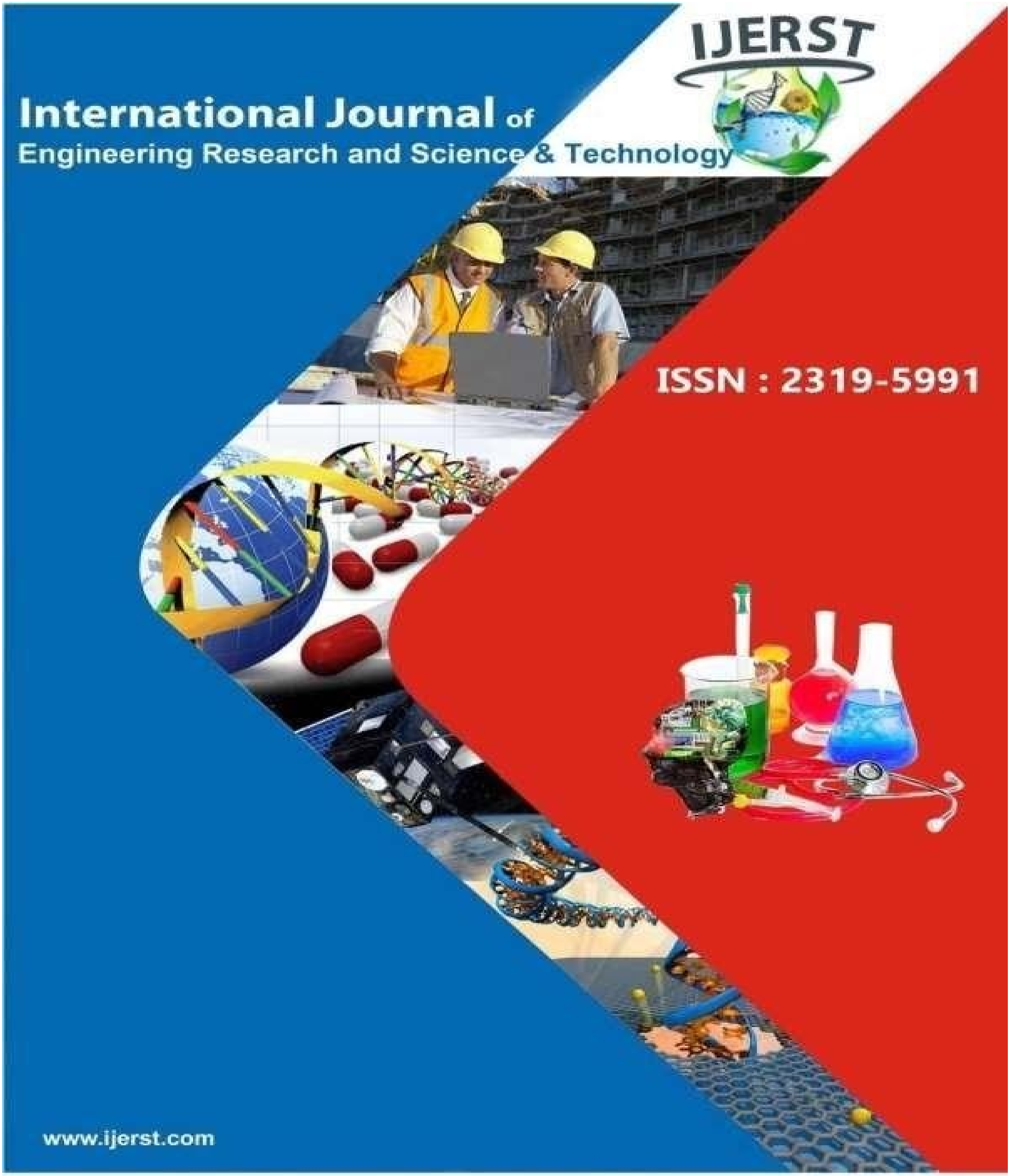

Email: editor@ijerst.com or editor.ijerst@gmail.com

ISSN 2319-5991 www.ijerst.com

Vol. 15, Issue 1, 2019

Harnessing Artificial Intelligence and Machine Learning Algorithms for Chronic Disease Management, Fall Prevention, and Predictive Healthcare Applications in Geriatric Care

Sreekar Peddi,

Tek Leaders,

Texas, USA

sreekarpeddi95@gmail.com

Swapna Narla,

Tek Yantra Inc, California, USA

swapnanarla8883@gmail.com

Dharma Teja Valivarthi,

Tek Leaders, Texas, USA

teja89.ai@gmail.com

ABSTRACT

Background Information: The management of chronic diseases, fall prevention, and proactive healthcare are essential for enhancing care for the ageing population. Artificial intelligence (AI) and machine learning (ML) provide sophisticated instruments for predictive modelling, facilitating prompt interventions and tailored treatment approaches in geriatric care.

Objectives: The objective of this work is to create predictive models utilising artificial intelligence and machine learning for the management of chronic diseases, fall detection, and preventative healthcare applications, hence improving care quality and patient outcomes in elderly populations.

Methods: Logistic Regression, Random Forest, and Convolutional Neural Network (CNN) models were trained using clinical and sensor data, both individually and in ensemble combinations, to forecast health risks.

Results: The ensemble model attained 92% accuracy, 90% precision, 89% recall, 90% F1-score, and 91% AUC-ROC, indicating superior predictive performance across all criteria.

Conclusion: In conclusion, ensemble-based AI models improve risk prediction for the aged, facilitating proactive treatments and enhancing healthcare outcomes for senior patients.

