PERFORMANCE STUDY OF MACHINE LEARNING ALGORITHMS USED FOR ALZHEIMER'S DISEASE DETECTION

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Abstract

Dementia is widely recognized. With age comes a dramatic surge in dementia cases. It is an irreversible brain disorder that impairs thinking, memory, and judgment, causing a person's cognitive ability to decline. Around 50 million individuals worldwide have dementia, and 10 million new cases are identified yearly. Therefore, solving this problem has become urgently necessary, and dementia must be diagnosed early for more advanced treatments to develop. Cognitive tests are used to assess a person's mental capacity to diagnose this condition early. In the present study, we tried to detect dementia in its early stages using machine learning approaches. Data collected for the analysis comprised gender, age, education, MMSE (Mini-Mental State Examination), CDR (Clinical Dementia Rating), ASF (Atlas scaling factor), handedness, and hospital visits for patients classified as demented or non-demented. We applied machine learning approaches such as KNN, DT (Decision Tree), and RF (Random forest) classifiers to analyze the data. Each algorithm is compared in a study. The most accurate algorithm will be employed to continue examining the data. Our suggested study used an additional tree classifier for deeper data analysis.

Keywords: Alzheimer, classifier, decision tree, voting classifier, LGBM

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INTRODUCTION

Alzheimer's is brought on by 60–70% of dementia cases. Alzheimer's disease is caused by a persistent decline in memory and other critical mental abilities (AD). A person who has Alzheimer's disease may exhibit minute indicators of perceptual error, incomplete relationships, trouble remembering details, and difficulty understanding visual imagery. People are more likely to get Alzheimer's (Memon M. H. 2019). Although the disease progresses, brain functions are irreversible. The possible medication therapy must be successful in the initial stages. The requirement for accurate diagnostic prediction in time for testing therapies may impede development or restrict early diagnosis made through learning assessment procedures. 2020 (Kishore, C.). The other steps include the patient's behavioral changes and psychiatric and neurological history.

In Alzheimer previous illnesses and conditions that affect older persons can also cause dementia. Two significant disorders that biomarkers associated with Alzheimer's disease are the increased accumulation of amyloid-β, plaques outside neurons, and the presence of tangles 3 within neurons. Neurons eventually suffer and die as a result of these modifications.

Monitoring changes in health, the development of clinical disease, and patient response to treatment are central to all research on this topic. Their most challenging task is developing valuable biomarkers that accurately reflect AD and MCI. In addition to early disease identification, their goal is to determine who is most prone to AD development. Doctors use magnetic resonance imaging (MRI), a non-invasive medical tool, to diagnose patients' illnesses and other health problems. MRI treatments typically use strong magnetic fields, radio frequency pulses, and a computer to obtain precise images of all the components inside the body. [1, 2, 3].

As previously indicated, it is difficult to pick the good indicators that suggest attributes helpful in discriminating between AD, MCI (mild cognitive impairment), and NC. Recently, classification systems and content-based retrieval algorithms have been used to identify Alzheimer's disease and MCI. [3].

Allowing users to compare the content of queried images to a database instantly, the CBIR system combines automated medical image classification algorithms with the specialized skills and experience of radiologists to produce accurate classification results. Help to get a vast database that is used to improve the performance and timeliness of image searches. This is similar to how classifications are used as references for searches.

The search process is often split into two phases. In the first phase, the system generates features of the query image, and in the next phase, the system compares these features with trained features.

DATASET

This dataset contains 150 subjects between the ages of 60 and 96. In 373 imaging sessions, each subject was scanned twice at least one year apart. Three or

RELATED WORK

Several techniques have been developed and studied different biomarkers and tools for detecting Alzheimer's disease. The extraction of MRI structural biomarkers associated with Alzheimer's disease has been a significant research focus in this field. [[9], [10], [11]].

For AD diagnosis, MRI biomarkers are required as a consistent benchmark for comparing and understanding the performance and relationship of different biomarkers.

