ALZHEIMER'S DISEASE PREDICTION

A Project Report in partial fulfillment of the degree

Bachelor of Technology

in

Computer Science & Engineering / Electronics & Communication Engineering

By

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DEPARTMENT OF COMPUTER SCIENCE & ENGINEERING

CERTIFICATE

This is to certify that the Project Report entitled "ALZHEIMER'S DISEASE PREDICTION" is a record of bonafide work carried out by the student(s) Anjali, Sai srujan, Bhavith bearing Roll No(s) 19K41A0539, 19K41A0540, 19K41A0450 during the academic year 2020-21 in partial fulfillment of the award of the degree of **Bachelor of Technology** in **Computer Science & Engineering / Electronics & Communication Engineering** by the S.R. ENGINEERING COLLEGE, Ananthasagar, Warangal.

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ABSTRACT

Aging concerns are on the rise as people's life expectancies arise. Alzheimer's disease is a type of dementia. Alzheimer's disease is a neurological brain disease that causes loss of memory. Early detection of this disease helps to prevent brain cell damage. Because there is no treatment, early discovery can significantly decrease or stop the progression of this disease. Deep learning models performed admirably in disease detection. As a result, researchers are working more on constructing deep learning models with the highest accuracy for early detection. This study will use brain imaging to assess the stage of the disease. We have also suggested a deep learning model for Alzheimer's disease diagnosis with the help of MRI data. We have developed a custom CNN model by using a data set. The data set we obtained is from Kaggle. It was first prepared and pre-processed. The model was well-trained by the data set. Our algorithm, unlike previous approaches, can detect different phases of Alzheimer's disease. We found that the model produced an accuracy of 92.39%.

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1. INTRODUCTION

Alzheimer's disease is a neurological disease that develops gradually and gets worse. It is responsible for several dementia cases approximately over 70%. Alzheimer's disease is believed to develop when abnormal levels of amyloid beta accumulate in the brain, disrupting neuronal functioning and connectivity and leading to a progressive loss of brain function. This diminished protein clearance ability is related to age, is regulated by brain cholesterol, and has been connected to other neurodegenerative diseases. As advancements in brain imaging techniques emerge, researchers can now see spread of abnormal amyloid in brain.

Memory loss, behavioral abnormalities, and physiological functioning increasingly decrease as the disease progresses, eventually leading to death. Alzheimer's disease is currently being researched as to what causes it. There may not be a single cause but rather a series of events that affect each individual, with age being the most common risk factor for Alzheimer's. Alzheimer's disease affected approximately five crore people worldwide by 2020. It primarily affects people over the age of 65, while up to 10% of cases afflict people in their 30s to mid-60s. It affects roughly 6% of adults while women are affected more frequently than males. Because Alzheimer's disease begins two decades or more before symptoms occur, people only observe the effects after years of brain changes. More than five crore people worldwide suffer from dementia, according to Alzheimer's Disease International (ADI). By 2050, this figure is anticipated to climb to 15.2 crores, suggesting that one person develops dementia every three seconds. While the rate of progression varies, the average life expectancy after diagnosis is between 3 to 9 years.

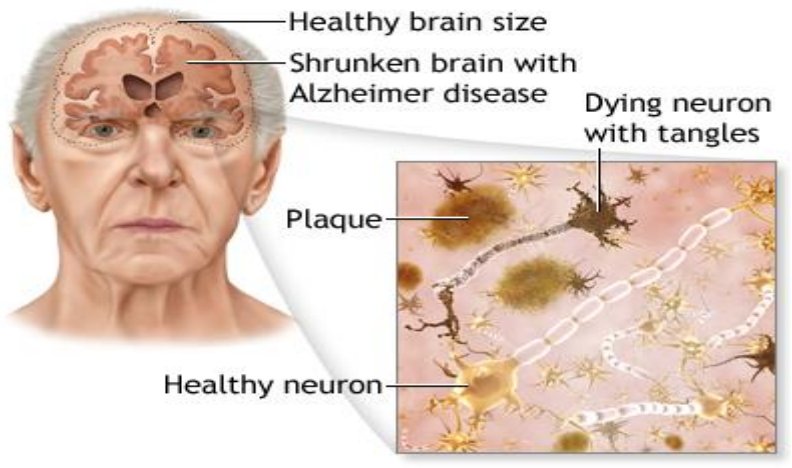

Figure 1: Neuron of an Alzheimer’s patient

Alzheimer's disease is classified into three stages extremely mild, mild, and moderate. Alzheimer's disease detection is still inaccurate until a patient reaches the intermediate stage. Physical and neurobiological exams, the Mini-Mental State Examination, and the patient's comprehensive history are all required for proper medical assessments. Physicians have just begun to use brain MRI to diagnose Alzheimer's disease.

