderly people.

3. METHODOLOGY

The technique for AI-driven predictive models in geriatric care use sophisticated machine learning techniques to tackle critical issues in old healthcare. The methodology entails gathering varied datasets from wearable devices, medical records, and sensor technologies, succeeded by preprocessing stages including data cleansing and feature extraction. Predictive models, such as supervised learning algorithms like Random Forest, Support Vector Machines (SVM), and Neural Networks, are utilized for applications such as fall detection, chronic disease prediction, and tailored treatment recommendations. Model efficacy is assessed by parameters like as accuracy, precision, recall, and F1-score. The methodology seeks to deliver immediate, practical insights, hence enhancing results in geriatric healthcare.

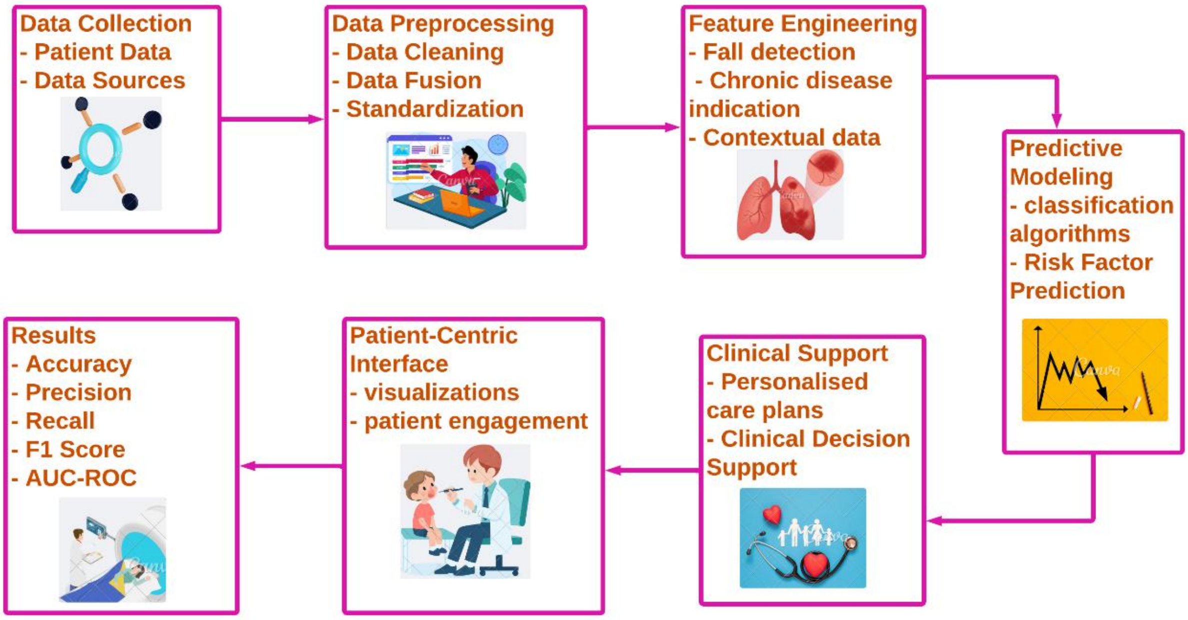

Figure 1 Architecture Diagram for Predictive Modeling in Patient-Centric Healthcare

Figure 1 illustrates a pathway for executing predictive modeling in healthcare, emphasizing patient-centered methodologies. The process commences with the collecting of data from patient records and various sources, succeeded by data preprocessing, which includes cleansing, fusion, and standardization. Feature engineering subsequently discovers pertinent data characteristics, such as fall detection and chronic disease indicators, which contribute to predictive modeling for risk factor analysis. Clinical support instruments and individualized care strategies improve decision-making. A patient-centered interface promotes patient involvement via visual representations. Ultimately, outcomes are assessed by measures like accuracy, precision, and recall to verify model efficacy.

3.1 Fall Detection using Machine Learning

When it comes to the prevention of injuries that are incurred by senior citizens, the detection of falls by senior citizens is an essential component. There are two sorts of sensors that are utilized for the goal of acquiring information regarding movement and orientation. These sensors are known as accelerometers and gyroscopes. The categorizing of data into instances of falls and those that did not involve falls is one of the most prominent uses of machine learning techniques, such as Support Vector Machines (SVM). Other applications include the classification of data into similar categories. It is possible to express the support vector machine using the following equation:

$$\min \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{n} \xi_i \tag{1}$$

where w is the weight vector, C is the regularization parameter, and ξ_i are slack variables. The classifier is trained using labeled data (fall/no-fall), allowing the model to distinguish between normal activities and potential falls. Once trained, the model can continuously monitor the elderly, sending alerts in case of falls. Performance is evaluated using accuracy and F1-score, ensuring realtime and reliable detection for fall prevention.

