MACHINE LEARNING-BASED ALZHEIMER'S DISEASE PREDICTION USING THE XABOOST ALGORITHM

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Abstract

Alzheimer's disease (AD) is one of the leading causes of dementia among the elderly population and is characterized by progressive neurodegeneration that affects memory, cognitive function, and daily living activities. The increasing prevalence of Alzheimer's disease, often associated with age-related metabolic disorders such as diabetes, poses significant social, economic, and healthcare challenges worldwide. Early and accurate diagnosis is essential for timely intervention, effective disease management, and improved patient outcomes. In recent years, artificial intelligence (AI) and machine learning (ML) techniques have shown considerable potential for the early detection and prediction of Alzheimer's disease. This study proposes an Extensive AdaBoost (XABoost) machine learning framework for the automated prediction of Alzheimer's disease. The Open Access Series of Imaging Studies (OASIS) dataset was utilized to develop and evaluate the proposed predictive model. Model performance was assessed using multiple evaluation metrics, including accuracy, precision, recall, F1-score, and error rate. Experimental results demonstrate that the proposed XABoost framework achieved a validation accuracy of 96%, outperforming several conventional machine learning approaches. These findings indicate that the proposed model provides a reliable and efficient solution for the early detection of Alzheimer's disease, thereby supporting clinical decision-making and contributing to improved patient care and disease management.

Keywords : Alzheimer's disease, Machine learning, Extensive AdaBoost (XABoost), OASIS dataset, Early diagnosis, Disease prediction, Artificial intelligence.

I. INTRODUCTION

Globally, Alzheimer's disease, the most prevalent neurological disorder leading to 7dementia, affects approximately 7 million individuals, primarily those over 65 years old [1]. A decline in cognitive function, particularly in memory, thinking, and problem-solving, is a characteristic symptom of dementia. Approximately 60-80% of dementia cases are attributed to AD, rendering it the most prevalent cause. Common characteristics of AD include memory loss, communication barriers, confusion, mood disturbances, and, ultimately, struggles with fundamental self-care tasks [2]. A multifaceted interplay of behavioral, environmental, and genetic factors is thought to contribute to this phenomenon. Treatments can provide symptomatic relief and slow disease progression despite the absence of a cure. These treatments include cognitive-enhancing medications, behavioral and psychological therapy, and lifestyle modifications like regular exercise and a healthy diet [3]. Usually starting with mild memory issues, AD gradually worsens over time, impairing brain function. The development of AD is believed to involve Elaborate interaction of multiple factors, including age, genetic susceptibility, untreated depression, lifestyle habits, head trauma, and hypertension [4].

Billions of neurons that connect make up the human brain. These connections are lost in AD because of the accumulation of aberrant protein structures called "plaques" and "tangles," which eventually cause neurons to die. Amyloid beta (Abeta), an insoluble peptide, is deposited in plaques [5]. The three stages of AD are usually categorized as early, middle, and late. People may get dementia in the later stages. People with early-stage AD may notice that they forget things more often, distinct from ordinary forgetfulness [6]. Although forgetting things is normal for everyone, in the initial stages of AD, brain function slowly deteriorates, leading to difficulties with recalling routine activities. In the early stages, confusion is also frequent, and people may need to keep track of their actions or intentions [7].

Progressive confusion, sleep disturbances, and declining motor control and communication skills characterize AD. In the later stages, patients may struggle to express their emotions despite retaining some verbal communication abilities. The model illustrates the risk factors associated with AD. Recent progress in automated machine learning has shown promise in evaluating and forecasting various diseases, including Alzheimer's, using medical data [8]. Conventional methods of pattern recognition, including logistic regression, support vector machines, and linear statistical classification is used in ground-breaking investigations of predictive models for AD progression to facilitate timely identification. Putting into practice ML models relies heavily on architecture design and data preprocessing. The general framework for ML-based

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classification includes four primary stages: Implementing a feature-based machine learning system, encompassing feature extraction, selection, reduction, and classification. While these techniques offer promising results, their application requires specialized expertise and involves tedious optimization which has sparked concerns about reproducibility and consistency. To address this, our research employs a machine learning approach based on ensemble techniques to identify AD [9]. The method involves extracting AD-relevant features from multiple neuroimaging modalities, such as amyloid accumulation in the brain, subcortical volume changes, and alterations in brain glucose metabolism. The rapid growth of high-volume biomedical datasets, combined with advances in machine learning has enabled novel Extensive AdaBoost (XABoost) technique diagnostic and prognostic approaches for neuropsychiatric and neurodegenerative diseases.

