International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING
ISSN:2147-6799 www.ijisae.org Original Research Paper

Emerging Approaches in Machine Learning for Identifying Alzheimer's disease ADNI Using Classification Methodologies

Rajasree R. S.[1]*, Brintha Rajakumari S.[2]

Submitted: 16/01/2024 **Revised**: 24/02/2024 **Accepted**: 02/03/2024

Abstract: Among elderly individuals, among the most common causes of memory loss is Alzheimer's disease (AD). Also, a sizeable amount of individual's worldwide experience metabolic issues including diabetes and Alzheimer's disease. Degenerative brain changes are brought on by Alzheimer's disease. This sickness can make more people inactive as the older population increases since it affects their cognitive and physical capabilities. Their relatives as well as the financial, industrial, and social sectors may be affected by this. To identify these illnesses sooner, researchers have recently looked into several deep learning, machine learning, and other methodologies. AD individuals can recuperate from this completely while experiencing the least amount of harm by receiving early treatment and timely detection. The model's quality is determined by means of reliability, precise, recall, and F1-measure using the freely accessible series of maging modalities (OASIS) dataset. Our results demonstrated that with the AD dataset, the voting classifier had the highest prediction performance of 95%. As a result, with precise identification, Forecasting models have the ability to significantly cut the yearly incidence and mortality from Alzheimer's disease.

Keywords: *Machine Learning, Alzheimer's, Voting, kNN, DT, XG boost, CBIR technologies, Correlation-based Feature Selection, Open Access Series of Imaging Research (OASIS), MMSE*

1. Introduction

Alzheimer's disease frequently starts out with minor memory issues that get worse over age, impairing brain function. Although the precise origin of Alzheimer's disease is not entirely understood, a number of factors, including ageing, genetic susceptibility, untreated clinical depression, exercise habits, severe neck injury, and sustained hypertension, are believed to be contributing to its progression. A individual might experience ongoing forgetting in the beginning stages of Alzheimer's disease, which is strikingly different from ordinary unconsciousness shown in Figure 1. Everyone eventually forgets things, but in the beginning phases of the dementia, a person's brain function slowly and steadily deteriorates, making it challenging to acknowledge daily chores. Early on, bewilderment is also typical, and a person could lose track of what they have been doing or just what they planned to do.

As previously said, choosing the appropriate features that indicate traits helpful to distinguishing between AD, MCI, and NC remains difficult recently, AD or MCI were determined using an interactive medical picture classification system and concept-based image retrieval tools. [3].

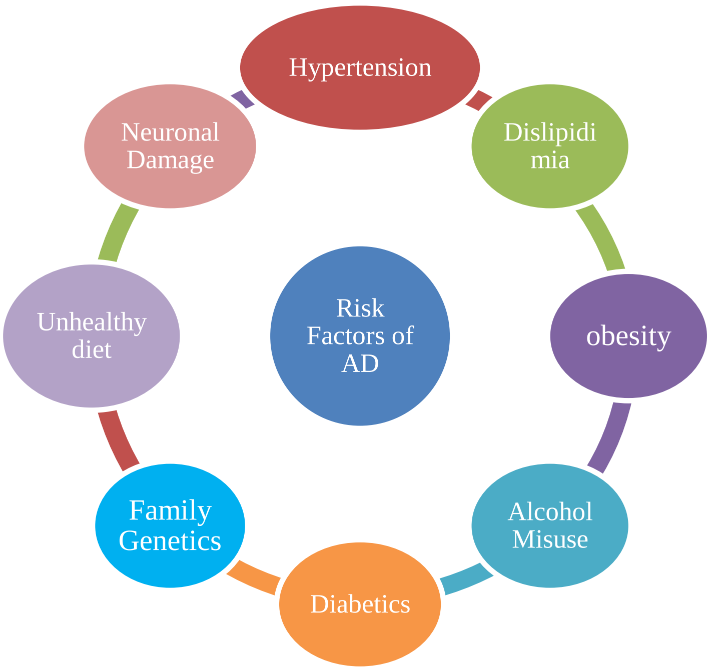

Fig. 1. Factors of Dementia

By integrating CBIR technologies, that enable members to instantaneously evaluate the information of a search query against such a database, combine computerized diagnostic image different classifiers with the experience and knowledge of physicians' aid in obtaining accurate categorization outcomes. Similar to how categorization is used as a reference for retrieval, massive databases are taken into account to improve picture retrieval performance and timeliness.

*[1]Research Scholar, Bharath Institute of Higher Education and Research, Chennai, Tamil Nadu.Email:rajasreecse@gmail.com**
[2]Associate Professor,Bharath Institute of Higher Education and Research, Chennai, Tamil Nadu. Email: brintha.ramesh@gmail.com

The method of retrieving a picture generally consists of two main steps: the first stage develops this phase 2 matches these newly formed features to those already listed in the library. The first stage creates features that correspond to a specific input image. The critical challenge is to use various image processing and operation methods to find an acceptable representation of the image content. Additionally, it's crucial to have sufficient distributional spacing between the features.

