Automated Diagnosis of Alzheimer Disease

Abstract

Currently, the diagnosis of Alzheimer's is a long process, with the outcome largely based on the opinion of the doctor. The reason for this is the lack of precise tools, and the extent of time and effort it takes to diagnose Alzheimer's. As a result, around 55% **of people with Alzheimer's die without ever being diagnosed as Alzheimer's patients.** Therefore, the purpose of this project is to create an automated tool that could accurately diagnose Alzheimer's with the help of MRI scans of subjects and patients information. So, this model can change how patients are diagnosed and the number of patients diagnosed.

Approach

We used **CNN** (Convolutional Neural Networking) because of its capability to mimic biological systems. In this project, we will use features like image processing and classifiers to train and test through collected data sets.

The details are as follows:

Database for training and testing:

1. We had two sets of data available to us that are Clinical and MRI data.
2. By using those datasets, we had collected images for MRI scans of subjects having Alzheimer disease and subjects those are healthy.

Image feature extraction of MRI scans using image processing.
Extracted feature vector is than passed to our NN for training and optimizing our model.

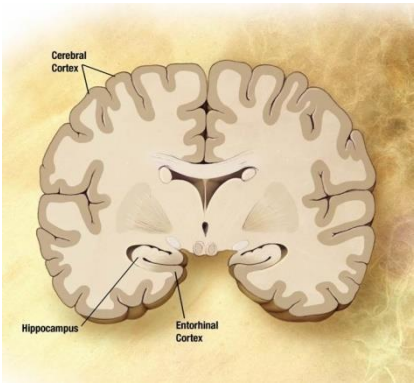
Alzheimer and its cause:

It is a disease that can be found in any age group. It is associated with loss in memory of an individual. It includes problems with language, disorientation, not

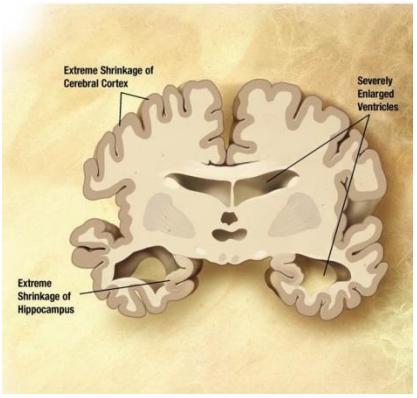
managing self-care and behavioural issues. Gradually, patient loses his/her bodily functions, which ultimately leads to death.

It is caused by plaque accumulation of abnormally folded **amyloid beta** protein and **tau protein** in the brain. Due to this accumulation, neuron network system starts to disintegrate which results in loss of memory.

There are no test sets or methods used to diagnose Alzheimer disease. Diagnosis of Alzheimer is a tedious process, doctors usually conduct multiple brain scans, blood tests, cognitive tests, research on previous medical history and/or genetic testing. The difference in normal and diseased brain is shown below:



Normal Brain



Diseased brain

Data and challenges:

We have two types of data available to us:

- Clinical data: In this we have fields like a person clinical sessions ID, age, sex, Subject ID and his health condition.

2	OAS30001_ClinicalData_d0000	OAS30001	65.149895	Cognitively norma
3	OAS30001_ClinicalData_d0339	OAS30001	65.149895	Cognitively norma
4	OAS30001_ClinicalData_d0722	OAS30001	65.149895	Cognitively norma
5	OAS30001_ClinicalData_d1106	OAS30001	65.149895	Cognitively norma
6	OAS30001_ClinicalData_d1456	OAS30001	65.149895	Cognitively norma
7	OAS30001_ClinicalData_d1894	OAS30001	65.149895	Cognitively norma
8	OAS30001_ClinicalData_d2181	OAS30001	65.149895	Cognitively norma
9	OAS30001_ClinicalData_d2699	OAS30001	65.149895	Cognitively norma
10	OAS30001_ClinicalData_d3025	OAS30001	65.149895	Cognitively norma
11	OAS30001_ClinicalData_d3332	OAS30001	65.149895	Cognitively norma
12	OAS30001_ClinicalData_d3675	OAS30001	65.149895	Cognitively norma
13	OAS30001_ClinicalData_d3977	OAS30001	65.149895	Cognitively norma
14	OAS30002_ClinicalData_d0000	OAS30002	67.206024	Cognitively norma
15	OAS30002_ClinicalData_d0751	OAS30002	67.206024	Cognitively norma
16	OAS30002_ClinicalData_d1169	OAS30002	67.206024	Cognitively norma
17	OAS30002_ClinicalData_d1508	OAS30002	67.206024	Cognitively norma
18	OAS30002_ClinicalData_d1850	OAS30002	67.206024	Cognitively norma
19	OAS30002_ClinicalData_d2263	OAS30002	67.206024	Cognitively norma
20	OAS30002_ClinicalData_d2585	OAS30002	67.206024	Cognitively norma
21	OAS30002_ClinicalData_d2961	OAS30002	67.206024	Cognitively norma
22	OAS30003_ClinicalData_d0000	OAS30003	58.77344	Cognitively norma

- MRI data: In this we have fields like a person MRI sessions ID (It is associated to his/her brain scan images), subject ID and age.

