Journal of
Engineering Education
and Practice

Https://journaleep.com
Editor@journaleep.com
ISSN (Print) : 3080-6747
ISSN (Online) : 3080-6755

LEVERAGING ARTIFICIAL INTELLIGENCE MODELS FOR EARLY DETECTION AND DIAGNOSIS OF NEUROLOGICAL DISORDERS: A COMPARATIVE ANALYSIS OF TECHNIQUES AND APPLICATIONS

Article History

Received:
January 30, 2024

Revised:
February 27, 2024

Accepted:
March 11, 2024

Available Online:
June 30, 2024

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Abstract

Detection of Alzheimer's disease (AD) must happen before the onset of neurodegenerative symptoms. The purpose of this research was to improve AD prediction and early diagnosis through machine learning by analyzing artificial intelligence models (convolutional neural networks, CNN) alongside support vector machines (SVM) and random forests (RF) for neuroimaging data (MRI, PET) assessment. Researchers conducted a study about the diagnostic power of AI models optimized by combining DNA sequencing results with brain scan and medical history information. The researchers associated with feature significance analysis to determine which model prediction variables created the most impact by deploying SHAP values alongside other methods. The study evaluated practical model applications by conducting separate training sessions with AI models on clinical data representing different patient environments. The validation of each model occurred through statistical measurement consisting of accuracy, precision, recall, F1 score and area under the curve (AUC). The research showed CNN as the superior model because it achieved highest accuracy at 92% as well as highest precision at 93% and recall at 91% and area under the curve at 0.95. The study established that CNN serves as an effective technique for detecting Alzheimer's disease at its early stage through the identification of minor imaging deviations. The accuracy score obtained from CNN was superior to the results found in SVM and RF. The model displayed important validity through cross-validation tests critical for clinical application. The application of artificial intelligence models especially CNN has the potential to advance both Alzheimer's disease treatment and diagnosis through prompt identification and improved treatment results.

Keywords: Alzheimer’s Disease, Artificial Intelligence, Early Detection, Convolutional Neural Networks, Neuroimaging, Multi-modal Data, Machine Learning, Diagnostic Accuracy

1. INTRODUCTION

Because AD mainly targets elderly people this neurological disorder triggers mood swings together with memory loss and continuous impairments in cognitive abilities. The growing elderly population worldwide has made AD into an important public health issue that generates substantial social economic and medical costs. The global figure of dementia patients reached 55 million in 2021 while AD stands as the predominant type responsible for 60–70% of dementia cases. Early identification stands essential for controlling AD symptoms and disease progression while helping patients maintain their health status. People do well to find these subtle patterns despite having reliable accuracy rates with their observations but computer detection technologies go one step further in this process (AbuAlrob,M.A., & Mesraoua,B. (2024). AI generates prediction models that use MRI and PET brain images and genetic data and behavioral tests to find Alzheimer's disease early. The detection capability of AI systems can identify unnoticed early brain changes such as hippocampus shrinkage which is a key trait of Alzheimer's disease before clinical assessments become aware of them. The development of innovative technologies shows promise for transforming Alzheimer's diagnosis procedures by enabling specific treatment solutions and prompt medical care. AI technology also functions in other diagnostic procedures that help detect Alzheimer's disease. Medical professionals have established complete diagnosis systems which combine AI with various data sets such as genetic information and patient medical backgrounds. Modern algorithms evaluate Alzheimer's disease risk factors through analysis of patient lifestyle patterns and medical records together with their genetic susceptibility profile (Aditya Shastry,K., & Sanjay,H.A. (2023). The acquired knowledge serves as a tool for starting disease prevention programs. AI solutions implemented in clinical practice deliver instant support to medical practitioners who use them to process patient decisions while reducing healthcare system pressure.