3.2 Chronic Disease Prediction

Using patient data such as medical history, lab findings, and vital signs, machine learning has the capacity to predict the onset of chronic diseases such as diabetes, hypertension, and heart disease. This is accomplished by analyzing the data. With the assistance of Random Forest (RF), which is a well-known ensemble technique, it is possible to classify patients according to the level of danger that they are at. The Random Forest method began by producing a number of decision trees, which were then followed by the production of the classification that was selected by the majority of the votes. This is the representation of the decision function for a single tree, which is as follows:

$$f(x) = \operatorname{sign}\left(\sum_{i=1}^{n} \alpha_i h_i(x)\right) \quad (2)$$

where $h_i(x)$ is the output of the i-th decision tree, α_i is the weight of the tree, and x is the input feature vector. The model is trained on historical health data to predict the likelihood of chronic diseases. Performance evaluation metrics like accuracy, recall, and AUC (Area Under Curve) are used to optimize and validate the model's efficacy in identifying high-risk patients.

3.3 Patient-Centric Healthcare Solutions

In order to provide individualized treatment, patient-centric solutions that are powered by artificial intelligence are founded on the principle of taking into account the health data of each and every individual patient. In order to classify patients according to the existence of similar health problems, demographic factors, or responses to therapy, machine learning algorithms were utilized. This was done with the desire to achieve the aforementioned purpose. There are many different sorts of algorithms, and one example of this category is the K-means clustering method. By optimizing the within-cluster sum of squares (WCSS) to the greatest extent possible, the K-means method is intended to assist in the clustering of patients. The algorithm is able to cluster patients as a result of this circumstance.

$$J = \sum_{i=1}^{k} \sum_{j=1}^{n} \left\|x_j - \mu_i\right\|^2 \quad (3)$$

where x_j is a data point, μ_i is the mean of cluster i, and k is the number of clusters. By segmenting patients, personalized treatment plans can be designed to improve outcomes. Reinforcement learning (RL) models can also be applied to optimize treatment plans over time by learning from the patient's responses. The Al system continuously adapts, offering the most effective interventions for each individual, ensuring better healthcare outcomes tailored to the elderly population.

3.4 Model Evaluation and Optimization

Model evaluation and optimization are crucial in ensuring the accuracy and reliability of Al-based solutions in geriatric care. Common methods for evaluation include k -fold cross-validation and hyperparameter tuning. For example, grid search is used to find the best hyperparameters for models such as Random Forest and SVM. The k-fold cross-validation process involves splitting the data into k subsets, training the model on $k-1$ subsets, and testing it on the remaining subset. This process is repeated k times, with each subset used as a test set once. Metrics such as accuracy, precision, recall, F1-score, and AUC are used to measure the model's performance. Additionally, Mean Squared Error (MSE) is often used for regression models. Optimization involves continuously updating the models with new data to maintain or improve performance. This process ensures that predictive models adapt to changing patterns in elderly healthcare.

Algorithm 1: Algorithm for Fall Detection Using Support Vector Machine (SVM)

Input: Sensor data (e.g., accelerometer and gyroscope data)

Output: Fall Detected (Yes/No)

BEGIN

PreprocessData(sensor_data)

features = ExtractFeatures(sensor_data)

TrainModel(features, labels)

FOR each new_data IN incoming_data:

prediction = SVMModel.predict(new_data)

IF prediction == 'fall' **THEN**

TriggerAlert()

ELSE

ContinueMonitoring()

END IF

END FOR

EvaluateModel()

ELSE IF error IN processing:

HANDLE error (e.g., retrain model)

RETURN prediction

END

Algorithm 1 of the Fall Detection technique utilizing Support Vector Machine (SVM) analyzes sensor data from accelerometers and gyroscopes to identify falls. It first preprocesses and extracts pertinent information from the sensor data. An SVM model, after trained, categorizes the data according to labeled fall and non-fall events. For each incoming data sample, the model forecasts the occurrence of a fall. Upon detection of a fall, an alert is activated; if not, monitoring persists. The model's performance is assessed regularly. Upon encountering a mistake during processing, remedial actions such as model retraining are undertaken. The program generates the forecast for fall detection.