Artificial intelligence has advanced significantly in recent years, and AI technology has grown in popularity. Traditional methods rely on manual feature extraction, which looks to be time-consuming and highly reliant on technical skills and recurrent tries. As a result, deep learning, particularly convolutional neural networks, is an effective technique. The purpose of this study is to develop a CNN model that can predict Alzheimer's disease early by using MRI data. It is frequently employed in the medical field. The data sets are created using MRI scans. Convolutional Neural Network (CNN) is a type of Feedforward Neural network with a deep structure and convolution processing. They are one of the typical deep learning algorithms that can learn representations by the concept of image processing, it can efficiently decrease the dimension of a huge quantity of data into a small amount of data while keeping picture characteristics. We developed a deep convolutional neural network model that learned features directly from the MRI images. Our suggested model is capable of classifying different phases of Alzheimer's disease.

2. LITERATURE REVIEW

Many researchers have conducted studies on Alzheimer’s disease prediction throughout the last few decades to develop advanced machine learning models for Alzheimer's Disease diagnosis using MRI data. Some most popular approaches include support vector machines, logistic regressors, random forest classifiers, and many more. Wang et al. [1] suggested a CNN framework based on a multi-modal MRI analytical approach using DTI or Functional Magnetic Resonance Imaging data. The framework classified patients as AD, NC, or amnestic mild cognitive impairment. Although it obtained good classification accuracy, using 3D convolution instead of 2D convolution is predicted to yield superior results. Wang et al. [2] studied an eight-layer CNN structure. Six convolutional layers and two fully linked layers were used in the feature extraction method. The results revealed that max-pooling and the LReLU performed well with utmost accuracy.

The authors Yildirim, Muhammed & Çinar, and Ahmet[3] used the Resnet50 model, one of the CNN-based architectures, which served as the foundation for the method enhancement. The

accuracy rate of 78 percent has grown to 90 percent with the Hybrid model they built from the Resnet50 architecture. Jyoti Islam et al. [4] proposed a convolutional neural network capable of detecting Alzheimer's disease and classifying the current stage of the disease. They demonstrated a network composed of three deep convolutional neural networks with some varied topologies. The authors examined their outcomes with different model training methods for the identification and classification of Alzheimer's disease. With a small dataset, this method achieves 93 percent accuracy. Atif Mehmood et al. [5] presented a new method to diagnose Alzheimer's disease in its early stages. The authors proposed using the network Googlenet to identify Alzheimer's disease. The latter was made of numerous layers. They are made of many convolution modules of size 1 X 1, 3 X 3, and 5 X 5, which are processed in parallel on the characteristics card generated by the previous layer.

The authors[6] introduce a unique methodology for Alzheimer's disease classification from MR images for medical support. Database containing over a thousand patients. This work addresses two problems: the first is the development of a classification system for classifying MR images as normal or with Alzheimer's disease, and the second is the identification and classification of normal subjects, MCI patients, and AD patients. It is worth noting that this final study could provide a tool to aid in the early detection of dementia. The methodology includes extraction of wavelet features from MRIs, dimensionality reduction, training-test subdivision, and classification using SVM. Korolev et al. [7] demonstrated that an equivalent performance was possible when the residual network and plain 3D CNN designs were applied to 3D structural MRI brain scans, the results revealed that the depth and complexity of the two networks were considerably different.

Martinez-Murcia et al. [8] explore AD data analysis using deep convolutional autoencoders. Extracted MRI features that describe an individual's cognitive symptoms as well as the underlying neurodegenerative process using data-driven deconstruction of MRI pictures. The distribution of the collected features is then examined using regression and classification analysis, and the influence of each coordinate of the autoencoder manifold on the brain is estimated. MMSE scores, together with imaging-derived markers, can predict AD diagnosis with greater than 80% accuracy.

3. DESIGN

3.1 REQUIREMENT SPECIFICATION(S/W & H/W)

Hardware Requirements

- ✓ **System** : Intel Core i3, i5, i7 and 2GHz Minimum
- ✓ **RAM** : 4GB or above
- ✓ **Hard Disk** : 10GB or above
- ✓ **Input** : Keyboard and Mouse
- ✓ **Output** : Monitor or PC

Software Requirements

- ✓ **OS** : Windows 8 or Higher Versions
- ✓ **Platform** : Jupyter Notebook, Google Colab
- ✓ **Program Language** : Python