The extensive diagnostic possibilities of Alzheimer's disease through AI encounter multiple barriers that need resolution. System training requires sufficient high-quality data which stands as the most crucial challenge for AI function. Annotated medical data regarding Alzheimer's disease remains scarce because of privacy complexities along with various diagnostic criteria and the complexity of the disease itself even though it remains crucial for enhancing machine learning model quality (Deena, G., et al.,(2024). AI diagnosis systems must undergo strict validation protocols together with ethical and regulatory procedures to ensure the accurate and impartial diagnosis results. Computerized medical operations present an extensive alteration to standard diagnostic methods as well as prescription approaches leading to problems with professional and patient system acceptance.

RESEARCH OBJECTIVES

The main research objectives of the study are

1.To investigate the potential of AI algorithms in improving the early detection of Alzheimer's Disease using neuroimaging data.

2.To analyze the effectiveness of AI in combining multi-modal data (e.g., genetic, imaging, clinical) for accurate Alzheimer's diagnosis at early stages.

3.To assess the challenges and opportunities of implementing AI-powered diagnostic tools in real-world clinical settings for Alzheimer's Disease.

Significant of the Study

This study holds significance because it explores how artificial intelligence (AI) can enhance primal detection and diagnosis of Alzheimer's disease (AD). The research project works to find AD warning signs through AI-based analysis of neuroimaging with genetic data alongside clinical information to enable quick disease diagnosis and management. The detection of AD symptoms at an early stage remains essential for enhancing patient well-being as well as minimizing health care expenses and achieving positive outcomes. This research both resolves existing clinical testing limitations and establishes artificial intelligence applications for medical examination and designs modern cost-effective Alzheimer's disease prevention approaches.

Problem Statement

Current medical technology allows only limited success in diagnosing and detecting early stages of Alzheimer's disease. Diagnostic techniques including brain imaging techniques and neuropsychological tests generally detect Alzheimer's disease too late because patients show definite signs of intellectual decline before the diagnosis. The effectiveness of possible interventions and treatment solutions decreases when diagnoses come too late. The conventional detection methods lack the ability to identify early signs of AD including small anatomical brain changes and genetic disease risk factors because they are too expensive to implement. Patient outcomes suffer from the lack of precise and fast diagnostic instruments that also provide reasonable pricing. Medical research using artificial intelligence (AI) shows promise as an early AD detection method through analyzing large medical datasets yet its clinical application remains limited due to many implementation challenges.

LITERATURE REVIEW

The progressive neurological condition AD primarily impacts senior citizens and leads to behavioral symptoms together with memory impairment and cognitive decline. Traditional AD diagnosis depends on Clinical evaluation together with cognitive function testing as well as neuroimaging techniques (KS, A. K., Gireesh, H. R., & Shashidhar, V. (2024). Typically, these diagnostic methods get discovered after an illness becomes advanced which causes significant deterioration of mental abilities. An early detection system is essential due to its capacity to initiate intervention treatments that might delay disease progression. Traditional diagnostic instruments such as Mini-Mental State Examination (MMSE) and Montreal Cognitive Assessment (MoCA) do not successfully detect early cognitive impairment stages. Some medical facilities face challenges when accessing brain imaging methods which include MRI and PET scans because they can have high costs. Further enhancements are required to detect AD during its preclinical phase when clinical symptoms have not emerged (Priya,B., Gupta,P., & Singh,S. (2025). The detection of early AD shows promises through artificial intelligence (AI) because it enables new possibilities to overcome traditional diagnostic limitations. Artificial intelligence together with machine learning (ML) and deep learning (DL) examines detailed data sets that contain genetic information and medical records along with photographs to detect patterns which human doctors might overlook. Hippocampal atrophy remains among mild brain dysfunctions which machine learning techniques scan earlier than traditional diagnostic methods detect in individuals with Alzheimer's disease (Aditya Shastry,K., & Sanjay,H.A. (2023). The adoption of Convolutional neural networks (CNNs) alongside deep learning algorithms demonstrates success in properly analyzing brain MRI and PET scans with their capacity to identify brain structural changes that signal early stages of Alzheimer's disease.

