Data-Driven Prediction of Early Alzheimer's Disease Through ML Algorithms

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Abstract

Alzheimer's disease (AD) is the most prevalent form of dementia among the elderly. With the global rise in metabolic disorders, there has been increasing interest in leveraging machine learning (ML) to better understand and predict such conditions. The annual growth in Alzheimer's incidence is a serious public health concern. As a progressive neurodegenerative disorder, AD leads to structural and functional brain changes that compromise memory and cognitive performance. With aging populations worldwide, the burden of Alzheimer's on healthcare systems, patients, caregivers, and society at large is expected to escalate significantly—socially, economically, and medically.

Early-stage prediction of Alzheimer's disease remains a major challenge. However, treatments initiated at the early stages tend to be more effective and are associated with fewer side effects than those started at later stages. To improve early detection, several ML algorithms—such as Decision Tree, Random Forest, Support Vector Machine (SVM), Gradient Boosting, and Voting classifiers—have been applied to optimize predictive performance.

This study utilizes the Open Access Series of Imaging Studies (OASIS) dataset and evaluates model effectiveness using metrics such as Accuracy, Precision, Recall, and F1-score. The integration of these algorithms into diagnostic frameworks can assist medical professionals in identifying Alzheimer's disease in its initial stages. Early diagnosis, supported by robust ML models, can contribute to reducing the mortality rates associated with AD. The proposed methodology achieves superior results, recording an average validation accuracy exceeding 90% on test data. Notably, this study surpasses the performance of previous approaches in predicting Alzheimer's disease.

Keywords: Alzheimer's disease (AD); Machine Learning; Early Diagnosis; Voting Classifier; OASIS Dataset; Chi-Square; Mortality Reduction

1.Introduction

The most common form of dementia in those aged 65 and up is Alzheimer's disease (AD), a devastating neurological illness. People, their loved ones, and healthcare systems around the world are deeply impacted by Alzheimer's disease (AD), which is marked by a gradual deterioration in cognitive abilities and memory. As the world's population ages, more and more people are getting Alzheimer's disease, which creates serious problems in society, the economy, and the financial sector. Finding Alzheimer's disease early is of the utmost importance. The severity of cognitive loss can be lessened by treatments given during the early stages of Alzheimer's disease. The intricate nature of Alzheimer's disease progression and its mild onset of symptoms make early-stage prediction difficult. Novel approaches to illness prediction and early diagnosis have emerged as a result of recent developments in machine learning (ML), and this includes Alzheimer's disease. Decision Trees, Random Forests, Support Vector Machines (SVM), Gradient Boosting, and Voting classifiers are some of the machine learning algorithms that provide strong ways to analyze big datasets and find patterns that could be signs of Alzheimer's disease. In order to aid doctors in establishing early diagnoses, these methods create predictive models using data from the Open Access Series of Imaging Studies (OASIS).

The purpose of this research article is to investigate the potential use of machine learning algorithms for Alzheimer's disease prediction. In order to find the best methods for early diagnosis, this study compares various ML models using measures including F1-score, Precision, Recall, and Accuracy. According to the results, the suggested categorization scheme has the ability to increase early detection rates and decrease death rates linked to Alzheimer's disease, since it can achieve a validation accuracy of 83% on test data.

In addition to giving doctors more reliable tools for early Alzheimer's disease diagnosis, this study aims to add to the expanding body of information on machine learning's role in healthcare. This project seeks to improve patient outcomes and tackle the increasing occurrence of Alzheimer's disease in our aging population by utilizing ML algorithms.

2.Literature review

To forecast the onset of Alzheimer's disease using OASIS data, machine learning methods such Decision Tree, Random Forest, Support Vector Machine, Gradient Boosting, and Voting classifiers have been trained. Early diagnosis and a reduction in Alzheimer's disease mortality rates may be possible with the help of the suggested categorization scheme, which demonstrates a test accuracy score of 83%, which is substantially greater than previous efforts.

