CLASSIFICATION OF SEVERITY OF ALZHEIMER'S DISEASE USING BRAIN SCANS

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ABSTRACT

Alzheimer's disease is a progressive neurological disease that degenerates brain cells leading to memory loss and destroying other critical mental functions leading to behavioral changes and eventually death. Currently, there is no known cure, but it is very important to perform early diagnosis as required preventative measures can be taken. Research suggests that there is correspondence between different aspects of the brain like gray matter distribution and severity of Alzheimer's disease. The Magnetic resonance imagining (MRI) scans give information about the structural changes in the brain that can be used to classify the severity of Alzheimer's disease. In this paper, we aim to deploy machine learning models and deep learning-based models to analyze MRI scans and classify them into 1) Mild demented 2) Moderate demented 3) Non demented and 4) Very mild demented.

1. INTRODUCTION

Alzheimer's disease (AD), or Alzheimer's, is a neurodegenerative disease, one of the most common causes of dementia in the elderly people. According to the CDC, in 2020, 5.8 million Americans aged 65 years or older had Alzheimer's disease and it is the sixth leading cause of death in the United States [1]. Alzheimer's disease diagnosis is very complex because of different symptoms that patients might show, both at the cognitive and behavioral level. An early Alzheimer's detection provides a better chance of benefitting from treatment. Progress in neuroimaging techniques has been critical in determining the anatomical and functional changes in the brain linked to Alzheimer's disease. However, integrating vast volumes of data on a big scale is becoming increasingly difficult. As a result, innovative machine learning (ML) methods that allow for the classification of large amounts of data using algorithms are gaining popularity.

In this paper, we have classified Magnetic resonance imagining (MRI) scans based on the criticality of the disease. We have used three models for classifying and determining the best results. The three models are Convolutional Neural Networks, Transfer Learning and Random Forest. We used an open-source dataset available on Kaggle as 'Alzheimer's dataset' which contains multiple MRI scan images belonging to different levels of classification of dementia. Section 2 presents prior work done in this field, Section 3 discusses the dataset we have used in detail, Section 4 defines the algorithms we have used to implement our models, Section 5 describes how we have implemented our models, Section 6 summarizes the results, Section 7 is the conclusion and suggests future direction for our project and Section 8 lists all the references we have used for this paper.

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2. RELATION TO PRIOR WORK

A wide variety of projects were carried out for detection and classification of Alzheimer's disease in recent years. This section will talk about some of the works. One of the approaches was using SVMs on diffusion tensor imaging data to identify patients with Alzheimer's or not. The classifier was able to good accuracy and sensitivity.[2] Another approach was using three algorithms - SVM, K-Means, and Naive Bayes - to identify if patients had Alzheimer's disease or cognitive impairment. The unsupervised algorithms were observed to perform better compared to SVM.[3]

Deep learning techniques are also being implemented due to their ability to understand complex features. One approach of that kind was training a CNN with a softmax classifier on MRIs. By using this method, various complex patterns of the scanned images could be discovered.[4]

All the above-mentioned approaches aim at using the scanned image data to identify patients with Alzheimer's disease or and the severity. We aim to solve the same in this paper.

3. DATASET DESCRIPTION

We used a Kaggle dataset[5], that was divided into four separate classes (Mild Demented, Moderate Demented, Non-Demented, Very Mild Demented) based on the severity of the disease. The dataset consists of 6400 images, each image with size of 208x176 pixels as we were able to get better performance compared to other combinations.

We rescaled the images to 176x176 size and flipped the images horizontally to generate more data because the dataset alone was not sufficient and was resulting in poor accuracies. The dataset was then split into train and testing subsets with the test set containing 0.2% of the images. The train dataset was again split with 0.2% as validation data. The train dataset was then resampled using SMOTE, this was done to reduce the skewness in the data because compared to the other class, there are very few images in one class.