Numerous studies [12] have been conducted on the use of CAD in the analysis of dementia. Medical imaging of Alzheimer's disease has been studied using structural MRI measurements [3]. The main goal of this work was to improve image search performance while using as few attributes as possible. A feature vector was constructed from brain volume and thickness measurements. A subset was selected using a CFS method which is a correlation-based feature selection to filter out unwanted, potentially noisy, or redundant data. Other studies [1, 2] focused on the Open Access Series of Imaging Studies (OASIS) on measurements of brain structures.

SYSTEM METHODOLOGY

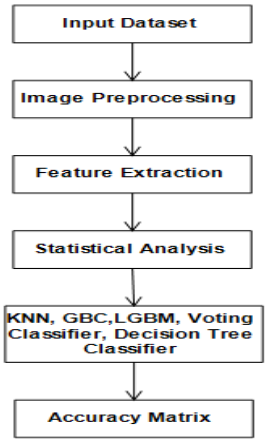


Fig. 1. The Proposed Layout

Four different T1-weighted MRI scans acquired in one scan session will be made for each patient. All subjects were right-handed, male and female. Throughout the study, 72 patients were classified as non-demented. Sixty-four subjects enrolled in

this study were identified as having dementia on their first visit. They remained intact across a series of scans that included 51 patients with mild to moderate Alzheimer's. Another 14 subjects were classified as non-demented at the first visit but later diagnosed with dementia.

Image Pre-Processing

Initially, data doesn't in normalize form it contains missing values and redundant information, which causes system failure and un accurate results, so it required some transformation before analysis. The dataset was further processed after being obtained using ADNI. Smoothing, normalizing, accounting for the slice-dependent temporal shift, and correcting head motion were all part of the pre-processing stages. Finally, we obtained raw data for 72 thickness measurements and 66 volumetric measurements using Free Surfer.

Superior frontal, superior parietal, rostral middle frontal, inferior parietal, supramarginal, caudal front of frontal, post central, frontal pole, superior parietal, precuneus, surgical site, 4rigone, precentral, paracentral, lateral temporal , posterior, anterior, isthmus and caudal cingulate frontal lobe structures.

RESULT & DISCUSSION

The relationship between the patient's dementia and the MRI test parameters is this section's major topic (G. Uysal 2019). (G. Uysal 2019). Finding the relationship between the states of the data through a graph will help us to foresee the correlations between the data extraction, which is the primary purpose of this experimental inquiry. Understanding the nature of the data and how it correlates is vital to choosing the optimal technique. Table 1 contains the minimum, maximum, and average values for each feature of graph implementation.

Performance Measures:

In most neurodegenerative conditions, it is crucial to take a high positive rate to identify every subject as having Alzheimer's disease as promptly as feasible. Still, in the meantime, we also need to verify that the false positive rate is low. The best way to gauge performance is the area under the curve. The confusion matrices are obtained while determining the models' accuracy, as shown in fig. Data of a given attribute or data are presented through a -correlation matrix. The most highly associated characteristics are assessed before the proper procedure is utilized. The data points are defined using hyperplanes. Arguments for the dataset may be located on any side of the hyperplane, which is further mappable as distinct classes.

The correlational values of the chosen features determine the hyper-parameter range. Once the data set has been separated into training and test sets, the intended model is fed. The technique is repeated for all the given algorithms, and practical accuracy calculations are shown in the Tables.

Decision Tree Classifier

Traditional data categorization approaches like decision tree classification have various uses in various academic sectors. There are many alternative techniques to building decision trees as branch-like components. The decision tree has a root node; leaf nodes stand for the class labels, while non-leaf nodes are the intermediate nodes. The data attribute chooses the root node with the highest weight in decision-making. The data values of each node govern a decision tree's splitting mechanism.