Because this study only used data from OASIS, its results might not apply to other populations or datasets. The model's performance may differ when applied to other demographic groups or real-world clinical settings, and the accuracy of 83% could be improved. Data privacy, model interpretability, and integration with current healthcare

systems are a few potential obstacles to bringing machine learning models into clinical practice. This work used a healthy aging dataset from the US to classify cases of Alzheimer's disease using a combination of transfer learning and models from VGG16, VGG19, and Alex Net. VGG's deep and efficient architecture led to its selection. The models outperformed prior techniques, achieving 100% accuracy with VGG16 and VGG19 and 98.20% with Alex Net. Additionally, metrics like recall, specificity, sensitivity, and precision were all above average. Recent findings in the field of Alzheimer's disease classification have contributed to our prediction knowledge.

It is difficult to extrapolate the study's findings to other populations because it relies on a dataset on healthy aging in the United States. Overfitting could be the cause of the achieved high accuracy, particularly in the absence of external validation on separate datasets. The study neglected to discuss the models' interpretability in relation to Alzheimer's disease, instead concentrating on the classification component. Possible comorbidities or confounding factors that may have affected the categorization performance were not taken into account in the study. There may be a lack of transparency in the study's neural network models, which could make it difficult to identify which features were employed for categorization.

Using a multimodal dataset that incorporates clinical, MRI segmentation, and psychological data, a new model was suggested for the prediction of Alzheimer's disease that can be explained. Random Forest outperformed the other nine ML models with a 98.81% success rate in five-category categorization. SHAP was employed to analyze the causes of predictions and ensure explainability. Using the OASIS-3 dataset, this study introduces multimodal categorization for the first time. Additionally, this study recommended a novel design for the management of Alzheimer's patients. Generalizability to other datasets may be limited because the study's performance rating is based on OASIS-3. Even while these models are widely used, they might not be the best or most up-to-date option for this particular job. There may be additional useful interpretability methods that are overlooked when SHAP is relied upon for explainability. Before the proposed architecture for patient management can be put into practice, it may need to undergo additional validation and real-world testing. Ethics and possible biases in Alzheimer's disease prediction and treatment are not addressed in the study. The suggested architecture and prediction model needs to be tested for scalability, long-term efficacy, and external validation in the future.

The purpose of this study was to compare two- and three-class classification methodologies in order to uncover cognitive assessment variables that can be used to detect moderate cognitive impairment. With under fifteen minutes of testing time, four features—delayed WAIS Logical Memory, trail-making, patient and informant memory questions— met the sensitivity requirement of 94.53%. Sensitivity was raised to 95.18% with the addition of four additional characteristics. The results indicate that these characteristics may be useful for detecting cognitive impairment at CDR 0.5 and higher. Potentially limiting the study's larger applicability is its limited generalizability to certain demographics or circumstances. Additional validation in bigger and more diverse groups

may be necessary to determine the sensitivity and specificity of the found traits. No investigation into the role of confounding variables or co-morbidities in influencing the detected cognitive traits was conducted in the study. Considering the intricacy of the condition, the results might not adequately depict the spectrum of cognitive deficits observed in early-stage Alzheimer's disease. Results may not be as trustworthy as they may be due to interrater variability or inconsistent administration of the cognitive tests. It is crucial for clinical decision-making to investigate if the detected cognitive traits can predict the progression to dementia over the long term. Unfortunately, this was not done.