3.2 FLOW CHART

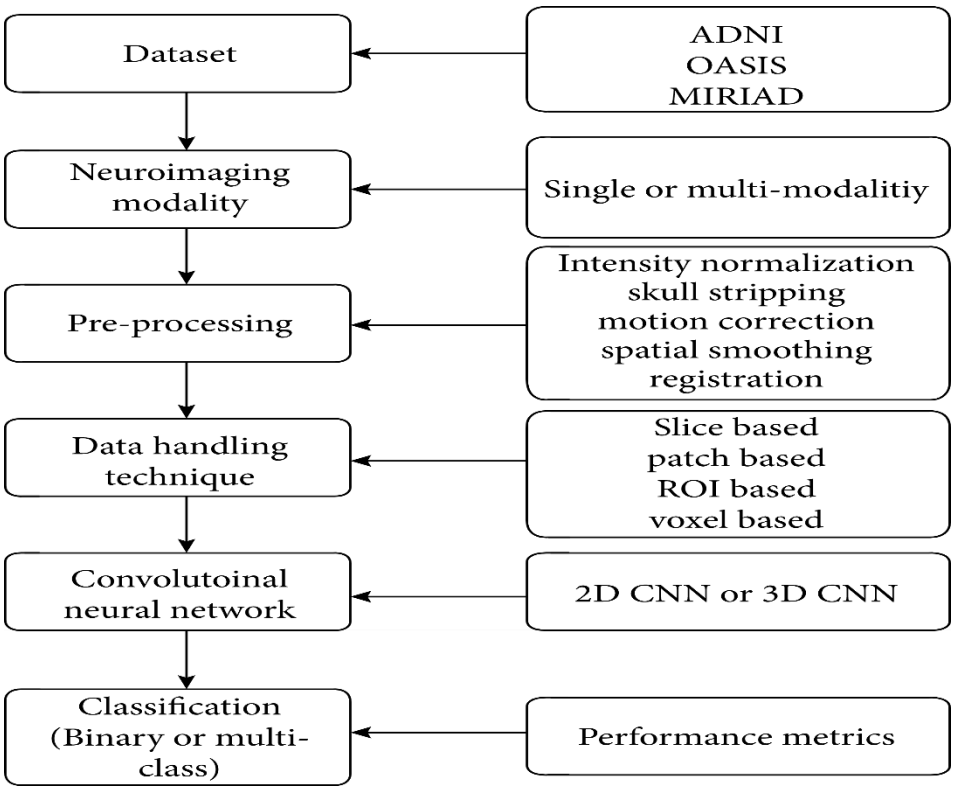

Figure 2: Flow chart

4. DATA SET

The team has found MRI related data that was generated by the Open Access Series of Imaging Studies (OASIS) project that is available both, on their website and on kaggle that can be utilized to train various neural network models to identify patients with very mild to moderate Alzheimer's.

The MRI data consists of 6410 images of brain with dimensions 176 X 208 that are classified into 4 types:

- Non Demented
- Very Mild Demented
- Mild Demented
- Moderate Demented

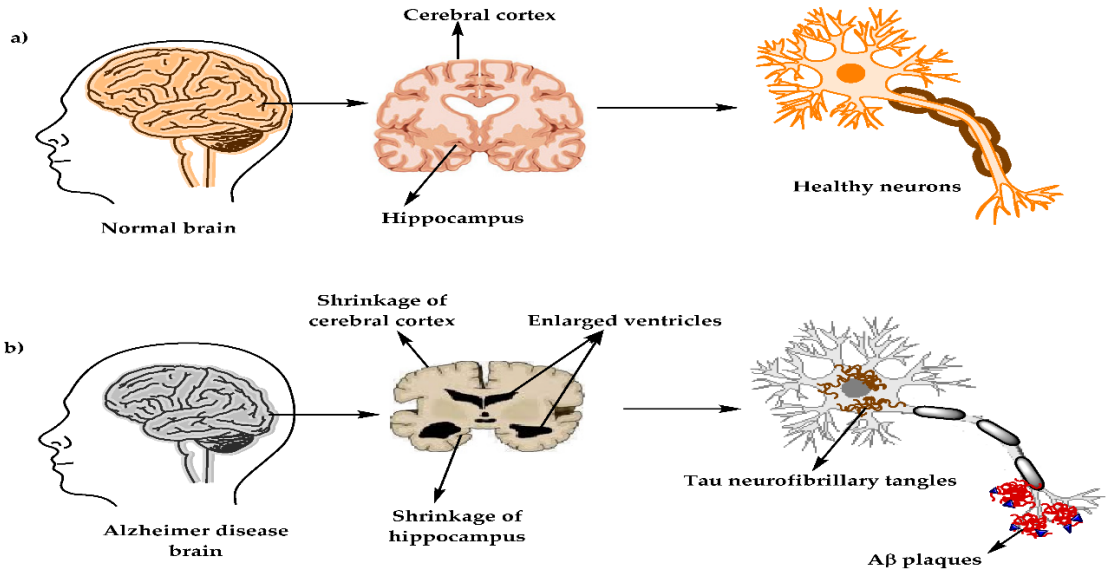

Figure 3: Normal brain vs Alzheimer disease brain

MRI Data Images

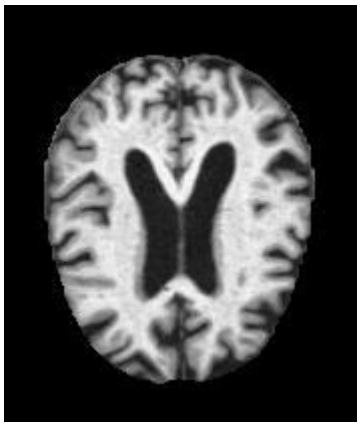

Figure 4: Mild Demented

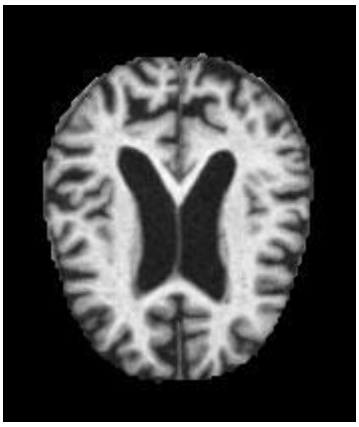

Figure 5: Moderate Demented

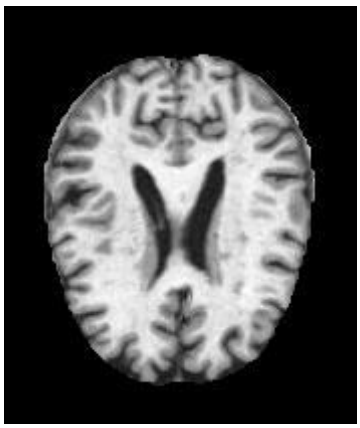

Figure 6: Non Demented

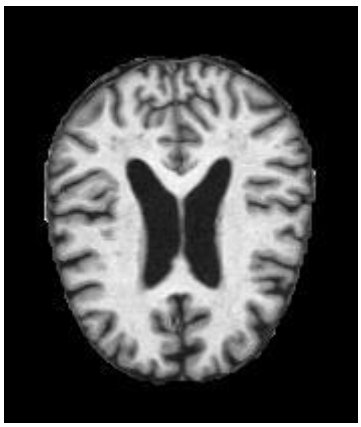

Figure 7: Very Mild Demented

5. DATA PRE-PROCESSING

ImageDataGenerator class allows us to randomly rotate images through any degree between 0 to 360º, it takes parameters like rescale, brightness_range, zoom_range, data_format, fill_mode and horizontal_flip.

- Rescale = 1./255 is to transform every pixel value from range [0,255] to [0,1], and the benefits are it treat all images in same manner, some images are high pixel range, some are low pixel range. The images are all sharing the same model, weights and learning rate.
- brightness_range = [0.8, 1.2]
- zoom_range = [0.99, 1.01]
- data_format = "channels_last"

- fill_mode = “constant”
- horizontal_flip = True

The flow_from_directory method is useful when the images are sorted and placed in there respective class/label folders. This method will identify classes automatically from the folder name, it takes parameters like directory, target_size, batch_size, shuffle.

- directory = path of the dataset located
- target_size = [176, 176]
- batch_size = 6410
- shuffle = False

```
IMG_SIZE = 176
IMAGE_SIZE = [176, 176]
DIM = (IMG_SIZE, IMG_SIZE)
ZOOM = [.99, 1.01]
BRIGHT_RANGE = [0.8, 1.2]
HORZ_FLIP = True
FILL_MODE = "constant"
DATA_FORMAT = "channels_last"
work_dr = IDG(rescale = 1./255, brightness_range=BRIGHT_RANGE,
zoom_range=ZOOM, data_format=DATA_FORMAT, fill_mode=FILL_MODE,
horizontal_flip=HORZ_FLIP)
train_data_gen = work_dr.flow_from_directory(directory=WORK_DIR,
target_size=DIM, batch_size=6410, shuffle=False)
```

Data is split into features and target variable.

```
train_data, train_labels = train_data_gen.next()
```

Getting to know dimensions of the dataset:

```
print(train_data.shape, train_labels.shape)
```

(6410, 176, 176, 3) (6410, 4)

Split dataset:

Firstly split the dataset into features and target variable, then by using the train_test_split method, split the data into a training set and test set.