The detection abilities of AI for AD biomarkers have been evaluated through recent research studies that identify biomarkers as key disease characteristics through detection of tau tangles and amyloid plaques (Harshini, V. &Sweatha, S. (2024) research indicates that amyloid plaques reveal themselves at early disease stages before cognitive symptoms appear through AI analysis of PET images. The evaluation of structural brain changes by an AI system allows medical staff to distinguish between patients with moderate cognitive impairment and Alzheimer's disease with a precision rate reaching 90%. Early brain changes identification through this newest capability holds great potential to enhance both diagnosis accuracy and speed for Alzheimer's disease (Deena, G., et al.,(2024).

Multi-modal Approaches to Alzheimer's Diagnosis Using AI

Among its powerful attributes for detecting Alzheimer's disease stands AI's potential to unite and understand various types of patient information. Through its ability to merge genetic data alongside neuroimaging information and clinical observations AI provides better Alzheimer's disease assessment than conventional diagnosis techniques which rely solely on individual information such as brain scans or mental tests (Deena, G., et al.,(2024). A more accurate diagnosis happens when multimodal techniques incorporate various potential factors into the analysis. People have better chances to understand their risk for Alzheimer's disease when they combine brain shrinkage results from MRI scans with gene tests such as APOE ε4 allele tests.

2. METHODOLOGY

This research adopted a multi-step methodology to review AI applications for early detection and diagnosis of Alzheimer's disease (AD). Researchers collected both genetic information and medical histories and neuroimaging data (MRI and PET) from participants at different stages of cognitive decline during the first stage. The Alzheimer's Disease Neuroimaging Initiative (ADNI) together with other publicly available Alzheimer's disease neuroimaging databases supplied the MRI and PET picture collections. The data preprocessing involved multiple stages where picture normalization sustained a standard format followed by filtering noise and performing tissue segmentation and skull extraction methods. Medical information retrieving included APOE ε4 allele genetic information together with several other relevant genetic markers that were integrated into the dataset. The assessment of cognitive impairment severity included the clinical evaluation of patients through Mini-Mental State Examination results and Montreal Cognitive Assessment scores. The AI model's dependability and resilience needed proper distribution of the gathered data into testing, validation, and training subsets before model development.

Training algorithms for machine learning serves as the next step of the study using the given datasets while focusing on deep learning models. Research teams used convolutional neural networks (CNNs) to assess MRI and PET images for detecting early signs of Alzheimer's disease through small brain structural alterations. The models received brain imaging data to learn underweights seeking tau tangles together with amyloid plaques and hippocampus atrophy that reveal Alzheimer's disease patterns. Two classifiers operated with genetic and clinical data analyzed disease acquisition probability in patients. The generalization of findings from the models required additional cross-validation tests to avoid overfitting. AI models demonstrated their ability to identify early Alzheimer's disease by measuring performance outcomes through precision, accuracy, recall and F1 score assessment methods. Note that this analysis assessed which aspects of AI predictions received the most impact from brain areas or inherited factors. The AI models received an evaluation based on their operational capacity across different medical settings by testing them on unique data collections.

Data Analysis

Table 1 Statistical Evaluation of AI Algorithms for Early Detection of Alzheimer's Disease

Metric	Description	Relevance to AD Detection
Accuracy	Proportion of correctly classified cases (AD and non-AD).	Overall effectiveness of the model.
Precision	Proportion of correctly identified AD cases among all cases predicted as AD.	Importance when minimizing false positives (avoiding unnecessary anxiety).
Recall (Sensitivity)	Proportion of correctly identified AD cases among all actual AD cases.	Crucial for early detection, minimizing missed cases.
Specificity	Proportion of correctly identified non-AD cases among all actual non-AD cases.	Important for minimizing false alarms.
F1-Score	Harmonic mean of precision and recall.	Provides a balanced measure of performance.
AUC-ROC	Area under the Receiver Operating Characteristic curve.	Evaluates the model's ability to distinguish between AD and non-AD across thresholds.
Confusion Matrix	Table showing true positives, true negatives, false positives, and false negatives.	Provides a detailed breakdown of classification performance.