Many people become immobile as a result of Alzheimer's disease (AD) , the most common form of dementia. The OASIS dataset has been used to develop a machine learning model that can detect AD with a high accuracy of 96% using the voting classifier. In order to recover from Alzheimer's disease (AD), early diagnosis and treatment are essential, and ML algorithms may help reduce AD death rates. When tested on various datasets or in real-world situations, the model's performance could differ. The results may not be applicable to other populations because they are based on the OASIS dataset. The intricacies of actual AD diagnosis and therapy might not have been adequately captured by the study's emphasis on memory, accuracy, precision, and F1 score. Input data quantity and quality may affect the model's AD prediction performance. The model's practical use might be affected by ethical concerns and possible biases in the dataset that was utilized to train it. Since a wrong diagnosis could have serious ramifications, it's crucial to think about the possibility of false positives and negatives in practical settings.
The key to early treatment and risk awareness for Alzheimer's disease (AD) is an accurate diagnosis. Early Alzheimer's disease diagnosis using deep learning (DL) is now commonplace. The literature emphasizes the promise of DL in the early detection of AD. Predicting AD before manifestation is still tough, and present computer detection approaches have limitations due to innate observations. There are still limitations to DL's ability to predict AD before clinical start, but it shows promise for early AD diagnosis. We need more studies to improve DL's prediction powers for AD early diagnosis.

Observations made by humans are the current limiting factor in machine detection methods. Predicting Alzheimer's disease before symptoms appear is still a difficult task. It is still early days for DL's predictive skills to be fully developed for use in early AD diagnosis. Challenges in identifying early-stage Alzheimer's disease (AD) before symptoms appear. Predicting Alzheimer's disease before it shows symptoms is challenging. Improving DL's accuracy and predictive capacities for early AD detection requires more research. Using structural MRI data in particular, researchers are aiming for an automated Alzheimer's disease diagnosis by machine learning. Improving precision, avoiding overfitting, and studying particular brain regions are all part of their plan. On the GARD dataset, they achieved an accuracy of 90.05 percent using ensembles of convolutional neural networks (CNNs) for feature extraction and softmax cross-entropy for classification. This degree of precision is on par with the most cutting-edge approaches. This study only looks at sMRI, which limits its applicability to other modalities. Data scarcity led to the deployment of the patch-based technique, which may impact generalization. Because this dataset was created by a single research institution, its

applicability to different groups or time periods may be limited. The method's accuracy might change depending on the dataset's demographics or origin. Other essential aspects associated to AD diagnosis may be overlooked because to the concentration on certain brain landmarks. In practical diagnostic contexts, using CNN ensembles might increase computing complexity. In this article, we follow the progression of ideas surrounding dementia and Alzheimer's disease from its earliest descriptions all the way up to the current diagnostic criteria that include biomarkers. In doing so, it draws attention to how our understanding of these illnesses and the words used to describe them have developed up to the year 2015. There is a focus on how historical information is becoming more relevant in controlling the increasing frequency of Alzheimer's disease and how complicated the condition is.

The review might overlook important breakthroughs since it doesn't cover changes after 2015. Because it is mostly based on articles found in the LILACS and Medline databases, it may miss important contributions made by other researchers. Dementia and Alzheimer's disease diagnosis and treatment present unique difficulties, and an overemphasis on past developments may fail to do justice to these issues. Cultural and social factors impact how these illnesses are seen and treated, but this review may not fully analyze them. Genetic research and tailored therapy have had a profound effect on our understanding and management of Alzheimer's disease; however, this article may not cover that extensively. There has to be more of an emphasis on how past research on dementia might inform present and future approaches to the field. To aid in the diagnosis of Alzheimer's disease (AD) from neuroimaging data, a new attention-based 3D ResNet design is suggested. This method not only finds critical brain areas for AD diagnosis, but it also enhances classification performance. Changes in gray matter accompany the capture of key brain regions by the attention-based network, according to experiments involving 532 participants, suggesting possible biological markers.

