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A Comparison of Machine Learning Algorithms for Alzheimer's Disease Prediction

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Abstract

Lately, Alzheimer's disease has emerged as a big worry. Approximately 45 million individuals are afflicted with this illness. Alzheimer's is a degenerative brain disease that mostly affects the elderly and has an unclear aetiology and pathophysiology. Dementia is the primary cause of Alzheimer's disease, as it gradually affects brain cells. This sickness caused people to lose their capacity to read, think, and many other skills. By forecasting the illness, a machine learning system can lessen this issue. The primary goal is to identify dementia in a range of people. This research discusses the findings and analysis related to the identification of dementia using several machine learning models. The method has been developed using the Open Access Series of Imaging Studies (OASIS) dataset. Despite the dataset's limited size, some significant values are present. Many machine learning models have been applied and the dataset examined. For prediction, decision trees, random forests, logistic regression, and support vector machines have all been employed. The system has been used both with and without fine-tuning. When the results are compared, it is discovered that the support vector machine produces the best outcomes of all the models. Among a large number of patients, it had the highest accuracy in identifying dementia. The technique is easy to use and can identify individuals who may be suffering from dementia.

Keywords: Machine learning, Alzheimer's disease, Data set, Logistic Regression, SVM, Decision tree.

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Introduction

The study of computer programmes that use statistical models and algorithms to learn by inference and patterns without explicit programming is known as machine learning (ML).[1] Machine learning algorithms automatically improve with experience. In order to determine the output automatically, it finds methods, trains models, and applies the acquired approach.[2] Additionally, machine learning systems are capable of adapting to changing surroundings.

A model is a machine learning system that has been taught with an algorithm in a machine learning system to recognise particular kinds of patterns.[3] by which it analyses the information and uncovers any hidden structures within a dataset.[4] The formula that depends on input and output functions and applies it to fresh data in order to anticipate the response is determined by feature extraction and the dataset's known replies.[5] As a result, the model's algorithm uses a set of data for training, develops a method to predict the output, and then stores that process for use in the future.

A supervised machine learning model called a support vector machine (SVM) applies classification methods to two-group classification issues. Support vector machine is a quick and reliable classification technique that excels when given little data to work with.[6] SVMs are a class of related supervised learning methods that are applied to regression and classification issues.[7]

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The proper regression analysis is the logistic regression model. Predictive regression analysis is known as logistic regression.[8] Logistic regression is a technique used to categorise data and show the link between one dependent binary variable and one or more independent nominal, ordinal, interval, or ratio-level variables.[9]

A decision tree algorithm divides the data into subsets in a machine learning system. The goal of a decision tree is to condense the training set into the smallest tree feasible.[10] The decision tree is a supervised classification technique that forecasts an example target class in its leaf node and performs a split test in its internal node.[11] To determine the "best" splitting, decision tree algorithms are utilised to categorise the attributes that need to be assessed at each node.[12] Decision trees are frequently employed in categorization issues due to their consistency and adaptability.

An algorithm for supervised learning is the random forest. Random forest is a flexible, user-friendly machine learning technique that typically yields excellent results even in the absence of hyperparameter adjustment.[13] Some of the most popular algorithms also have a straightforward architecture and variety.[14]

Logistic regression can only be used on linear problems; support vector machines (SVM) can be used on nonlinear ones as well. SVM extracts maximum margin solution, which allows it to operate outliers better. When it comes to handling collinearity, decision trees outperform logistic regression. Decision trees work better for categorical values than logistic regression. A random forest is a collection of randomly produced decision trees where the majority vote determines the expected result. Compared to random forests, decision trees are less precise and dependable. While decision trees use hyper rectangles in the input space.

Nowadays, a lot of medical diagnosis uses machine learning models.[15–19] In order to diagnose Alzheimer's disease, this article compares several machine learning performances. Alzheimer's syndrome is an inherited, irreversible brain disorder that gradually impairs memory, thinking, and the capacity to carry out essential tasks.[20] Alzheimer's disease causes a significant percentage of neurons to stop functioning and lose synaptic connections.[21] People in their 30s to mid-60s are not frequently affected by Alzheimer's disease.[22] Alzheimer's disease symptoms can include changes in sleep patterns, anxiety, despair, and trouble performing simple tasks like writing or reading. Aggressive behaviour and poor decision-making are also common.[23]

Ten to twenty years before symptoms appear, Alzheimer's disease and its precursors start to alter the structure of the brain.[24] It gradually impairs thinking skills and causes memory damage.[25] Dementia is the primary cause of this illness. According to a report, there are between 40 and 50 million dementia sufferers globally, and by 2050, there will be approximately 131.5 million.[26] Figure 1 illustrates that around 70% of dementia patients come from low-income nations.

