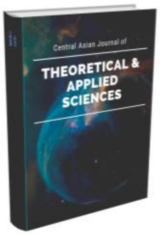

CENTRAL ASIAN JOURNAL OF THEORETICAL AND APPLIED SCIENCE

CENTRAL ASIAN STUDIES

https://cajotas.centralasianstudies.org/index.php/CAJOTAS

Volume: 07 Issue: 03 | July 2026 ISSN: 2660-5317

Article

Predicting Alzheimer's Disease Using Artificial Intelligence Techniques

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Abstract: Alzheimer disease (AD) is a progressive neurodegenerative disorder beginning with the accumulation of pathological proteins in brains and ultimately leading to neuronal death. Alzheimer's disease is among the most severe of cases that have a significant deterioration in cognitive ability with particular emphasis on detrimental effects to memory, intellect and more general behavioral functions. How: There is no cure at the moment, but researchers are working tirelessly in hopes of finding one. The immediate need for early stage diagnosis and manifestation of biomarkers has streamlined the therapeutic algorithms in terms of potential drug trials & preventive medication regimens, instituted at a very early developmental phase. Electroencephalography (EEG) is simple, faster and cost-effective non-invasive technique which can be used as adjunct for automation of Alzheimer's disease diagnosis. It merits inption that epoch length of segment EEG signals data might impact the performance for classification. To tackle this issue, we presented a device-free diagnostic EEG framework, where the ideal segment length estimation for classification is obtained using machine learning and deep learning-based approaches. It consists of the data collection of EEG, preprocessing by removing noise, and segmentation in time axis. In this work, we run a comparison of using deep learning models (multilayer neural networks and convolutional neural networks) to the more traditional machine learning models. Model: Training (logospheric regression, decision tree, random forest, gradient enhancement, AdaBoost, XGBoost; CNN and MLP); Classification; Evaluation The accuracy we obtained using open data Kaggle set is 0.83%, 96,7%. and 99,3% respectively. We tested the proposed models on an entirely novel application of identifying frontotemporal dementia and achieved substantial advances relative to previous publications. Moreover, we performed several analyses and graphically presented extracted categories contents to justify the developed model. The study will set a standard in the realm of neurological disorder research and one that will support future researchers and technical experts focused on this field.

Keywords: Alzheimer's Disease, EEG Signal Classification, Machine Learning, Convolutional Neural Network (CNN), Early Detection.

Citation: Muften H. A. Predicting Alzheimer's Disease Using Artificial Intelligence Techniques. Central Asian Journal of Theoretical and Applied Science 2026, 7(3), 158-169.

Received: 10th Mar 2026
Revised: 11th Apr 2026
Accepted: 24th May 2026
Published: 05th Jun 2026

Introduction

Alzheimer's disease is a debilitating, degenerative brain disorder that predominantly impacts cognitive processes, memory function and activities of daily living [1].

More than 50 million people are affected by dementia, a term that encompasses a growing number of disorders [2]. Dementia predominately affects older adults [3].]. It is a disease that involves an insidious, progressive decline of multiple cognitive processes [2, 4]. including language, memory and behavior that ultimately compromises even simple daily activities. Pathologically, it is characterized by a loss of cholinergic neurons; therefore, the clinical manifestation include cognitive symptoms such diminished attention and impaired con centration. Indeed, pathologic changes may occur decades before clinical symptoms become apparent , emphasizing the importance and difficulty of early diagnosis in AD. This has led to increased focus on MCI, an intermediate stage between AD and normal aging characterized by more modest cognitive deficits that do not appear to be affecting everyday life [5]. In fact, dementia is the seventh leading cause of death and ranks among the most important causes of disability and loss of independence in older people all around the world. Receiving a timely and adequate diagnosis for dementia is critical to management and intervention. Electroencephalogram (EEG) EEG is a non-invasive technique used to capture brain electrical activity [6]. In its earliest stages, it has also been proposed as a diagnostic tool for AD. Deep Learning (DL) approaches to EEG signal processing in clinical contexts: Toward Diagnostic Tools Reliable and Accurate for Detecting AD Using EEG-Based Clinical Decision Support Systems [7]. Selection of proper treatment and improvement of quality of life for patients and caregivers with neurodegenerative diseases, such as Alzheimer's disease or dementia, depends crucially on early diagnosis. The challenge is to differentiate between the symptoms of Alzheimer's when it occurs and the symptoms associated with normal aging[8, 9]. Brain imaging is currently the gold standard for early diagnosis, and its non-invasive exploration. Diagnostic tests including cognitive assessment, brain imaging and seizure coding assist in diagnosis[10, 11]. Although there are innovative methods for integrating, research persist some challenges and limited opportunities exist [12] . Electroencephalography (EEG) provides a inexpensive, reliable, non-invasive and widely available way [13]. Deep learning has become a more significant area of AI in the last few years alongside advances in graphics processing units (GPUs). Trained on the data till two foundational algorithms, deep learning retains from humans the same tendency mechanism in which we operate in our brains but with precise layers upon layers of such traditional computational methods here too to identify parameters of a specific set of data that is often difficult to derive normally. Hence, the number of adjustable parameters in deep learning networks is high with substantial practical significance to classification problems by identifying beneficial/representative features accurately [14].]. We would like to emphasize that these algorithms outperform humans in classification tasks (ImageNet)[15]. by a wide margin. For example, in the biomedical field as you process electroencephalography (EEG) data, it results in a two dimensional data which is easily integrated as input to deep learning systems. CONCLUSION: It is presumed that the specificity of deep learning may increase the precision in the diagnostic and prognostic EEG signals extracted specifically from Alzheimer's disease patients, mild cognitive impairment subjects or healthy adults. In order to test this hypothesis, new AI-based signal processing methods were developed to shape the high dimensionality of EEG signals and use final input images for deep learning systems. With this aim in mind, a deep neural network was pretrained. The system was subsequently validated via cross-validation to check its classification results[16].

