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# COMPREHENSIVE ANALYSIS OF MACHINE LEARNING ALGORITHMS TO DETECT ALZHEIMER'S DISEASE USING PREDICTOR FACTORS

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**ABSTRACT**

Alzheimer's disease (AD) is an irrecoverable encephalopathy. The condition diminishes intellectual capacity and causes memory loss. To collect pertinent images and train to identify AD and its phases, computer-aided diagnostic approaches with image retrieval have created a new perspective in MR imaging. Although computer-assisted techniques have achieved considerable research advancements, the viable diagnosis method available in clinical practice still needs improvement. Recently, there has been a proliferation of high-scale results displayed by more advanced machine-learning approaches in various domains. This paper focused on classifying the subjects who potentially can have Alzheimer's disease with machine learning and Deep learning techniques. The models encompassed OASIS dataset for diagnosing the disease. Clinicians can diagnose and classify these disorders using the proposed classification approach. The computational algorithms can help practitioners in reducing the average annual fatality rates of Alzheimer's disease by early diagnosis. Extensive research was done to find the significant predictor parameters and measure how well the model works using performance metrics, which gives its uniqueness. The performance of the extra tree classifier was superior when compared with other ML models, with an accuracy of 86%. The Deep Neural Network (DNN) acquired an optimum accuracy in the binary classification with 92%.
**Keywords:** *Alzheimer's Disease, Machine Learning, Brain Disorder, Predictor Factors, OASIS*

## 1. INTRODUCTION

Alzheimer's disease (ad) is a debilitating condition characterised by the steady decline of memory and other cognitive abilities in younger age groups and beyond. Typically, the signs and symptoms of ad grow slowly and become severe enough to interfere with a person's daily routine [1]. Few survive longer than ten years, and the reasons for this vary widely depending on various circumstances. The early detection of this disease is essential to develop an effective treatment plan, but diagnosing ad is complex, notably in the initial stages of the disease [2]. Individuals who are just experiencing minor symptoms may be able to continue working, driving, and participating in their favourite pastimes with infrequent assistance from family members and friends [3]. On the other hand, alzheimer's is a chronic illness, which means that its symptoms worsen over time. There is a wide range of variation in the rate at which it advances and the abilities that are impacted. Although medicines can temporarily improve the ability of neurons in the brain to interact with one another and, as a result, alleviate symptoms for variable amounts of time, alzheimer's disease cannot be cured by them [4]. Figure. 1 depicts a normal brain and an ad-affected brain. Please follow these specifications closely as papers which do not meet the standards laid down, will not be published.

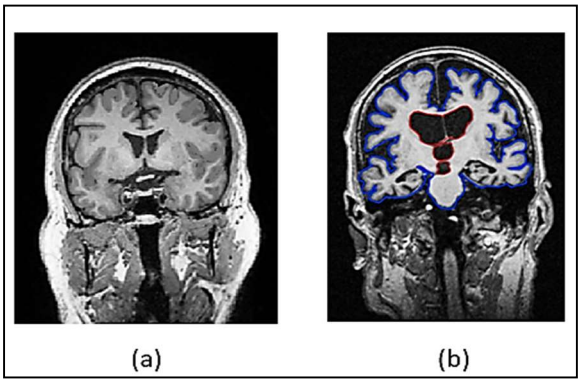

*Fig.1 (A) A Normal Brain (B) Alzheimer's Affected Brain*

About 20% of respondents aged 40 and older, according to Alzheimer's Association research, have memory impairment, an early phase of AD. According to the Mental Health Gap Action Program, Alzheimer's is an elevated health issue that calls for rapid intervention [5]. The accumulation of the protein beta-amyloid, which takes the form of plaques, in the brain and knotted strands of the protein tau, which take the formation of tangles, among neurons are the main hallmark of Alzheimer's disease. These alterations are followed by neuron death and brain tissue injury [6].

As a result of the extensive data gathering, the use of sophisticated technology for prediction, and the involvement of an experienced medical practitioner, the early identification of this illness is a time-consuming and costly process. Since automated systems are more accurate than human logic, it is possible to utilize them in clinical decision-making systems. Researchers have examined Alzheimer's disease using MRI pictures, genetic information, blood and CSF biomarkers, and clinical record data obtained from the MRI scan (AD). As a consequence, they could determine whether a person had dementia or not. [3]. Various Alzheimer's disease (AD) screening methods have been developed to enhance the disease's detection and track its progression. Some clinical screening tests to diagnose the impairment include the Mini-Mental State Examination (MMSE), Clinical Dementia Rating (CDR), Global 2Dementia Scale, Functional Activities Questionnaire, and Neuropsychiatric Inventory Questionnaire [7]. A decision-support system for medicine uses information gleaned from laboratory tests or characteristics derived through medical imaging to assess a patient's health accurately [8]. The current work performed a comparative analysis of machine learning algorithms in identifying AD and non-AD patients.