The loss of brain function, comprehension, recognition, thinking, and behavioural skills to the point where a person has difficulties with day-to-day activities and behaviours is known as dementia.[28] It is rare for persons with dementia to be unable to control their emotions, and they can even change who they are as individuals.[29] The severity of dementia ranges from the mildest stage onwards.[30] It mostly affects those who are elderly. Other than treatment, there is no cure.[31]

Information about Alzheimer's sufferers in Bangladesh is scarce. Based on the most recent statistics available, Bangladesh is ranked 152nd in the world for Alzheimer's and dementia mortality, with 9,917 deaths, or 1.26% of all deaths, reported to the WHO in 2017.[32] Alzheimer's disease awareness is now in its early stages in Bangladesh. As a result, affected patients and their families frequently deal with a variety of problems.[33] There is not much money available

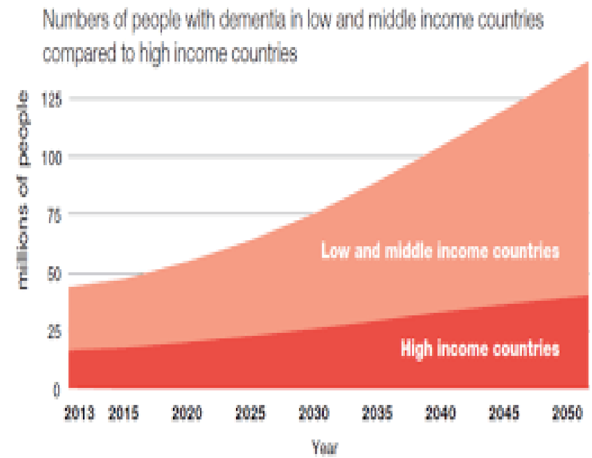

Figure 1: Number of people with Dementia in millions[27]

for Alzheimer's research. Bangladesh, a nation with a lower middle class, is not yet equipped to handle Alzheimer's patients.[34]

In addition, a worldwide study[35] found that about 25% of adult Bangladeshis are overweight, which is the main risk factor for Alzheimer's disease. As a result, the likelihood of Alzheimer's disease increasing.[36] In order to provide a diagnosis and therapy for Alzheimer's disease, doctors typically do a medical and family history as well as a psychiatric history from the perspective of experts such neurologists, neuropsychologists, and geriatric psychiatrists.[37]

Research indicates that things could become better if people can identify Alzheimer's early and start treatment when the illness is still in its early stages.[38] To do this, they must precisely forecast how the illness would advance from a mild condition to dementia. Early Alzheimer's disease prediction can be more accurate with the use of machine learning technologies. Although there are numerous machine learning systems, their predictions are often erroneous and inconsistent. They also struggle with underfitting and overfitting. In order to help medical technicians, we have therefore built a model that uses machine learning to identify Alzheimer's disease early. It will confirm and display whether or not someone has Alzheimer's disease.

Methods and Methodology

This part covers the block diagram, flow diagram, dataset feature description, evaluation matrices, and other system components.

Selecting a Data sets

The system's primary objective is to forecast dementia in various people using a variety of characteristics. The technique has been developed using longitudinal Magnetic Resonance Imaging (MRI) data from OASIS.[39] In the realm of machine learning, the dimensions of the OASIS dataset are quite tiny, measuring 373 rows by 15 columns. Table 1 lists the eight attributes that were taken into consideration for the final result: gender (M/F), age, years of education (EDUC),

Table 1: OASIS dataset of proposed machine learning system

Dataset	Class	# of Subjects	Sex		Age		MMSE		# of MRI Scans
			M	F	Mean	Std	Mean	Std	
OASIS	AD	100	41	59	76.76	7.11	24.32	4.16	100
	HC	316	119	197	45.09	23.11	29.63	0.83	316
ADNI	AD	192	101	91	75.3	7.5	23.3	2.1	530
	MCI	398	257	141	74.7	7.4	27.0	1.8	1126
	HC	229	120	109	75.8	5.0	29.1	1.0	877
IBSR	HC	18	14	4	71	-	-	-	18
MICCAI	HC	35	-	-	-	-	-	-	35

2.1. Public Dataset for Brain MRI

2.1.1. OASIS

Table 2: Dataset description of proposed machine learning system

Features	*Description*
M/F	Gender
Age	Person's age
EDUC	Years of education
SES	Socioeconomic status
MMSE	Mini-mental state examination
eTIV	Estimated total intracranial volume
nWBV	Normalized whole brain volume
ASF	Atlas scaling factor

socioeconomic status (SSE), mini-mental state examination (MMSE), estimated total intracranial volume (eTIV), normalised whole brain volume (nWBV), and Atlas scaling factor (ASF). A standardisation technique has been used to scale the dataset for range values. The amount of standard deviations that separate a raw score's value above or below the observed or measured object's mean value is known as the standard score. It is calculated as follows: $z=(x-\mu)/\sigma$. σ is the standard deviation and μ is the mean in this case.