Related work

Machine Learning (ML)

Using the tunable Q-wave transform (TQWT) to represent the subfrequency signals, a model for detecting Alzheimer's disease from electroencephalography (EEG) signals was proposed by Puri et al. They chose a number of properties, including entropy and fractal-based features, on which they performed machine-learning classifications using classifiers like support vector machines (SVMs), k-nearest neighbor (k-NN) algorithm. Then, a 10-partition cross-validation test was performed on data from the model to evaluate the classification performance with an accuracy of 96.20%. Although the results were promising, this model was still based on a lot of manually designed properties which led to an increase in complexity[17]. Bury et al., on the other hand, used EMD on EEG signals in another study. Classification method used: Hayworth index Features were classified using machine learning algorithms, with least squares vector machine (LS-SVM) obtaining 92.90% accuracy. The study is a good application of the data analysis method, but it has a major limitation in that it requires manual feature selection instead of using machine learning[18]. Escudero and co-workers applied multiscale entropy analysis (MSE) to electroencephalography (EEG) data from subjects with Alzheimer's disease as well as healthy controls. Statistical methods were used to classify the extracted nonlinear features with an accuracy of 90.91%. Nonetheless, the paper emphasizes functioning entropy-based features and computational areas (source of distinction) related to cognitive disorders, one disadvantage is that its automatic acknowledging both spatial and temporal complexities cannot be built in as part of artificial engineering[19]. Abásolo et al. spectral entropy and sample entropy based on EEG signals of people with Alzheimer's disease compared to healthy people. They used a dataset of 22 patients and series of statistical techniques for classification. They achieved a model accuracy of 77.27%, this proves to be an inefficient method, as expected from its simplicity[20]. Other works Neto E, Biessmann F, Aurlien H et al. Employed EEG spectral features and linear systematic discriminative analysis. The study consisted of a sample consisting of 228 people groups (114 Alzheimers group &118 control) Their validation shows that with an accuracy of 67%, old-school linear classifiers might fail on complex datasets such as EEG data[21]. An example of this is the work by Zhao et al., where transient EEG features were identified using a combination Boltzmann machine + support vector machine classifier and surpassed accuracy achieved by conventional statistical analysis in distinguishing between patients with Alzheimer's disease and health subjects. But their model was still based on features[22]. Using Spectral and Coherence Features and Grouping-learning Classifiers like grouping trees Their study in Oltu, Akşahin, & Kibaroğlu (2013) on EEG Data In categorizing the three classes, the experiment reached 96.5% in accuracy. Their results were very good on, but this method suffers from the problem of feature selection[22]. Nayana et al. implemented a randomized forest classifier and trained it on spectral power density features from EEG signals from different datasets. This classifier achieved an accuracy of 84.78%, which is lower than those achieved by deep learning techniques, indicating the inefficiency of machine learning methods for this data set[23].