Without explicitly coding, the Machine Learning technique is the research of software programs that employ mathematical models and algorithms to understand through reasoning and correlations [9]. Algorithms created for machine learning are designed to gain knowledge from their experiences and automatically improve. It identifies approaches, educates modelling techniques, and dynamically selects results using the learnt strategy. Systems that learn dynamically can also modify themselves in response to shifts in their surroundings [10].

Deep Neural Networks (DNNs) are powerful tools for classification tasks because they can learn complex representations of the input data. DNNs can be used for a wide range of classification tasks, including image classification, speech recognition, and natural language processing. The architecture of a DNN typically consists of multiple layers of interconnected artificial neurons, with each layer contributing to the abstraction and representation of the input data. They have been shown to achieve state-of-the-art performance on many benchmark datasets, and are widely used in industry, academia and medical research.

The machine learning and deep learning platform are trained and designed to detect particular characteristics and patterns using its unique algorithm. The OASIS dataset is used in the current work to conduct a hierarchical analysis of all available data points, which includes dementia diagnosis. The optimum models is tested using several tuned parameters [11].To provide evidence that the proposed method is useful, its performance is assessed using performance metrics, and an investigation into the significance of individual features in diagnosing the disease is carried out. Since AD is a non-curable disease, so it's necessary to address it at an early stage. The computational models are essential in identifying the disease at the initial stage through various predictor factors and brain images. It would be a supporting system for medical practitioners.

The current research contributes to the binary classification of AD and Non-AD subjects with clinical test results from the Oasis dataset. The classification process is carried out by machine learning and deep learning techniques.it also emphasizes feature ranking to understand the impact of factors in identifying the affected subjects.

This paper is organized as follows: Section 2 discusses research that has been performed; Section 3 inscribes the dataset and the significance of each factor; Section 4 provides a thorough description of the proposed methodological approach and an explanation of the classifiers; Section 5 presents the results of the experiment; It discusses an experiment performed with machine learning models and hyper tuned DNN model on this provided OASIS dataset, and the findings explain the performance metrics and accuracy of the classifier. Section 6 concludes with a conclusion and future work.

## 2. RELATED WORK

The onset of the disease can be predicted using ML algorithms by applying a strategy for

selecting and extracting features. The categorisation is then performed using the dataset from the oasis. The section provides an overview of the various approaches to the data processing to diagnose brain diseases with ML and DL. This article uncovered the most methods for detecting and identifying brain abnormalities, which can be utilised to enhance future diagnostic techniques. This paper [12] uses autoencoders with deep convolutional networks to investigate AD's data exploration. Data-driven breakdown of MRI images lets us identify characteristics that signal neurodegeneration and cognitive disorders. After that, classification and its analysis are carried out to inspect the distribution of features on the broad spectrum of possible integrations. Additionally, a computation is performed to determine how each coordinate impacts the brain in the autoencoder manifold. Scores on the clinical test records and signs from brain scanning can be applied to diagnose Alzheimer's disease more than 80% of the time.

This particular piece of research in research in [13] suggested an approach known as composite hybrid feature selection. The purpose of this method is to extract new features and select the ones most useful for making a clinical diagnosis of AD. By carefully choosing the most variables, it is possible to obtain high recall and precision classification outcomes. The SVM was applied to predict dementia from the OASIS dataset, and the paper attained an accuracy of 68.75%. However, the prediction level reached throughout this study is relatively low. The article applies several machine learning methods to the given dataset to predict whether or not the patients would develop dementia. When doing tenfold cross-validation, the gradient boosting classifier achieved the highest accuracy rate, whereas the KNN classifier achieved the lowest precision rate.

The paper [14] presented an ML-based pipeline for classifying dementia. Deep learning techniques have been implemented in many domains, including image processing and analysis. Most of the time, categorisation did not involve feature engineering or image preparation, which added to their appeal. These methods work well with enormous, skewed datasets specifically for image processing and their classification. MRI data can accurately discriminate AD from normal controls and forecast whether the subject will acquire stable or transformed MCI as AD. The research paper [15] based on machine learning proposed a technique in which the brain's cortical thickness is aided in forecasting the evolution of Parkinson's disease subjects from a secondary memory deterioration to Alzheimer's. The results were significantly improved when the technique was combined with clinical factors.