It is possible that the diversity of AD patients is underrepresented in the sample size of 532 subjects. The suggested architecture requires additional validation to determine its generalizability to diverse demographics or imaging procedures. The findings of the attention mechanism necessitate knowledge of neurology and could be difficult for laypeople to understand. White matter abnormalities and Alzheimer's disease classification are both studied using diffusion MRI . Extrapolating from T1-weighted MRI and PET data, a methodology was developed for the repeatable assessment of AD categorization using diffusion MRI. Classification outcomes were improved by feature selection (FS), leading to a balanced accuracy increase from 0.76 to 0.82 for CN vs AD tasks. With similar outcomes for mean diffusivity (MD) and fractional anisotropy (FA), voxel-wise features often outperformed regional features. Instead of data imbalance, low performance on MCI tasks might have been caused by few data samples. Results were unreliable and too optimistic when FS was not nested validated, leading to a relative increase in balanced accuracy of up to 40%. Very little is known about how extra steps like picture preparation, feature rescaling, and cross-validation affect classification accuracy. It is possible that the study did not take into consideration the fact that different imaging techniques and research centers may produce diffusion MRI data of varying

quality. The potential applicability of the results to different demographics and time periods not included in the ADNI study is left unexplored. There is a passing reference to T1w MRI, but no real investigation into how the two modalities compare; this could restrict our knowledge of the benefits and drawbacks of diffusion MRI. There is a lack of research into how particular demographic or clinical aspects affect classification performance, which could restrict the framework's usefulness in a wider context. Using 5-fold cross-validation, the article compares LR, KNN, SVM, and GBC, four Machine Learning algorithms that have been used to forecast cardiac illness. It discovers that XGBoost Classifier and Extreme Gradient Boosting Classifier with GridSearchCV produce the best results in testing and training accuracy. The study's overarching goal is to provide a novel approach to model generation that may be applied to solve practical problems in the field of heart disease prediction. Not much detail about the methods used to preprocess the dataset and choose features. The selected Machine Learning algorithms have not been thoroughly examined for any biases or possible downsides. Important for making healthcare decisions, the study doesn't deal with how comprehensible the models are. Very little is said about how well the models can be applied to different types of patients and different kinds of healthcare facilities. The prediction accuracy of this model has not been compared to that of more conventional clinical risk assessment tools. The study could benefit from a more thorough examination of the privacy and ethical concerns raised by healthcare predictive models.

Subjective cognitive decline (SCD) patients and healthy controls were studied using various MRI modalities to build neural networks. The combined networks achieved a high prediction accuracy for SCD people, with the default mode network (DMN) and salience network (SN) being the primary highlights. Enhanced functional connection, decreased morphological connectivity, impaired memory performance, and elevated AV45 SUVRs were all found to be associated in multiple linear regression models. Because of the limited sample size, the results may not be applicable to a broader population. The study's cross-sectional methodology precludes drawing any conclusions about cause and effect. It is possible to overfit or add biases into the prediction model by using multiple kernel learning-support vector machines. Lacking information on how SCD develops into Alzheimer's disease, the study did not follow participants over time. By narrowing our attention to certain brain networks, we risk missing other possible biomarkers or areas associated with SCD. Results may not be applicable outside of the specific study institution due to differences in imaging methodologies and procedures.

The purpose of this study was to determine whether a five-stage machine learning pipeline could effectively categorize OASIS brain MRI scans as indicative of Alzheimer's disease. In order to analyze the dataset, which consisted of 343 MRI sessions from 150 individuals, scores such as MMSE, CDR, and ASF were used. The research found that using a Random Forest classifier yielded very accurate results. It is possible that the results cannot be applied to other datasets because the study only used OASIS. It is possible that additional indicators for Alzheimer's disease may be unnoticed if just three scores (MMSE, CDR, and ASF) are used for analysis. It is necessary to validate the Random Forest classifier's generalizability since its performance could change when used

with datasets from different sources. The intricacy of Alzheimer's disease, which encompasses a range of behavioural and cognitive symptoms, may have been overlooked by the study due to its concentration on magnetic resonance imaging (MRI) brain scans. It would have been helpful to have the participants' demographics from the study to make sense of the findings. The study did not address ethical concerns about the use of medical data or the consequences of automated categorization systems.