The eight dataset features that were taken into account for the suggested model to predict Alzheimer's disease are listed in Table 2 along with a brief description of each feature. The attributes are primarily numerical. Hand, M/F, and group are categorical. Each of these terms characterises the patient's state and helps the machine learning algorithm identify the patient's dementia stage.

BlockDiagram

The machine learning system's block diagram is displayed in Figure 2. The system makes use of the OASIS dataset, which

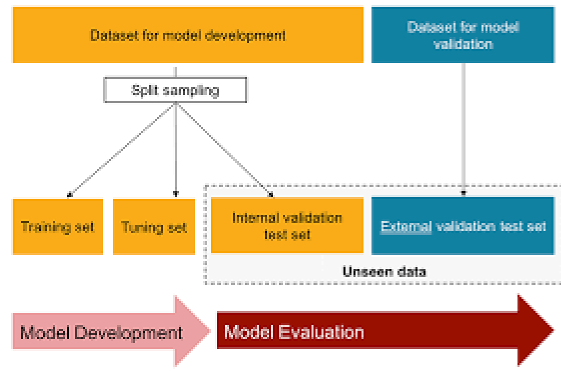

Figure 2: Block diagram

has all the values and properties. Initially, we conducted an analysis of the dataset to identify any categorical values, and we found that it contains multiple categories. Among them, the columns for group attributes and gender are assigned the numerical values 0 and 1. We have used the "correlation matrix" function based on group attributes to examine the correlation between the qualities and have presented the results for better understanding. The group attribute had a stronger association with gender, SES, and ASF. The dataset is next examined to make sure there are no null or missing values. There are 19 and 2 missing values in the SES and MMSE columns, respectively. The SES feature and the target attribute are closely correlated, as was previously mentioned. Because of this, some rows' missing values were left in place. Rather, the missing values for both features are filled in using the median value.

The goal value has then been established so that the model can forecast, and the characteristics have been allocated to produce the prediction. The dataset was then divided into testing and training subsets. The split was done via random sampling, yet this leads to an imbalance between the testing and training halves. With a training-validation size of 80% and a testing size of 20%, stratified sampling has been used. Following that, the features have been scaled via standardisation. To further better grasp the scenario, several histograms and scatterplot visualisation have been applied to the training split. After then, the system started to be trained. Scikit-learn has been used to implement each and every model.

Flowchart Diagram

SVM Flowchart. The flow diagram for the entire SVM model is displayed in Figure 3. First of all, the support vector machine has been put into practise without being adjusted. Without any fine adjustment, SVM utilises the radial basis function (RBF) as the kernel and treats regularisation parameter C as 1. The model has then been fine-tuned using the grid search. Then, for the parameter combinations, various regularisation parameters have been chosen, including values C, gamma values, and four distinct kinds of kernels: poly, sigmoid, RBF, and linear. Furthermore, all potential combinations have been assessed using 5-fold cross-validation. After then,

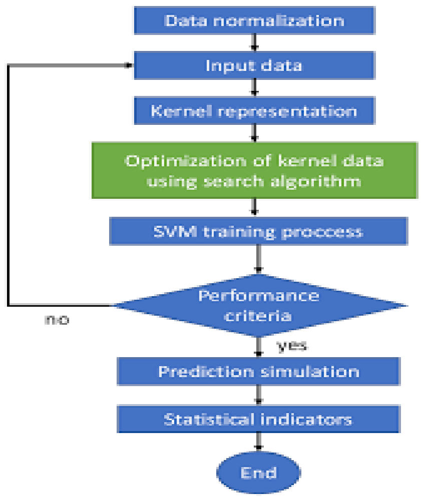

Figure 3: Flowchart of SVM

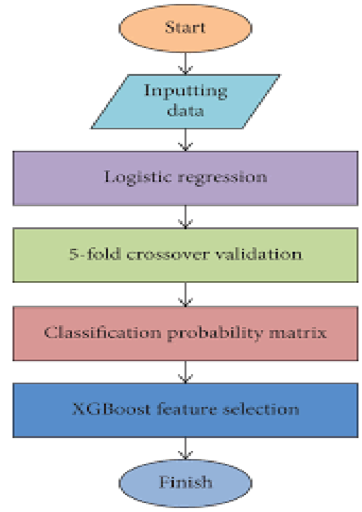

Figure 4: Flowchart of logistic regression

there was a noticeable improvement when the model was trained once more. This version has been used to calculate the confusion matrix.