1.1 Contribution

Emerging approaches in machine learning for identifying Alzheimer's Disease (AD) using classification methodologies have made significant contributions to the field. These approaches leverage the power of machine learning algorithms to analyze large datasets from the Alzheimer's Disease Neuroimaging Initiative (ADNI) and accurately classify individuals as either AD patients or healthy controls.

One major contribution is the development of novel feature extraction techniques that capture relevant information from various data sources, such as neuroimaging scans, genetic data, and clinical assessments. These features provide valuable insights into the underlying patterns and biomarkers associated with AD, enabling classification that is more accurate.

Additionally, researchers have explored different classification algorithms, including support vector machines, random forests, and deep learning models, to improve the accuracy and robustness of AD classification. These algorithms are trained on labeled data from ADNI, allowing them to learn patterns and make predictions on new, unseen data.

Overall, the emerging approaches in machine learning for identifying Alzheimer's Disease using classification methodologies have the potential to revolutionize early detection and diagnosis. By accurately identifying individuals at risk of developing AD, these approaches can facilitate timely interventions and improve patient outcomes.

2.Related Work

With the help of numerous biomarkers that have been proposed, examined, and studied, A powerful medical imaging method for detecting AD is structural MRI. A critical area of research in this area now centers on the extraction of effective structural Magnetic resonance biomarkers of AD [[9], [10], [11]]. Volume is typically utilized as a biomarker in the diagnosis of numerous diseases, not solely from the hippocampal but also from other regions of interest (ROI), which have also been investigated, like the ventricular contraction [15], the cortex [14], and the complete brain [16]. Architectural studies, such as cortical width measurement [17, 18], form [4, 5], surface [19, 20], and closeness of neural systems [6], are another type of universal biomarker for the identification of AD. When examining several MRI the standard benchmark data would indeed be required for methodology comparisons, biomarkers for Clinical examination, understanding the performance of different biomarkers, and understanding the connections between them.

Based on structural MRI measures, medical image retrieval for AD has been investigated [3,12]. The primary goal of this effort was to recover image retrieval performance with the least amount of attributes. The Correlation-based Feature Selection (CFS) algorithm was used to filter out any inappropriate, potentially noisy, and unnecessary information from the feature set, which contained assessments of the brain's volume and thickness. Other research [1, 2] investigated at the Open Access Series of Imaging Research (OASIS) dimensions and breadth estimates of the brain's anatomy.

3. System Methodology

3.1 Data set

There are 150 people in this dataset, whose ages range from 60 to 96. Each issue was scanned twice or more, with at least a one-year interval between scans, for a total of 373 imaging sections. For each patient, three or four different T1-weighted MRI scans performed in a single scan session are shown. Both for men and women, as well as all of the subjects, are right-handed. 72 of the participants in the trial were labelled as non-demented throughout. At the time of their initial visits, 64 of the study's subjects were deemed to be mentally ill. For subsequent scans, they persisted, including in 51 cases with soft to moderate Alzheimer's ailment. Another 14 subject were first categorised as non-demented but were later categorised as demented.

3.2 MRI pre-processing

Preprocessing is a pivotal step in the quest to identify and detect Alzheimer's disease, encompassing a range of techniques tailored to different data modalities. These steps may include skull stripping to remove non-brain tissues, spatial normalization to align images into a standardized anatomical space, and intensity normalization to correct for variations in scanner settings or image acquisition protocols. By standardizing and enhancing the quality of neuroimaging data, preprocessing facilitates the extraction of meaningful features and patterns that can be used to distinguish between healthy individuals and those with Alzheimer's disease.

Furthermore, clinical data, including cognitive assessments and demographic information, are vital sources of information for Alzheimer's disease detection.

Preprocessing clinical data involves tasks such as feature extraction to capture relevant cognitive measures or demographic variables, data cleaning to address inconsistencies or missing values, and normalization to scale features to a common range. By preprocessing clinical data, researchers and clinicians can uncover valuable insights into the cognitive decline associated with Alzheimer's disease and develop predictive models capable of identifying individuals at risk or tracking disease progression over time.

Extraordinary data combinations, misplaced values, and superfluous in sequence can be found in datasets, producing false findings. Therefore, the data's quality must be raised before performing an analysis. The dataset was obtained via ADNI and then further processed using Free Surfer. Finally, using Free Surfer, we gathered raw data for 66 volumetric and 72 thickness measurements shown in figure2 and 3.

Head size and intracranial volume were used to standardize the cerebral cortex and white matter measurements, third and fourth ventricles, inferior lateral ventricle, cerebellum cortex, hippocampus, amygdala, caudate, putamen, pallidum, and white matter of the cerebellum. Superior frontal, superior parietal, rostral middle frontal, imperfect gyrus, take place within the boundaries, posteriorly middle frontal, condition can result, anterior cingulate, pars includes a number of features, parietal triangularis, precentral, escorts, the posterior cerebral, dorsal pole, inferior parietal, diagonal estimation, posterior, and superior are some instances of the frontal lobe structures.