The purpose of this research is to investigate the feasibility of multi-class AD stage classification using rs-fMRI and the ResNet-18 architecture. High rates of accuracy for CN, SMC, EMCI, LMCI, MCI, and AD phases were reached by the models using a cohort of 138 participants from the ADNI. Findings indicate that fMRI and deep learning techniques have promise for the early detection of Alzheimer's disease and its development. The results may not be applicable to a broader population due to the small sample size of 138 participants drawn from the ADNI database. Accurately detecting phases of AD with rs-fMRI may be challenging due to the complexity of brain structures and processes. One neuroimaging modality, rs-fMRI, may not be able to detect all forms of AD pathology or give a thorough diagnosis. It is possible that the characteristics employed to measure performance (precision, recall, etc.) do not adequately reflect the complexity of AD categorization. The research may have restricted future investigations into alternative deep learning models that might improve classification accuracy by focusing only on the ResNet-18 architecture. It is unclear whether the findings can be applied to different people or environments apart from the ADNI group.

Dementia and other cognitive impairments are symptoms of Alzheimer's disease, a neurological illness for which there is now no treatment. In order to halt its advancement, an early diagnosis is essential. Factors like age, frequency of visits, MMSE score, and degree of education can be fed into machine learning algorithms to foretell the onset of Alzheimer's disease. Due to the intricacy and variety of Alzheimer’s disease progression, the accuracy of projections may vary. Both the amount and quality of the data used to train machine learning models are susceptible to bias and limitations in the data set. Predictions based on psychological variables may miss certain important aspects of Alzheimer's disease progression. When using personal data for prediction, there are ethical considerations about data privacy and consent. Distinctions in illness manifestation and therapeutic efficacy may go unaccounted for by predictive algorithms. Skill is necessary for interpreting machine learning algorithm outputs to prevent incorrect diagnosis or inaccurate forecasts.

3. Proposed methodology

There are three main components to the suggested method. To begin, pandas was used to load the Alzheimer's disease dataset in order to preprocess the data. Since this research made use of a longitudinal dataset, a study chronology was required for a better understanding of the results. We began by checking if the data seemed to be collected at a baseline or at a specific point in time; if so, how cross-sectional. Subsequently, all of the data was thoroughly analyzed, which involved comparing the primary research

components with the relevant data obtained at each visit. The main data source for this study is longitudinal MRI scans. The study contained magnetic resonance imaging (MRI) data from 150 patients ranging in age from 60 to 96 years. We made sure to scan every patient a minimum of once. No one is left- handed. An additional 72 patients were deemed "non-demented" during the course of the research. Throughout the course of the study, 64 patients who were initially classified as "Demented" continued to be in this category. The MRI dataset is described in Table . With identifiers ranging from 4,751 to 6,900, this dataset includes detailed medical records for 2,149 patients. Factors related to lifestyle, medical history, clinical measurements, cognitive and functional evaluations, symptoms, and an Alzheimer's disease diagnosis are all part of the dataset. Researchers and data scientists can use the data to study Alzheimer's risk factors, create prediction models, and do statistical analysis.

Table 1 Dataset Info

S.No.	Attributes	Description
1	ID	Identification
2	M/F	Gender (M if Male, F if Female)
3	Hand	Handedness
4	Age	Age in years
5	EDUC	Years of education
6	SES	Socio Economic Status
7	MMSE	Mini Mental State Examination
8	CDR	Clinical Dementia Rating
9	eTIV	Estimated Total Intracranial Volume
10	nWBV	Normalize Whole Brain Volume
11	ASF	Atlas Scaling Factor
12	Delay	Delay

