Musfiq

Introduction

Alzheimer's disease is a progressive neurologic disorder, it causes the brain to shrink and brain cells to die. It becomes more severe over time, and it is not curable. Every country has elderly with dementia. However, the number is alarmingly increasing in the least developing and developing nations. Research has shown that by 2040, 71% of dementia patients will be from developing nations, and the number will double every 20 years. There is low awareness about dementia in those countries. Many people in those countries think the loss of memory is a typical aging problem. The lack of diagnostic assessment, cost of diagnosis deters people from diagnosis of dementia. The cost of MRI is too expensive for many.

There are several factors in dementia. Age and gender are also essential factors. Females are more like to be affected by Alzheimer’s disease than Male [4]. Low education level, Low social class, income, depression, head trauma, epilepsy, diabetes, and stroke are relevant factors [6]. All these factors can be used with cognitive tests to early diagnosis of AD. The lower cost of diagnosis will open doors for many poor people and people living in the rural area for alzeimar desis diagnosis.Early confirmation of Alzheimer's disease may be helpful to start proper treatment early and save lives.

Literature Review

Predicting Alzheimer's disease is a popular research field A significant amount of work has been done in this field. MRI and PET data analysis is the dominant subfield in predicting Alzheimer's disease. For example

Gopi Battineni et al. used MRI data to develop different ML models to predict dementia in the elderly. They trained four Machine Learning models. The combination of all four models with selective features achieved an Accuracy of 98%.

Biomarkers analysis and longitudinal data analysis for classification and progression are also much popular. A few of them are,

Courtney Cocherane et al. Instead of using MRI data, used longitudinal lifestyle interventions. They achieved more than 90% accuracy and recall in predicting Alzheimer's disease.

XIN HONG et al. focused on identify time relative biomarkers associated with disease status. They found that the Cortical Thickness Average (TA) is significant in predicting Alzheimer's disease progression.

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Dataset:

For this study, we used the OASIS [14] longitudinal data. OASIS is the Open Access Series of Imaging Studies.

OASIS Dataset provides several independent variables including sociodemographic and clinical variables, sociodemographic variables are

Gender

Age:

Years of Education (EDUC):

Socioeconomic Status (SES):

The Clinical variables are:

Mini-Mental State Examination score (MMSE): The MMSE is a 30-point questionnaire widely used to assess cognitive impairment in clinical and research environments.

Clinical Dementia Rating (CDR): The CDR is a 5-point scale used to characterizing and tracking a patient's

dementia level. CDR is estimated based on a semistructured interview of the subject and the caregiver

(informant) and the clinician's clinical judgment.

And MRI variables are:

Estimated total intracranial volume (eTIV):

Normalize Whole Brain Volume (nWVB):

Atlas Scaling Factor (ASF):

Data processing:

First, we removed all the rows with empty data. Initially, we had 373 subjects, but after modifying our dataset, we had 354 subjects. Then we used the One-hot encoder to encoded all categorical variables. Finally, we split the data into two parts, the train set and the test set. We used 80% of the data for training our models and 20% for testing purpose.

We conducted our experiment in two steps. In the first step, we included all the MRI data and longitudinal lifestyle data like age, gender, income, education, and other lifestyle data and neuropsychological scores like MMSC. In the second step, we excluded all the MRI-related data and did the same experiment again. Our dataset has multiple classes like demented, non-demented, and converters.

Khadir anda

Machine learning algorithms

After processing our data, we moved onto selecting an efficient Machine learning. We used both classification and ensemble learner algorithms

we started with several Machine learning models. We first run all the models without hyper-parameter tuning. We only selected the models that had more than 50% accuracy and recall. Some models performed very poorly. For example, KNeighbours Classifier trained with MRI data only got an accuracy score of 45.07% and recall 0.45. So, we did not invest time in tunning hyper-parameters of these models.

We got five models that performed well: Random Forest Classifier, Gaussian NB, Linear SVC, Logistic Regression, and Ada boost classifier. So, we moved on to tunning these models. The supervised learning module performs a ten- fold cross-validation and grid search over selected features for each model.

We used the same procedure for both of our experiment.

Hyperparameter Tuning

Hyperparameters define the architecture of the model. The same machine learning model can require different constraints, weights, or learning rates to generalize different data patterns. First, we defined a grid of parameters and multiple values for each parameter. Then we used GridSearchCV to find the best hyperparameters for the model. After finding the best parameters the first time, for the numerical value parameters like n\_estimators, we changed the list of values, this time, we took values close to the previous best and ran again to get the maximum accuracy recall possible.

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Ensemble Architecture

Ensemble Method is a machine learning technique where several Machine learning models are used to produce an optimal model. Ensemble algorithms perform better if there are significant differences or diversity among the models.

In our model, we used the Averaging method. We used the soft voting classifier to ensemble the models. The Soft voting classifier sums the probabilities of all the models and predicts the class with the highest probability. For the model with MRI data, we ensembled four models they are, Random Forest, LinearSVC, Logistic regression and Ada Boost. For The non-MRI model, we ensembled five models, the fifth model is the Gaussian NB. We didn’t use KNeighbours model because it performed poorly. We tried several combinations and found these combinations yield the highest accuracy and recall score.

Results:

We compared the result in different scales like Accuracy, F1 score, Recall, Precision. Accuracy is the percentage of correct predictions for the test data

While experimenting with MRI data, We got the best Accuracy and a recall score from AdaBoost Classifier. It had an Accuracy score of 96.07%, Recall of 0.96.

The results of our hybrid model were not as good as the individual models. Our hybrid model scored an Accuracy score of 92.55%, a Recall score of 0.93.

While experimenting with non-MRI data, Our best performing model was the Random forest classifier. This model scored an Accuracy score of 90.14%, a Recall of 0.90, both LinearSVC, and the AdaBoost classifier. models achieved an Accuracy score of 89.14%,

We got our best result when we combined all the models. Our Hybrid model scored an Accuracy score of 93.37%, a Recall of 0.93, a Precision of 0.93, and an F1 score of 0.93.The AUC score for this hybrid model was 0.917. In our training with MRI data KNeighbors Classifier performed very poorly. However,

in this case, when trained without MRI data, this model performed better.

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Results Analysis

If we compare our two experiments, we can see our overall Accuracy decreased with non-RMI data analysis. Previously our best model had 96.07% Accuracy, but when we removed all the MRI data, our Accuracy was 93.37%. So, we got an Accuracy drop of 3%. When it comes to detecting a patient, we always want to avoid False Negatives. So, we can consider the recall score for selecting our optimal model. The Recall was decreased from 0.96 to 0.93. Which is not a significant drop.

Conclusion,

So, we can see, there is not a significant gap in our test. Though the Non-MRI method has good results, it is not perfect. Some Demented patients may not be detected with this approach. It is recommended to do an MRI test if possible for better detection and avoid the risk of false-negative prediction. False-negative predictions can be dangerous sometimes when it comes to detecting a disease. However, the

non-MRI methods can provide reliable results when there is a lack of diagnostic assessment or cannot afford an MRI test. This will reduce their initial cost by a margin. The non-MRI method can be used to raise awareness in developing nations, as most of them are unaware of Alzheimer's disease.

These results can be further improved by counting more factors related to AD, like depression, head trauma, epilepsy, diabetes, and stroke and similar factors. We firmly believe our research will pave the way to raise awareness and cheap diagnosis of AD with excellent efficiency.

Thank you for watching my presentation.