4. ALGORITHMS

We implemented three different approaches for classifying the images, the first one being a CNN, the second one is also a CNN but through transfer learning, and the last one is a RandomForest Classifier.

4.1 Convolutional Neural Network (CNN)

A CNN is a deep neural network primarily used for image classification problems. Because the images itself are large enough, using a simple neural net to back propagate and update the weights would require a lot of computation power. A CNN aims to do this efficiently by gradually reducing the size of the image and extracting features such as edges, lines, curves, etc.

CNN usually consists of three different layers, they are:
1) Convolutional Layer
2) Activation Layer
3) Pooling Layer

a) Convolutional Layer
The convolutional layer uses kernel of some size which is just a matrix that performs dot product operations. This layer is the most important layer of all, and it is responsible for extracting the features from the image.

b) Activation Layer
A CNN with just convolutional layers is simply a linear classifier and it would almost be impossible for it to detect features. In order to solve this problem, the Activation Layer introduces non-linearity through some functions, such as the Rectified Linear Unit (ReLu) and the sigmoid function. The most common functions are the Rectified Linear Unit (ReLu) and the sigmoid function.

A ReLu function can be defined as below:

$$f(x) = \max(0, x)$$

Sigmoid is defined as follows:

$$f(x) = 1/1+e^{-x}$$

c) Pooling Layer
Pooling Layer is used to decrease the size of the input vectors by preserving important features. There are two types of pooling layers commonly used: MaxPooling and AveragePooling.

4.2 Transfer Learning

When existing machine learning models are repurposed to solve a new problem, it is known as transfer learning. Transfer learning refers to using knowledge acquired during previous training to complete a new task using the knowledge gained during previous training. The new task will be linked to the previously learned task, for example, categorizing objects in a particular file type. To adapt the previously trained model to new data, it usually requires a high level of generalization. Transfer learning means we do not have to retrain the model.

Transfer learning implies that we will not have to do the training again from the beginning for every new task. A model can be trained on an available labelled dataset and then applied to a similar job that may require unlabeled data via transfer learning.

4.2.1 ResNet152

A ResNet is a kind of artificial neural network (ANN) that is based on pyramidal cell constructions in the cerebral cortex. Skip connections, or shortcuts, are used by residual neural networks to jump past some layers. The majority of ResNet models use double- or triple-layer skips with nonlinearities (ReLU) and batch normalization in between. To learn the skip weights, an additional weight matrix can be utilized. These models are known as HighwayNets.

As ResNet has many variants, each of which operates on a similar concept, but with a different number of layers. ResNet152 is the variant that operates on 152 layers. ResNet can have a deep network of 152 layers by learning the residual representation functions instead of learning the signal representation directly.

4.3 Random Forest

A random forest is a supervised machine learning system that is developed from decision tree algorithms. It uses ensemble learning, which is a technique used to solve complicated problems by combining several different classifiers. Many decision trees together make a random forest. Bagging or bootstrap aggregation are used to train the forest created by the random forest.

This algorithm determines the outcome based on the predictions of decision tree. It predicts by averaging the output of various trees. As the number of trees grow, the precision of the result improves.

5. IMPLEMENTATION

We used Keras framework and sklearn to implement all the three models. The images were first preprocessed by converting them to numpy arrays and performing operations such as scaling, rotating, and zooming, using Keras ImageDataGenerator. Later, the train data was resampled using SMOTE to reduce the skewness in the data.

5.1 Convolutional Neural Network (CNN)

We designed a CNN that takes numpy arrays as input which is then passed through a series of 10 convolutional layers and pooling layers. The output of these layers is then passed through a series of Dense layers and finally we get a matrix of (nx4) size, where ‘n’ is the number of examples and 4 is the number of classes. This CNN was trained for 150 epochs with Adam optimizer and categorical cross entropy loss. This model attained an accuracy of 85.94%.