The test_size = 0.25 that is 25% of data for testing and remaining 75% for training purpose.

6. METHODOLOGY

Convolutional layer: It is the main building block of a CNN. It contains a set of filters or kernels, parameters of which are to be learned throughout the training. The size of filter is usually smaller than the actual image. Each filter convolves with the image and creates an activation map.

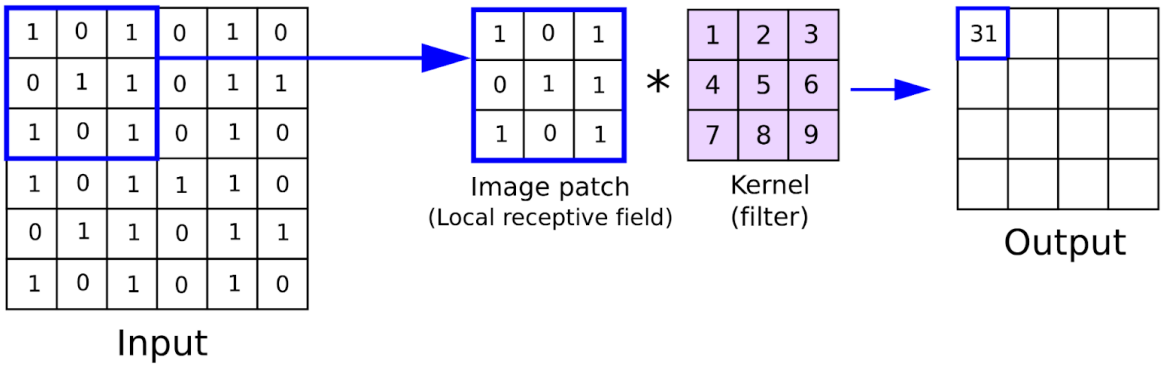

Figure 8: Convolutional layer

Pooling layer: Its function is to progressively reduce the spatial size of the representation to reduce the amount of parameters and computation in the network. Pooling layers operates on each feature map independently.

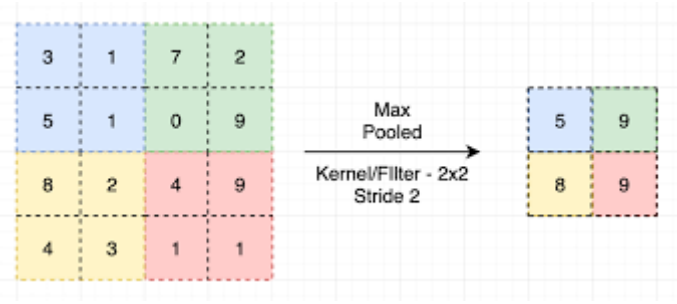

Figure 9: Pooling layer

Flattening layer: It is used to convert all the resultant 2-Dimensional arrays from pooled feature maps into a single long continuous linear vector. The flattened matrix is fed as input to the fully connected layer to classify the image.

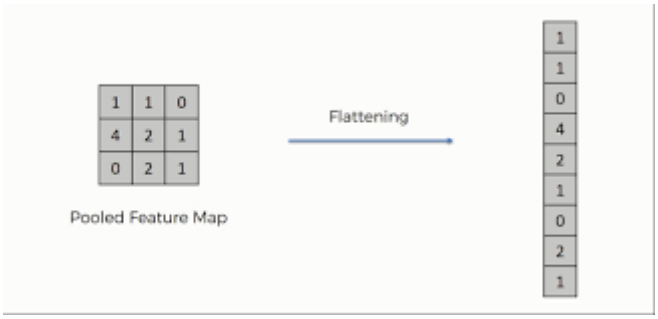

Figure 10: Flattening layer

Dense layer: It is simple layer of neurons in which each neuron receives input from all the neurons of previous layer, thus called as dense. Dense layer is used to classify image based on output from convolutional layers.