Logistic Regression Flowchart. The flow diagram for the entire logistic regression model is displayed in Figure 4. Similar to the SVM, the logistic regression model has also been used in this manner. It establishes the variables that are dependent and independent. It creates decision boundaries and forecasts probability using the sigmoid function. The l2 penalty and various regularisation parameter values C have been employed for the fine tuning, which is the only variation.

Decision Tree Flowchart. The decision tree model's overall flow diagram is displayed in Figure 5. The decision tree model employs the same methodology. After the model was trained without any fine-tuning, the optimal parameter values were discovered by grid search. In this case, the depth of the tree is assessed using a range of 1 to 10, and the quality of the tree is assessed using the Gini criterion, which has been set at a fixed value. It makes more detailed decisions and chooses each node. It forecasts the outcomes for the optimal solution following an analysis of every node's selection.

Random Forest Flowchart. The flow diagram for the entire random forest model is displayed in Figure 6. It is an assortment of decision trees. The decision tree and the method are the same. The data is preprocessed, and a few random samples are chosen for training from the dataset. Every chosen sample results in the formation of a decision tree. Initially, no fine-tuning was done during the training of the random forest model. Grid search, like the SVM, has been used with 5-fold cross-validation and various parameter combinations, including the number of random forest trees (n_estimators), the function to use for the number of features to take into account at each split, the levels of the tree, and the process of choosing training samples for each tree. To measure the quality of the tree, the Gini criterion has been used. e entropy criterion has also been tried in the model, but Gini criterion provides better accuracy.

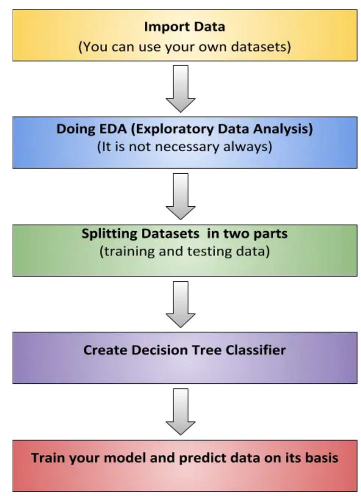

Figure 5: Flowchart of decision tree

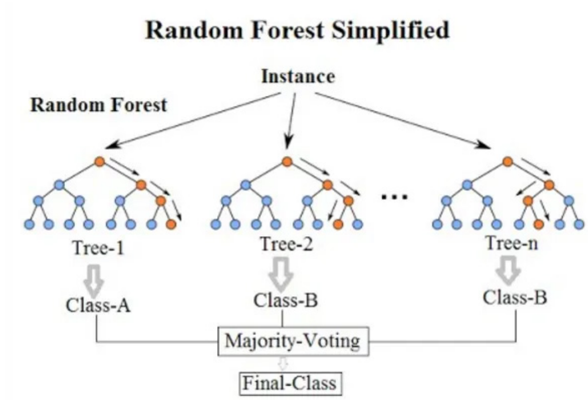

Figure 6: Flowchart of random forest

Evaluation Matrices. The confusion matrix diagram is displayed in Figure 7. A performance assessor for machine learning's categorization models is the confusion matrix. The confusion matrix has been used to assess each produced

Table 3: Comparison table of models

Model	*Accuracy (%*	*Recall (%)*	*Precision (%)*	*Precision (%)*	*F1 score*
SVM	92.0	91.9	91.9	91.9	91.9%
Logistic regression	74.7	70.3	76.5	74.6	73%.3
Decision tree	80.0	59.4	100	79.7	74.5%
Random forest	81.3	70.3	84.4	81.2	76.7%