5.2 Transfer Learning through ResNet152

We used ResNet152 neural net which was pretrained on a huge collection of images and is around 152 layers deep. This model was trained for 150 epochs with Adam optimizer. Although this neural net is deep enough it still couldn’t improve our accuracy over CNN. This model attained an accuracy of 83.59%.

5.3 Random Forest Classifier

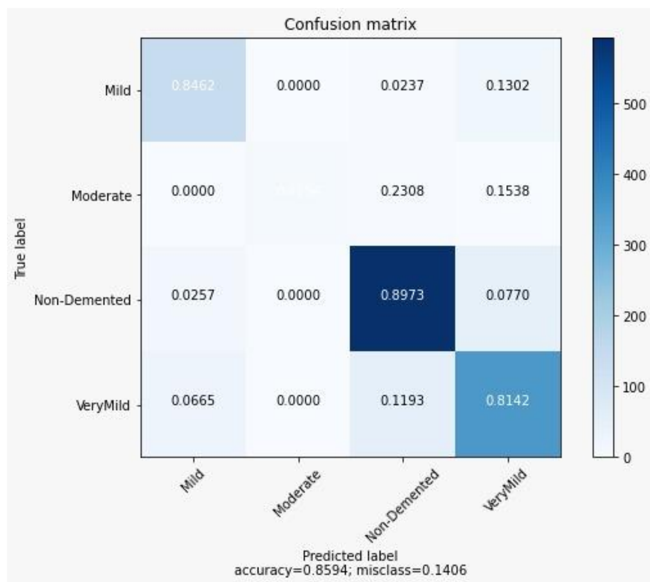
The Random Forest Classifier cannot take image arrays as input, so we flattened the images by reshaping them so that we get a 2d matrix of size (nxd). This matrix was then used as an input to Grid Search over the params of Random Forest. The best params from the grid search gave us an accuracy of 74.9%.

We also observed that we could classify the images into just two classes instead of four to check if a given patient has Alzheimer’s or not. So, we used this Random Forest Classifier and combined the rest of demented labels into one class to classify into one of the two classes. This model attained an accuracy of 80.23%.

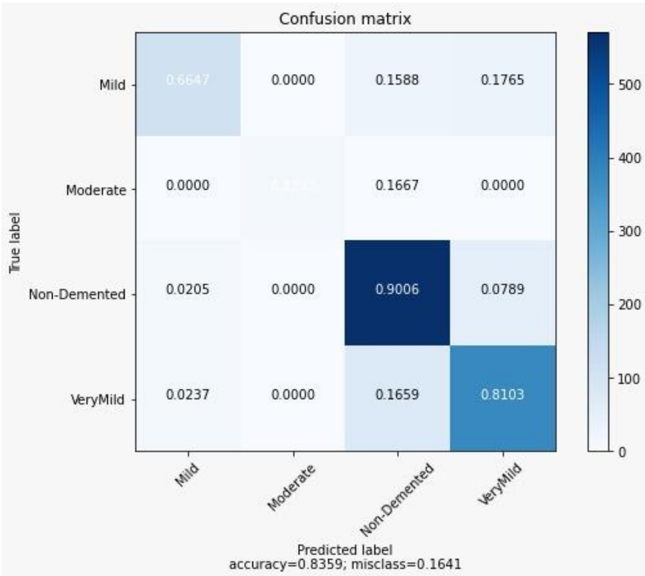
The reason RandomForest is able to perform well enough even though the number of features is very high is because RandomForest doesn’t use all the features and uses only the most important n^1/2 features.