Deep learning

Touheid et al. The model structured directly to classify EEG signals for the early diagnosis of (2015) Alzheimer's disease is based on convolutional neural network. For their study, they examined patients with Alzheimer disease, frontotemporal dementia, and healthy controls with EEG data. Firstly a preprocess step has been performed on data by the removing noise, segments will be classified into different time periods. Ten-fold and single-element cross-validation were used to assess CNNs, resulting in accuracy estimates of 97.08% & 96.90%. These results suggests how well CNNs have adapted to the feature extraction task for EEG signals. But the segmentation technique used affects the performance of a CNN model[23]. Lin and Huang using VGG-16, ResNet-18, Inception to build a deep learning model trained on pre-trained multi-convolutional neural networks. They applied EEG data from 66 Alzheimer disease diagnosed, and it cannot be said with a degree of confidence patients identified as AD/MCI, images including the mild cognitive impairment (MCI) 60 healthy individual. This model is based on converting EEG signals to functional communication networks and classifying through a Multilabel voting based clustering technique. The accuracy of this model was 97.90%. This model demands heavy preprocessing steps and requires sophisticated computing infrastructure[24]. Alghamdi et al. Note that It was in 2025 when a hybrid deeplearning model based on an ensemble learning and a three-dimensional convolutional neural network (3D-CNN) is suggested for Alzheimer's detection using EEG signals. The model was tested using two datasets and recorded an accuracy of 99.02%. The experiment results imply that the use of an ensemble method on top of the deep learning technique makes the system more robust and accurate. However, this model incurs higher computational cost and is not applicable in real-time applications[25]. Nayana et al. EEG signals are mostly compared in 1D CNN and 2D CNN model by 15. The research showed that, the highest accuracy of 91.13% recorded by using 2D CNN and better traditional Machine Learning approaches was confirmed. The results reaffirm deep learning capabilities on feature extraction, while performance baseline were dependent on the respective datasets[23]. Morabito et al. Continous wavelet transform extended the idea of representing EEG signals as 2D RGB images used convolutional neural network model for classification. They were able to reach an accuracy of 85%, indicating that image-based representations of EEG signals can be very effective. But transforming EEG signals to images does not come without another computational cost[26]. Ferri et al. operated on stacked auto-encoding models under the neural DNN framework to classify electroencephalography (EEG) signals of individuals with Alzheimer or healthy subjects. Their model got 80% accuracy which is an okayish in terms of other models[27]. Ieracitano et al. robust electroencephalography (EEG) signal to convert into grayscale images using respect spectral power density and classification using CNN. They obtained an accuracy of classification with 92.95% for this model[28]. Miltiadous et al. present a two-input CNN-based method with transformer encoders for the classification of EEG signals. The new model was able to correctly identify Alzheimer's disease with an accuracy of 83.28%. Performance wise even with such sophisticated architecture it is less as the other deep learning approach[29]. Using Convolution Neural Network Chen et al proposed an integrated network and Vision Transformer (ViT) for EEG data classification. They were 87.33% accurate in classifying Alzheimer's patients versus healthy people. The addition of transformers aids in feature learning but adds complexity to the network[30]. Bi et al., using deep learning and a deep probabilistic classifier based on topographic EEG maps, classified Alzheimer's patients, patients with mild cognitive impairment, and healthy subjects with 95.04% accuracy [31]. The researchers also created a deep neural network that can classify EEG data using convolutional neural network algorithms, as well as autocoding. They were able to do this with 92% accuracy which is an improvement over the previous methods in their study[32].

Electroencephalography EEG spectra used to classify patients with mild cognitive impairment MCI and healthy individuals using CNNs or Vision Transformers researchers Şeker and Özerdem The model they developed reached 99.2% accuracy, illustrating the power of combining deep learning algorithms with spectral data[33]. Datta et al. When it comes to model-prepared convolution neural network, they developed a multilayered one-dimensional CNNP model for clinically proven EEG signal classify into stages of dementia. It obtained 97.31% accuracy and emphasized the suitability of DL for capturing time-dependent EEG data[34]. In their paper Dao et al. used the method of deep learning on date up to October 2023. implemented a 1D-CNN model with data augmentation of the EEG time-series signals Using deep learning technics enabled the performance to be enhanced[35].

Methods and materials

Building on previous studies, we continued this approach to encourage researchers in this field by conducting a detailed analysis to identify the most suitable model for predicting Alzheimer's disease. Before describing our work here, we trained eight classification models to understand deep learning/machine learning classifiers (logical regression, decision tree, random forest, gradient optimization, AdaBoost, XGBoost) and convolutional neural networks/multilayer neural networks. All datasets used in this research were obtained from Kaggle. Data processing included cleaning, deleting missing data, scaling features using Standard Scaler, and balancing categories using category weighting. By augmenting the data on the optimized image dataset, we were able to find the best model. To achieve this, we divided the process into key stages, each of which is explained in detail below. Figure 1 illustrates our study methodology.