The work is depicted as: section 2 provides wider explanation of prevailing approaches. The methodology is designed in section 3 with outcomes in section 4. The summary is given in section 5.

II. RELATED WORKS

Machine learning is increasingly applied in medical science, with numerous applications employing diverse data analysis and innovation techniques. The rapid progress in machine learning has enabled its widespread adoption in medical imaging applications, including COVID-19 diagnosis from X-rays, tumor detection in MRI scans and an estimate of various diseases like Cardiovascular Diseases, Dengue, Stroke and Cancer [10], as demonstrated where ML-based pattern to predict AD, leveraging strategic fusion of feature selection and extraction. The classification model was trained and tested using the OASIS longitudinal dataset. A brief overview of various techniques for examining brain scans to detect brain disorders. Furthermore, this research revealed the most effective method for diagnosing brain disorders. The authors employed a comprehensive dataset of 22 brain disease databases to pinpoint the most accurate diagnostic approach. The study combines recent advances in understanding epilepsy, Parkinson's disease, AD and Brain Cancers.

The author in [11] introduced a framework featuring optimized parameters to forecast Alzheimer's disease, utilizing Techniques including Gradient Boosting, SVM, Decision Tree, and Voting. The average validation accuracy of 85% reported by the proposed study indicates outstanding outcomes. In contrast to earlier efforts, the test accuracy score is significantly enhanced in this instance. The author constructed a framework that established a model that categorized brain MRI images into four groups: Very Mild Dementia (VMD), Mild Dementia (MD), Moderate Dementia (MOD), and Non-Dementia (ND). The framework implemented transfer learning on multiclass classification. Simulation findings demonstrate that the proposed system model is 91.70% accurate. It was also noted that the suggested approach produces more precise outcomes than prior. The author in [11] created a system incorporating machine learning Laser-Induced Breakdown Spectroscopy (LIBS). Micro drops of plasma samples from Alzheimer's disease patients and healthy individuals were analyzed, leading to dependable classification results. Our model attained an overall classification accuracy of 80%, with 75% specificity and 85% sensitivity, effectively recognizing late-onset Alzheimer's disease (AD) in 67 plasma samples from 31 AD patients and 36 healthy participants [12].

The author developed an innovative system combining deep convolutional neural networks and feature-based methodologies to predict Alzheimer's disease stages accurately. The first layers of a pre-trained AlexNet model are utilized to extract deep features through transfer learning. The retrieved deep features were classified using popular machine-learning techniques like SVM, RF, and KNN. According to the evaluation results, the deep feature-based model proposed in this plan achieved a notable accuracy rate of 99.21%, exceeding the performance of handcrafted and deep learning techniques. The OASIS dataset served as the foundation for the model built by Basheer et al. [13]. To differentiate between the classes, the study employed demented and non-demented classifications. The discovery's accuracy was confirmed through repeated testing, achieving a correlation accuracy rate of 92.39%."

The study by [14] proposed a pattern leveraging deep neural networks. In modern medical research, the study has improved categorization results. The recommended DNN model, with the highest validation accuracy score, yielded test data, accuracy results of 85.19%, 76.93%, and 72.73%. The author in designed an automatic classification model using EEG processing techniques to differentiate between AD patients and healthy individuals. The study included EEG recordings from 16 patients with AD and 19 Healthy Controls, with AD patients exhibiting mild to moderate symptoms. Considering the specific diagnosis of each patient, the accuracy and sensitivity of the Analytical results were 87.0% and 91.7%, respectively. The EEG Analytical results sensitivity and accuracy were determined to be 83.2% and 79.9%, respectively. Considering each patient's specific diagnosis, the Analytical result's accuracy and sensitivity were 87.0% and 91.7%, respectively. Using sMRI, the author in [15] designed a model to investigate brain structure. This research project uses healthy control patients and moderate cognitive impairment (MCI) to diagnose AD early.