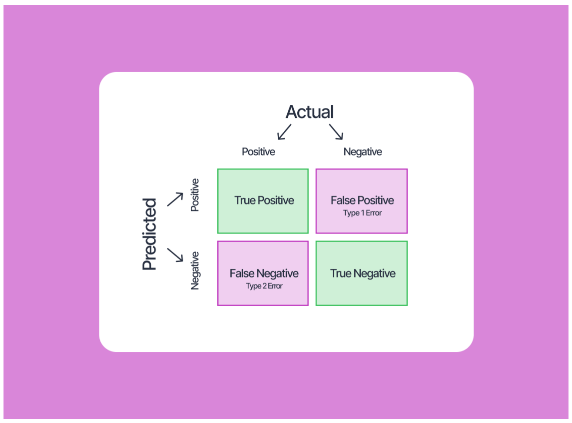

Figure 7: Diagram of confusion matrix

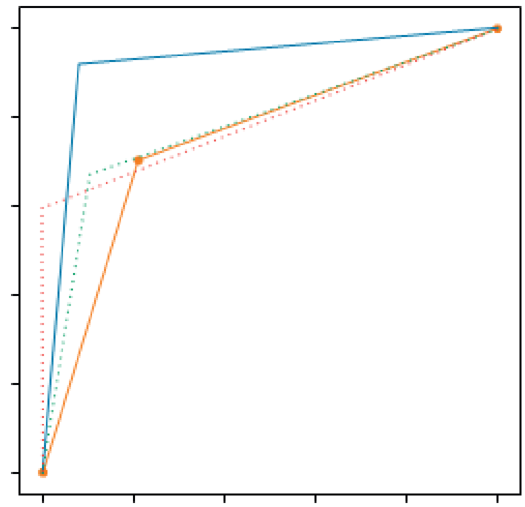

Figure 8: Plotting of ROC and comparison of AUC

model's performance. The confusion matrix shows the proportion of accurate and inaccurate predictions made by our models. It classified the values that were predicted incorrectly as false positives and false negatives, and it classified the values that were correctly predicted as true positives and true negatives. The accuracy, precision-recall trade-off, and AUC have been used to gauge the model's performance once all of the predicted values have been arranged in the matrix.

Results and Analysis

This section covers the model's functions, predictions, analysis, and ultimate outcomes.

Data Visualization

Hisogram. Figure 8 displays the training and validation set histogram. The dataset's ratios are shown in the histogram. It can be seen from the M/F plot that the dataset's male-to-female ratio is 60% to 40%. Every patient in the dataset is at least 60 years old. The bulk of SES is 2, while the MMSE is 30. The majority of the patients had 12.5 years of schooling. Furthermore, the ASF, nWBV, and eTIV are all somewhat high.

The correlation matrix shows how the show's features are connected to one another. The primary focus feature for dementia detection is the group. Patients are diagnosed with dementia if the group value is higher than 0.5. The correlation matrix shows that the likelihood of developing dementia increases with the values of ASF and SES. Additionally, it has been noted that men are more likely than women to get dementia. SVM Model, Logistic Regression Model, Decision Tree Model, Random Forest Model.

Plotting of the receiver operating characteristic (ROC) and AUC comparison are displayed in Figure 8. The system employed the following evaluation measures because it was a classification problem: accuracy, recall, area under the curve (AUC), and confusion matrix. It is clear by combining the output from every model that the support vector machine (SVM), or more precisely the support vector classifier, produced the best overall performance across all measures. The decision tree classifier, however, produced the most accurate true positive outcome. The models have grid search used for fine-tuning. Consequently, the outcomes are optimal for that specific dataset. Random forest and decision tree models have been shown to exhibit some overfitting.

Comparison Table: The models' comparison table is displayed in Table 3. The table unequivocally shows that, out of all the models in the system, SVM is the best model. Its F1 score, area under the curve, accuracy, and recall are all higher.

Conclusion

The system's primary goal is to forecast the onset of Alzheimer's. The "MRI and Alzheimer's" dataset, made available by the Open Access Series of Imaging Studies (OASIS) project, has been used to predict dementia or

Alzheimer's disease in adult patients. The missing values in the dataset have been filled in and visualised. Preprocessing has been done on the data to eliminate any superfluous features. To ensure that the values fit into the ML models with ease, they were standardised. SVM, logistic regression, decision tree, and random forest models have all been trained using the dataset. Accuracy, recall, AUC, and confusion matrix have all been employed as evaluation metrics. All produced models have been fine-tuned using the grid search method in order to improve the system outcome.

Using SVM, the system produced the best result for this specific dataset. An overfitting problem affected a more sophisticated model, such as the random forest classifier. Out of all the models, the SVM model has been deployed with the best outcomes. A bigger dataset and other machine learning models, like Ada Boost, KNN, Majority Voting, and Bagging, could be used in the future to enhance the system models. This will improve the system's performance and dependability. By simply entering MRI data, the ML system can assist the general public in gaining an understanding of the likelihood of dementia in adult patients. It is hoped that this would enable individuals receive early dementia treatment and enhance their quality of life.

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