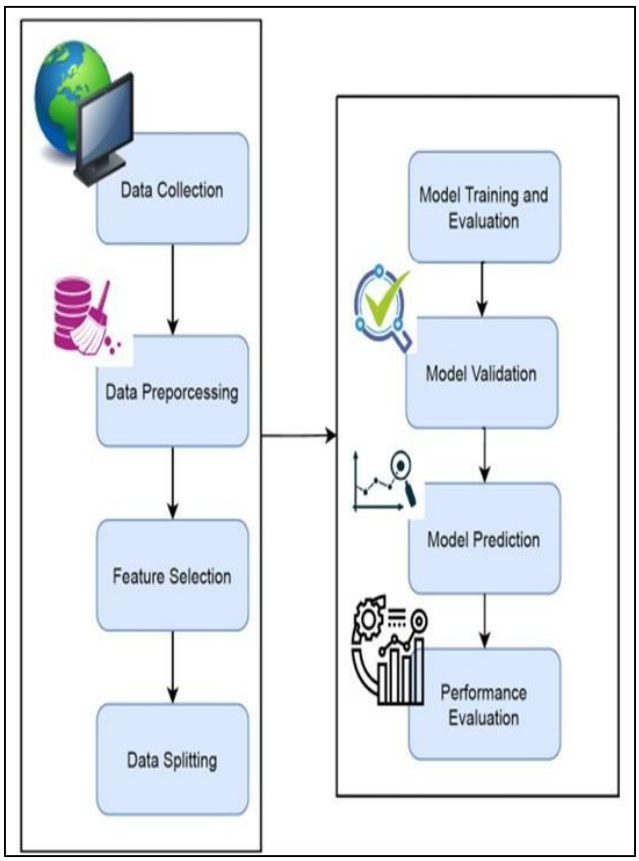

Figure 1 System Architecture

3.1. Gathering Information

During this phase, a variety of data-mining techniques were employed to cleanse and prepare the data. This includes many other tasks, such as dealing with missing values, extracting features, transforming features, etc. We found 9 rows in the SES column that were missing values. Two approaches are taken to deal with this matter. Eliminating rows when values are missing is the quickest and easiest fix. Imputation, which means to substitute missing values with their corresponding values, is another method for filling in data gaps. With only 140 measures to work with, imputed data should improve the model's performance. After removing the 9 rows that had missing values in the SES attribute, the median value is utilized for imputation.

3.2. Analysis of Data

In this part, we covered the correlations between dementia and each MRI characteristic. We used this exploratory data analysis technique to estimate the correlations before extracting or analyzing the data. This allowed us to explicitly describe the data relationships using a graph. This data might be useful for future data interpretation and analysis by guiding the selection of appropriate methods.

3.3. Selecting Features

In machine learning, feature selection plays a crucial role. Using hundreds of samples, this study applies feature selection to Alzheimer's disease clinical data. There are three different approaches to feature selection: filter, wrapper, and embedding. During the pre-processing stage, a filter approach is frequently employed. An further method that is fundamental to the feature subset is the wrapper method. The Embedded method integrates the filter and wrapper methods, concluding the process. In this study, we picked the three most popular feature selection methods: correlation coefficient, information gain, and chi-square.

3.4. Correlation Coefficient

The mathematical formula for the covariance of two variables, X and Y, is
$\rho(X,Y) = Cov(X, Y)/ \sigma X \sigma Y$.

The linear relationship between two variables is measured by their covariance. It is simple to discover a correlation between the different Alzheimer's phases by using correlation coefficients. This method's main flaw is that it relies on data obtained from many different sources, making it extremely vulnerable to outliers.

3.5. Information Gain

To get the information gain value when attribute D is chosen, subtract the lower node's entropy from the upper node's entropy.
Gain (D) = I (s1, s2, s3, sn) - E (Feature D)

Chi-Square: This approach is useful for studying relationships between diet and obesity and other categorical factors. Chi - Square = (Observed - Expected)2/expected

3.6. Algorithm: Preparation and Splitting the Data

Choose Some Information: M.F., Age, EDUC, SES, MMSE, eTIV, nWBV, ASF, CDR
Train Data iterate through all rows in the data set using the round function with an inner loop of 0.8 iterations. @Choose 80% of the trainer data The TrainData indexes are a sample of (1:nrow(data)) from the Train_Data.