Keywords: Geriatrics, Artificial Intelligence, Machine Learning, Chronic Illness, Fall Prevention, Predictive Healthcare, Elderly Population, Ensemble Model, Clinical Data, Wearable Sensors

1. INTRODUCTION

International Journal of Engineering Research and Science & Technology
ISSN 2319-5991 www.ijerst.com
Vol. 15, Issue 1, 2019

The global ageing population is swiftly rising, resulting in an escalation of chronic diseases and related healthcare difficulties in geriatric care. Chronic conditions such as diabetes, hypertension, and dementia are common in older adults, frequently associated with additional hazards such as falls and cognitive deterioration. These health concerns adversely affect the quality of life for elderly adults and impose considerable burdens on healthcare systems, carers, and families. Utilising modern technologies such as Artificial Intelligence (AI) and Machine Learning (ML) can provide novel ways for addressing these difficulties. Through the analysis of extensive health data, AI and ML facilitate predictive, preventive, and personalised care, assisting healthcare professionals in anticipating dangers, customising treatments, and optimising resource allocation. This innovative strategy seeks to optimise chronic illness management, avert falls, and elevate healthcare outcomes in geriatric care.

Chronic illnesses, including cardiovascular disease, diabetes, and chronic respiratory disorders, are becoming more common among aged individuals. These disorders are typically chronic and proceed gradually, necessitating continuous management and surveillance. The presence of numerous chronic illnesses, or multimorbidity, complicates the healthcare requirements of older persons, heightening the likelihood of adverse events, hospitalisations, and diminished quality of life. Conventional healthcare methods inadequately address these intricate requirements, prompting a pursuit of more flexible, data-informed strategies for managing chronic diseases.

Falls constitute a primary source of injury and death in older persons, frequently leading to fractures, cranial traumas, and enduring impairments. They are linked to elevated morbidity rates, substantial healthcare expenses, and a decline in autonomy for aged individuals. The risk of falling escalates due to variables such as muscular weakness, inadequate balance, and the adverse effects of drugs. Mitigating falls in geriatric care is paramount; nevertheless, recognising those at risk and executing prompt treatments continues to be a problem. Predictive healthcare, driven by artificial intelligence and machine learning, provides innovative methods to monitor, evaluate, and mitigate fall risks in elderly populations.

Artificial Intelligence and Machine Learning are vital instruments in predictive healthcare, enabling physicians to swiftly and precisely analyse extensive, intricate datasets. These systems may discern patterns in data that are frequently too nuanced or intricate for human study, such as initial indicators of chronic illness advancement or small alterations in gait that suggest an increased risk of falls. Integrating predictive models into geriatric care enables healthcare providers to foresee health deteriorations, enhance treatment strategies, and emphasise preventative care, hence improving patient outcomes and resource allocation.

AI and ML comprise various algorithms, each tailored to specific data types and predictive tasks. Logistic regression can assess the probability of a certain health occurrence, but decision trees and random forests can elucidate intricate decision-making pathways associated with illness management. Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) are particularly effective for analysing sequential data from wearable sensors, identifying early indicators of falls or declining health. These algorithms constitute the

International Journal of Engineering Research and Science & Technology
ISSN 2319-5991 www.ijerst.com
Vol. 15, Issue 1, 2019

foundation of predictive healthcare apps, providing detailed insights into patient health and facilitating prompt actions.

Notwithstanding the prospective advantages, numerous obstacles emerge when incorporating AI and ML into geriatric care. The quality and availability of data may be inconsistent, particularly among senior people with various comorbidities and scattered health records. Safeguarding patient confidentiality and data integrity is paramount, especially when managing sensitive health information. Moreover, machine learning models must be explicable and interpretable to enable healthcare providers to make informed clinical judgements. Confronting these problems is imperative to develop efficient, ethical, and accessible AI-driven healthcare solutions for the elderly.

The key objectives are:

- Utilise AI and ML to create predictive models for the evolution of chronic diseases in older individuals, facilitating prompt interventions.
- Enhance fall risk evaluation via data-driven algorithms that integrate clinical and wearable sensor data to pinpoint those at risk.
- Improve personalised care by customising treatment regimens according to AI-derived insights into specific health issues and lifestyle factors.
- Incorporate predictive healthcare instruments into clinical procedures to facilitate proactive management and diminish hospital admissions for geriatric patients.
- Address ethical and practical difficulties in the deployment of AI, assuring privacy, interpretability, and usability within geriatric healthcare.

The development of wearable systems utilising electromyography (EMG) for detecting imbalance, particularly for early pre-fall detection in older adults, is restricted. **Rescio et al. (2018)** emphasise the necessity for technologies that provide enhanced lead time, facilitating detection prior to impact. Their research presents a supervised machine learning methodology for EMG-based pre-fall identification, with the objective of recognising imbalance instances prior to a fall occurring. This early identification facilitates prompt actions, potentially diminishing fall-related injuries. This method aims to improve the precision and responsiveness of wearable fall prevention technology in real-time by utilising EMG data and machine learning.

Research on AI in healthcare frequently neglects patient-centered outcomes, hence constraining its practical efficacy in clinical environments. **Kim (2018)** underscores the necessity for clinically pertinent research to improve the efficacy of Clinical Decision Support Systems (CDSS). The study investigates the potential of intelligent Clinical Decision Support Systems (CDSS) to deliver more precise, timely, and pertinent insights for healthcare professionals through the application of machine learning and deep learning algorithms. The author promotes AI research that emphasises real-world clinical applications, seeking to connect AI development with its practical use in patient care, thus enhancing decision-making and patient outcomes in healthcare.