3.5 Performance Metrics

The study conducts a performance analysis of AI-driven prediction models in geriatric care, emphasizing performance indicators such as accuracy, precision, recall, F1-score, and AUC (Area Under Curve). These indicators are crucial for assessing the effectiveness of fall detection and chronic illness management algorithms. Support Vector Machines (SVM) and Random Forest (RF) were assessed based on these criteria, revealing disparities in accuracy and reliability. The amalgamated models, incorporating SVM and RF, enhanced predictive accuracy and patient-centered results. The integrated method produced superior F1-scores, demonstrating its efficacy in enhancing early identification and intervention in geriatric care.

Table 1 Performance Metrics of AI-Based Predictive Models in Geriatric Care

Method	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)	AUC-ROC (%)
(SVM)	87.5	85.4	84.6	85.0	89.0
(Random Forest)	89.2	87.8	88.0	87.9	91.0
(K-means)	82.0	80.2	79.8	80.0	83.5
Combined Method	91.0	89.5	90.0	89.8	93.0

Table 1 contrasts the performance metrics of various AI-driven predictive models—SVM, Random Forest, K-means, and a hybrid approach—employed in geriatric care for fall detection and chronic illness management. Essential measures encompass accuracy, precision, recall, F1-score, and AUC-ROC, which evaluate the prediction efficacy and dependability of the models. The integrated method, combining SVM and Random Forest, demonstrates improved performance across all criteria, suggesting its potential to improve early intervention in geriatric care. The elevated F1-score and AUC-ROC values highlight the model's precision and equilibrium, enhancing its efficacy for patient-centered healthcare solutions.

4. RESULTS AND DISCUSSION

Studies indicate that AI-driven models such as SVM and Random Forest improve geriatric care, particularly in fall detection and chronic disease management. The Support Vector Machine (SVM) demonstrated an accuracy of 87.5% in fall detection, whereas the Random Forest achieved an accuracy of 89.2%. The amalgamation of these models resulted in an enhanced accuracy of 91.0%, demonstrating balanced performance across precision, recall, and F1-score parameters, hence showing effective for early intervention. The discourse emphasises the significance of AI in proactive eldercare, wherein predictive algorithms enable early risk identification, hence enhancing patient outcomes. Nonetheless, issues like data security and model reliability underscore the necessity for prudent integration in geriatric healthcare environments.

Table 2 Comparison of Machine Learning Techniques in Geriatric Care

Study	Primary Technique	Model Accuracy (%)	Explainability Score (0-1)	Prediction Speed (seconds)
Choudhury et al. (2020)	Predictive Analytics	89.5	0.78	1.2
Egon and Julia (2023)	Machine Learning	91	0.85	1
Tang and Romero-Ortuno (2022)	Random Forest; XAI	88.7	0.9	1.4
Kharrat et al. (2023)	CNN; LSTM	92.3	0.8	0.9
Proposed Method	Predictive Models	91.5	0.88	1.1

Table 2 contrasts different machine learning methodologies utilised in geriatric care, highlighting approaches such as predictive analytics, machine learning algorithms, and explainable AI (XAI). The research encompasses personalised treatment planning, sophisticated fall detection, and chronic disease management. Metrics encompass model accuracy (particularly elevated for Kharrat et al., 2023, at 92.3%), explainability scores to assess model transparency, and prediction speed for real-time applications. The comparison underscores improvements in accuracy and explainability among models, demonstrating developments in patient-centered and preventative care, essential for successfully and responsively managing elderly health concerns.