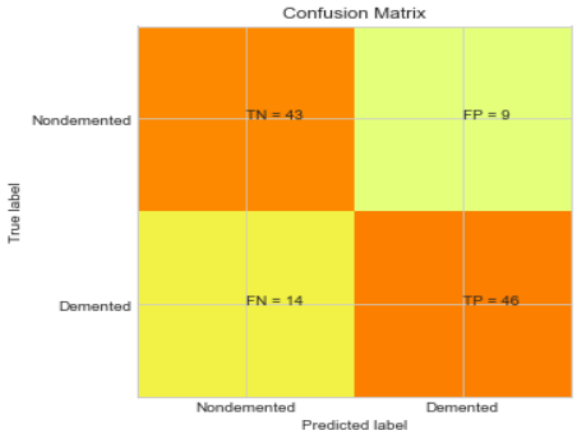
Confusion Matrix:
[[43 9] [14 46]]

Classification Report:

The precision, recall, and F1 score are shown in Table 1.

Table 1: Performance statistics (Precision, Recall, F1 score, Support)

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



Accuracy = TP+TN/P+N

Accuracy =79.24

Voting Classifier

Voting is one of the important ways to combine predictions from various earning systems. Voting classifiers aren't technically classifiers but wrappers for several ones that be trained and assessed concurrently to profit from their specific

qualities. We may use different algorithms and ensembles to prepare data sets and anticipate outcomes. A majority vote on a forecast can be gained in two ways:

Voting HARD: Hard voting is the most fundamental type of majority voting. The class with the most significant votes (Nc) will be selected. The majority vote of each classifier is utilized to construct our forecast. Hard voting is the simplest example of majority voting. Here, we predict the class label y^y using the majority (plurality) vote of each classifier.

$$\hat{y} = \arg \max_i \sum_{j=1}^{m} w_j \chi_A\big(C_j(\mathbf{x}) = i\big)$$

$$\hat{y} = \text{mode}\{C_1(\mathbf{x}), C_2(\mathbf{x}), \ldots, C_m(\mathbf{x})\}$$

Soft voting implies summing the probability vectors for each predicted class (for all classifiers) and picking the one with the most outstanding value (recommended only when the classifiers are suitably calibrated) (recommended only when the classifiers are well calibrated) (recommended only when the classifiers are well calibrated).

Soft voting predicts class labels based on the classifier's expected probabilities pp. This strategy is recommended only if the classifier is well-tuned.

$$\hat{y} = \arg \max_i \sum_{j=1}^{m} w_j p_{ij}$$

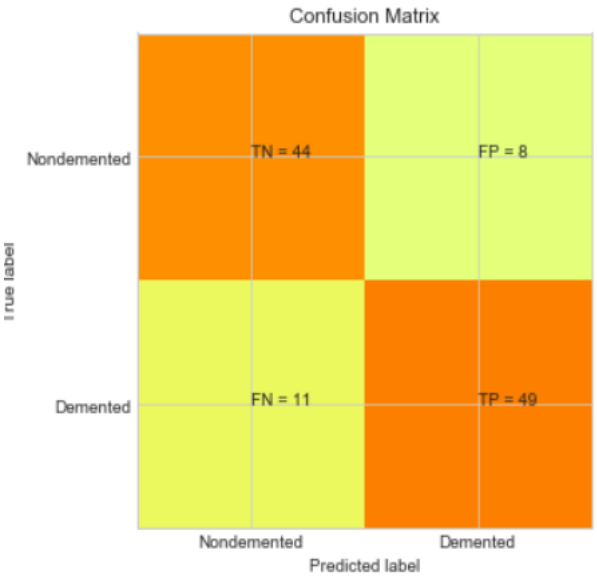
Where $w_j w_j$ is the weight that can be assigned to the jth classifier

Confusion Matrix:
[[44 8] [11 49]]

Classification Report:
Precision, recall, and F1 scores are shown in Table 2.