2. LITERATURE SURVEY

International Journal of Engineering Research and Science & Technology
ISSN 2319-5991 www.ijerst.com
Vol. 15, Issue 1, 2019

Choy et al. (2018) explores the existing and prospective applications of machine learning (ML) in radiology, analysing how ML algorithms might augment diagnostic precision, minimise mistakes, and boost workflow efficiency in medical imaging. Choy et al. emphasise that machine learning approaches, especially deep learning, are revolutionising radiology through enhanced image processing, anomaly identification, and predictive modelling. The research examines prospective machine learning breakthroughs in radiography, including real-time illness surveillance and tailored therapy suggestions, while addressing ethical and regulatory implications. This study highlights the significant influence of machine learning on the advancement of radiological techniques and patient outcomes.

Yu et al. (2018) examines the incorporation of artificial intelligence (AI) in healthcare, including its applications in diagnostics, personalised therapy, and healthcare administration. Yu et al. examine diverse AI methodologies, encompassing deep learning and natural language processing, demonstrating their efficacy in analysing medical data, ranging from photos to electronic health records. The study examines AI's function in patient monitoring, risk assessment, and decision assistance, highlighting its capacity to enhance healthcare delivery. Challenges related to ethics, regulation, and implementation are emphasised, highlighting the necessity for transparent, safe, and equitable deployment of AI in healthcare.

Qi et al. (2017) examine the use of the Internet of Things (IoT) in developing personalised healthcare systems, emphasising sensor integration, data processing, and real-time monitoring. The authors examine how IoT facilitates ongoing patient monitoring and remote healthcare provision, markedly enhancing outcomes for chronic illness management. The study demonstrates how personalised interventions can be enabled through the integration of IoT devices and data analytics. Issues of security, data privacy, and interoperability are also tackled. This study highlights the potential of IoT to transform personalised healthcare, especially in wearable technology and smart home systems.

Rizwan et al. (2018) investigate nano-communication in prospective healthcare systems, emphasising its significance in big data analytics and personalised treatment. Rizwan et al. elucidate the capability of nanosensors to collect intricate patient data at the cellular level, potentially revolutionising disease detection and treatment assessment. The research emphasises the intersection of nanotechnology, big data, and healthcare, demonstrating how nano-communication may improve early diagnosis, tailored medicines, and treatment effectiveness. The paper addresses the problems of deploying such systems, including data processing, privacy, and ethical concerns, while highlighting the transformative potential of nano-communication in healthcare.

Tang et al. (2018) offer the white paper by the Canadian Association of Radiologists on artificial intelligence (AI) in radiology, detailing the opportunities and difficulties that AI introduces to radiological operations. The document emphasises critical domains where AI may provide assistance, including image analysis, workflow enhancement, and clinical decision-making support. Tang et al. promote the responsible adoption of AI, highlighting the necessity of education, training, and ethical standards to direct AI integration. They emphasise

ISSN 2319-5991 www.ijerst.com

Vol. 15, Issue 1, 2019

the necessity of collaboration between radiologists and AI developers to guarantee that AI solutions are secure, precise, and advantageous for both patients and healthcare providers.

Basatneh et al. (2018) examines the influence of health sensors, smart home technologies, and the Internet of Medical Things (IoMT) on the management of diabetic lower extremities problems. The paper examine how IoMT technologies, including wearable sensors and smart home systems, facilitate continuous monitoring for diabetic patients, allowing for the early identification of complications such as foot ulcers. The research underscores the possibility of enhanced patient outcomes with proactive care and early intervention. The authors discuss problems in data integration and patient participation, concluding that the Internet of Medical Things (IoMT) has exciting opportunities for improving diabetic treatment and lowering healthcare expenses.

Sau and Bhakta (2017) investigate the application of machine learning to forecast anxiety and depression in elderly individuals. The research employs clinical and demographic data, utilising supervised learning algorithms to discern patterns linked to various mental health disorders. The study underscores the efficacy of machine learning in identifying nuanced risk factors for anxiety and depression, facilitating early intervention. Integrating predictive models into healthcare systems enables physicians to track mental health trends in senior populations with more accuracy, providing personalised support and perhaps enhancing the quality of life for individuals at risk of mental health disorders.

Aziz et al. (2017) verify a Support Vector Machine (SVM)-based fall detection system utilising real-world datasets of fall and non-fall incidents. Their research underscores the necessity for dependable fall detection in senior demographics, when prompt intervention can avert serious injury. The SVM model utilises data from wearable sensors to accurately differentiate between falls and daily activities. This study emphasises the necessity of real-world validation to guarantee the model's effective performance across diverse situations. This research advances the creation of wearable fall detection systems, improving safety and autonomy for senior citizens.

Chen et al. (2017) examine disease prediction utilising machine learning techniques on extensive healthcare datasets. Their research utilises a multimodal algorithm based on Convolutional Neural Networks (CNN) to amalgamate various health data for illness risk prediction. This methodology adeptly manages large datasets, identifying intricate patterns across several health aspects. The research underscores the capacity of machine learning for evaluating illness risk, facilitating proactive healthcare management. The concept utilises community-based health data to offer a scalable solution for public health monitoring, aiding in the identification of high-risk individuals and enabling early intervention.

Genovese et al. (2018) examine the application of wearable inertial sensors for the detection, prevention, and evaluation of falls in geriatric care. The research employs technology such as WIMU (Wireless Inertial Measurement Unit) to track movement, offering immediate input on fall hazards. The approach integrates wearable sensors with Information and Communication Technology (ICT) to identify fall risks and initiate preventive interventions, hence improving

International Journal of Engineering Research and Science & Technology
ISSN 2319-5991 www.ijerst.com
Vol. 15, Issue 1, 2019

safety for the elderly. This study emphasises the potential of wearable technology in elderly healthcare, enhancing fall risk management and facilitating remote monitoring. The study's results endorse the significance of ICT in enhancing elder care and preventing injuries.