To identify mild dementia, the paper [16] utilised machine-learning approaches and compared these Machine Learning models to linear discriminant analysis and logistic regression models. The data used for training and testing purposes comprised 83 and 30 cases, respectively. Many neural network models were created and deployed to analyse medical health data. The authors of the paper [17] developed three different deep learning architectures to understand and analyse clinical and genome data using MRI and PET imaging data, respectively. The models achieved classifying Alzheimer's and other forms of cognitive impairment.

The current research looked for individuals diagnosed with Alzheimer, and the primary objective is to locate subjects who could show early signs of the disease [18]. All subject data are trained using the OASIS datasets, which are utilised with various machine learning methods and DNN. This enables accurate discrimination between persons who are affected and those who are healthy while maintaining excellent efficiency and speed.

## 3. DATASET

The detection of dementia in various people based on a variety of characteristics is the proposed system's primary objective. The model was validated using Open Access Series of Imaging Studies (OASIS) data. The final result was determined by considering eight factors, including age, gender, education and socioeconomic status, mini-mental state examination, the intracranial volume of the brain, normalised whole brain volume and the atlas scaling factor. The spectrum values of the dataset have been scaled using a standardisation technique [19]. Table 1 describes the eight features examined for the proposed Alzheimer's disease classification model.

*Table 1. Feature Description Of Classification Factors*

| Attributes | Description |
|---|---|
| EDU- Years of Education | Education status of each individual |
| SES-Socio Economic Status | It correlates Alzheimer's with the socioeconomic position and condition of the individuals and ranks them on a scale from 1 to 5, with one being the highest and five the |

| | |
|---|---|
| | lowest. |
| MSE- Mental State Examination | A cognitive examination score used extensively in clinical and research settings to assess cognitive decline. |
| CDR- Clinical Dementia Rating | The CDR is a measurement scale that ranges from one to five points and describes six distinct cognitive and functional performance categories related to Alzheimer's disease. |
| eTIV- Estimated Total Intracranial Volume | eTIV is a crucial predictor of future volumetric assessment of the human brain's area, especially in the research of degenerative brain ailments that get worse over time because it can be used as a stand-in for the brain's maximum capacity before the disease starts. |
| nWBV- Normalize Whole Brain Volume | This component stands for the total weight of the brain. Brain normalisation is beneficial to individual subject data because it permits reporting of reported active regions in a conventional spatial reference system. This is a significant advantage. To accomplish brain normalisation in volume space, it is common to practice warping each brain into a region that is (more or less) shared. |
| ASF- Atlas Scaling Factor | Reliability and validation of automated atlas-based head size normalisation compared with human measurement of total intracranial volume for the investigation of morphometric and functional data across the young, elderly, and dementia-affected populations. |

## 4. METHODOLOGY

The recommended methodology is endowed with identifying and classifying the Alzheimer's disease (AD) stage as demented and non-demented. It can be achieved in three steps, which are as follows: (1) Data preprocessing, (2) feature extraction and data splitting, and (3) fine-tuned machine learning models and DNN for classifying the stages of AD. Figure. 2 describes the framework of the proposed system.

Three main stages can be identified in the suggested strategy. The work initiated with preprocessing the data by building a research chronology, as it was necessary to understand the data in detail as the longitudinal dataset was used. Ascertaining whether or not the data showed up to be cross-sectional, either at a reference point or at a particular point in time, was our first task. Following this, a comprehensive evaluation of the data was carried out, as well as a correlation between the primary components of the research and the pertinent information and data gathered during each appointment.

Machine learning and deep learning techniques were used for datasets related to AD as well as other cognitive impairment issues to offer a new realm to the ability to anticipate the disease at an early stage. The fact that the datasets unexplored on Alzheimer's disease are unreliable and have the same information makes it harder for the algorithms used to look at them to be accurate. To efficiently prepare the data for analysis before evaluating machine learning algorithms, records with undesirable qualities, missing values, and redundant records must be removed from the dataset. The data must be divided into training and testing sets before the model can be constructed. The training set provided a firm ground for the model, and the test set was used to validate previously undiscovered data. The performance metrics are used to assess how well each model performs in the binary classification of AD.