Table 2: Performance Statistics for Voting Classifier

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



LGBM Classifier
Light GBM is a high-performance gradient-boosting framework based on a decision tree approach that can be used for ranking, classification, and other machine learning applications. It splits the tree optimally by leaf found on a decision tree strategy, unlike other boosting methods that split the tree by depth or level rather than by leaf. So, when growing on the same leaf using light GBM, the leaf-by-leaf approach reduces loss more than the stepwise algorithm and can rarely achieve very high performance by all existing boosting methods. You get precision. It's also swift, thus the moniker 'light'.
For example, we need a construct known as a decision tree to load functions from the input space X into the gradient space G. The training set containing examples like x1, x2, and up to xn items is assumed to represent an n-dimensional vector in the space X. It is represented using a technique of means of the succeeding formula.
"Y=Base_tree(X)-lr*Tree1(X)-lr*Tree2(X)-lr*Tree3(X)"

$$V_{j|0}(d) = \frac{1}{n_o}\left(\frac{\left(\sum_{\{x_i \in 0: x_{ij} \le d\}} g_i\right)^2}{n^j_{1|0}(d)} + \frac{\left(\sum_{\{x_i \in 0: x_{ij} > d\}} g_i\right)^2}{n^j_{r|0}(d)}\right)$$

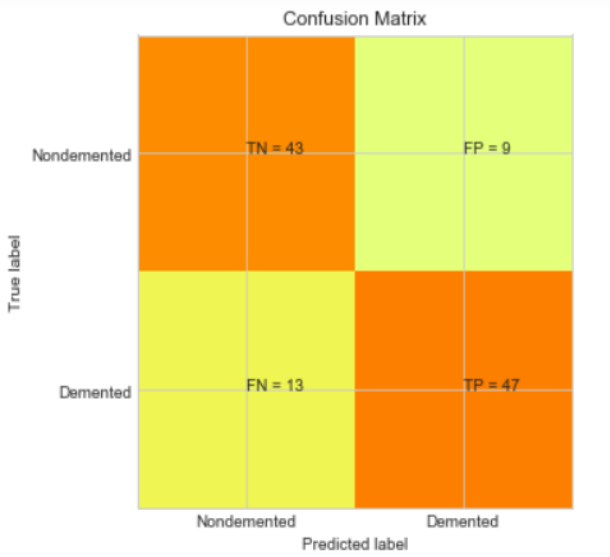
where $n_O = \sum I[xi \in 0], n^j_{l|O}(d) = \sum I[xi \in 0: xij \le d]$ and $n^j_{r|O}(d) = \sum I[xi \in 0: xij > d]$.

Confusion Matrix:

[[43 9] [13 47]]

Classification Report:

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



Accuracy: 80.12

Gradient Boosting Classifier

GB classifier is a robust predictive classifier model which combined multiple small learning models.

Algorithm:

The first phase of gradient enhancement is to develop a base model for predicting observations inthe training data set. Mathematically, the first step can be written as follows:

$$F_0(x) = \underset{\gamma}{\operatorname{argmin}} \sum_{i=1}^{n} L(y_i, \gamma)$$

Here L is our loss function Gamma is our predicted value loss function will be:

$L = \frac{1}{n}\sum_{i=0}^{n} (y_i - \gamma_i)^2$

Here,

$Y_{i=}$ observed value, and gamma is the predicted value. In the next phase,

Calculate the pseudo residuals.

Decision trees are often used when implementing gradient boosting. On the other hand, optimizing the model hyperparameters requires some operational decisions. We can adjust several arguments/hyperparameters to attain the model's best accuracy. We can do this by changing the model's learning rate. We'll want to test the model's performance on the training set at several learning rates, and then use the optimal learning rate to generate predictions.