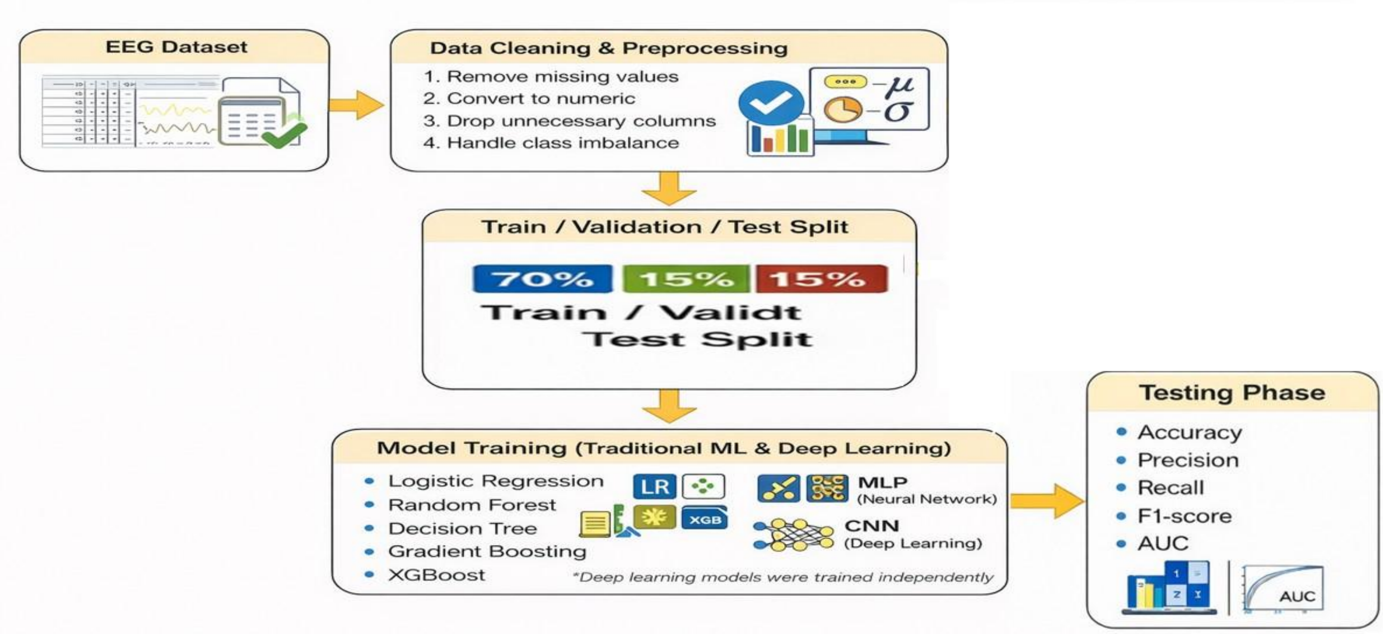


Figure 1. Study Methodology Diagram.

Dataset

The data collection phase is among the most critical stages to kickstart any study given that modern deep learning methods are less reliant on feature extraction and need large datasets. We obtained the data evaluated in our study through the Kaggle platform (https://www.kaggle.com/datasets/ucimachinelearning/eeg-alzheimers-dataset). This data set included 848,640 records, with 17 variables that represented different electroencephalography (EEG) signals from the scalp recorded during the same time frame plus also including continuous variables indicating electrical activity in specific EEG electrode locations according to the International System of Units (ISU) 10-20: Fp1, Fp2, F7, F3,Fz,F4,F8,T3,C3,Cz,C4,T4,T5,P3,Pz,P4. These channels measure brain activity in the temporal, frontal, central, and parietal lobes. There was also one binary (int64) variable: status, which is the patient's diagnosis (for example patient versus control group or stages of Alzheimer's disease). Dataset Size878,641 rows × 17 columns Types: 16 continuous variables (float64) and one categorical variable (int64). In machine learning and deep learning, we implemented on this data to classify EEG signals (healthy individuals vs Alzheimer patients), identify brain activity patterns, carry out feature extraction and dimensionality reduction techniques (principal component analysis, wavelet transforms), time series EEG readings.

1- Data pre-processing and cleaning

The first step was uploading an EEG dataset from CSV and working with it using the appropriate separator. Then unnecessary columns and columns with missing values were removed, while column names were stripped off spaces. As for the second place, here is the state property to be proceeded on (target variable) and it was validated before moving to further operations. Also, since all columns in the dataset were converted to numeric, which is essential for training machine learning algorithms. To ensure accuracy of input data, Rows with various missing values was deleted. The dataset was then partitioned into independent variables and a target variable. To stratify the dataset into training, validation and testing datasets, we checked the balance or imbalance of classes in the data. Finally, the properties were scaled using StandardScaler, first for the training data set and then for both the validation and testing datasets.