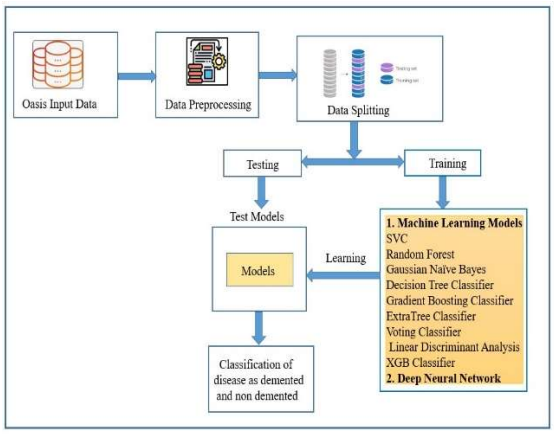


*Fig. 2 Proposed Framework*

## 5. EXPERIMENTAL SETUP

This section describes the list of significant criteria researched for the suggested work. The evaluations are performed on a Windows 10 CPU (Intel i7) clocked at 2.10 GHz and 8 gigabytes of random access memory. The software requirements for the model are determined by utilising Python (3.76), the Keras framework, and Tensorflow (2.3.1), which is the backend and contains the machine learning model libraries. One of the most challenging aspects of constructing models is picking the hyperparameter combinations to employ with a looping approach to increase the accuracy and efficacy of the model. The following classifiers were used to classify AD from normal subjects.

### 5.1 Support Vector Classifier (SVC)

The Support Vector Machine seeks the optimal hyperplane to divide the distinct classes by optimising the gap between the sample data points and the hyperplane. The SVC's primary goal is to classify the data by fitting it to a "best fit" hyperplane. The penalty factor for the standard error is C [22]. It balances properly in identifying training samples with a seamless bounding box. It operates on the nonlinear hyperplane representation known as the RBF kernel function. In support vector machine classification, it is frequently employed. The Euclidean formula can identify the distance between the two feature vectors. For non-linear hyperplanes, the gamma parameter affects the results as well. The best the training data set fits the classifier, the higher the gamma value [23].

### 5.2 Gaussian Naïve Bayes

Gaussian Nave Byes is employed when all the sample data in a given dataset are numeric. It demonstrates a normal distribution. The probability density function is characterised by the mean and standard deviation [24]. It is used to compute each dataset's characteristics. After evaluating this, determine the probabilities for each sample using the mean and standard deviation when any sample data pattern appears.

### 5.3 Random Forest

A decision tree is employed as the primary classifier in an RF. For classification purposes, the random forest classifier generates a forest of decision trees from a randomly chosen training data sample. The test object's class outcome is determined by aggregating the results from multiple decision trees [25]. The proposed work has implemented the classifier with several trees as 200, the quality of split measured Gini, maximum the depth of tree as 8, and no of features considered for splitting is based on the auto method.

### 5.4 Linear Discriminant Analysis (LDA)

Linear Discriminant Analysis (LDA) is a crucial method for differentiating between patient data and features of healthy individuals. It helps the supervised learning approach identify a base vector layout by allowing for the deduction of feature variables [26]. LDA aims to locate a linear combination of predictors that differentiates between two targets accurately.

### 5.5 Decision Tree

Decision trees are a decision-making tool that connects possible outcomes to possible options. Tree-based learning falls under supervised learning models, which provide prediction models with stability, high accuracy, and interpretability. The algorithm positions the property with the highest value at the tree's or its root's beginning. Afterwards, the training set is subdivided into subgroups based on the extracted features. The suggested work made use of the C5.0 decision tree. It calculates the ideal grouping variable and segmentation point using the information gain rate, considering the quantity of information acquisition and the cost of gaining it [27]. It has examined settings such as entropy to quantify the quality of splits in the tree; the maximum depth assumed to be 5, the optimal split method for determining the division at each node, and random state values ranging from 0 to 28 to govern the randomness of the estimator.

### 5.6 eXtreme Gradient Boosting (XGBOOST)

XGBoost, also known as eXtreme Gradient Boosting, is a set of gradient-boosting algorithms designed for contemporary data science problems and tools. XGBoost's primary advantages are that it is extremely scalable, quick to run, and frequently outperforms other algorithms. Additionally, it uses a more regularised model formalisation to prevent over-fitting, which provides it with superior performance [28]. It is a popular machine learning algorithm for supervised learning. The tuned hyperparameters are base score, booster, estimators, child weight, thread, subsample, job and gamma 5.