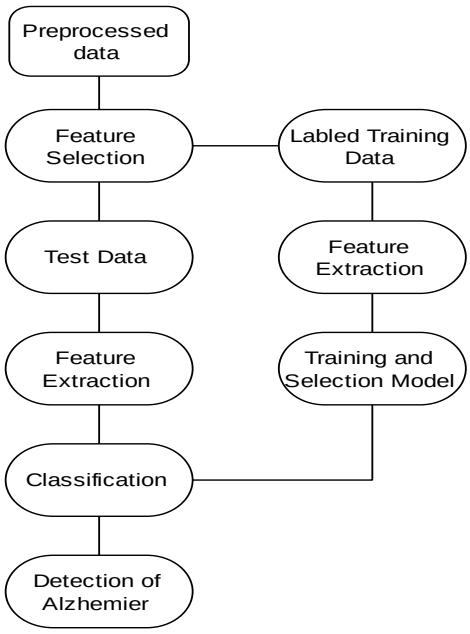


Fig 2: Flow graph of Gradient Boosting Classifier

This step can be written as follows:

$$r_{im} = -\left[\frac{\partial L(y_i, F(x_i))}{\partial F(x_i)}\right]_{F(x)=F_{m-1}(x)} \quad \text{for } i = 1, \ldots, n$$

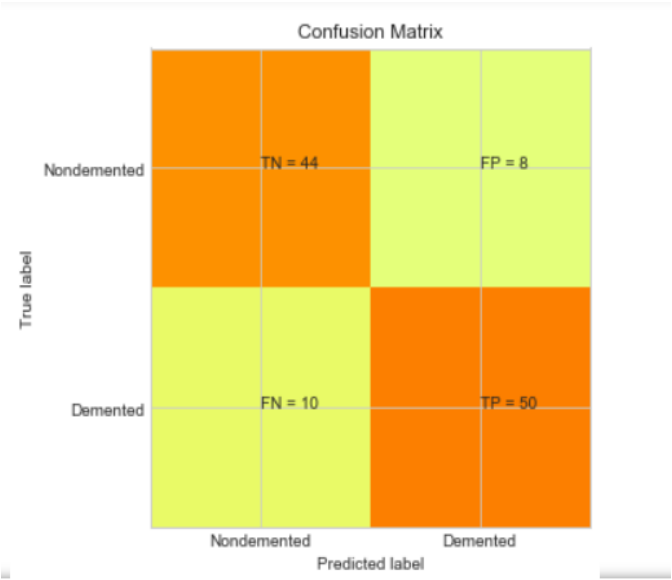
Here F (x_i) is the previous model, and m is the number of DTs made. In this step, we find the output values for each decision tree leaf.

Confusion Matrix:

[[44 8] [10 50]]

Classification Report:

Value	precision	recall	F1-score	support
0	0.81	0.85	0.83	52
1	0.86	0.83	0.85	60
Avg/total	0.84	0.84	0.84	112



Accuracy: 83.29

K-Nearest Neighbours Classifier:

K-NN is a machine learning classifier that is simple to use. In knn, a majority decision of its neighbors determines whether a picture is normal or abnormal in k-NN categorization. The image is allocated to the class with the most occurrences among its k closest neighbors. K is a positive integer that should be kept as small as possible. An MRI is allocated to the class normal or AD that is more prevalent among its k nearest neighbors using a distance function. The Euclidean distance function has been explored in this study.