#Vectors are made out of indeces at random.

TrainML receives data from the TrainData indexes. A dataset for training is created. CDR ~ M.F + Age + EDUC + SES + MMSE + eTIV + nWBV is the split formula. There are five units, N=5. Divide to nWayCrossValidation using n rows of data and n as the parameter. *#5 folds of cross-validation are produced.*

3.7. Classifier Models

3.7.1. Decision Tree (DT)

An overview of the decision tree provides a model for continually splitting the data depending on the feature cutoff values using a tree structure. As a result of splitting, instances are divided into subsets. The word "leaf node" describes the outermost node in a tree, whereas "internal node" describes the innermost component. When features interact significantly with the target, a decision tree becomes quite useful.

3.7.2. Random Forest (RF)

Because it does not suffer from overfitting, a random forest model outperforms decision trees. Decision trees in random forest models are all slightly distinct from one another. The ensemble predicts outcomes by combining the results of each decision tree model (bagging) using the majority voting algorithm. This results in less overfitting yet each tree's predictive power is preserved.

3.7.3. Support Vector Machine (SVM)

Using suitable hyper planes in a three-dimensional environment, this technique assigns a class to each data point. Our goal in employing SVM (25), is to locate a hyperplane that divides instances of two types of variables that occupy adjacent clusters of vectors. Closer vectors to the hyperplane are considered support vectors. Support vector machines (SVMs) apply training and test data. The training data is segmented according to the attributes and goal values. Constructed from test data, a model for predicting target values is generated by SVM

3.7.4. XGBoost

The acronym for "eXtreme Gradient BOOSTting" is XGBoost. The term describes the steps taken to optimize the performance and speed of gradient-boosted decision trees. Gradient boosting machines are typically not particularly scalable and take a long time to construct because model training is sequential. XGBoost prioritizes performance and speed.

3.7.5. Voting

Combining the forecasts from several earning algorithms can be as easy as voting. In order to take use of their unique qualities, several voting classifiers are trained and evaluated simultaneously; these classifiers are more like wrappers than genuine classifiers. We can forecast the end result by training data sets with various methods and ensembles. When making a forecast, there are two methods to get a majority vote.

- **Hard voting:** For a simple majority vote, "hard voting" is the way to go. Here, we'll select the class that received the most votes (Nc). All of the classifiers' votes together form our prediction.
- **Soft voting:** Recommended only when classifiers are well-calibrated, "soft voting"

is tallying up the probability vectors for each predicted class across all classifiers and selecting the one with the highest value.

3.8. Validation of Model

The overfitting issue is mitigated through model validation. When training an ML model, cross validation is an important step in determining the model's correctness. Creating a noise-free ML model is no easy feat. Therefore, cross validation is carried out in this study, dividing the entire dataset into n equal-sized halves. Using the n-1 divisions, the ML model is trained for each iteration. The average of all n-folds is used to evaluate the method's performance. Using ten-fold cross validation, the ML model was trained and evaluated ten times in this study.

4.Results

Table 2 Precision Values without tuning and tuning with hyperparameters

Model	Precision Normal	Precision With HP
XGBoost	81.2%	81.4%
Ada Boost	81.2%	81.4%
Random Forest	80.6%	81.2%
Support Vector Machines	74.4%	74.4%
Naive Bayes	73.9%	73.2%
Logistic Regression	72.2%	72.7%
k-Nearest Neighbors	66.3%	69.9%
Neural Network	69.5%	69.5%

In the paper, algorithms are hyper parameter tuned and get the results. the above table 2 explains the performance result comparison of algorithms. Below table 3 explain about the performance table after hyperparameter tuning with algorithms.