### 5.7 Voting Classifier

A voting classifier (VC) is a collaborative analytical, computational approach for integrating model accuracy and prediction. It is a method for forecasting the result class label depending on the majority vote while gathering classifier statistics. Instead of building several classification methods and assessing the overall accuracy of each separately, a unified composite model is developed. This cooperative model, trained by separate models, predicts the class label by averaging the number of class votes expected for each set of class labels. The forecasting made by the computation models used by this strategy is likely reliable. It helps improve the ensemble's performance while also being more productive than utilising a single model in the ensemble [29]. One type of machine learning ensemble model is called the voting ensemble technique. This model integrates the predictions of a large number of different models. During the current investigation, the system employed the "hard voting" approach; it estimates the category that receives the most votes by compiling the results of each classifier and obtaining results. The “hard voting “method achieved higher results than the “soft voting” method. The VC approach utilised the following classifiers: Extra Tree Classifier, Gradient Boosting Classifier, Ada Boost Classifier, and Random Forest Classifier.

### 5.8 Extra Trees Classifier

The different trees approach produces many decision trees, but their distribution is random and non-replaceable. This builds a dataset with unique samples for each tree. A specific number of feat each tree's complete collection of characteristics for each tree. The random selection of a splitting value for a feature is the most essential and distinctive property of additional trees [30]. Instead of computing a locally optimal value to split the data using Gini or entropy, the randomly selects a split value at random. Thus, the trees become diverse and uncorrelated. The tuned hyperparameters of the classifier are criterion as Gini, 250 estimators, the minimum samples split and leaf as 2 and 1, maximum features used ‘sqrt’ function, and a maximum depth of the tree as 10.

### 5.9 Gradient Boosting Classifier

Gradient boosting is a machine-learning approach that constructs a prediction model by combining multiple weak machine-learning classifiers into a unique, robust classification model. In addition, it enables random, discrete loss function optimisation. The model is tuned with the following parameters: learning rate=0.1, n_estimators= 100, subsample=1.0, loss=’log_loss’, max-depth-3, max_features=’auto’, random state= 1.0

### 5.10 Deep Neural Network

A Deep Neural Network (DNN) is a type of machine learning model that is designed to mimic the behavior of the human brain. It is composed of multiple layers of interconnected artificial neurons that allow the network to learn complex features and patterns from input data. The architecture of a DNN typically includes an input layer, one or more hidden layers, and an output layer. Each layer is made up of a large number of neurons, and each neuron is connected to neurons in the adjacent layers through weighted connections. The weights are adjusted during the training process to optimize the performance of the network.

$$h_i = \phi\left(\sum_j W_{ij}x_j + b_i\right) \quad (1)$$

$$y_i = \phi\left(\sum_j W_{ij}h_j + b_i\right) \quad (2)$$

Where x and y are the input and output units, w is the weight and h is the hidden layers allotted for the network. ϕ is the activation function. DNNs are commonly used in a wide range of applications, including image recognition, speech recognition, natural language processing, and predictive analytics. They have achieved state-of-the-art performance in many tasks, such as object recognition, speech synthesis, and machine translation. However, they require a large amount of data and computational resources to train, which can be a limitation in some applications.

## 6. RESULT ANALYSIS

The primary objective of the work is to analyse how efficiently different machine learning architectures and Deep Neural Network can classify Alzheimer's disease and compare their performance with predictive factors. Our method utilised the OASIS dataset's in machine-learning network models and DNN with tuned hyper parameters. The work has employed to achieve a binary classification

of Alzheimer's stages and identify parameters that are highly impacted in classifying the disease. Utilising the Extra tree classifier yielded the most substantial increases among the ML models, which resulted in classification accuracy, precision, recall and F1-score of 84%, 86%, 85%, and 84%.

The experiment relied on a deep neural network model with hyper-parameters that were fine-tuned for maximum precision. The model has used optimal parameters for DNN with a 7-hidden-layers network including different neurons in each hidden layer, ReLU as the activation function for each hidden layer, and Adam as the optimizer. The model has been used using a.001 learning rate and 400 iterations.

The particulars of the suggested DNN for AD's enhanced hyper-parameters are shown in Table 2. The DNN classifier achieved an accuracy of 92%, precision of 90%, and recall of 92% and F1-score of 91%. The DNN network with its hyper tuned parameters was able to achieve optimum performance with predictor variables.

Table.2 Hyper-parameter optimization in DNN Model.

| Hyperparameter | Optimized value |
|---|---|
| Hidden Layer | 64,128,64,256,128, 64,256 |
| Activation Function | ReLu |
| Learning rate | .001 |
| Iteration | 400 |
| Optimization Algorithm | Adam |
| Batch Size | 32 |
| Output function | Softmax |

Table 3 depicts the results of each model based on the performance metrics. After the model's creation, various indicators and approaches were applied to identify difficulties regarding overfitting and parameter-tuning. The confusion matrix is used to conduct performance reviews for binary classification and to report the results of those reviews. Precision, recall, accuracy, and F-score were the metrics utilized in calculating the performance evaluation measures.