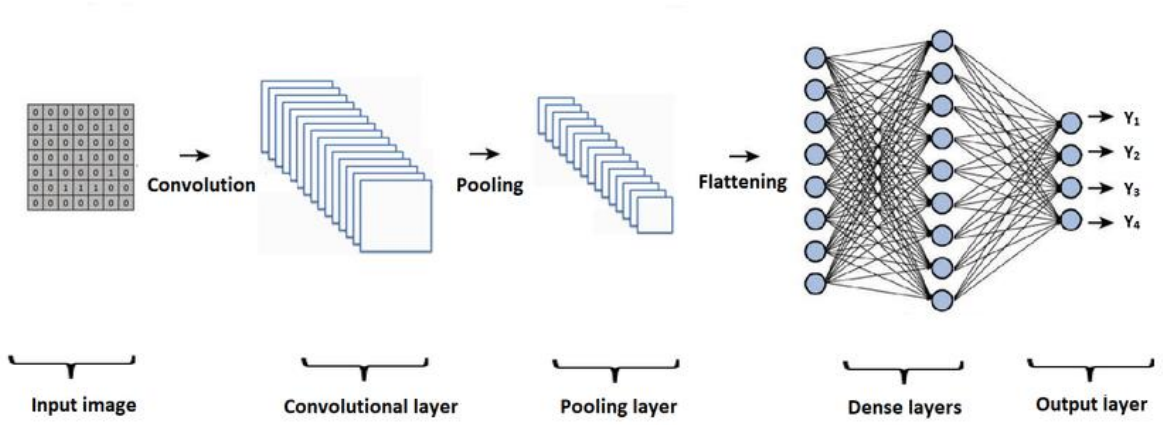

Figure 11: Architecture of CNN

We have made a custom CNN model with the following steps:

Step 1: Initializing CNN model to Sequential( ).

Step 2: Adding 1st Convolution layer with 32 filters with filter size of 3 X 3, input shape of 176 X 176, activation function 'relu' and pooling layer of pool_size 2 X 2.

Step 3: Adding 2nd convolution layer and pooling layer.

Step 4: Flattening the layers.

Step 5: Making full connection by using 4 dense layers.

- 1st Dense layer consists of 128 neurons with activation function relu.
- 2nd Dense layer consists of 256 neurons with activation function relu.
- 3rd Dense layer consists of 512 neurons with activation function relu.

- 4th Dense layer or Output layer consists of 4 neurons with activation function softmax.

Step 6: Compiling CNN model with optimizer = “adam”, loss = “categorical_crossentropy”, metrics = “accuracy”.

Step 7: Fitting CNN model to images by using training data, testing data and number of epochs as parameters.

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d (Conv2D)             (None, 174, 174, 32)      896

 max_pooling2d (MaxPooling2D  (None, 87, 87, 32)       0
 )

 conv2d_1 (Conv2D)           (None, 85, 85, 32)        9248

 max_pooling2d_1 (MaxPooling  (None, 42, 42, 32)       0
 2D)

 flatten (Flatten)           (None, 56448)             0

 dense (Dense)               (None, 128)               7225472

 dense_1 (Dense)             (None, 256)               33024

 dense_2 (Dense)             (None, 512)               131584

 dense_3 (Dense)             (None, 4)                 2052

=================================================================
Total params: 7,402,276
Trainable params: 7,402,276
Non-trainable params: 0
```

Figure 12: Model summary

7. RESULTS

By evaluating the model with validation data, we got validation accuracy of 92.39%

```
test_scores = model.evaluate(val_data, val_labels)