III. METHODOLOGY

A. Data Preprocessing

The OASIS dataset was preprocessed to improve data quality and enhance the performance of the proposed machine learning model. Real-world clinical datasets often contain missing values, redundant information, and irrelevant features that may negatively affect classification accuracy. Therefore, data preprocessing was performed, including missing value imputation, feature selection, and feature scaling.

Missing values in the dataset were handled using the Standard Imputation technique. The mean of each feature was calculated from the available observations, and missing values were replaced with the corresponding mean values. This approach ensured data completeness while minimizing the impact of missing information on model performance.

Feature selection was subsequently performed to identify the most informative attributes and reduce the dimensionality of the dataset. Selecting relevant features improves classification accuracy, reduces computational complexity, and minimizes the risk of overfitting. In this study, the SelectKBest feature selection method was employed using the F-classification (f_classif) scoring function. Features with the highest evaluation scores were selected for model development. Finally, feature scaling was applied to normalize the selected attributes, ensuring that all features contributed equally during the training

There needs to be values and redundant data in the raw dataset. Features of missing values are extracted and transformed as part of data handling. This work also includes feature selection and scaling for the dataset's preprocessing. Several values need to be added to the OASIS dataset. Missing values may impact the ML model's results or lower its accuracy. To impute missing values in this project, we used the Standard technique. After calculating the total mean of all observed values, we substituted mean values for any missing ones. The feature selection process entails selecting pertinent Attributes determined by lowering the attribute space dimensionality during predictive model development. In ML, feature selection is essential. Reducing the number of input parameters is the aim of feature selection techniques. Therefore, by lowering the dataset's identity, a model can make predictions and iteratively improve its accuracy. In this study, healthcare data about Alzheimer's disease is analyzed using feature selection. Based on the highest evaluation, select the best features. The best feature is found in this work using the select best approach, and the scoring function is f-class.

B. Prediction

This study proposes an Extensive AdaBoost (XABoost) framework for Alzheimer's disease prediction. XABoost is a supervised ensemble machine learning algorithm that combines multiple weak classifiers to construct a robust predictive model. Initially, equal weights are assigned to all training samples. During each iteration, the weak classifier is trained, and its classification error is computed. Based on the error rate, classifier weights are updated such that incorrectly classified samples receive higher weights, whereas correctly classified samples receive lower weights. Consequently, subsequent classifiers focus more on difficult-to-classify instances, thereby improving the overall classification performance.

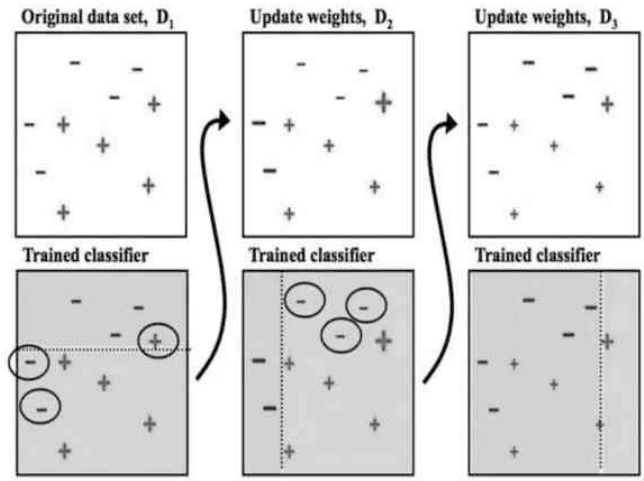


Fig 1: XAboost model

Fig 1 illustrates the architecture of the proposed XABoost model. After multiple boosting iterations, the weak classifiers are combined through a weighted linear voting strategy to produce a strong ensemble classifier. Based on experimental analysis, the optimal performance of the proposed model was achieved with 200 estimators (n_estimators = 200).