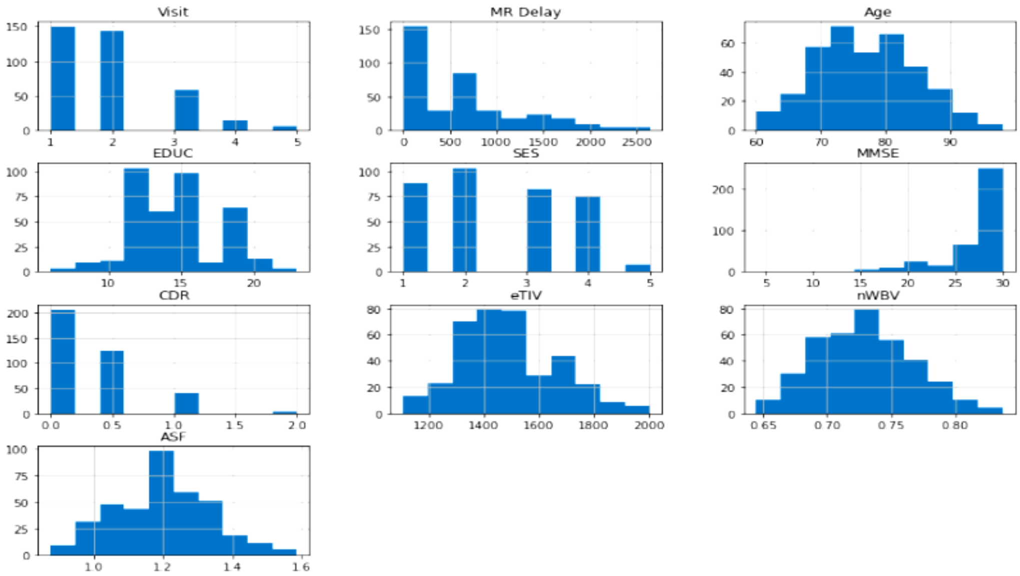

Fig. 2. Histogram Analysis

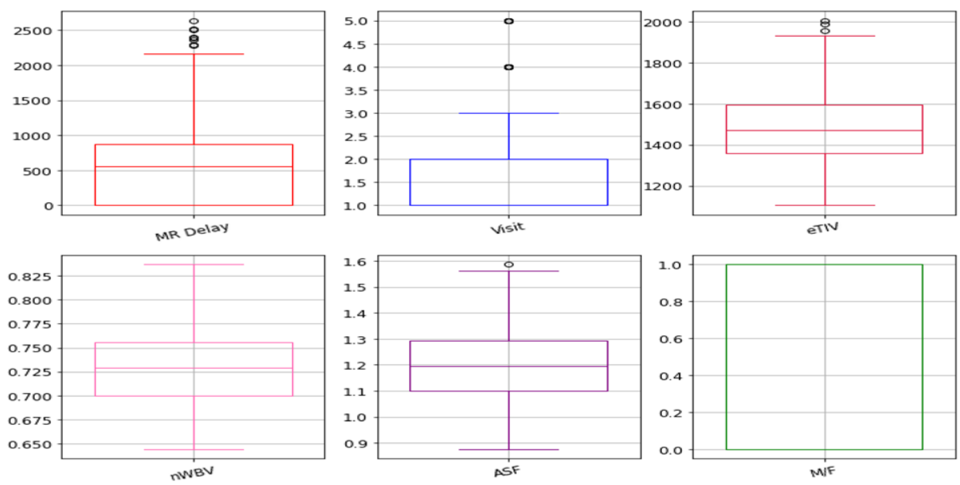

Fig.3. Box Plot Representation Correlation Analysis

3.3Analysis of methodologies

The machine employed for the present article included an intel core CPU running at 2.3 GHz, 8 GB of RAM, and the Microsoft Windows operating system. Data from OASIS was used, which was subsequently homogenized and given specific features. Standardization increases precision. The workflow of the proposed work is shown in Figure 4.