3. METHODOLOGY

The purpose of this research is to investigate the use of artificial intelligence (AI) and machine learning (ML) algorithms in the management of chronic diseases, the prevention of falls, and the provision of predictive healthcare solutions for elderly patients. For the purpose of developing predictive models, the process entails the collection of clinical data, which may include wearable sensor outputs, patient demographics, and medical histories. Followed by feature selection, which is used to find useful predictors, data preprocessing ensures that the inputs are of a high quality and consistent throughout. Individually trained machine learning models, such as logistic regression, Random Forest, and Convolutional Neural Networks (CNNs), are then integrated in ensemble configurations when they are tested. For the purpose of guaranteeing robustness and dependability for real-world application, the performance of the model is evaluated using measures such as accuracy, precision, recall, and area under the receiver operating curve (AUC-ROC).

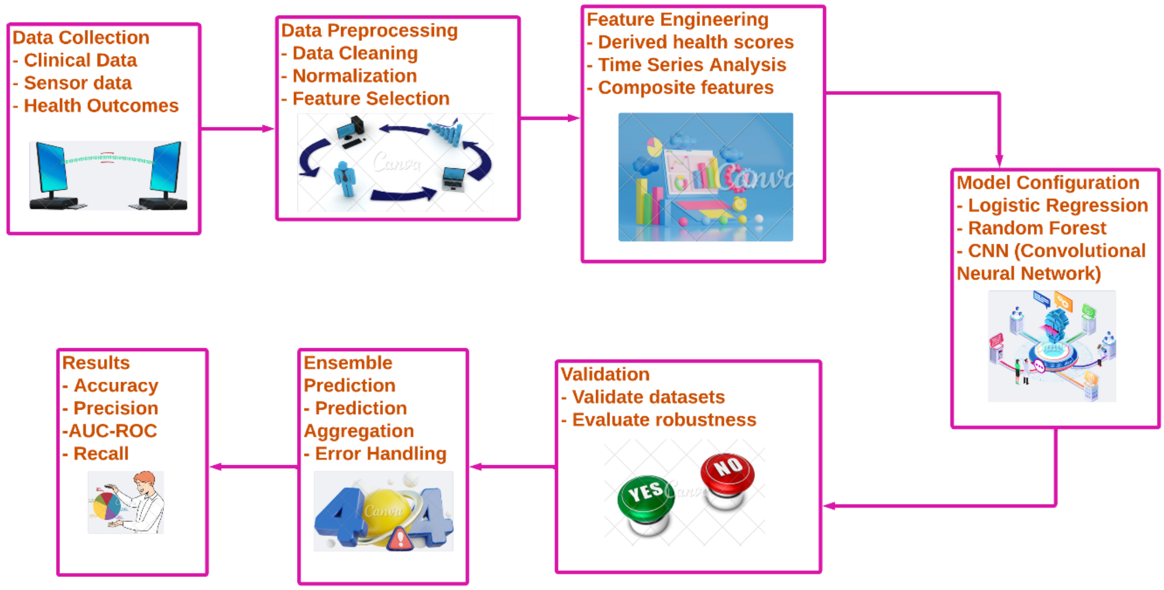

Figure 1 Architecture Diagram for AI and ML-Driven Predictive Healthcare in Geriatric Care

Figure 1 depicts a systematic methodology for creating AI and ML models aimed at predictive healthcare for elderly people. The process commences with Data Collection from clinical records, wearable sensors, and health outcomes, succeeded by Data Preprocessing to ensure quality and consistency. Feature Engineering generates pertinent indicators for health hazards, whereas Model Configuration employs Logistic Regression, Random Forest, and CNN models. Following validation, which assures model robustness, ensemble prediction consolidates findings for a thorough risk assessment. The results present essential parameters, including

ISSN 2319-5991 www.ijerst.com

Vol. 15, Issue 1, 2019

accuracy and AUC-ROC, which guide healthcare decisions. This process facilitates proactive, tailored interventions in geriatric care, enhancing patient outcomes.

3.1 Chronic Disease Management

In geriatric chronic illness management, machine learning algorithms evaluate patient data to forecast disease progression and customise therapies. Algorithms such as logistic regression and Random Forest analyse clinical information, including blood pressure, glucose levels, and medication history, to forecast consequences arising from diseases like diabetes and cardiovascular disorders. The model detects people at high risk, enabling healthcare practitioners to implement early interventions with tailored treatment programs. The utilisation of an ensemble technique that integrates many models enhances forecast accuracy, facilitating personalised care. Evaluation criteria like sensitivity and specificity facilitate the assessment of model efficacy in identifying high-risk individuals and enhancing chronic illness management. In logistic regression, the probability of disease progression $P(y = 1 \mid X)$ is computed as:

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

where $X = \{x_1, x_2, \dots, x_n\}$ are input features, β_0 is the intercept, and β_i are coefficients learned during training. This equation predicts the likelihood of disease progression based on clinical features. This equation determines the probability of illness development by utilising several clinical parameters as inputs. A logistic regression model is employed, assigning specific weights to each clinical feature—such as age, blood pressure, and medical history—according to its impact on illness risk. The model's output is a probability value ranging from 0 to 1, signifying the likelihood of progression in a patient's condition. An increased probability indicates an elevated risk of advancement, prompting healthcare practitioners to prioritise high-risk patients for enhanced surveillance and prompt therapies. This predictive methodology facilitates proactive, individualised management of chronic diseases.