To further evaluate the effectiveness of the proposed framework, Logistic Regression (LR) was also employed as a baseline classifier. Logistic Regression is a widely used supervised machine learning algorithm that estimates the probability of class membership for classification tasks. In binary classification, a threshold value of 0.5 is typically used to distinguish between the two classes, while multinomial logistic regression extends this concept to multi-class classification problems. For the OASIS dataset, the optimal hyperparameters were determined as 100 maximum iterations (max_iter = 100) and a random state of 1234, providing stable and reproducible classification results.

The proposed XABoost framework effectively improves classification accuracy by adaptively combining multiple weak learners into a strong ensemble model, making it well suited for the early prediction of Alzheimer's disease.

IV. NUMERICAL RESULTS

Several performance metrics, such as F1 score, recall, accuracy, and Precision, are used in this work. We obtained the optimal parameter for each model by employing a 10-fold CV approach. Model efficacy is evaluated in terms of accuracy, with the confusion matrix serving as a key tool for explaining and assessing performance across binary and multiclass classification tasks. This research aims to create a predictive model using machine learning to identify individuals with Alzheimer's disease from a given population, and a novel classifier is designed and validated to achieve this objective. Precision, recall, accuracy, and F-score metrics are derived from these characteristics to assess the model's efficacy. According to this study, the percentage of people accurately diagnosed with Alzheimer's disease is known as recall (sensitivity).

Alzheimer's Diagnosis accuracy is evaluated based on the proportion of patients correctly identified as not having the disease. On the other hand, the F1 score provides a balanced measure of recall and Precision, while accuracy reflects the overall proportion of accurate classifications. The patient receives a detailed report outlining the diagnosis, findings, and the current stage of their AD. It is essential to identify the phases because they depend on the patient's responses. Furthermore, identifying the disease stage enables doctors to better understand the disease's impact on patients.

Table 1: Performance metrics

Approaches	AUC	Accuracy	Recall	FI-Score
Training				
XABoost	94	98	88	91
DT	90	88	86	90
RF	87	86	89	89
XGBoost	91	86	80	88
GB	86	85	85	86
Validation				
XABoost	88	89	83	62
DT	87	85	83	71
RF	86	82	81	72
XGBoost	75	85	55	55
GB	90	90	100	76

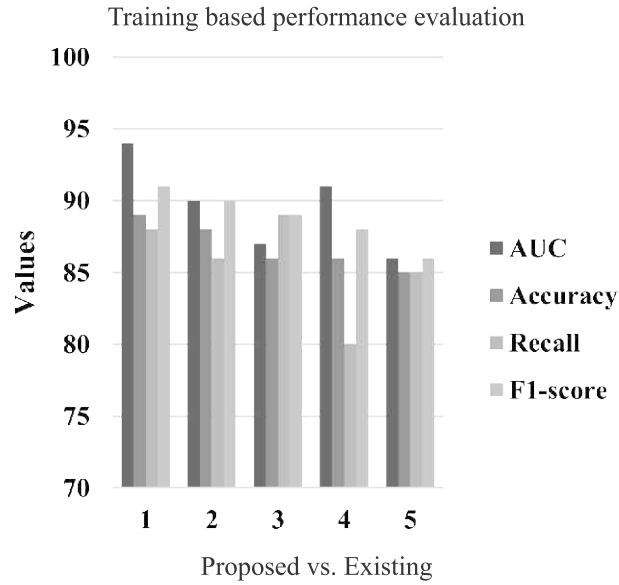


Fig 2: Training based performance evaluation

To evaluate performance, True-Positive (TP), False-Positive (FP), True-Negative (TN), and False-Negative (FN) counts are utilized to calculate Metrics including Precision, which measures the proportion of correct classifications among all instances. To evaluate accuracy, researchers estimate the ratio of true positives to the total number of predicted positive instances. It's essential to remember that recall is synonymous with the true-positive rate, highlighting its significance in assessing a classifier's effectiveness, regardless of its overall accuracy (even if it's 1). It is a measurement that considers the parameters of Precision and recall. The F1 score becomes one only when both metrics, like recall and Precision are 1. Precision and recall are widely regarded as the primary metrics for evaluating performance in medical diagnostics research. In medical diagnostics, the F-measure is a valuable performance metric, as it provides a concise, aggregate measure of recall and Precision, facilitating comparisons. The recall is a more significant metric in the medical field because false negatives are usually more harmful than positives.