Exeremental

Classification

A study of diagnosing Alzheimer's disease using EEG with both classical machine learn- ing and deep learning algorithms. Deep Learning algorithms, on the other hand, can automatically extract features from the data; Classical machine learning approaches and Deep Learning who use statistical learning methods.

1- Machine learning

1-1 logistic regression

We decided on Logistic regression model as our best model, this is because logistic regression is perfect candidate for any binary classification problem with two classes of the predicted target variable. It avoids many of the pitfalls associated with linear regression, keeps predictions bounded between 0 and 1, has interpretable coefficients that can be described in terms of a probability ratio.

2-1 Decision trees

While implementations of decision trees are extremely simple and relatively easier to interpret compared with other models, an intuitive idea is that at some point in the classification process we want a differentiator. These kinds of algorithms perform very well for tabular data where the inference rule is learned iteratively by dividing the feature space into segments based on feature values. Hence they are capable of doing faster operations on electroencephalography (EEG) data with its non-linear characteristics. Decision trees are non-parametric, which means they do not make any assumptions about the distribution of data, unlike linear models. As a result, they can detect intricate patterns from the dataset and offer the decision-making process in an easy way for users. Yet these algorithms also have great scalability too, at least for larger datasets that requires parameter tuning.

3-1 Random forest

The random forest algorithm is implemented as that group learning method which adds tree correlation for each feature. Random forest improves the generalizability of the model and reduces overfitting by constructing many trees based on random sub-samples of data and combining their predictions. Due to its ability to deal with high-dimensional data alongside monitoring complex functional processes, this model is particularly suitable for the classification of electroencephalography (EEG). Additionally, the random forest offers a ranking of feature importance, which can yield useful information regarding how informative each mechanism for a given EEG channel is in terms of classifying the data to predict disease seriousness.

4.1 Gradient boosting

Gradient boosting was selected as it enables the construction of predictive models that combine weak training models in a symbolic way. With every new model trained on data, it such that it corrects errors made by previous models and improves accuracy. This approach is well-suited for structured data, such as electroencephalography (EEG) signals, from which it is able to capture complex and nonlinear relationships. Despite needing fine tuning and being compute-intensive, it frequently yields superior prediction capability over individual models.

5-1 AdaBoost algorithm

Amsterdam based on adaptive Boosting algorithm (AdaBoost) A clustering method proposed for classification, AdaBoost focuses on giving more weight (or importance) to misclassified samples. The iterative reweighting mechanism enables the model to progressively apply more focus on harder problems. AdaBoost is both an efficient classifier and works well with weak learning models, so it is also a good candidate for comparison with the other clustering methods. However, it can be sensitive to noise and outliers.

6-1 XGBoost

XGBoost was selected for its high speed and accuracy with cluster classification problems. This is a smart application of the gradient boosting technology and we are up to a plan dedicated to withhold overfitting and advance sample quality. Furthermore, XGBoost is very scalable due to its simplicity in tree learning and parallel processing implementation. Given its ability to process such different information and provide significant insights, the performance of DeepSEN in classifying Alzheimer disease based on Electroencephalography (EEG) improves further.

2- Deep learning

1-2 Multilayer Perceptron (MLP)

Deep learning models for nonlinear complexity handling in data have been based on the Multilayer Perceptron (MLP). Unlike many machine learning models, MLPs—namely multilayer perceptrons — learn behavioral representations in a multi-level fashion, chaining fully connected layers together. MLPs directly operate on tabulated EEG events and are able to capture a more complicated interaction between those events. On the other hand, MLPs need careful hyperparameter tuning and might require large data sets to surpass smaller models.

2-2 Convolutional neural networks (CNNs)

Convolutional neural networks (CNN) are commonly used to assess how well they can identify spatial patterns from electroencephalography (EEG) data. CNN is originally designed for image data, although EEG features have been reformulated on a 2D framework, which supports convolution. One possible form is convolutional neural networks since they excel at modeling local dependencies and spatial correlation amongst channels in the EEG signal, which can enhance classification performance. But the quality of actual models may have less importance because it has fewer features. Convolutional Neural Networks, therefore, offer a strong incentive into the applicability of deep learning methods on biomedical signal classification.

These models give us the wide opportunity to assess the interpretability and comparison of classified models, clustering methods, and deep learning methods in electroencephalography-based Alzheimer Disease classification.