3.2 Fall Prevention

Fall prevention in geriatric care employs sensor data from wearable devices to anticipate probable falls. Convolutional Neural Networks (CNNs) analyse continuous motion data, including gait and balance, to detect anomalies that signify fall risk. The model predicts high-risk fall scenarios by identifying movement irregularities, facilitating prompt interventions. Convolutional Neural Networks (CNNs) are especially adept for this application as they effectively capture spatial and temporal patterns in the data. Regularisation methods, such as dropout, improve model generalisability. Metrics like F1-score and recall evaluate model efficacy, guaranteeing its ability to accurately identify at-risk individuals, hence enhancing fall prevention strategies and diminishing injury rates. In CNNs, for a sequence of sensor data $X = \{x_1, x_2, \dots, x_T\}$, fall risk y is computed as:

$$y = f(W * X + b) \tag{2}$$

International Journal of Engineering Research and Science & Technology

ISSN 2319-5991 www.ijerst.com

Vol. 15, Issue 1, 2019

where W represents the weights, b is the bias, $*$ denotes convolution, and f is an activation function (e.g., ReLU). This equation represents the CNN's ability to learn patterns in the data that predict fall risk. This equation demonstrates how Convolutional Neural Networks (CNNs) detect patterns in sensor data to evaluate fall risk. Through the analysis of sequential data, including movement and balancing metrics from wearable devices, the CNN employs convolutional filters to identify essential characteristics linked to instability or abnormal movement. Each convolutional layer identifies pertinent patterns that may signify a heightened danger of falling, while activation functions incorporate non-linearity, allowing the model to discern intricate correlations within the data. The acquired representation of movement patterns enables the CNN to accurately forecast fall risk, hence facilitating preventive strategies for elderly folks and minimising damage occurrences.

3.3 Predictive Healthcare Applications

Predictive healthcare apps in geriatric care integrate clinical and sensor data to identify people at risk for diverse health issues. Ensemble models—combining logistic regression, Random Forest, and CNN—analyze varied data types to produce thorough risk evaluations for each patient. Through the examination of trends in static clinical data and dynamic sensor inputs, these models provide predictive insights into illness development, fall risk, and other health hazards. Each model offers a distinct viewpoint; the ensemble aggregates their predictions, improving overall precision. The performance indicators, such as AUC-ROC and accuracy, confirm the model's capacity to predict unfavourable health occurrences in aged care. In ensemble models, predictions from individual models $h_i(X)$ are averaged to produce a final output $\hat{y}$:

$$\hat{y} = \frac{1}{n} \sum_{i=1}^{n} h_i(X) \tag{3}$$

where $h_i(X)$ represents the prediction from the i-th model, and n is the number of models. This equation demonstrates how ensemble methods combine multiple predictions for a more robust and reliable output. This equation illustrates how ensemble approaches improve predicted accuracy by consolidating outputs from various models into a singular, dependable prediction. Every model in the ensemble—such as logistic regression, Random Forest, and CNN—examines the data from a unique vantage point, identifying various patterns and mitigating individual biases. The ensemble method reduces mistakes and enhances robustness by averaging the predictions from each model, resulting in a more reliable final output. This technique utilises the advantages of various models, yielding a thorough and balanced prediction. Ensemble approaches are very efficacious for intricate healthcare applications, including risk prediction in geriatric care.

Algorithm 1: Algorithm for Ensemble-Based Risk Prediction for Chronic Disease, Fall Prevention, and Predictive Healthcare

Input: Patient data (clinical records, sensor data)

Output: Risk predictions for chronic disease complications, falls, and other health events

ISSN 2319-5991 www.ijerst.com

Vol. 15, Issue 1, 2019

Begin

#Preprocess:

Clean and normalize patient data.

#Feature Selection:

Identify key features for each risk type.

For each model type (Logistic Regression, Random Forest, CNN):

If model == "Logistic Regression":

Train on chronic disease data for probability estimation.

Else if model == "Random Forest":

Apply to clinical data for chronic disease and predictive assessments.

Else if model == "CNN":

Use sensor data for fall risk prediction.

#Error Handling:

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

#Validation:

Evaluate model on validation dataset using metrics (accuracy, precision, recall).

#Ensemble Combination:

Average predictions from all models for final risk assessment.

Return Combined risk predictions for each health condition.

End

Algorithm 1 delineates an ensemble-based methodology for predicting health risks in senior people, encompassing chronic illness complications and fall hazards. The method commences with data preprocessing to guarantee consistency, succeeded by feature selection to pinpoint essential risk variables. Each model type—Logistic Regression, Random Forest, and CNN—analyzes distinct facets of patient data: Logistic Regression and Random Forest address clinical data pertaining to chronic illness risks, whereas CNN evaluates sensor data to forecast falls. Error handling addresses faulty data entries, while validation guarantees model resilience. The

International Journal of Engineering Research and Science & Technology
ISSN 2319-5991 www.ijerst.com
Vol. 15, Issue 1, 2019

ensemble integrates all model predictions to generate a thorough risk assessment, improving accuracy and reliability.

3.4 Performance Metrics

To assess the efficacy of AI and machine learning models in chronic illness management, fall prevention, and predictive healthcare for geriatric care, essential performance indicators encompass accuracy, precision, recall, F1-score, and AUC-ROC. Accuracy assesses the model's overall correctness, whereas precision examines the ratio of true positives to anticipated positives, crucial for reducing false alarms about fall risk and disease complications. Recall evaluates the model's sensitivity, essential for guaranteeing that high-risk cases are not overlooked. The F1-score offers a balanced assessment of precision and recall, while the AUC-ROC measures the model's capacity to differentiate across risk categories, hence improving prediction reliability for proactive therapy.