print("Test Accuracy: %.2f%%"%(test_scores[1] * 100))
```

```
51/51 [==============================] - 1s 14ms/step - loss: 0.8723 - accuracy: 0.9239
Test Accuracy: 92.39%
```

Figure 13: Validation accuracy

Comparative Results

For evaluating the performance of the proposed model training and testing accuracies are very useful. To get better accuracy the model needs to be trained using different epochs. We trained the data set using our custom CNN architecture. We used 100 epochs to train the data. We found the accuracy of our proposed model is 92.39%.

Epochs	Train accuracy	Validation accuracy
1	0.5084	0.5340
10	0.9965	0.8478
20	0.9992	0.9133
50	1.0000	0.9226
100	1.0000	0.9239

Table.1. Training and validation accuracies

Epochs	Train loss	Validation loss
1	1.0178	0.9607
10	0.0122	0.7645
20	0.0035	0.5490
50	1.2204e-06	0.6779
100	1.6541e-08	0.8723

Table.2. Training and validation loss

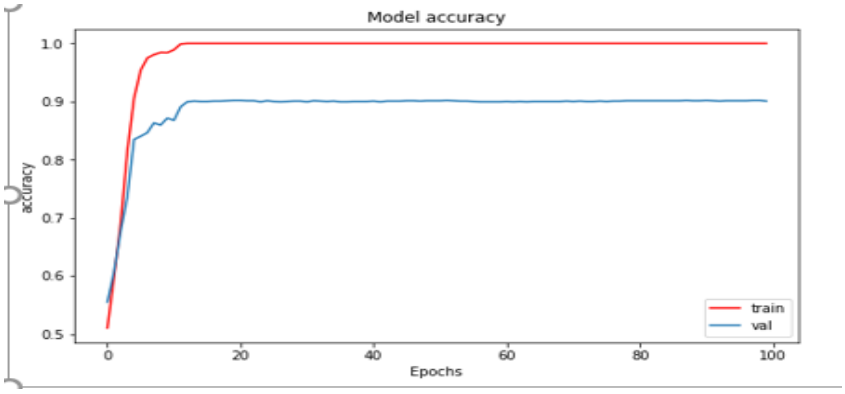

Figure 14: Model accuracy train and test vs Epochs

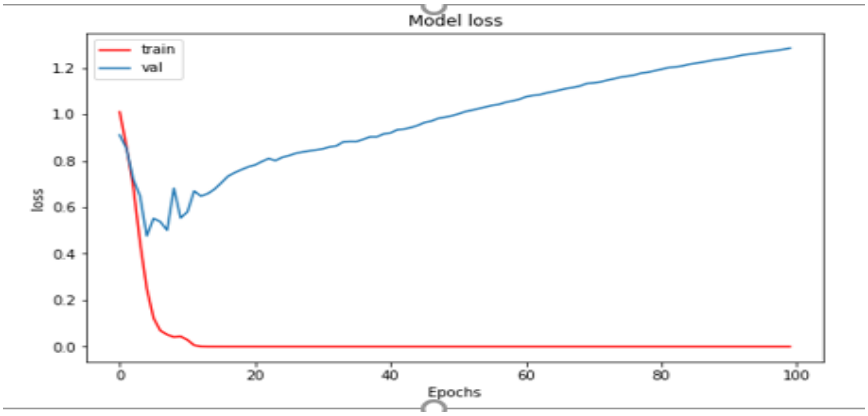

Figure 15: Model loss train and test vs Epochs

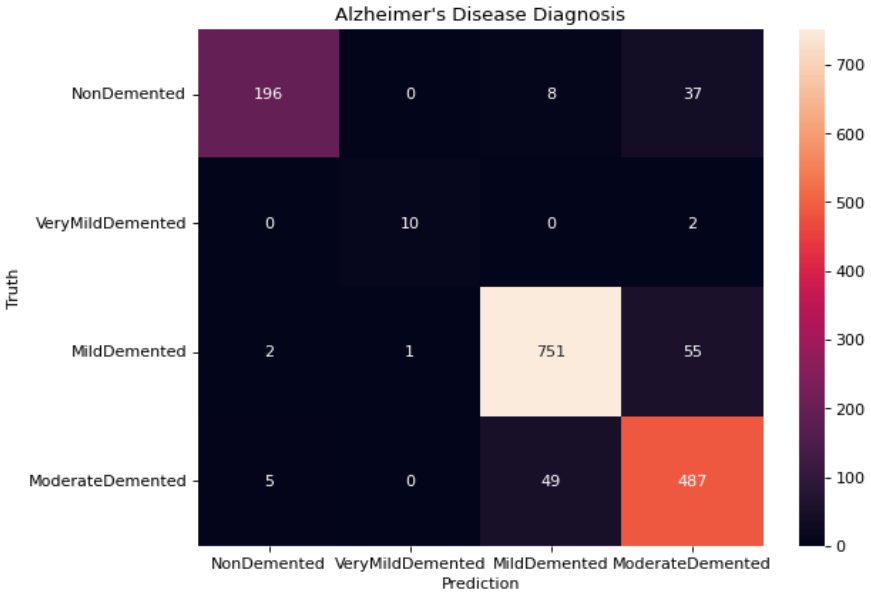

Figure 16: Confusion matrix

8. WEB APPLICATION

The model is saved in h5 format for the future use.

Web application is made using flask by dumping the saved h5 file to it.

Figure 17: Choosing file to predict disease

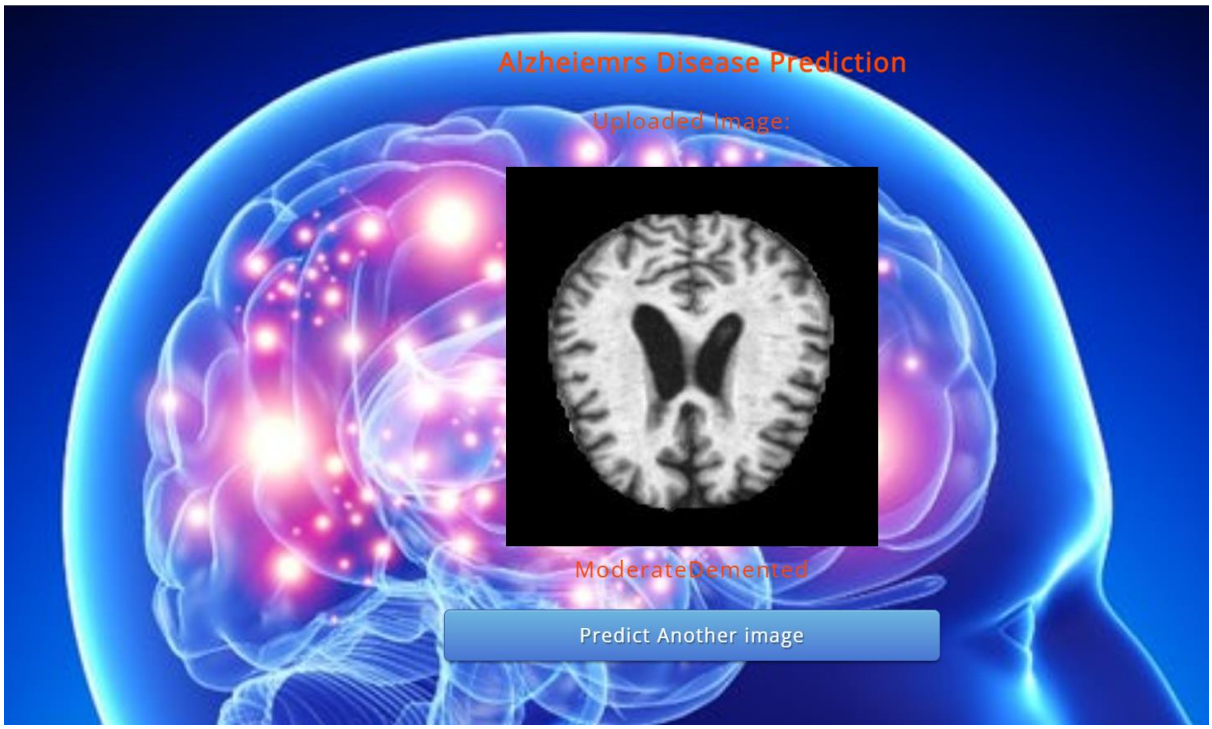

Figure 18: Predicted output of chosen file

9. CONCLUSION

This is a project for image classification of Alzheimer's disease detection into 4 types they are non demented, very mild demented, mild demented and moderate demented. The proposed framework is based on deep-learning CNN architectures which is a custom CNN model with an accuracy of 92.39% and we built a web application based on this model, it helps doctors and patients to check AD remotely, determines the Alzheimer's stage of the patient based on the AD spectrum, and advises the patient according to its AD stage.