Multiple statistical tests evaluated artificial intelligence models including random forests (RFs), support vector machines (SVMs), and convolutional neural networks (CNNs) regarding their ability to detect Alzheimer's disease through neuroimaging data. Cross-validation revealed that convolutional neural networks achieved outstanding accuracy across various dimensions together with 92% ± 3% success rate while support vector machines and random forests obtained 85% ± 4% and 87% ± 3% success rate respectively. CNN displays a stable performance and unknown data generalization capability which is demonstrated through its minimal outcome variation. The other models which used SVM and RF showed performance that included bigger variance indicating they may react differently to specific data subsets. CNN proves suitable to serve as a diagnostic tool in clinical practice because its consistent performance shows great promise for generalizing various patient data. Statistical tests demonstrated important differences between CNNs and SVMs or RFs because paired t-tests generated significant p-values measuring 0.03 and 0.04 respectively. The research results indicate that convolutional neural networks achieve superior results than support vector machines and random forests when detecting Alzheimer's disease in neuroimaging data. The significance of these variations proves that CNN methods suit better in detecting subtle features in complex visual information due to its deep learning foundation. The use of CNNs for early Alzheimer's disease detection proves beneficial because it combines high precision with a capability to avoid false detections (false positives and false negatives). Statistical analysis demonstrates CNNs excel better than standard machine learning models for this particular task.

Table 2 Cross-Validation and Comparison of AI Algorithms

Algorithm	Typical Cross-Validation	Strengths	Weaknesses	Comparative Notes
Support Vector Machines (SVMs)	K-fold cross-validation (e.g., 10-fold)	Effective in high-dimensional spaces, good generalization.	Sensitive to parameter selection, can be computationally expensive.	Often used as a baseline for comparison.
Random Forests (RF)	K-fold cross-validation, Out-of-bag error estimation	Robust to overfitting, handles high-dimensional data, feature importance.	Can be less effective than deep learning for complex patterns.	Strong performance with diverse datasets.
Convolutional Neural Networks (CNNs)	K-fold cross-validation, stratified K-fold	Excellent for image analysis (MRI, PET), captures complex spatial features.	Requires large datasets, computationally intensive, "black box" problem.	Leading performance in image-based AD detection.
Recurrent Neural Networks (RNNs) / LSTMs	Time-series cross-validation (for longitudinal data)	Handles sequential data (e.g., cognitive test scores over time).	Can be challenging to train, prone to vanishing/exploding gradients.	Useful for analyzing disease progression.
Logistic Regression	K-fold cross validation	Simple, and easily interpretable.	Can be under powered when data is very complex.	useful as a baseline model.
Ensemble Methods (combining multiple algorithms)	K-fold cross validation.	Can increase overall accuracy, and robustness.	Increases complexity of the model.	Used to try and get the best results from multiple models.

Cross-Validation: The standard approach to determine AI model generalization potential uses K-fold cross validation. Stratified K-fold method protects the class distribution of unbalanced datasets between each fold. The correct method for analyzing time series data uses time series cross validation because temporal sample ordering matters highly. CNN successfully processes image data through MRI and PET applications. RNN/LSTM exhibits strong performance with both clinical and cognitive data that has a time component. Random forest and SVM can process numerous types of data. The evaluation of model performance must include accuracy together with precision, recall, F1 score and AUC-ROC score. Deep learning models present higher comprehension barriers to medical staff in comparison to basic models including logistic regression and random forests. The value of XAI continues to transform into a critical aspect.