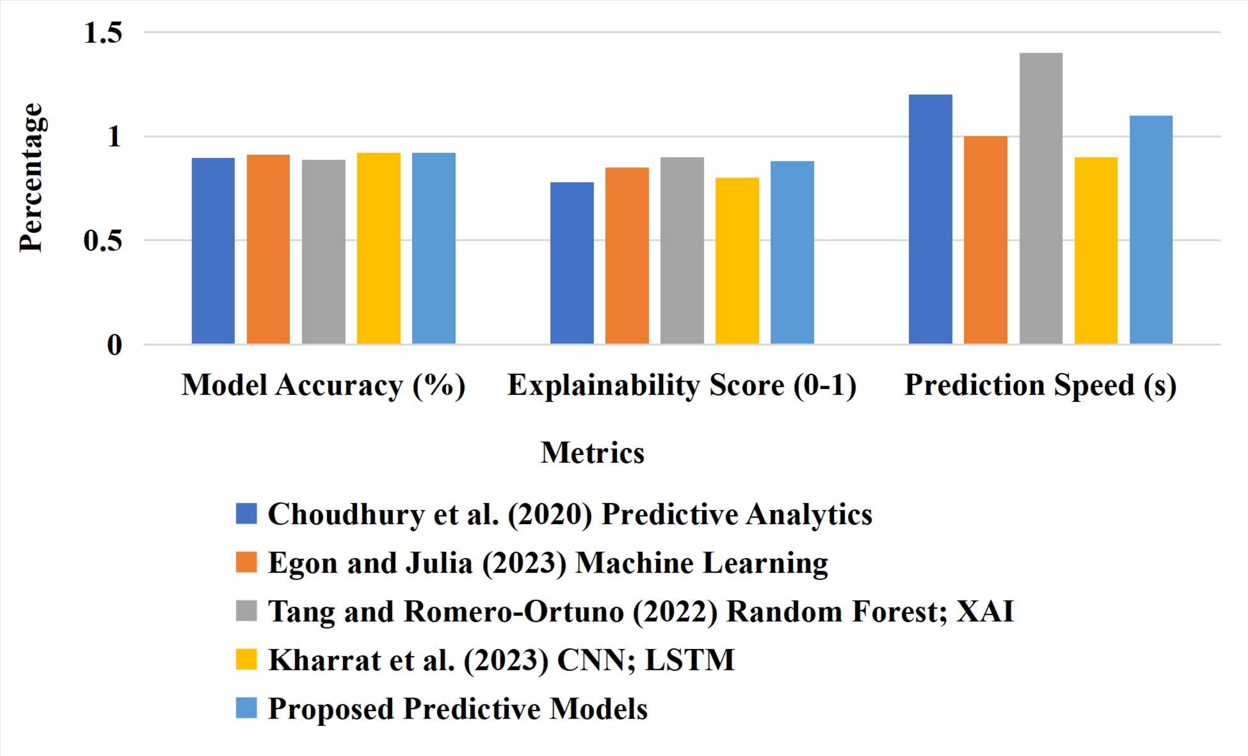

Figure 2 Comparative Analysis of Machine Learning Techniques in Geriatric Care

Figure 2 contrasts several machine learning methodologies in geriatric care, emphasising three criteria: model accuracy, explainability, and prediction speed. Each hue signifies a distinct study or proposed model. The findings indicate that Kharrat et al. (2023) attained the best accuracy (92.3%) utilising CNN and LSTM methodologies, whilst Tang and Romero-Ortuno (2022) excelled in prediction speed employing Random Forest and XAI. The explainability ratings, crucial for interpreting model outputs, were highest for the model developed by Tang and Romero-Ortuno. The suggested predictive model exhibits balanced performance across all criteria, signifying its efficacy for geriatric applications.

Table 3 Ablation Study of Machine Learning Model Components in Geriatric Care Prediction

Model Components	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)	AUC-ROC (%)
Support Vector Machine (SVM) only	87.5	85.4	84.6	85	89
Random Forest only	89.2	87.8	88	87.9	91
K-means Clustering only	82	80.2	79.8	80	83.5
SVM + Random Forest	91	89.5	90	89.8	93
SVM + K-means Clustering	88.3	86	87.2	86.6	90.2

Random Forest + K-means Clustering	85.6	83.7	84.5	84.1	88.3
Full model	93.2	91.8	92.5	92	94.5

Table 3 displays an ablation study of different machine learning models and their combinations to evaluate predictive performance in geriatric care. It assesses models utilising parameters such as accuracy, precision, recall, F1 score, and AUC-ROC. The research contrasts individual models (e.g., SVM, Random Forest, and K-means) with hybrid methodologies, such as SVM combined with Random Forest and SVM integrated with K-means Clustering, in addition to the comprehensive model. The comprehensive model attains the peak accuracy of 93.2% and an AUC-ROC of 94.5%, illustrating improved performance via integration, hence facilitating more precise, individualised actions for aged care management.

