

Comparative Study of Machine Learning Models for Alzheimer’s Detection

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Abstract - Alzheimer's disease (AD) is a neurodegenerative disorder of uncertain cause and pathogenesis that primarily affects older adults and is the most common cause of dementia. It is significant to detect the initial presence of AD, which is mainly done using MRI (Magnetic Resonance Imaging). The proposed machine learning models take into consideration various attributes related to dementia and predict AD.

Key Words: Machine Learning, Alzheimer’s detection, Predictive Analytics.

1. INTRODUCTION

Alzheimer's is the most common cause of dementia, a general term for memory loss and other cognitive abilities serious enough to interfere with daily life. Alzheimer's disease accounts for 60 percent to 80 percent of dementia cases. Alzheimer's is not a normal part of ageing. The greatest known risk factor is increasing age, and the majority of people with Alzheimer's are 65 and older. Although current Alzheimer's treatments cannot stop Alzheimer's from progressing, they can temporarily slow the worsening of dementia symptoms and improve quality of life for those with Alzheimer's. Thus, helping the doctors detect early-stage Alzheimer's using machine learning will definitely help the society on a whole.

In developing countries like India, the population is more and the number of suffering people are also more but comparatively lesser number of experts are available. It's not possible for them to give treatment to all and it takes a lot of time for a doctor to gain expertise. The Computer-Aided Design (CAD) systems will help them to gain deeper insights and master the domain. As the disease is reversible if diagnosed at an early stage, there is a possibility that the patients may not have to suffer for the rest of their life. CAD systems could be used to reduce the number of mortality and reduce the waiting time to see the specialist. Employing the technology, especially Artificial Intelligence (AI) techniques in medical applications could reduce the cost, time, human expertise and medical error.

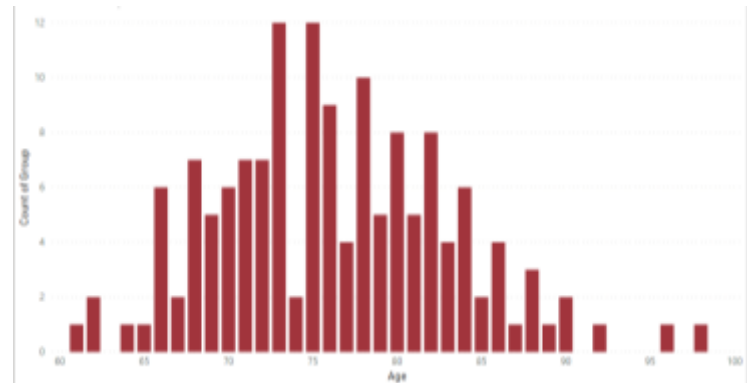


Fig -1: Range of people suffering from AD

The primary objective of this research is to develop methods and algorithms to identify or classify types of neurodegenerative diseases. The main research activities specifically focus on investigating and improving the feature extraction of information on the neurodegeneration of the brain.

1.1 AI reinforced detection

Artificial intelligence (AI) is enabling the machines to “think” like humans. The ability of AI to make data-driven decisions and to identify shared characteristics among data points are especially relevant to medicine. The process of detection when infused with AI, tremendous progress can be made in terms of the overall efficiency and results of the process. The machine (AI) is made to learn the nuances the given process, detection of AD in the given case. By many iterations and deployment of changes to improve accuracy and precision, the machine gradually learns to map the input to the correct output.

This AI reinforced detection provides a constructive solution to the problem. AI consists of many sub-domains and many different models; amongst which every model is specialized for a specific task, and in the task detection of AD, the performance of these models is evaluated and compared.

2. LITERATURE REVIEW

Use of AI in the domain of healthcare has seen vast popularity in recent years, albeit it has a long history. In the 1970s an expert system was designed for aiding progress in healthcare. Continuous research and development are features of this domain. Many researchers have attempted to address this topic and a brief overview of which is presented in the forthcoming section.

Moradi E et al. [1] has proposed a technique for identifying mild cognitive impairment (MCI) as a transitional stage between age-related cognitive decline and AD. A novel MRI-based biomarker that was developed using machine learning strategies. Noteworthy techniques used in this model included using semi-supervised learning on data available from AD patients and performing feature selection using regularized logistic regression, removing aging effects from MRI data before classifier training to prevent possible confounding between changes due to AD and those due to standard aging, and construction of an aggregate biomarker by learning separate MRI biomarker and subsequently combining age and cognitive measures about MCI subjects by applying random forest classifier.

Zhang Y et al. [2] have proposed a computer-aided diagnosis (CAD) system for MRI images of brain-based on Eigen brains. This approach uses key slices from the 3D volumetric data generated from the MRI and then generates eigen brain images based on EEG. Subsequently, usage of kernel support vector machines is included that are trained by particle swarm optimization.

3. EXPLORATORY DATA ANALYSIS

Establishing the relationship between features of the MRI test and dementia is a crucial step in understanding and eventually developing a machine learning model that maps the inputs to the output (input being the features of MRI and output being the presence or absence of AD). Usage of multiple graphs is implemented to achieve the same.