Table 3 Performance with Algorithms After Hyper Parameter Tuning

Model	**Accuracy**	**Precision**	**Recall**	**F1-Score**
Decision Tree Classifier	80.46	0.80	0.79	0.78
Random Forest Classifier	86.92	0.85	0.81	0.80
SVM Classifier	81.67	0.77	0.70	0.79
XGBoost Classifier	85.92	0.85	0.83	0.85
Voting Classifier	85.12	0.83	0.83	0.85

Confusion Matric of the best model we have seen below in the figure .

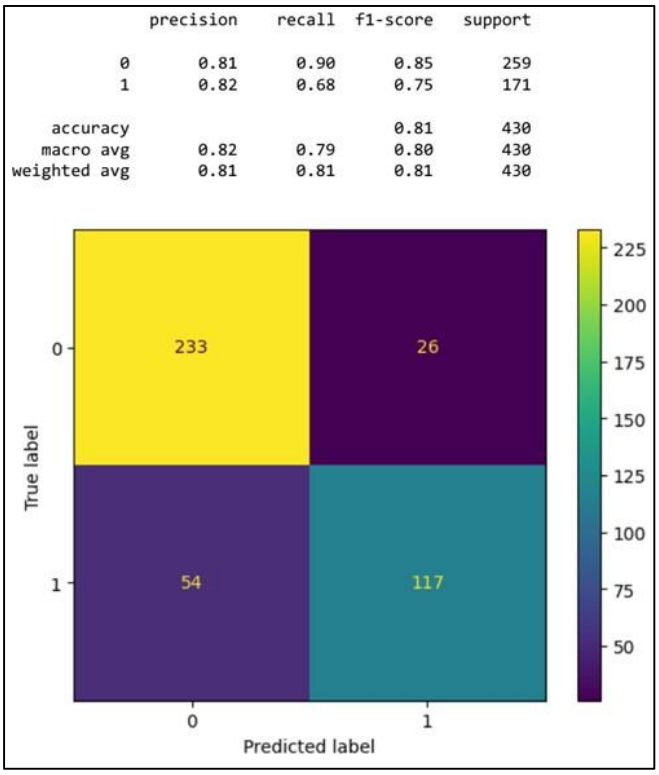

Figure 2 Confusion Matrix of Best Model AdaBoost Classifier and XGBoost Classifier

5. Conclusion

Alzheimer's disease (AD) presents a significant and growing challenge to public health due to its high prevalence and profound impact on individuals and society. Early diagnosis is critical in managing AD, as treatments are more effective when administered in the initial stages of the disease. However, the subtle and complex nature of early AD symptoms makes timely diagnosis challenging.

This research explored the application of various machine learning (ML) algorithms, including Decision Trees, Random Forests, Support Vector Machines (SVM), Gradient Boosting, and Voting classifiers, to predict Alzheimer's disease using data from the Open Access Series of Imaging Studies (OASIS). The performance of these models was evaluated using metrics such as Precision, Recall, Accuracy, and F1-score.The findings indicate that the proposed ML classification scheme can achieve a validation accuracy of 83% on test data, which is significantly higher than many existing methods. This high accuracy underscores the potential of ML models to assist clinicians in the early diagnosis of AD, thereby facilitating timely and effective intervention. The study demonstrates that machine learning algorithms can be valuable tools in the fight against Alzheimer's disease. By enabling early detection, these models can help reduce the annual mortality rates associated with AD and improve the quality of life for affected individuals. Moreover, the implementation of ML-based diagnostic tools in clinical settings can alleviate some of the

social, financial, and economic burdens posed by this disease. Future research should focus on refining these models, incorporating larger and more diverse datasets, and exploring additional features that may further enhance predictive accuracy. By advancing the capabilities of ML in medical diagnostics, we can move closer to a future where diseases like Alzheimer's can be identified and treated at the earliest possible stage, significantly improving patient outcomes.

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