Performances Metrics

We performed the confusion matrix to measure how four models have performed; actually, following definitions are served for evaluation: True Positive (TP) is thermal image data that was correctly classified; False Negative (FN) is thermal image data that was incorrectly classified; FP indicates corrected incompletely classified thermal image information and True Negative (TN) represents incorrectly classified thermal image data.

$$\text{acuracy} = \frac{TP+TN}{TP+TN+FP+FN} \quad (1)$$

$$\text{Precision} = \frac{TP}{TP+FP} \quad (2)$$

$$\text{Recall} = \frac{TP}{TP+FN} \quad (3)$$

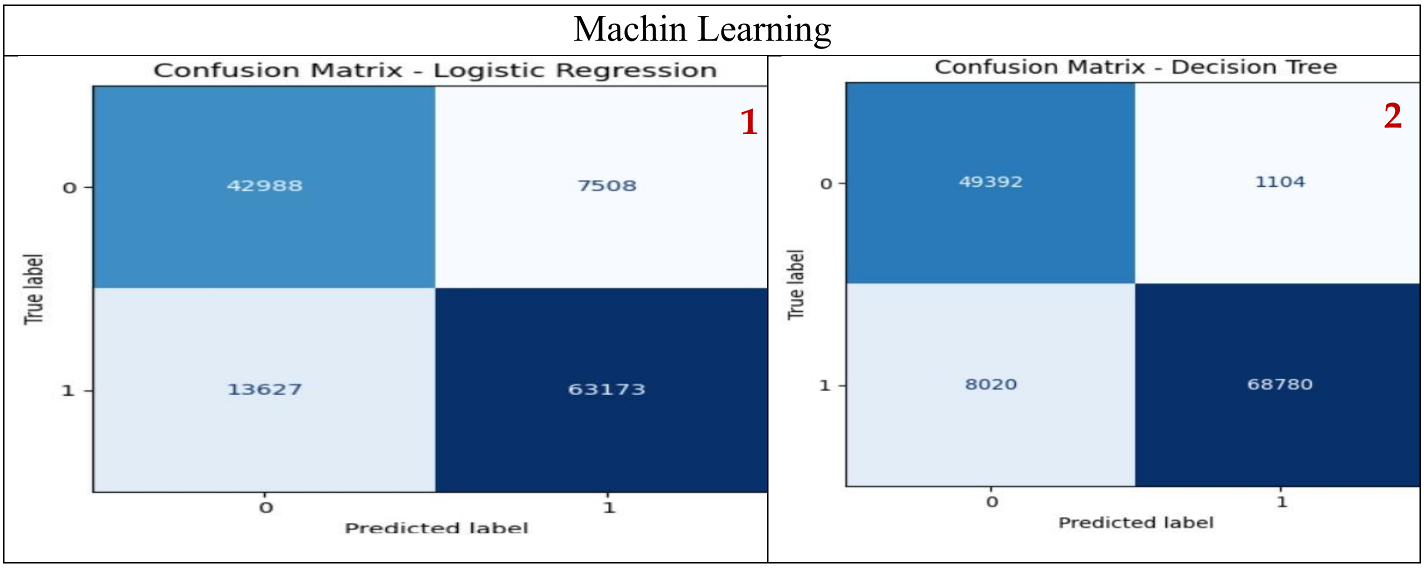
$$\text{F1 Score} = \frac{2.\ TP}{2.\ TP+FP+FN} \quad (4)$$

Results

Table 1 shows the classification accuracy, F1 score, precision, and recall, based on an EEG dataset. Figures 2 and 3 illustrate the relationship between size classification and damage assessment, as well as the damage matrix for both deep learning and machine learning, based on the EEG dataset.

Table 1. View models accuracy results.

Machin Learning				
Type model	Accuracy	F1-Score	Precision	Recall
Logistic Regression	0.833	0.856	0.893	0.822
Decision Tree	0.927	0.937	0.984	0.895
Random Forest	0. 986	0.988	0.997	0.980
AdaBoost	0. 968	0.973	0.973	0.973
Gradient Boosting	0. 986	0.988	0.988	0.988
XGBoost	0.992	0.993	0.996	0.991
Deep Learning				
CNN	0.998	0.9990	0.9991	0.9989
MLP	0.999	0.999	0.9999	0.999