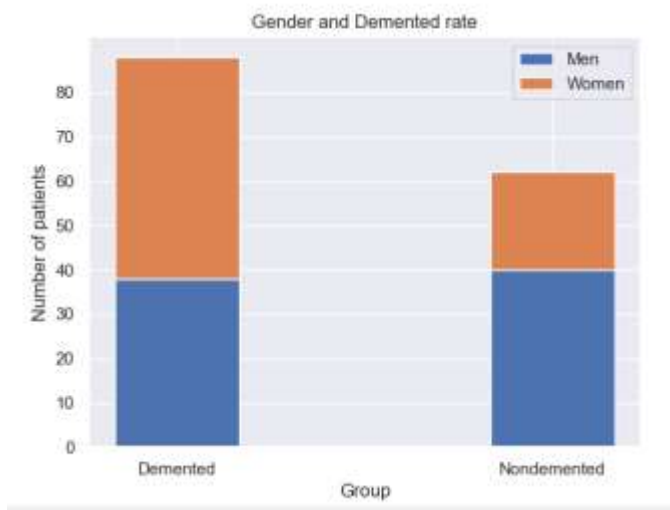


Fig -2: Gender-wise distribution of dementia

The graph illustrated in fig. 2 suggests that men are more likely to be affected by dementia than women. This suggests that gender and dementia are correlated.

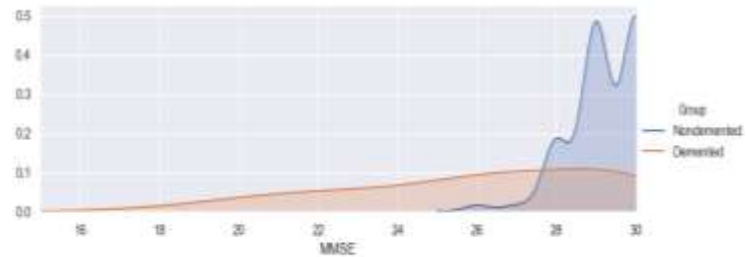


Fig -3: Distribution of MMSE for demented and non-demented group

The graph in fig. 3 shows that MMSE (Mini Mental State Examination) value is more for the demented group than the non-demented group. This suggests that MMSE is inclusive of the feature set for the prediction model.

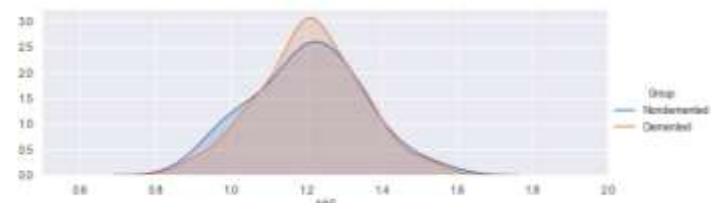


Fig -4: Distribution of ASF for demented and non-demented group

The graph in fig. 4 indicates that ASF (Atlas Scaling Factor) value is also more for the demented group than the non-demented group. This results in the addition of ASF in the feature set.

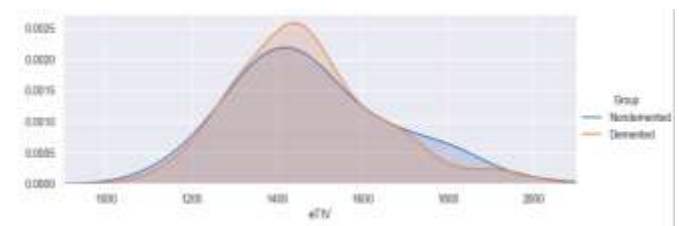


Fig -5: Distribution of eTIV for demented and non-demented group

The graph in fig. 5 proposes that eTIV (Estimated Total Intracranial Volume) value is higher for the demented group than the non-demented group. This results in the presence of ASF in the feature set.

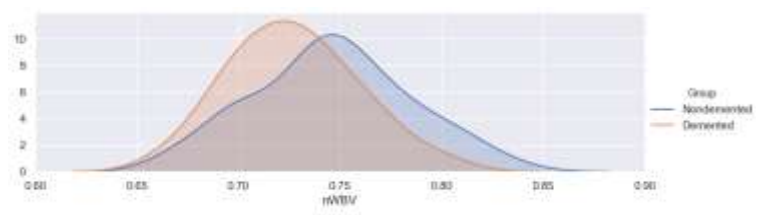


Fig -6: Distribution of nWBV for demented and non-demented group

The graph in fig. 5 intimates that nWBV (Normalize Whole Brain Volume) value is more for the demented group than the non-demented group. This suggests the inclusion of nWBV in the feature set.

Conclusions drawn from the analysis:

1. Men are more likely to be demented (an Alzheimer's disease) than women.
2. Demented patients were less educated in terms of years of education.
3. The nondemented group has higher brain volume than the demented group.
4. A higher concentration of 70-80 years old in the demented group than those in the nondemented patients.