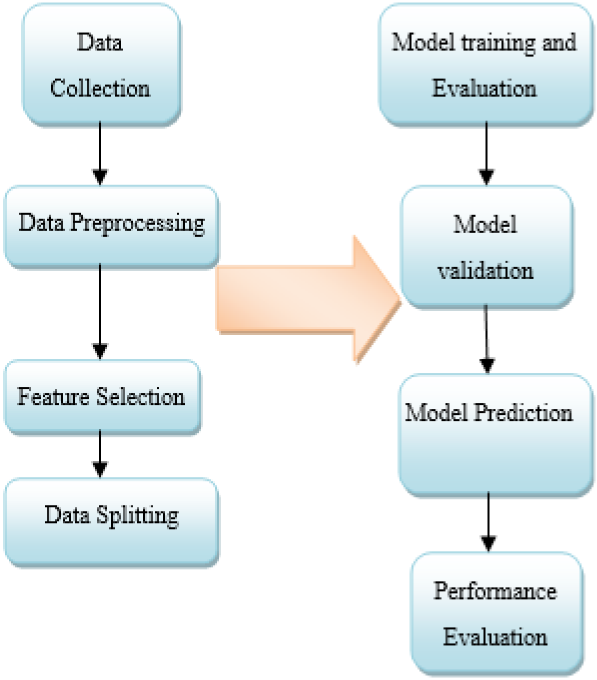

Fig. 4. Workflow of the Methodologies

4. Classifiers and its Performance Measures

As a rule of the thumb for degenerative diseases, a positive significant rate is required to diagnose each person with Alzheimer's disease as soon as possible. But, we additionally must make sure that perhaps the misdiagnosis rate is low in the interim. The contour area is the most effective measure for evaluating efficiency. The correctness of the models is determined by calculating the uncertainty matrices. A correlation matrix is used to offer data for a certain feature or set of data. When choosing the best approach, the aspects that are most closely related are taken into account. Hyperplanes are used to describe the data points. Any end of the higher dimensional space may contain arguments again for information, which are further individually addressable as various classes.

The excitable range is determined by the squared correlations of the selected characteristics. The desired model is fed after the original data has been split into sets for training and testing. The process is performed for all the listed techniques, and the estimations for actual efficiency are provided underneath.

The Parameters taken for the comparison of the analyzing models for identification of alzhemiers disease is given below,

$$Accuracy=TP+TN/TP+TN+FP+FN \quad (1)$$

$$Precision=TP/TP+FP \quad (2)$$

$$Recall=TP/TP+FN \quad (3)$$

$$F1=2\times Precision\times Recall/Precision+Recall \quad (4)$$

4.1 Decision Tree Classifier

The decision tree algorithm iteratively splits the data into subsets based on the most informative features, aiming to maximize the homogeneity of samples within each subset with respect to the target variable (i.e., presence or absence of Alzheimer's disease). At each node of the tree, the algorithm selects the feature that best separates the data into distinct groups, typically using measures such as Gini impurity or information gain.

One advantage of using a Decision Tree Classifier in Alzheimer's disease detection is its ability to generate easily interpretable models that can reveal important biomarkers or cognitive patterns associated with the disease. Clinicians can gain insights into the decision-making process of the algorithm, potentially leading to a better understanding of the underlying mechanisms of Alzheimer's disease.

However, Decision Tree Classifiers may suffer from overfitting, especially when dealing with high-dimensional data or noisy features. To mitigate overfitting, techniques such as pruning, limiting the tree depth, or using ensemble methods like Random Forests can be employed.

When contrasted to other models, decision trees are the traditional machine learning technique and yield outcomes with a better degree of accuracy. The splitting of data was carried out under different settings according to an algorithmic technique that was created Table 1. Decision trees have been praised in many research as a great method for performing predictive analyses. In the process of predicting AD, we start with the tree root characteristic and contrast it to various tree node properties. We investigate Figure 5 the branch related to that value and go on to the next node based on the correlation.

Table 1. Simulation Results of Decision Tree

	precision	recall	F1-score	support
Class 0	0.75	0.83	0.79	52
Class 1	0.84	0.77	0.80	60
Avg/ Total	0.80	0.79	0.79	112

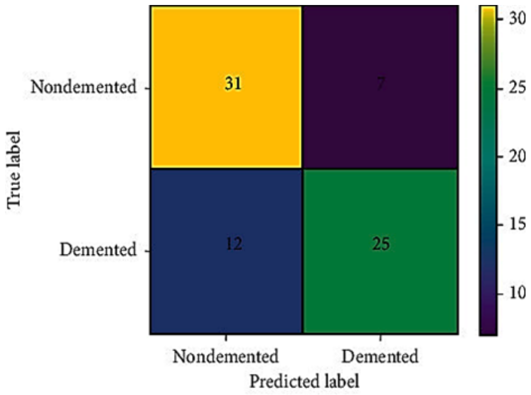

Fig. 5. Confusion Matrix on Decision Tree

4.2Voting Classifier

Voting constitutes solitary quickest ways to combine the prediction from different learning algorithms Figure 6. Voting technique are merely wrappers for many classifiers that are simultaneously trained and evaluate in order to take use of their distinct description. Data points are taught using a wide range of algorithms and combinations to anticipate the outcome.