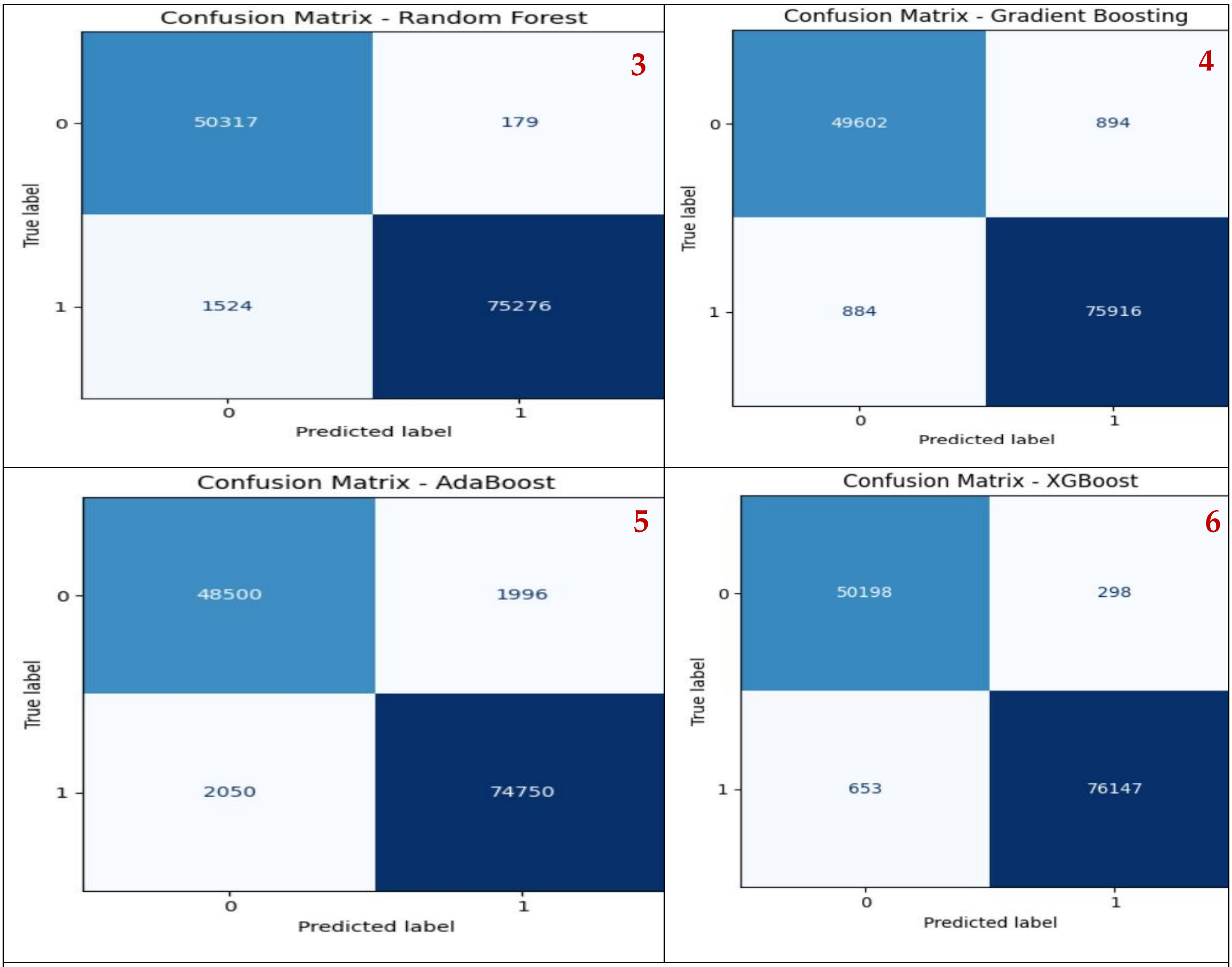


Figure 2: Confusion matrices of the Machin Learning models: (1: Logistic Regression, 2: Decision Tree, 3: Random Forest, 4: Gradient Boosting , 5: AdaBoost , 6: XGBoost)