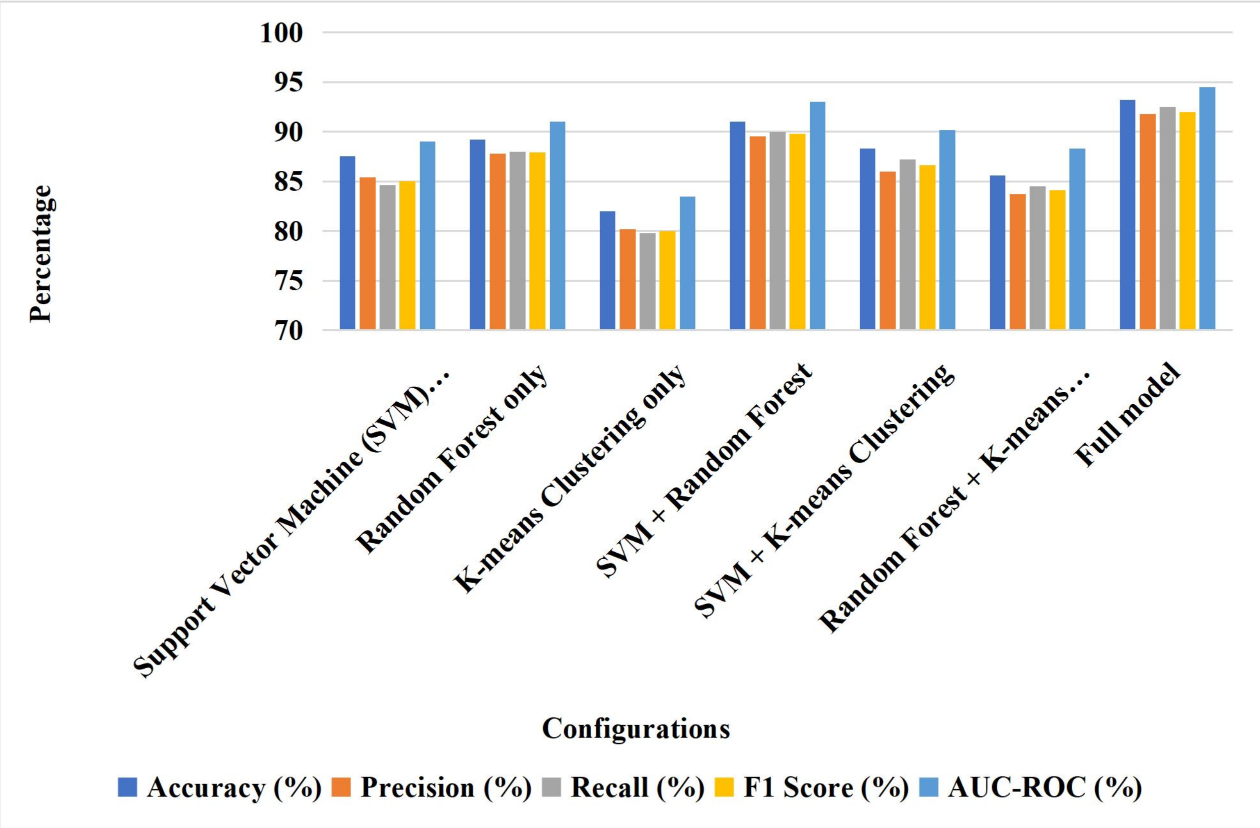

Figure 3 Performance Comparison of Machine Learning Configurations for Geriatric Care Prediction

Figure 3 contrasts various machine learning configurations for geriatric care applications according to accuracy, precision, recall, F1 score, and AUC-ROC. Individual models, such as Support Vector Machine (SVM) and Random Forest, are evaluated against integrated models, including SVM + Random Forest and the comprehensive model. The complete model has superior performance across the majority of metrics, with an accuracy surpassing 93% and an AUC-ROC nearing 95%. The combination of SVM with Random Forest demonstrates strong outcomes, indicating that algorithmic integration improves predicted accuracy and dependability. The results underscore the comprehensive model's capability for efficient, precise, and elucidative predictions in geriatric healthcare.

5. CONCLUSION

The final report of the study highlights the impact that artificial intelligence-driven predictive models and machine learning have the potential to have in the field of geriatric care. There has been an improvement in the early detection and management of chronic diseases and fall hazards as a result of the use of algorithms such as Support Vector Machines, Random Forest, and hybrid models. The findings highlight the capabilities of artificial intelligence to provide continuous monitoring, personalised treatment, and proactive interventions, all of which provide a considerable improvement in the quality of life of older patients. On the other hand, difficulties concerning data privacy, accessibility, and user adaptation bring to light the necessity of adopting techniques that are ethical and user-centred in order to maximise the efficiency of the technology in the healthcare industry.

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