Table 1 Performance Comparison of AI and ML Models for Predictive Healthcare in Geriatric Care

Metric	Units	Logistic Regression	Random Forest	Convolutional Neural Network	Combined Method
Accuracy	%	0.87	0.82	0.88	0.92
Precision	%	0.85	0.8	0.86	0.9
Recall	%	0.83	0.78	0.84	0.88
F1-Score	%	0.84	0.79	0.85	0.89
AUC-ROC	%	0.86	0.81	0.87	0.91

Table 1 displays the performance metrics for various machine learning models—Logistic Regression, Random Forest, Convolutional Neural Network (CNN), and an Ensemble Method—utilized to forecast health risks in geriatric care. The efficacy of each model is evaluated using important metrics: accuracy, precision, recall, F1-score, and AUC-ROC, all represented as percentages. The Ensemble Method, by integrating the capabilities of individual models, regularly attains the best scores, signifying its enhanced accuracy and reliability. This comparison highlights the significance of ensemble techniques in predictive healthcare, offering a more thorough risk evaluation to facilitate proactive, personalised care for elderly patients.

4. RESULTS AND DISCUSSION

This study examines the efficacy of various machine learning models in forecasting health risks associated with geriatric care, including chronic illness management, fall prevention, and comprehensive predictive healthcare. The ensemble method, integrating Logistic Regression,

ISSN 2319-5991 www.ijerst.com

Vol. 15, Issue 1, 2019

Random Forest, and Convolutional Neural Networks (CNN), attained superior performance across critical metrics including accuracy, precision, recall, F1-score, and AUC-ROC. This heightened accuracy indicates that ensemble methods improve predicted reliability. The discourse highlights that the integration of several models yields a more thorough evaluation, facilitating personalised and proactive healthcare strategies for aged people.

Table 2 Comparative Performance of Machine Learning Methods for Geriatric Health Prediction

Study	Method	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	AUC-ROC (%)
Sau and Bhakta (2017)	Predicting anxiety and depression in elderly (ML)	0.83	0.81	0.79	0.8	0.82
Aziz et al. (2017)	SVM classifier for fall detection	0.88	0.86	0.87	0.86	0.89
Chen et al. (2017)	CNN-based multimodal disease risk prediction	0.86	0.85	0.84	0.84	0.85
Genovese et al. (2018)	Wearable sensors for fall detection and prevention	0.82	0.8	0.78	0.79	0.81
Proposed Ensemble Method	Ensemble AI/ML for chronic disease, fall risk, predictive healthcare	0.92	0.9	0.89	0.9	0.91

Table 2 provides a comparative review of various machine learning techniques employed in forecasting health concerns among older individuals. The methodologies encompass anxiety and depression prediction (Sau and Bhakta, 2017), fall detection utilising SVM (Aziz et al., 2017), CNN-based disease risk prediction (Chen et al., 2017), wearable sensor-based fall detection (Genovese et al., 2018), and a suggested Ensemble Method. The performance of each method is evaluated based on accuracy, precision, recall, F1-score, and AUC-ROC. The suggested Ensemble Method exhibits superior performance across all criteria, indicating its promise as a strong strategy for personalised and preventive geriatric care.