Deep Learning

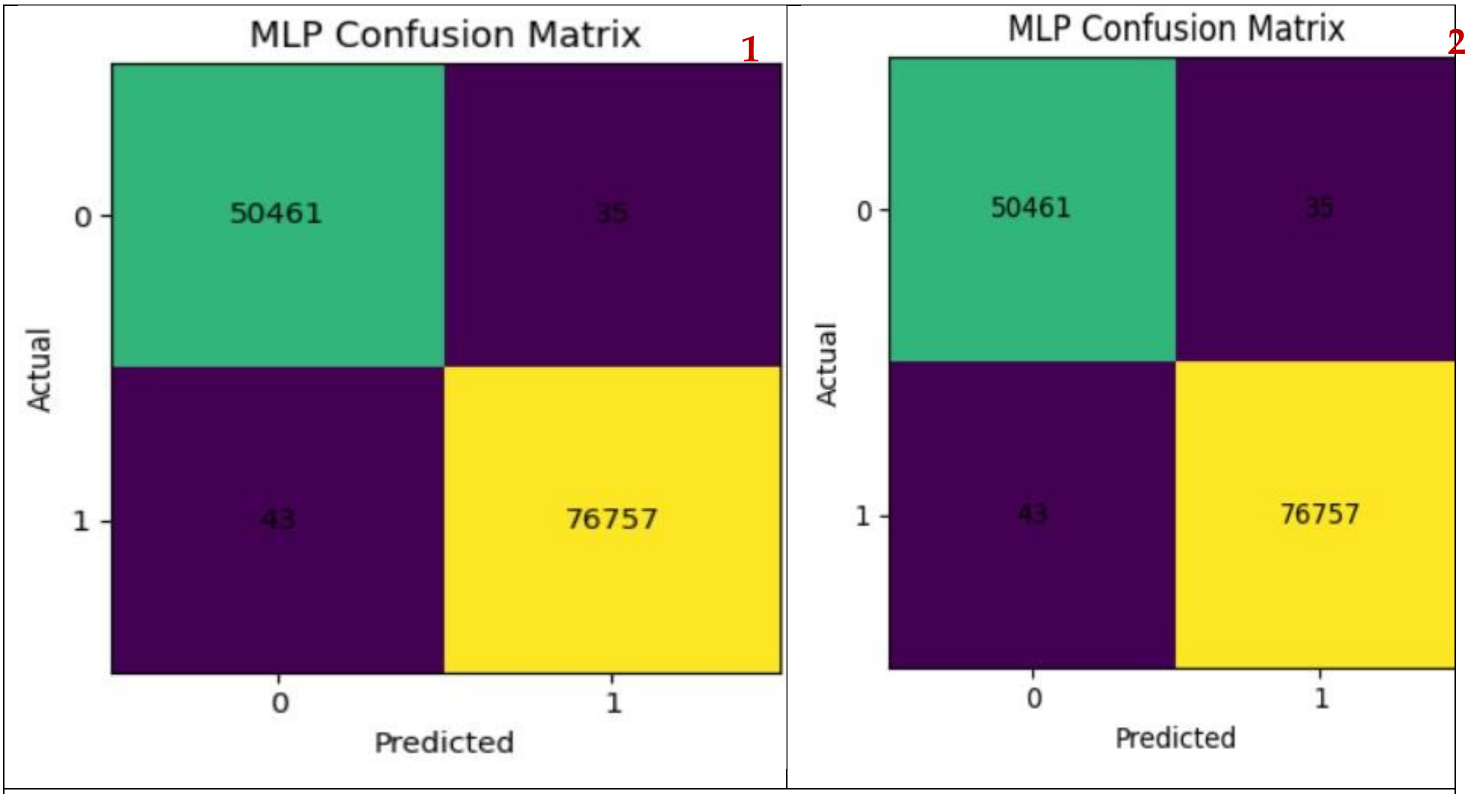


Figure 3: Confusion matrices of the Deep Learning models : (1: MLP, 2: CNN)

Conclusion

In this paper, we use artificial intelligence methods such as machine learning and deep learning to diagnose Alzheimer's disease at an early stage accurately. Multiple types of models were trained and their performance was compared across common evaluation metrics, accuracy, F1 score, recall and precision.

The machine learning models demonstrated good to excellent performance according to the results. Here, even the Logistic Regression model gives us the minimum accuracy of 0.833; while different advanced models like Decision Tree, Random Forest, and Gradient Boosting worked better. Then with Random Forest and XGBoost, we achieve very high results: from 0.979 (Random Forest) to 0.992 (XGBoost), prove that these methods are highly efficient in data processing and pattern extraction.

In contrast deep learning models made intelligence that was readily apparent from the latter. We observed that the CNN model produced an accuracy of 0.998 and highest accuracy (0.999) but MLP with all other metric values near-to-perfect as shown in table below (Table4). This demonstrates how readily these models are able to handle complex data and find hidden correlations in it.

In summary, the findings demonstrate that deep learning approaches surpass classical machine learning in AD diagnosis and have tremendous potential for complementing the early diagnostic systems as well as enhancing medical decision-making capability.

Future work

Future works can facilitate better fitting properties of the models by using larger and multi-modal datasets (e.g. MRI and EEG). Hybrid and transformer-based approaches, the advanced models can be explored to improve the performance. In addition, it also means to prevent overfitting by validation and hyperparameter tuning. Lightweight real-time systems for practical use in medical and mobile applications, together with improved interpretability of models to increase user confidence in the operation, should also be developed as solutions for early diagnosis.

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