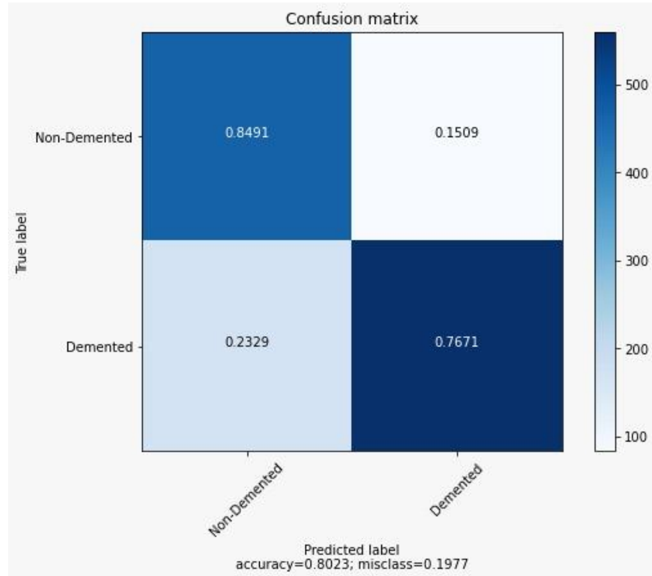
6. RESULTS

6.1 Convolutional Neural Network (CNN)

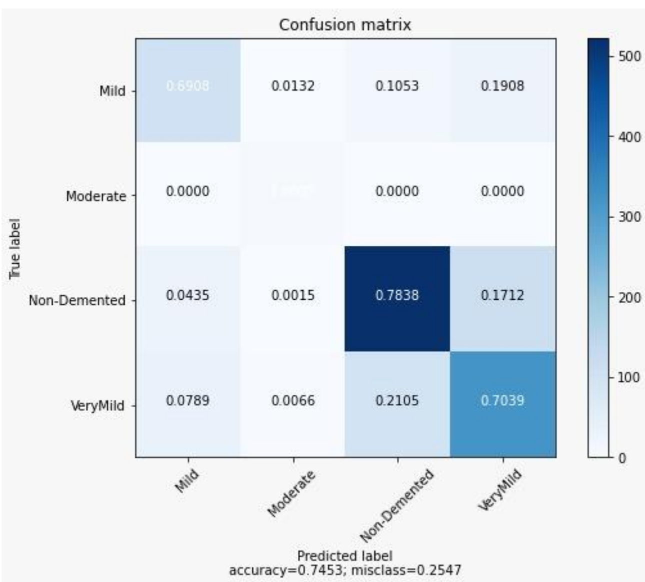


6.2 ResNet





6.3 Random Forest



These are the results of classification we have obtained for our models, and we can see that the Convolutional Neural Network performs most efficiently resulting in the highest accuracy. We have tried experimenting with various image sizes, multiple parameters and optimizers and we tested a few other algorithms. These are the best results we could obtain.

7. CONCLUSION AND FUTURE DIRECTION

We have decided to devise a solution to make detecting a deadly disease like Alzheimer's easier. We identified it's sense of imminent danger and realized how important detecting it is. We have implemented three established machine learning models which are, Convolutional Neural Network, Transfer Learning and Random Forest, to provide with concrete results of classifying MRI scans to determine if the patient is detected with 'Very Mild', 'Mild', 'Moderate' level of dementia or is not detected with dementia. Our implementation gave the accuracy for Convolutional Neural Network as 86%, the accuracy for ResNet as 84% and Random Forest as 75% approximately. In our work we concluded that Convolutional Neural Network model is the most efficient for this purpose and provides reliable results.

For future work, we would like to explore the possibility of extracting features from the scanned images regarding different regions in the brain. We would also like to explore on different types of scan data like PET to understand the impact on deep learning training.

8. CONTRIBUTIONS

This paper scrutinizes the relationship of overall competency levels of individual project participants with project success. Our team had great communication and our collaboration in completing tasks and meeting milestones we have set for ourselves is commendable. Every member had many ideas to contribute, and we have worked and tried all of them. Every member contributed significantly to the success of this project in every area. But every team member focused on the working of one model primarily. Sai Kiran Jella worked on Convolutional Neural Network model. Manaswini Nuti worked on Transfer learning algorithm and Akhila Sakiramolla worked on implementing Random Forest. Sai Kiran also visualized the implementation of Random Forest with only two labels – 'Non-Demented and Demented'.

9. REFERENCES

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