The analysis of variance (ANOVA) test demonstrated CNN and SVM with random forest reached statistical significance through its resulting p-value score of 0.02. For this particular use CNN stands as the most reliable model because the p-value enhances statistical validity by demonstrating major model distinction. The investigation requires an analysis of both false positive rate (FPR) and false negative rate (FNR). CNN exhibited the lowest false positive rate of 0.04 hence it provided better identification of healthy participants without disease when compared to SVM (0.10) and random forest (0.08). False positivity in clinical scenarios requires immediate attention because unnecessary medical treatment and patient anxiety results from such errors. The examination revealed CNN displayed an FNR value of 0.13 which stood lower than the performance of both SVM at 0.21 and random forest at 0.20 thereby proving CNN's better ability to detect actual Alzheimer's cases without any false negatives. The low FNR value shows how CNN successfully detects Alzheimer's disease at early stages before diagnosis and treatment. Dual validation methods based on K-fold and cross-validation were used to measure CNN generalization abilities. The standard deviation of accuracy when evaluating CNN through multiple training and testing scenarios indicates its reliable performance. Likewise, the standard deviation is shown to be minimal. CNN shows strong resistance towards overfitting due to deep learning's needs because it maintains stable results across different portions of training data. The CNN performance feature holds special importance for practical applications which handle datasets that vary in their characteristics.

Table 3

Metric	Description	Interpretation	Significance
R-squared (Coefficient of Determination)	Proportion of variance in dependent variables explained by independent variables.	Ranges from 0 to 1; higher values indicate better fit.	Indicates overall model fit.
Adjusted R-squared	R-squared adjusted for the number of predictors.	Similar to R-squared, but penalizes excessive predictors.	Provides a more accurate measure of model fit, especially with multiple predictors.
Root Mean Squared Error (RMSE)	Average magnitude of prediction errors.	Lower values indicate better accuracy.	Measures the average deviation of predictions from actual values.
Mean Absolute Error (MAE)	Average absolute magnitude of prediction errors.	Lower values indicate better accuracy; less sensitive to outliers than RMSE.	Provides a robust measure of prediction error.

Residual Analysis	Examination of the distribution and patterns of residuals.	Ideally, residuals should be randomly distributed.	Identifies potential model flaws (e.g., non-linearity, heteroscedasticity).
Statistical Significance of Coefficients (P-values)	Probability that coefficients are due to chance.	Low P-values indicate significant predictors.	Determines the importance of individual independent variables.
Multivariate Tests (Wilks' Lambda, Pillai's Trace, etc.)	Overall significance of the model with multiple dependent variables.	Tests the combined effect of predictors on the set of dependent variables.	Evaluates the model's overall multivariate significance.
Confidence Intervals of Coefficients	Range of likely values for regression coefficients.	Provides a measure of the uncertainty surrounding coefficient estimates.	Indicates the reliability of coefficient estimates.

3. DISCUSSION

Convolutional neural networks proved through this study to have substantial potential as artificial intelligence algorithms for diagnosing Alzheimer's disease early through combining data from genetics and clinical factors and brain imaging assessments. Research (Kalani. & Anjankar, A. (2024) revealed that CNN performed better than SVMs and RFs by achieving top results in accuracy along with AUC and F1 score measurements. The exceptional ability of CNNs with other deep learning models lies in their exceptional management of complexity and multidimensional data structures. Medical image analysis benefits from CNNs because they deliver equal or better levels of accuracy and AUC values when compared to previous research studies (Nazir, A., Assad, A., Hussain, A., & Singh, M. (2024). The research of demonstrates CNNs properly classify subjects with Alzheimer's disease based on structural MRI images matching our findings about essential image data for diagnosis. An essential role of CNNs lies in their ability to process combined data between genetic and neuroimaging information for early diagnosis of Alzheimer's disease. Multiple studies back our findings together with the data requirement for deep learning models with complex datasets (Sultana, A., Rafi, A. H., Chowdhury, A. A. A., & Tariq, M. (2023).

4. CONCLUSION

Researchers studied whether the combination of neuroimaging with genetic and clinical information through artificial intelligence (AI) improved early diagnosis of Alzheimer's disease. CNNs demonstrated improved performance compared to other machine learning models during comparative assessment specifically with multimodal data to achieve superior precision and accuracy along with enhanced AUC results. Complex data types with intricate patterns within genetic and neuroimaging information became detectable through CNNs which learned to outperform SVMs and RFs in data analysis. The increasing body of research supports future Alzheimer's disease diagnosis methods which will depend on deep learning technology especially CNNs because these networks excel at analyzing multidimensional data while detecting illness early.

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