10. REFERENCES

[1].Wang Y, et al. A novel multimodal MRI analysis for Alzheimer's disease based on convolutional neural network. 2018 40th Annu Int Conf IEEE Eng Med Biol Soc 2018; 754–757.

[2]. Wang SH, Phillips P, Sui Y, Liu B, Yang M, Cheng H. Classifcation of Alzheimer's disease based on an eight-Layer convolutional neural network with leaky rectifed linear unit and max pooling. J Med Syst. 2018; 42(5):85.

[3]. Yildirim, Muhammed & Çinar, Ahmet. (2020). Classification of Alzheimer's Disease MRI Images with CNN Based Hybrid Method. Ingénierie des systèmes d information. 25. 413-418. 10.18280/isi.250402.

[4]. Islam, J. & Zhang, Y. (2018), Brain MRI analysis for Alzheimer's disease diagnosis using an ensemble system of deep convolutional neural networks, Brain Informatics.

[5]. Atif Mehmood et al," A Deep Siamese Convolution Neural Network for Multi-Class Classification of Alzheimer Disease", brain sciences, 10, January 2020.

[6] Herrera, Luis & Rojas, Ignacio & Pomares, Hector & Guillén, Alberto & Valenzuela, Olga & Banos, Oresti. (2013). Classification of MRI Images for Alzheimer's Disease Detection. Proceedings - SocialCom/PASSAT/BigData/EconCom/BioMedCom 2013. 846-851. 10.1109/SocialCom.2013.127.

[7]. Korolev S, Safullin A, Belyaev M, Dodonova Y. Residual and plain convolutional neural networks for 3d brain MRI classifcation Sergey Korolev Amir Safullin Mikhail Belyaev Skolkovo Institute of Science and Technology Institute for Information Transmission Problems, 2017 IEEE 14th Int. Symp. Biomed. Imaging (ISBI 2017). 2017; 835–838.

[8]. Martinez-Murcia FJ, Ortiz A, Gorriz JM, Ramirez J, Castillo-Barnes D. Studying the manifold structure of Alzheimer's disease: a deep learning approach using convolutional autoencoders. IEEE J Biomed Health Inform. (2020) 24:17–26. doi: 10.1109/JBHI.2019.2914970.