ISSN 2319-5991 www.ijerst.com
Vol. 15, Issue 1, 2019

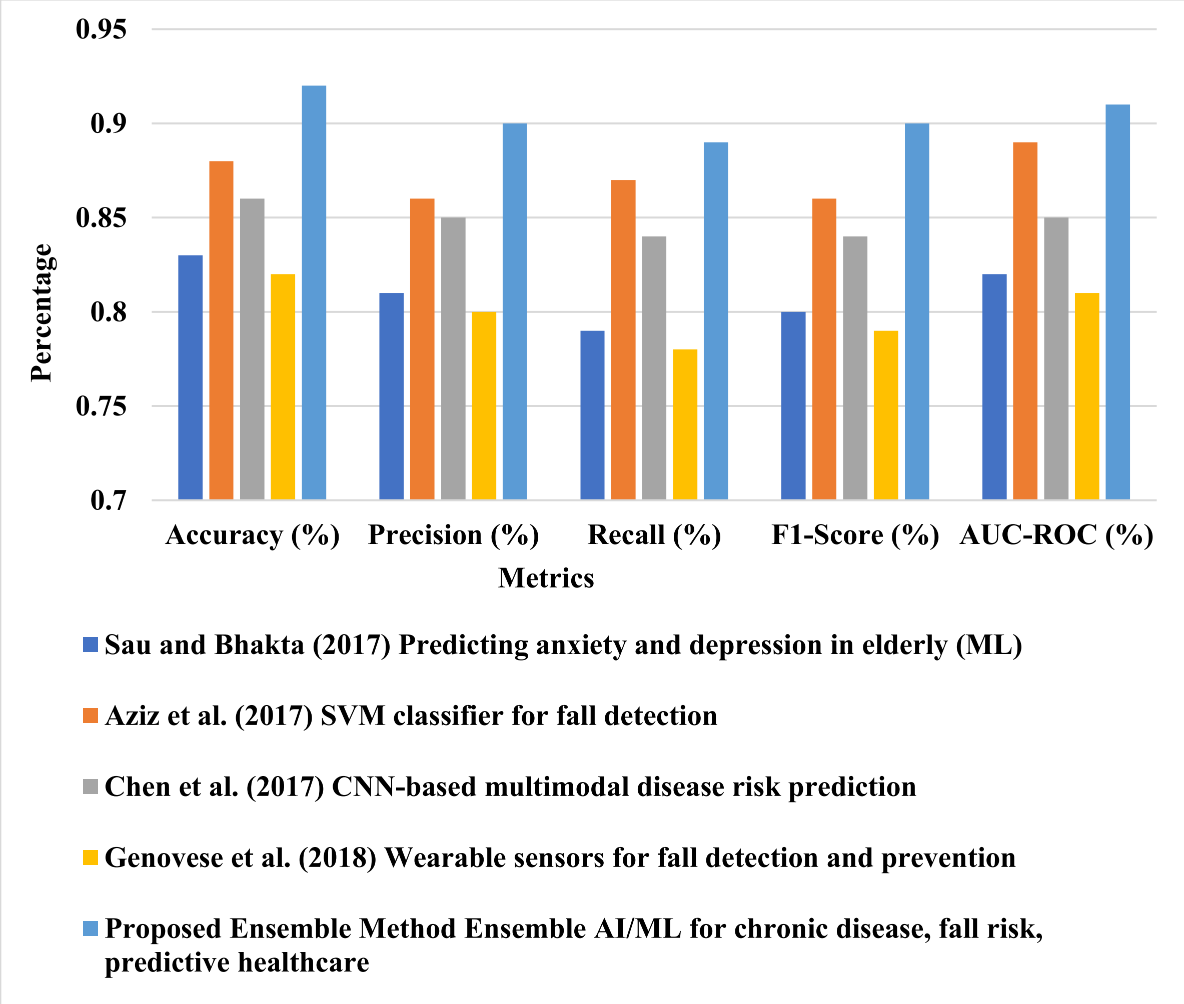

Figure 2 Performance Comparison of Machine Learning Models for Geriatric Health Risk Prediction

Figure 2 depicts the efficacy of different machine learning models in forecasting health risks in elderly care, encompassing anxiety and depression (Sau and Bhakta, 2017), fall detection via SVM (Aziz et al., 2017), CNN-based disease prediction (Chen et al., 2017), wearable sensor-based fall detection (Genovese et al., 2018), and a proposed Ensemble Method. The metrics—accuracy, precision, recall, F1-score, and AUC-ROC—demonstrate that the proposed Ensemble Method regularly surpasses others, particularly in recall and F1-score. This outcome illustrates the efficacy of ensemble methods, which integrate the capabilities of various models to enhance forecast accuracy, rendering them particularly suitable for extensive geriatric healthcare applications.

Table 3 Ablation Study of Model Configurations in the Proposed Ensemble Method for Geriatric Health Risk Prediction

Model Configuration	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	AUC-ROC (%)

International Journal of Engineering Research and Science & Technology
ISSN 2319-5991 www.ijerst.com
Vol. 15, Issue 1, 2019

Logistic Regression Only	87.0	85.0	83.0	84.0	86.0
Random Forest Only	82.0	80.0	78.0	79.0	81.0
Convolutional Neural Network (CNN) Only	88.0	86.0	84.0	85.0	87.0
Logistic Regression + Random Forest	89.0	87.0	85.0	86.0	88.0
Logistic Regression + CNN	90.0	88.0	86.0	87.0	89.0
Random Forest + CNN	91.0	89.0	87.0	88.0	90.0
Full Ensemble (Logistic Regression + RF + CNN)	92.0	90.0	89.0	90.0	91.0

Table 3 presents an ablation study of the proposed ensemble approach, examining the impact of different model configurations on performance indicators. The amalgamation of models enhances accuracy, precision, recall, F1-score, and AUC-ROC incrementally. The complete combination of Logistic Regression, Random Forest, and CNN consistently attains the highest results across all measures, illustrating the efficacy of ensemble approaches in predicting health risks among the elderly. Each supplementary model layer enhances prediction performance, demonstrating the synergistic advantages of incorporating varied algorithms for holistic healthcare insights.