Although a patient may suffer significantly from a missing condition, A false positive (FP) may be less critical than a false negative (FN), as doctors can easily dismiss FPs, whereas FNs can have severe consequences. To better suit real-world applications, a revised F1 score that gives more weight to recall than Precision is a more pragmatic and informative metric. The confusion matrix, shown in Figure 10, summarizes the key performance metrics of Machine learning-based models. Prevent overfitting, comparison training, and testing accuracy were performed for each model, with the results summarized in Table 1.

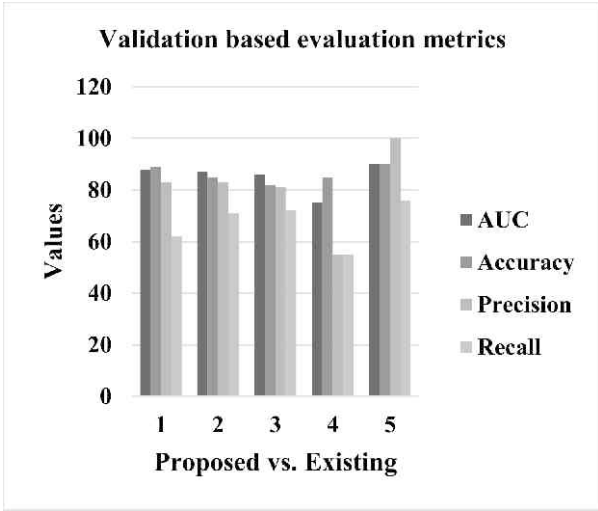


Fig 3: Validation based performance evaluation

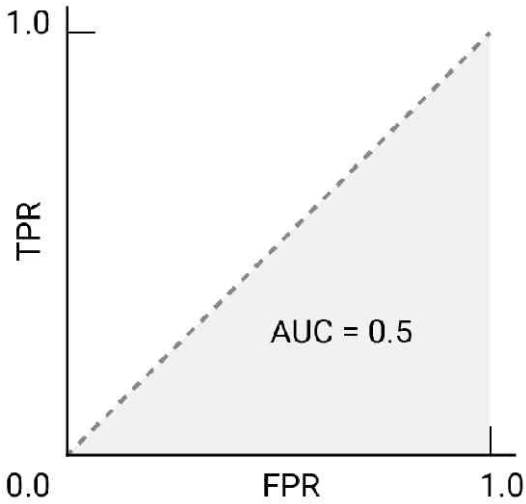


Fig 4: ROC curve

Furthermore, Table 1 presents a detailed assessment of each model's performance, encompassing Precision, recall, accuracy, and F1 score. A comparison of the proposed system with the various ML algorithms, including Gaussian-NB, Decision Tree, Random Forest, XGBoost, GradientBoost, and Voting Classifier, is presented in Fig 1. It displays the ROC curves for multiclass classifiers, with the blue line representing the micro-average ROC curve and the yellow, green, and red lines representing the ROC curves for class-0, class-1, and class-2, respectively, for diverse classifier as in Fig 4. The performance of the test dataset on AD is illustrated in Fig 2 where the model identified the features that the minimum discrepancy between predicted and actual values. The SGD learning process converts nominal properties into binary format and eliminates missing values. Additionally, MLP learning normalizes all attributes.