4	OAS30001	OAS30001_MR_d0757
5	OAS30001	OAS30001_MR_d2430
6	OAS30001	OAS30001_MR_d3132
7	OAS30002	OAS30002_MR_d0371
8	OAS30002	OAS30002_MR_d0653
9	OAS30002	OAS30002_MR_d2340
10	OAS30002	OAS30002_MR_d2345

We had found a common data field as **Subject ID**, so, we used this to sort the data sets subject wise. Now as we can identify the respective sessions of a specific person, we found that number of sessions were different in both the datasets. So, we used age as a next feature to identify the subject's condition.

Problems with data:

1. Connecting MRI and Clinical data.

We had MRI data relating to Clinical data by a common thread as **Subject ID** in both the datasets. Therefore, we used this to sort clinical data and MRIs for a particular person. We found that number of sessions conducted for both information were different in both the datasets. So, we used age (at which scans were done in MRI sessions) as secondary feature to identify the health status at some age of patient. We related health status corresponding to a particular MRI report on behalf of the clinical data present.

TYPE-1: Subject_1

MRI Data	Clinical Data
Image_1(Age: 66)	Clinical_11(Age:60, Healthy)
	Clinical_12(Age:64, Healthy)
	Clinical_13(Age:67, Healthy)
	Clinical_14(Age:70, Healthy)

TYPE-2: Subject_2

MRI Data	Clinical Data
Image_1(Age: 66)	Clinical_11(Age:60,Alzheimer)
	Clinical_12(Age:64,Alzheimer)
	Clinical_13(Age:67,Alzheimer)
	Clinical_14(Age:70,Alzheimer)

So, as shown for subject_1 we have MRI scans at age of 66 and the person's health status at 64 and 67 years of age is healthy so we estimated the scan to belong in normal section while training our model. Similarly, it was done for another one. As, it was given that the subject is having Alzheimer in all his clinical records, we took the scan in diseased section for our training dataset.

2. Converting images to .png format

Data downloaded was available in .nii zip files so we had to convert all the data to our required format but prior to that we had to figure out a method to read our data. So, upon searching a lot we found that we can convert the image to .png format using **X-medcon.** It converts 3-D MRI scans to 2-D slices along three different axes that are: coronal(X-Z plane), sagittal(Y-Z plane) and transaxial(X-Y plane). Out of these three, we choose coronal view for our model. In this view, we get a clear view of cerebral cortex, hippocampus region and area of atrophy. Therefore, we went for this view.

3. Picking data from Haphazard database

Data available on website that we downloaded was very diverse. For example: a person for whom Alzheimer was diagnosed initially found having Alzheimer. The same person was found healthy in his later sessions. This is only one of much such diversity in data set that presented problems to us in picking of meaningful and desired data for our model.

Modelling:

First we define our model using the **Sequential( )** function, which allowed us to build a linear stack of layers, so, we treated each layer as an object that feeds data to the next one.

After that we added our first layer of **CNN**. Our input is a 64x64x3 array of pixel values. Here 3 refer to the RGB values. Each of the number in this array is given a value from 0 to 255 which describe the pixel intensity. Our CNN describes the probability of it being a certain class. The convolutional layer acts as a filter. The filter is an array of numbers which represents the weights at a particular layer.

Our filter acts as a feature identifier. As our filter slides it is multiplying its values with the pixel values in the image. The multiplication from each region are then summed up, and after we have covered all parts of the image we are left with the feature map which will just give us a prediction.
So the first layer learns to detect a low level feature, like curves. So if we place this filter on a part of the image with the curve, the resulting value will be a big number but when we placed it on a part without curve it gives zero. This is how the filter detects features.

Next, we passed this feature map through an activation layer called **ReLu**, or rectified linear unit. It replaces all the negative pixel values in the feature map with zero. This layer increases the non-linear properties of our model, which means our neural network can learn more complex functions than just linear functions.

After that we initialized **Maxpooling** layer. Pooling layer reduces the dimensionality of each feature map but retains the most important information. This reduces the computational complexities of our network. There are different types but in our case we have used **Maxpooling2D( ).**

So, the first three **CNN** layers are made by simply repeating this process twice more.

The output feature map is fed into the next convolutional layer. And the filter will learn to detect more abstract features.

After, we got a feature vector, we passed this to our neural network. We created it by one fully connected layer using **Dense( )**.

Now, we minimized the loss function, which measures the difference between the target output and the expected output. To do this we have taken the derivative of the loss with respect to the weights in each layer starting from the last.

Then we updated our network. We propagated our loss backwards for each layer, and then we updated each filter values so that the change in the direction minimizes our loss.

Then we defined our loss as **binary crossentropy**, which is the preferred loss function for binary classification problems.

Then we used optimizer, **adam**, which will perform gradient descent, and a list of metrics which we have set to **accuracy**.

Result and Discussion:

We got an accuracy of 61% for our training dataset, and 59% for our testing dataset. One of the reasons for this low accuracy is the lack of usable data that can be fed to the model. Also, there are many subjects, whose data were present in very complex form and hard to classify in either of the datasets, i.e. it was hard to say whether the subject was suffering from Alzheimer, any other form of dementia or was healthy. Even the method which we use to classify the data was not accurate and was predicted on the basis of age of the person mentioned in both datasets.