3. SYSTEM DESIGN

The architecture of the model is designed to iterate through the different models of machine learning to find the one with the most accurate and precise fit. This iterative process is characterized by calculation and fine-tuning of the internal parameters and the hyperparameters.

3.1 Approach used

The uniqueness of our approach is in the inclusion of metrics like MMSE and education in our model to train it to differentiate between normal healthy adults and those with Alzheimer's. MMSE is one of the gold standards for determining dementia and hence it is an important feature to include.

The same fact also made the approach flexible enough to be applied to other neurodegenerative diseases which are diagnosed using a combination of MRI features and cognitive tests.

Running every machine learning algorithm through k-cross-validation with 5 folds, the optimal values from the set of values is computed. The optimal set of parameters is then used to calculate the evaluation metrics for the given model.

3.2 Models

Different machine learning models are deployed in order to come up with the best fit model.

- 1) **Logistic Regression:**
Logistic Regression is a machine learning algorithm which is used for the classification problems. It is a predictive analysis algorithm and is based on the concept of probability.
Logistic Regression when applied to the given model, it results tabulated are as follows:

```
Best accuracy on validation set is: 0.700909090909
Best parameter for regularization (C) is: 10
Test accuracy with best C parameter is 0.75
Test recall with the best C parameter is 0.7
Test AUC with the best C parameter is 0.794444444444
```

Fig -7: Evaluation metrics for logistic regression

- 2) **Support Vector Machine (SVM):**
A support vector machine (SVM) is a machine learning algorithm that analyzes data for classification and regression analysis. SVM is a supervised learning method that looks at data and sorts it into one of two categories.
SVM when applied to the given model, it results tabulated are as follows:

```
Best accuracy on cross validation set is: 0.77150385846
Best parameter for c is: 100
Best parameter for gamma is: 0.1
Best parameter for kernel is: rbf
Test accuracy with the best parameters is 0.815789473684
Test recall with the best parameters is 0.7
Test recall with the best parameter is 0.822222222222
```

Fig -8: Evaluation metrics for SVM

- 3) **Decision Tree:**
Decision Tree Analysis is a predictive modelling tool that is constructed via an algorithmic approach that identifies ways to split a data set based on different conditions. Trees are a non-parametric supervised learning method used for both classification and regression tasks.
SVM when applied to the given model, it results tabulated are as follows:

```
Best accuracy on validation set is: 0.796329757199
Best parameters of M, d, m are: 14 5 7
Test accuracy with the best parameters is 0.842105263158
Test recall with the best parameters is: 0.8
Test AUC with the best parameters is: 0.844444444444
```

Fig -9: Evaluation metrics for decision tree

- 4) **Random Forest:**
A random forest is a data construct applied to machine learning that develops large numbers of random decision trees analyzing sets of variables. This type of algorithm helps to enhance the ways that technologies analyze complex data.
Random forest when applied to the given model, it results tabulated are as follows:

```
Best accuracy on validation set is: 0.778543195935
Best parameter of M is: 2
best parameter of LR is: 0.0001
Test accuracy with the best parameter is 0.842105263158
Test recall with the best parameters is: 0.65
Test AUC with the best parameters is: 0.825
```

Fig -10: Evaluation metrics for random forest

5) Adaptive Boosting (AdaBoost)
 Ada-boost or Adaptive Boosting is one of ensemble boosting classifier which combines multiple classifiers to increase the accuracy of classifiers. AdaBoost is an iterative ensemble method. AdaBoost classifier builds a strong classifier by combining multiple poorly performing classifiers so as to get high accuracy strong classifier. Random forest when applied to the given model, it results tabulated are as follows:

```
Best accuracy on validation set is: 0.778543195935
Best parameter for the maximum depth is: 1
Test accuracy with best parameter is 0.815789473684
Test recall with best parameters is 0.65
Test AUC with the best parameter is 0.825
```

Fig -11: Evaluation metrics for AdaBoost

4. CONCLUSIONS

Detection of AD by using machine learning algorithms resulted in novel results. The metrics calculated for each of the models is illustrated below.

Model	Accuracy	Recall	AUC
Logistic Regression (w/ imputation)	0.789474	0.75	0.791667
Logistic Regression (w/ dropna)	0.750000	0.78	0.700000
SVM	0.815789	0.78	0.822222
Decision Tree	0.815789	0.65	0.825000
Random Forest	0.868421	0.88	0.872222
AdaBoost	0.868421	0.65	0.825000

Fig -12: Comparison of evaluation metrics for the applied models

Building on the work previously done in the domain, the results achieved show promise, especially the result achieved using Random Forest. The predicted value using the Random Forest model is higher than the other models. It implies that there is potential for higher prediction rate if preprocessing of data is carried out with a higher level of expertise. The comparative study of the different models for detecting AD reveal that Random Forest yields the best result for the given dataset.

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