According to this research, recall, often referred to as sensitivity, is the proportion of patients diagnosed with Alzheimer's disease with high confidence. The proportion of persons correctly classified as not having Alzheimer's disease can be used as a metric to evaluate the accuracy of a diagnosis of the condition. Alternately, "F1" is the weighted average of "precision" and "recall," and "accuracy" is the fraction of persons who have been correctly categorized. Additionally, the models were used to evaluate the feature importance using a trained prediction model as the basis. Table. 4 describes average accuracy of each model's in classifying the disease stage and its graphical representation is given in Figure.4.

We aimed to predict the results of dementia from the clinical and MRI data with ML methods. We employed SVC, Random Forest, Decision Tree, XGBoost, Voting Classifier, Extra tree classifier, Gradient boost, and Ada Boost Classifier and evaluated each model's performance. After the model's creation, various indicators and approaches were applied to identify difficulties regarding overfitting and parameter-tuning. The confusion matrix is used to conduct performance reviews for binary classification and to report the results of those reviews. Precision, recall, accuracy, and F-score were the metrics utilised in calculating the performance evaluation measures.

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

$$\text{F-Measure} = (2(P*R))/(2(P+R)) \quad (2)$$

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

$$\text{Precision} = \frac{(TP)}{(TP+FP)} \quad (4)$$

According to this research, recall, often referred to as sensitivity, is the proportion of patients diagnosed with Alzheimer's disease with high confidence. The proportion of persons correctly classified as not having Alzheimer's disease can be used as a metric to evaluate the accuracy of a diagnosis of the condition. Alternately, "F1" is the weighted average of "precision" and "recall," and "accuracy" is the fraction of persons who have been correctly categorized. Additionally, the models were used to evaluate the feature importance using a trained prediction model as the basis. Table. 2 describes each model's performance in classifying the disease stage.

The performance metrics are: Accuracy (Acc), Precision (Pr), Recall (Re), F1 Score (F1). Table 3 shows the average accuracy each model acquired in classification, and its graphical representation is given in Figure.3. The extra tree classifier acquired an accuracy of 86\% in diagnosing and classifying the disease. The model focused on the binary

classification of the disease as AD & Non_AD and also worked on a set of predictor variables, which can be triggering factors in identifying the disease at varying levels.

*Table 3. Model Performance Metrics For The AD Classification*

| Models | Class | Acc | Pr | Re | F1 |
|---|---|---|---|---|---|
| Random Forest | AD | 77% | 85% | 79% | 82% |
| | Non_AD | 84% | 74% | 81% | 78% |
| SVC | AD | 70% | 86% | 70% | 77% |
| | Non_AD | 84% | 68% | 84% | 75% |
| DT | AD | 58% | 83% | 58% | 68% |
| | Non_AD | 84% | 60% | 84% | 70% |
| GNB | AD | 63% | 84% | 63% | 72% |
| | Non_AD | 84% | 63% | 84% | 72% |
| XG Boost | AD | 79% | 85% | 79% | 82% |
| | Non_AD | 81% | 74% | 81% | 78% |
| VC | AD | 77% | 89% | 77% | 82% |
| | Non_AD | 88% | 74% | 88% | 80% |
| LDA | AD | 60% | 87% | 60% | 71% |
| | Non_AD | 88% | 62% | 88% | 73% |
| ET | AD | 81% | 90% | 81% | 85% |
| | Non_AD | 91% | 78% | 88% | 82% |
| GB | AD | 74% | 89% | 77% | 82% |
| | Non_AD | 88% | 74% | 88% | 80% |
| DNN | AD | 94% | 89% | 92% | 91% |
| | Non_AD | 90% | 91% | 88% | 90% |