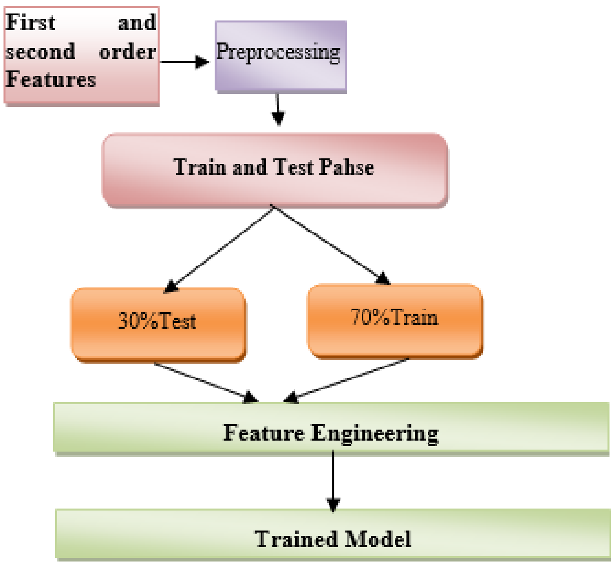

Fig. 6. Workflow of the Voting Classifier

A sort of statistical prediction model for aggregating forecasts from various versions is a voter classifier. When the findings of each base classifiers are combined, a voting learner is a technique to forecast the final feature class label using the greatest vote majorityTable 2. The main idea is to build a cohesive prediction method instead of building various classification models and figuring out each one's predictive performance separately.Hard casting represents the most basic form of qualified majority figure 7. In this case, the class (Nc) with the most vote will just be selected. Our projection is based on the results of each classifier's democratic majority.

Table 2. Classification result of voting classifier

	precision	**recall**	**F1-score**	**support**
Class 0	0.80	0.85	0.82	52
Class 1	0.86	0.82	0.84	60
Avg/total	0.83	0.83	0.83	112

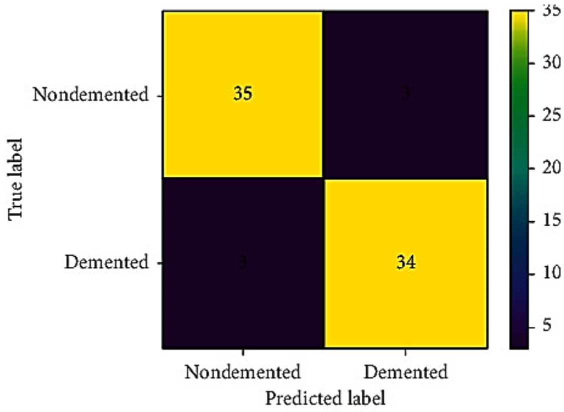

Fig. 7. Confusion Matrix on Voting Classifier

4.3 LGBM Classifier

Because of the effectiveness and quick efficiency, the Light GBM constitutes a more advanced variation of the Logistic Regression Machine Figure 8. It can accommodate a significant quantity of data without becoming complicated, unlike GBM and XGBM figure 9. On the opposite hand, it is inappropriate for data points with a smaller number. Light GBM promotes leaf wise expansion of the spanning tree over level-wise growth. Moreover, in light Glioblastoma, the primary node splits into two minor nodes while splitting into a third secondary node. Which of network cells has a bigger loss determines how it relates to the idea is split. Hence, the Light Gradient Boosting Machine (LGBM) heuristic technique will always be preferred because of the leaves partition.

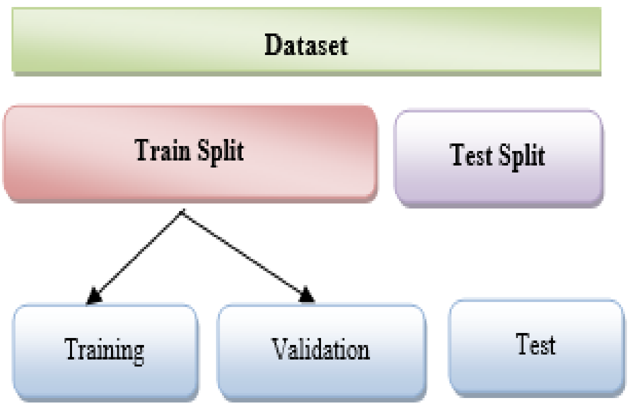

Fig. 8. Generic model for validation

Table 3. Classification result of LGBM Classifier

	precision	recall	F1-score	support
Class 0	0.77	0.83	0.80	52
Class 1	0.84	0.78	0.81	60
Avg/total	0.81	0.80	0.80	112

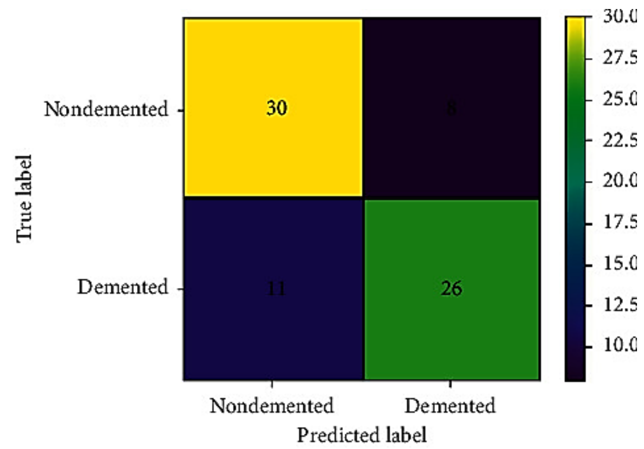

Fig. 9. Confusion Matrix on LGBM Classifier

Furthermore, LightGBM is efficient in handling high-dimensional data, which is prevalent in Alzheimer's disease detection studies, where hundreds or thousands of features may be extracted from neuroimaging scans, genetic data, and clinical assessments. LightGBM's ability to handle large feature spaces without requiring extensive preprocessing or feature engineering can streamline the model development process and improve prediction accuracy.