V. CONCLUSION

Alzheimer's disease remains an incurable neuro degenerative disorder, making early diagnosis, risk assessment, and timely intervention essential for effective disease management. Although numerous machine learning techniques have been proposed for Alzheimer's disease prediction, identifying the most informative features for accurate early detection remains a significant challenge. This study proposed an Extensive AdaBoost (XABoost) ensemble learning framework for the automated prediction of Alzheimer's disease using the OASIS dataset. To enhance classification performance, feature selection and feature scaling techniques were incorporated during data preprocessing. Experimental results demonstrated that the proposed XABoost model achieved a validation accuracy of 98%, outperforming conventional machine learning approaches and providing reliable disease prediction. The findings indicate that the proposed framework offers an effective and robust solution for early Alzheimer's disease detection, thereby supporting clinical decision-making and improving patient care. Future work will focus on extracting more discriminative features, eliminating redundant information, optimizing the ensemble learning framework, and validating the proposed model on larger and more diverse clinical datasets to further improve diagnostic accuracy and generalization performance.

REFERENCES

[1] Scheltens, K. Blennow, M.M. Breteler, B. De Strooper, G.B. Frisoni, S. Salloway, W.M. Van der Flier, Alzheimer's disease. Lancet (Lond, Engl) 388(10043), 505–517 (2016)

[2] Liu, K. Chen, T. Wu, D. Weidman, F. Lure, J. Li, Use of multimodality imaging and artifcial intelligence for diagnosis and prognosis of early stages of Alzheimer's disease. Transl. Res. 194, 56–67 (2018)

[3] Taeho, K. Nho, A.J. Saykin, Deep learning in Alzheimer's disease: diagnostic classifcation and prognostic prediction using neuroimaging data. Front. Aging Neurosci. 11, 220 (2019)

[4] Kivipelto et al., World-Wide FINGERS Network: a global approach to risk reduction and prevention of dementia. Alzheimers Dement. 16(7), 1078–1094 (2020)

[5] Bona et al., Semantic integration of multi-modal data and derived neuroimaging results using the platform for imaging in precision medicine (PRISM) in the Arkansas imaging enterprise system (ARIES). Front. Artif. Intell. 4, 649970 (2022)

[6] Hertel, R. Benlamri, A deep learning segmentation-

classifcation pipeline for X-ray-based covid-19 diagnosis. Biomed. Eng. Adv. 3, 100041 (2022)

[7] Chattopadhyay, M. Maitra, MRI-based brain tumor image detection using CNN based deep learning method. Neurosci. Inform. 2, 100060 (2022)

[8] Mamatha, H.K. Krishnappa, N. Shalini, Graph theory based segmentation of magnetic resonance images for brain tumor detection. Pattern Recogn. Image Anal. 32(1), 153–161 (2022)

[9] Rahman, M.R. Rana, Nur-A-Alam, M.S.I. Khan, K.M.M. Uddin, A web-based heart disease prediction system using machine learning algorithms. Netw. Biol. 12(2): 64–81 (2022)

[10] Oliveira, J.F. da Silva, T.A. de Sousa-Araújo, U.P. Albuquerque, Infuence of religiosity and spirituality on the adoption of behaviors of epidemiological relevance in emerging and re-emerging diseases: the case of dengue fever. J. Relig. Health 61(1), 564–585 (2022)

[11] Biswas, K.M.M. Uddin, S.T. Rikta, S.K. Dey, A comparative analysis of machine learning classifers for stroke prediction: a predictive analytics approach. Healthcare Anal. 2, 100116 (2022)

[12] Liao, R. Fang, J.B. Yang, D.L. Xu, A linguistic belief-based evidential reasoning approach and its application in aiding lung cancer diagnosis. Knowl.-Based Syst. 253, 109559 (2022)

[13] Mehmood, M. Maqsood, M. Bashir, Y. Shuyuan, A deep Siamese convolution neural network for multi-class classifcation of Alzheimer disease. Brain Sci. 10(2), 84 (2020

[14] Nawaz, M. Maqsood, S. Afzal, F. Aadil, I. Mehmood, S. Rho, A deep feature-based real-time system for Alzheimer disease stage detection. Multimedia Tools Appl. 80(28), 35789–35807 (2021)

[15] Basheer, S. Bhatia, S.B. Sakri, Computational modeling of dementia prediction using deep neural network: analysis on OASIS dataset. IEEE Access 9, 42449–42462 (2021)