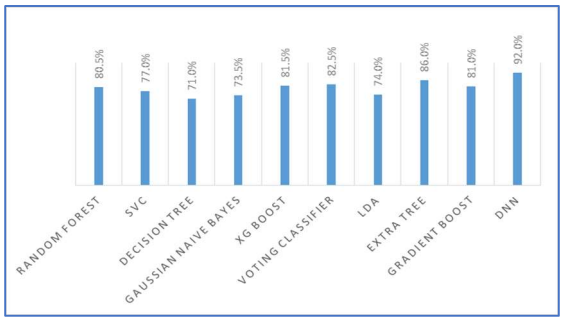


*Fig.3 Average accuracy of ML Models*

*Table 4. Average Accuracy Acquired For AD Classification*

| Evaluation Models | Accuracy |
|---|---|
| **1. Machine Learning Models** | |
| Random Forest | 80.5% |
| SVC | 77.0% |
| Decision Tree | 71.0% |
| Gaussian Naive Bayes | 73.5% |
| XG Boost | 81.5% |
| Voting Classifier | 82.5% |
| LDA | 74.0% |
| **Extra Tree** | **86.0%** |
| Gradient Boost | 81.0% |
| **2. Deep Neural Network** | **92.0%** |

### 6.1 Correlation Coefficient

Calculating the significance of a relationship between two variables requires using correlation coefficients. Consider two variables A & B, and their correlation can be calculated as follows:

$$\text{Correlation}(A, B) = (\text{Cov}(A,B))/(\sigma A \sigma B) \quad (5)$$

Where Correlation (A,B) is the sample correlation between two variables A & B and cov (A,B) depicts the covariance of A & B, σA & σB is the standard deviation of A& B.

The covariance denotes a measure of the linear relationship between two variables. Connecting the different stages of Alzheimer's disease can be accomplished quickly and easily through correlation coefficients. It does this by analysing the dispersion of two others and attempting to build a line that best fits the data. As a result, it indicates how far apart each data point is from the line that provides the most excellent correlation matrix of AD and the variables that predict it is depicted in Figure 4.

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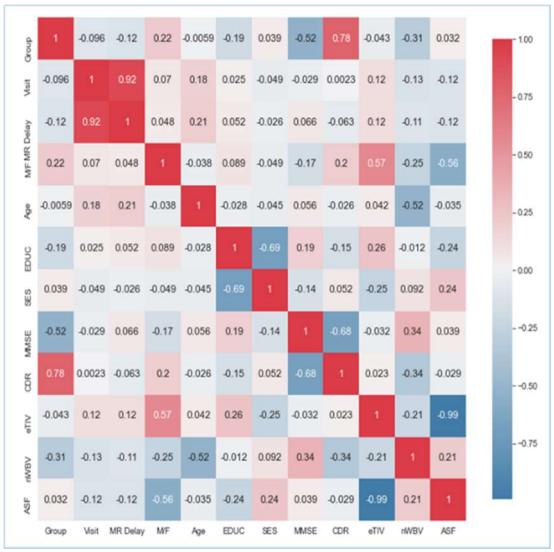
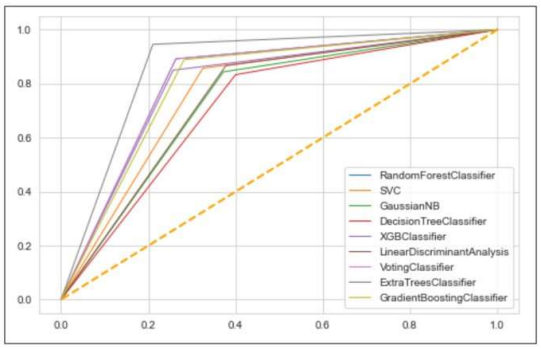



*Fig. 4 Correlation matrix of AD features*

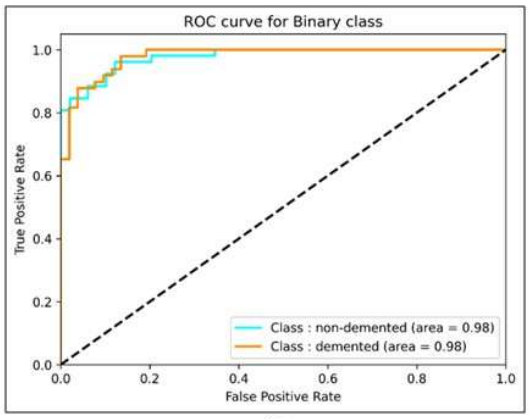
### 6.2 Discussion

The proposed models could diagnose and classify disease using MRI and clinical test data from the OASIS dataset. The data has undergone exploratory analysis to gain insight into the data and fill in the missing values. As a subsequent step, the datasets are preprocessed and normalised to be compatible with the proposed machine-learning models. To enhance performance, models are fine-tuned. Figure 5 depicts the time necessary to reach the threshold and illustrates model behaviour. The threshold value has been determined to be 1, T demonstrating that the classifiers assessed using the provided technique have valid results.