3.4 Gradient Boosting Classifier

A sort of classification algorithm called support vector classifiers combines a number of weak deep learning to Support vector classifiers, a type of learning algorithm, integrate series of failed teaching methods to create a successful leading to specific. Gradient improvement typically makes use of decisions trees Table 4. Decision tree algorithm is frequently used for slope enhancement Table 4.

Tuning the model's hyper parameters, on the other hand, necessitates some active decision making on our part. In order to generate a predictive model that has extraordinarily highest accuracy power and accuracy whenever working with a huge amount of information, GBM is a boosting approach that is typically used Figure 10. In hopes of improving fighting spirit over a symbolises, bolstering is a group of instructional methods that often combine the predictions of many base estimators figure 10. It creates a strong predictor by combining an assortment of weak or average predictors.

Table 4. Classification result of GB Classifier

	precision	recall	F-Measure	support
Class 0	0.81	0.85	0.83	50
Class 1	0.86	0.83	0.85	59
Avg/ Total	0.84	0.84	0.84	110

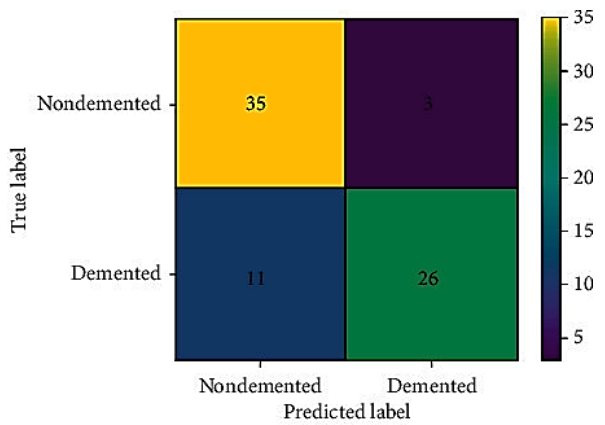

Fig. 10. Confusion Matrix on GBC Classifier

3.5 K-Nearest Neighbours Classifier

The technique of this segmentation is the assignment of a single data point to a class based on knowledge the classifier has acquired during training. Its task is to provide an input pattern expressed by a variable to one of the various predetermined groups. For the purpose of classifying an MRI brain imaging, the Classification algorithm Table 5 is the one that is currently in use in this study to identify the person as CN, MCI, or AD. This classifier uses a non-parametric method to generate its classifications and the algorithmic procedure is given below. There is no requirement for prior knowledge of the layout of the selected features acquired in training examples when a retraining feature group is introduced to a current training compendium.

Algorithm: KNN_Alzheimer_Detection

Input:

- train_data: Training data features

- train_labels: Labels corresponding to training data

- test_data: Test data features

- k: Number of neighbors to consider

Output:

- predictions: Predicted labels for test instances

Procedure:

1. Initialize an empty list to store the predictions.

2. For each instance in the test_data:

a. Compute the distance between the test instance and each instance in the train_data.

b. Store the distances along with their corresponding indices.

3. Sort the distances in ascending order and select the indices of the k nearest neighbors.

4. Retrieve the labels of the k nearest neighbors from train_labels.

5. Perform a majority vote among the retrieved labels to determine the predicted label for the test instance.

6. Store the predicted label in the predictions list.

7. Repeat steps 2-6 for all instances in the test_data.

8. Return the predictions list.

Table 5. Classification result of KNN Classifier

	precision	**recall**	**F-score**	**support**
Class 0	0.60	0.80	0.68	51
Class 1	0.72	0.54	0.63	59
Avg/ Total	0.68	0.65	0.64	100