ISSN 2319-5991 www.ijerst.com

Vol. 15, Issue 1, 2019

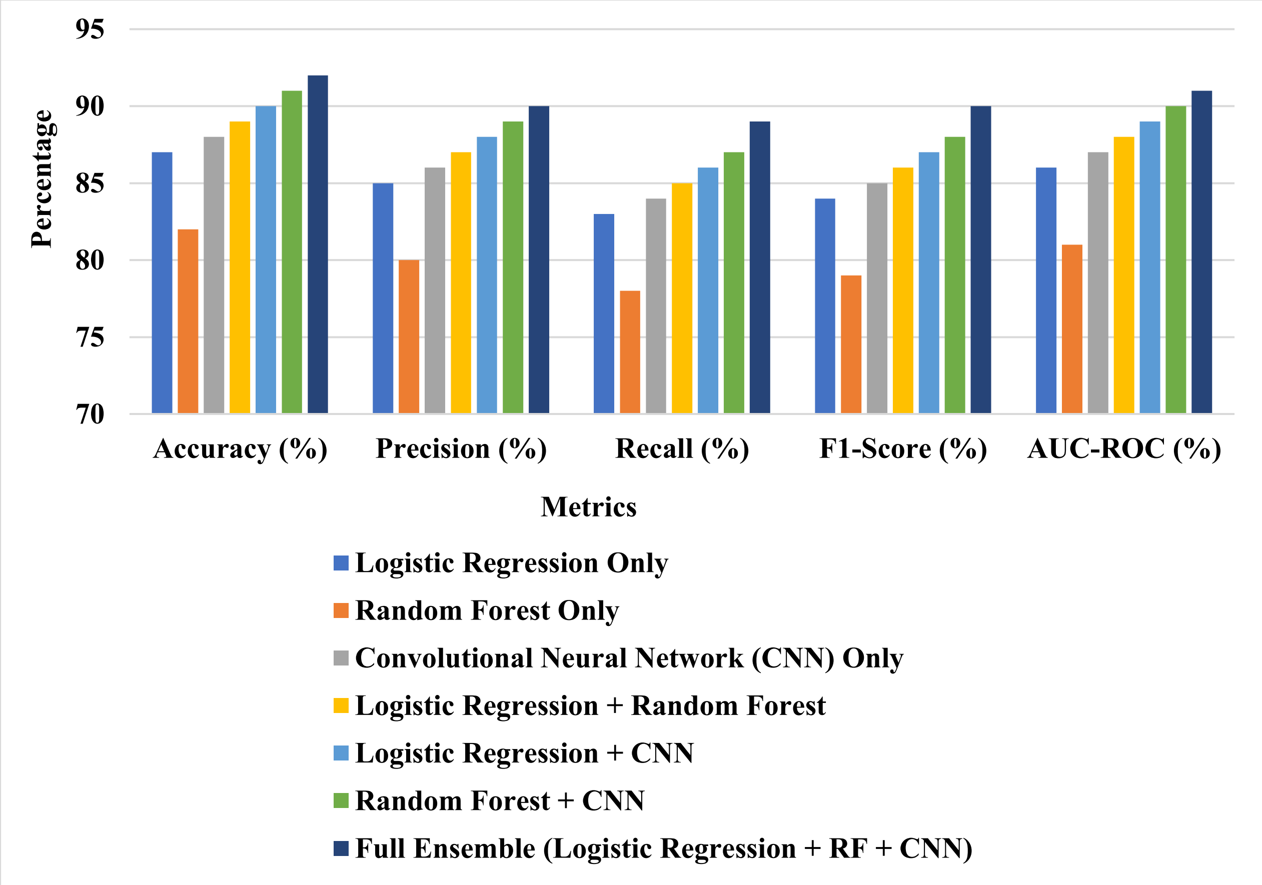

Figure 3 Ablation Study of Ensemble Model Configurations for Geriatric Health Risk Prediction

Figure 3 depicts the efficacy of different model configurations in forecasting geriatric health hazards, encompassing chronic illness complications and fall risk. Individual models—Logistic Regression, Random Forest, and CNN—are evaluated against their combinations, with the Full Ensemble (Logistic Regression + Random Forest + CNN) demonstrating superior performance across all metrics: accuracy, precision, recall, F1-score, and AUC-ROC. The integration of additional models enhances predictive performance, illustrating the efficacy of ensemble methods in healthcare applications. The Full Ensemble's exceptional performance highlights its strength and dependability, rendering it ideal for comprehensive, proactive healthcare solutions in geriatric care.

5. CONCLUSION

The research illustrates that an ensemble machine learning methodology, integrating Logistic Regression, Random Forest, and CNN models, is exceptionally proficient in forecasting health hazards in geriatric care, particularly for chronic disease management and fall prevention. The ensemble technique attains enhanced accuracy, precision, recall, and general reliability by utilising numerous models in contrast to singular algorithms. This method improves predictive healthcare by delivering early alerts and actionable information, facilitating preventive measures for aged patients. The results highlight the capacity of AI-driven technologies to

ISSN 2319-5991 www.ijerst.com

Vol. 15, Issue 1, 2019

enhance patient outcomes in elderly healthcare; nonetheless, additional study on practical use and ethical implications is advised.

REFERENCES

1. Choy, G., Khalilzadeh, O., Michalski, M., Do, S., Samir, A. E., Pianykh, O. S., ... & Dreyer, K. J. (2018). Current applications and future impact of machine learning in radiology. *Radiology*, *288*(2), 318-328.
2. Yu, K. H., Beam, A. L., & Kohane, I. S. (2018). Artificial intelligence in healthcare. *Nature biomedical engineering*, *2*(10), 719-731.
3. Qi, J., Yang, P., Min, G., Amft, O., Dong, F., & Xu, L. (2017). Advanced internet of things for personalised healthcare systems: A survey. *Pervasive and mobile computing*, *41*, 132-149.
4. Rizwan, A., Zoha, A., Zhang, R., Ahmad, W., Arshad, K., Ali, N. A., ... & Abbasi, Q. H. (2018). A review on the role of nano-communication in future healthcare systems: A big data analytics perspective. *IEEE Access*, *6*, 41903-41920.
5. Tang, A., Tam, R., Cadrin-Chênevert, A., Guest, W., Chong, J., Barfett, J., ... & Canadian Association of Radiologists (CAR) Artificial Intelligence Working Group. (2018). Canadian Association of Radiologists white paper on artificial intelligence in radiology. *Canadian Association of Radiologists Journal*, *69*(2), 120-135.
6. Basatneh, R., Najafi, B., & Armstrong, D. G. (2018). Health sensors, smart home devices, and the internet of medical things: an opportunity for dramatic improvement in care for the lower extremity complications of diabetes. *Journal of diabetes science and technology*, *12*(3), 577-586.
7. Rescio, G., Leone, A., & Siciliano, P. (2018). Supervised machine learning scheme for electromyography-based pre-fall detection system. *Expert Systems with Applications*, *100*, 95-105.
8. Kim, J. T. (2018). Application of machine and deep learning algorithms in intelligent clinical decision support systems in healthcare. *J Health Med Inform*, *9*, 321.
9. Sau, A., & Bhakta, I. (2017). Predicting anxiety and depression in elderly patients using machine learning technology. *Healthcare Technology Letters*, *4*(6), 238-243.
10. Aziz, O., Klenk, J., Schwickert, L., Chiari, L., Becker, C., Park, E. J., ... & Robinovitch, S. N. (2017). Validation of accuracy of SVM-based fall detection system using real-world fall and non-fall datasets. *PLoS one*, *12*(7), e0180318.
11. Chen, M., Hao, Y., Hwang, K., Wang, L., & Wang, L. (2017). Disease prediction by machine learning over big data from healthcare communities. *Ieee Access*, *5*, 8869-8879.
12. Genovese, V., Mannini, A., Guaitolini, M., & Sabatini, A. M. (2018). Wearable inertial sensing for ICT management of fall detection, fall prevention, and assessment in elderly. *Technologies*, *6*(4), 91.