On the other hand, the area beneath the proposed method, the DNN model classifier, is the most significant, which indicates that the model quickly converges and offers maximum accuracy. The X-Y axes of this curve depict the true positive rate (TPR) and false positive rate (FPR). Both the True Positive Rate and the False Positive Rate are calculated and plotted on a graph at various points throughout the process. The TPR is frequently referred to as the sensitivity of a diagnostic test. In contrast, the FPR is recognised for its specificity.




(a)




(b)

*Fig. 5 Roc curve of:- (a) ML Models, (b) DNN Model*

The confusion matrix is an orderly manner of relating the predictions to the original data classes. It is a class-wise distribution of the predicted performance of a classification model. The Figure. 8 depicts the confusion matrix obtained for machine-learning models and DNN. The model excels in analysing the non-dementia group more than the group with dementia, and among the nine classifiers, the extra tree classifier has shown remarkable performance. According to the Extra Tree classifier model, the true negative value for the binary classification of Alzheimer's disease stage was projected to be.94, while the true positive value was expected to be.81. The non-demented class is said to be accurately predicted; however, 19\% of the demented class is misclassified as non-demented, which necessitates more work. In DNN model, predicted true negative values and true positive values as .94 and.90.

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*Fig. 6 Confusion matrix of (a) Random Forest,(b) SVC, (c) Gaussian Naïve Bayes, (d) Decision Tree, (e)Extreme Gradient Boosting, (f) Linear Discriminant Analysis,(g) Voting Classifier, (h) Gradient Boost, (i) Extra Tree Classifier, DNN*




*Fig.7 Feature ranking of AD*

Figure .7 describes the ranking of features as determined by the univariate feature selection method. The top three key attributes are mmse, nwbv, and etiv, and the DNN classifier verifies feature significance accurately. The most crucial factor is the mmse, whereas the gender group is the least important.

The findings of the quantitative comparison of the suggested methodology with the most cutting-edge outcomes are explained in Table.5. These findings are used to evaluate the effectiveness of the current method. The comparison will consider the dataset, the number of classes, and the accuracy of each model as obtained according to its maximum level. According to the comparison findings, the suggested approach performs exceptionally well on the OASIS dataset.

*Table.5 state of art for comparing with other models*

| Papers | Models | Dataset | Accuracy |
|---|---|---|---|
| Baglat et al | Random Forest | OASIS | 86.8% |
| Battineni, Gopi et.al | SVM | OASIS | 68.75% |
| Pinaya et.al | Adversial Autoencoder | OASIS | 72.8% |
| Saratxaga CL et.al | Deep learning | OASIS | 88% |
| **Proposed** | **DNN** | **OASIS** | **92%** |
| | Extra tree classifier | | 86% |

## 7. CONCLUSION

Alzheimer's is a debilitating and irreversible disease; therefore, it is critical to lessen the chance of developing the disease, get an early diagnosis, and appropriately evaluate symptoms. According to the reviewed literature, several attempts have been made to diagnose alzheimer's using different computer-aided algorithms and micro-simulation methods. Despite these efforts, it has proven difficult to identify relevant characteristics that can diagnose alzheimer's disease in its earliest stages. The classification of ad groups into demented and non-demented categories is accomplished by applying the machine learning modelling and deep learning technique in the suggested work. As seen in the results and analysis section, the proposed method acquired an accuracy of 92% with DNN and 86% with Extra Tree classifier. Compared to the previous models used in this study DNN showcases best result.. The developed DNN model can handle hierarchical modelling challenges; it is computationally more efficient. Research in the future will focus on identifying and analysing unique qualities from predictor factors and brain scans that are more likely to assist in the timely identification of Alzheimer's disease. This research will also focus on removing irrelevant and redundant data from existing data sources to improve the precision of detection strategies. The current work solemnly focuses on identifying demented and non-demented subjects based on their clinical and MRI test result. The models has undergone vigorous research in determining the predictor parameter that highly impacts identifying the affected subjects.

Despite the fact that the research solely focused on the AD dataset and its binary classification, it is still possible to guarantee that the models will be able to successfully perform in other medical fields. In the future, the model will be able to work on projecting the progression time required to convert from extremely mild stage to moderate stage, which will enable both the practitioner and the patients follow up on the appropriate treatment.

### Data availability

The data used to support the findings of this study are available at https://www.oasis-brains.org/ as oasis_longitudinal.csv.

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### Conflicts of interest

We have no conflicts of interest to report regarding the present research work

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