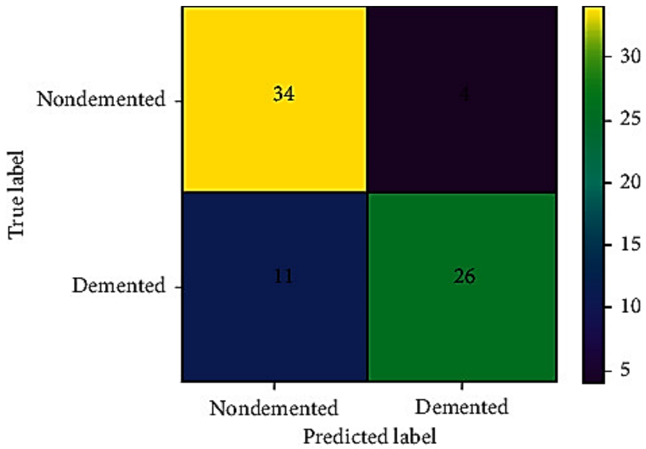

Fig. 11. Confusion Matrix on KNN Classifier

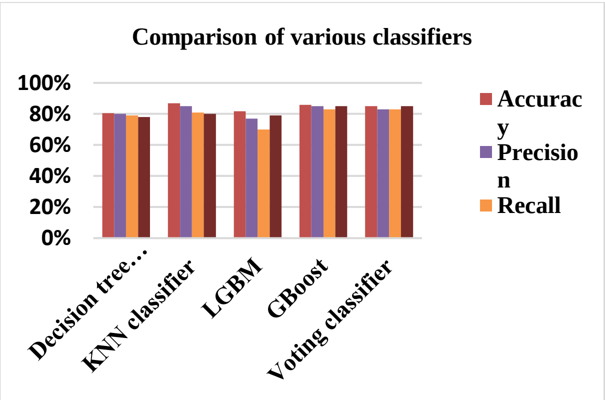

Fig. 12. Comparison on accuracy rate

The above figure 12 depicts the accuarcy rate of the classifiers among that the gradient boost is having the highest accuarcy rate.

5. Conclusion

In distinction to diagnose persons with dementia later than it has previously manifested, early recognition of dementia receive more attention in our research effort. Based on a recent study, abundant studies be being conducted utilizing a variety of methodologies to name AD. Machine erudition algorithms have several reimbursements since they decrease individual error and produce accurate and successful outcomes. With little to no person involvement, indicative times are summarized. Extra Tree classifier, one of the algorithms we used, produced the most noticeable, trustworthy, and accurate findings, with an accuracy rate of 93.14 percent.

The majority of mortality rates occurred as a result of delayed disease detection, with AD being one of them. Older patients in particular were affected by the dementia problem; these individuals can somewhat overcome this difficulty with early doctor intervention. Additionally, reducing MR delay could be a thorough preventative measure to lessen the likelihood of AD occurring. As a result, there is a greater possibility to save AD individuals in the future before they find themselves in desperate circumstances.

The clustering technique, which may provide a superior solution, can be used in the future to improve performance, along with alternative methods. In order to increase the accuracy of diagnosis techniques, future study will concentrate on the collection and evaluation of novel features that are more likely to help in identifying indicators of Alzheimer's disease as well as on the removal of redundant and unnecessary characteristics from existing feature sets. We will be able to train our algorithm to distinguish among healthy persons from those with Alzheimer's disease by including parameters like MMSE and Education.

Reference

[1] H. C. Achterberg, et al, "Hippocampal shape is predictive for the development of dementia in the normal, elderly population," *Hum. Brain Mapp.*, vol. 35, no. 5, p. 2359-2371–71https:, 2014. doi:10.1002/hbm.22333.

[2] P. Balaji et al., "Hybridized deep learning approach for detecting Alzheimer's disease," *Biomedicines*, vol. 11, no. 1, p. 149, 2023. doi:10.3390/biomedicines11010149.

[3] Bernstein et al., "MRI brain imagery processing software in data analysis" in Proc. 13th International

Conference. New York, NY, USA: MDA, Jul. 7-10 2018, pp. 61-74.

[4] E. E. Bron, et al, “Standardized evaluation of algorithms for computer-aided diagnosis of dementia based on structural MRI: The CADDementia challenge,” *Neuroimage*, vol. 111, pp. 562-579, 2015. doi:10.1016/j.neuroimage.2015.01.048.

[5] P. Carcagnì et al., “Convolution neural networks and self-attention learners for Alzheimer dementia diagnosis from brain MRI,” *Sensors (Basel)*, vol. 23, no. 3, p. 1694, 2023. doi:10.3390/s23031694.

[6] Demirhan, “Classification of structural MRI for detecting Alzheimer’s disease,” Int. J. Intell. Syst. Appl. Engineering, vol. 4, no. 1, pp. 195-198, 2016.

[7] Y. Du et al., “The effect of hippocampal radiomic features and functional connectivity on the relationship between hippocampal volume and cognitive function in Alzheimer’s disease,” *J. Psychiatr. Res.*, vol. 158, pp. 382-391, 2023. doi:10.1016/j.jpsychires.2023.01.024.

[8] F. Falahati, et al, “Multivariate data analysis and machine learning in Alzheimer’s diseases with a focus on structural magnetic resonance imaging,” *J. Alzheimers. Dis.*, vol. 41, no. 3, pp. 685-708, 2014. doi:10.3233/JAD-131928.

[9] X. Fang et al., “Ensemble of deep convolutional neural networks based multi-modality images for Alzheimer’s disease diagnosis,” *IET Image Process.*, vol. 14, no. 2, pp. 318-326, 2020. doi:10.1049/iet-ipr.2019.0617.