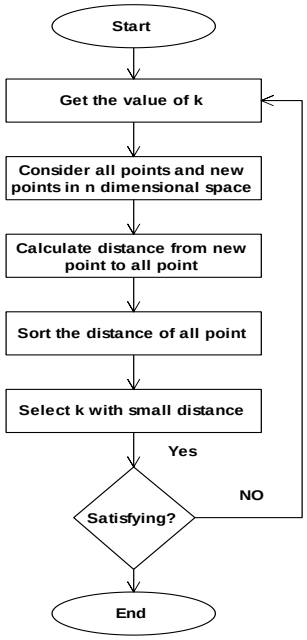


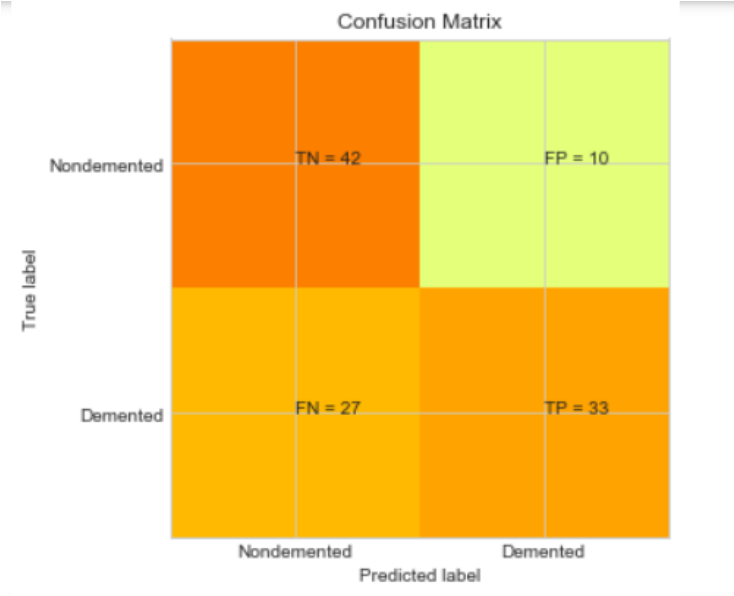
Fig.3. Flow graph of KNN algorithm

• Store all training examples<Xi, f (Xi)>
• Calculate f (Xq) for a given query instance Xq using k-Nearest Neighbor
• Nearest neighbor: (k=1)
– Locate the nearest training sample Xn, and estimate f(Xq) as
f(Xq) ←f(Xn)

Confusion Matrix:
[[42 10] [27 33]]

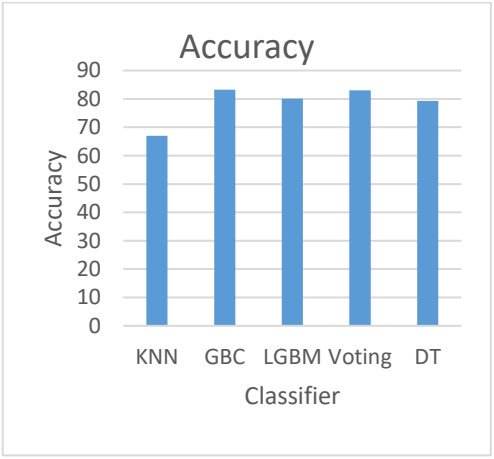
Classification Report:

Value	precision	recall	F1-score	support
0	0.61	0.81	0.69	52
1	0.77	0.55	0.64	60
Avg/total	0.69	0.67	0.67	112



Algorithm	**Accuracy (%)**
KNN	**66.94**
GBC	**83.29**
LGBM	**80.12**
Voting	**83.02**
DT	**79.24**

Table.1 Accuracy table of the algorithm used in research the overall accuracy of all algorithms has shown in the table. Based on analysis of GBC and voting, the classifier has proven good accuracy.



CONCLUSION

In contrast to diagnosing patients with dementia after it has already appeared, early detection of dementia receives more priority in our study endeavor. According to a recent study, several investigations are being undertaken to utilize various approaches to identify dementia. Machine learning algorithms have various benefits since they eliminate human error and create precise and effective solutions. With minimal to no human intervention, problem-solving timeframes are shortened. We have studied numerous algorithms on the given dataset and evaluated the system based on accuracy with a confusion matrix. In all other algorithms, GBC and voting classifier algorithm provides the best outcome on an accuracy basis. In the future, the system can evaluate various real-time datasets.

COMPLIANCE WITH ETHICAL STANDARDS

On behalf of all authors, the corresponding author states that there is no conflict of interest. We have just used the human brain dataset for research purposes which is available on the internet (e.g, Kaggle)

Ethical approval: This article does not contain any studies with animals performed by any of the authors

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