[10] J. Fortea et al., “Alzheimer’s disease associated with Down syndrome: A genetic form of dementia,” *Lancet Neurol.*, vol. 20, no. 11, pp. 930-942, 2021. doi:10.1016/S1474-4422(21)00245-3.

[11] E. Granot-Hershkovitz, et al, “APOE alleles’ association with cognitive function differs across Hispanic/Latino groups and genetic ancestry in the study of Latinos-investigation of neurocognitive aging (HCHS/SOL),” *Alzheimers Dement.*, vol. 17, no. 3, pp. 466-474, 2021. doi:10.1002/alz.12205.

[12] E. P. Hedges et al., “Reliability of structural MRI measurements: The effects of scan session, head tilt, inter-scan interval, acquisition sequence, FreeSurfer version and processing stream,” *Neuroimage*, vol. 246, p. 118751, 2022. doi:10.1016/j.neuroimage.2021.118751.

[13] D. L. G. Hill, et al, “Coalition against major diseases/European Medicines Agency biomarker qualification of hippocampal volume for the enrichment of clinical trials in predementia stages of Alzheimer’s disease,” *Alzheimers Dement.*, vol. 1, p. 0, 2014.

[14] S. Ingala et al., “Clinical applicability of quantitative atrophy measures on MRI in patients suspected of Alzheimer’s disease,” *Eur. Radiol.*, vol. 32, no. 11, pp. 7789-7799, 2022. doi:10.1007/s00330-021-08503-7.

[15] M. M. Islam et al., “Deep learning algorithms for detection of diabetic retinopathy in retinal fundus photographs: A systematic review and meta-analysis,” *Comput. Methods Programs Biomed.*, vol. 191, p. 105320, 2020. doi:10.1016/j.cmpb.2020.105320.

[16] H. Kalbkhani et al., “Robust algorithm for brain magnetic resonance image (MRI) classification based on GARCH variances series,” *Biomed. Signal Process. Control*, vol. 8, no. 6, pp. 909-919, 2013. doi:10.1016/j.bspc.2013.09.001.

[17] T. Kirill, et al, “Multi-stage classifier design”. JMLR: Workshop and Conference, *Proceedings*, vol. 25, pp. 459-474, 2012. doi:10.1007/s10994-013-5349-4.

[18] S. Lahmiri, “Integrating convolutional neural networks, kNN, and Bayesian optimization for efficient diagnosis of Alzheimer’s disease in magnetic resonance images,” *Biomed. Signal Process. Control*, vol. 80, p. 104375, 2023. doi:10.1016/j.bspc.2022.104375.

[19] LillemarkLene, et al, “Brain region’s relative proximity as a marker for Alzheimer’s disease based on structural MRI,” *BMC Med. Imaging*, vol. 14, no. 1:21https:, 21, 2014. doi:10.1186/1471-2342-14-21.

[20] S. P. Poulin, et al, “Amygdala atrophy is prominent in early Alzheimer’s disease and relates to symptom severity,” *Psychiatry Res.*, vol. 194, no. 1, pp. 7-13, 2011. doi:10.1016/j.pscychresns.2011.06.014.

[21] J. W. Prescott et al., “Diffusion tensor MRI structural connectivity and PET amyloid burden in preclinical autosomal dominant Alzheimer disease: The DIAN cohort,” *Radiology*, vol. 302, no. 1, pp. 143-150, 2022. doi:10.1148/radiol.2021210383.

[22] R. A. Nianogo et al., “Risk factors associated with Alzheimer disease and related dementias by sex and race and ethnicity in the US,” *JAMA Neurol.*, vol. 79, no. 6, pp. 584-591, 2022. doi:10.1001/jamaneurol.2022.0976.

[23] L. Sørensen, et al., “Early detection of Alzheimer’s disease using MRI hippocampal texture” *Hum. Brain Mapp.*, vol. 37, no. 3, pp. 1148-1161, 2016. doi:10.1002/hbm.23091.

[24] Tin, et al., “Genetic risk, midlife Life’s simple 7, and

incident dementia in the atherosclerosis risk in communities study," Neurology, vol. 99, no. 2, pp. e154-e163, 2022. doi:10.1212/WNL.0000000000200520.

[25] T. Katarina, et al, "Image retrieval for Alzheimer's disease based on brain atrophy pattern". International Conference on ICT innovations springer, Cham. 2017, pp. 165-175.

[26] J. Wang et al., "PET molecular imaging for pathophysiological visualization in Alzheimer's disease," *Eur. J. Nucl. Med. Mol. Imaging*, vol. 50, no. 3, pp. 765-783, 2023. doi:10.1007/s00259-022-05999-z.

[27] Z. Zhang et al., "Multimodal image fusion based on global-regional-local rule in NSST domain," *Multimed. Tools Appl.*, vol. 80, no. 2, pp. 2847-2873, 2021. doi:10.1007/s11042-020-09647-2.