DETECTION OF ALZHEIMER'S DISEASE USING DEEP LEARNING

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ABSTRACT

Alzheimer's Disease (AD) is a neurological disease and the most common cause of dementia in the age group 65 years and above. The accurate and timely diagnosis of the AD is crucial in order to prevent the progression of this irreversible disease. This paper concentrates on a method to detect Alzheimer's from MRI scans using machine learning approach. The proposed approach focuses on the hippocampal region of the brain. The texture features such as entropy, homogeneity, energy, contrast, correlation and variance are extracted from the hippocampus region using the Gray Level Co-Occurrence Matrix (GLCM). The area and shape feature are extracted using the Moment Invariants. CNN is used for image training and error-back propagation (EBP) in Artificial Neural Network (ANN) is used as the classifier for detection of various stages of AD. The proposed system gives an accuracy of 95% for CNN and 90% for ANN.

1. INTRODUCTION

Alzheimer's disease (AD) is a degenerative disorder of the brain that leads to memory loss. It is the most common form of dementia which is caused by the beta amyloid plaques in the brain. The plaques and tangles are some of the main features of the disease. As the number of Plaques and tangles increases, the healthy neurons begin to function less effectively and they gradually lose their ability to communicate and finally die which results in overall shrinkage of the brain tissues. The death of neurons particularly in the hippocampus restricts the ability to form new memories. The hippocampus is the first region in the brain which gets affected. It is the region in the brain that is responsible in forming memories and serves as a relay structure between the brain and the body. As Alzheimer's is a progressive and irreversible disease it progresses gradually following a distinct pattern of brain damage and can last for decades. The disease progresses slowly into three main stages namely mild, moderate and severe, where each stage has its own symptoms and challenges. The mild stage generally lasts for about an average of 2 to 4 years in which a person may function independently but may have memory lapses. In the moderate stage a person may require assistance in carrying out day to day activities and may experience increased difficulty with memory. This stage is probably the longest stage of the disease and may last for a duration of about 2 to 10 years. The final stage of the disease may last between a period of 1 to 3 years. In this stage, the memory and cognitive skills continue to worsen and the patient may require round the clock assistance as he/she loses the ability to respond to their environment. It is very important to diagnose the disease at an early stage before irreversible neural damage is done. The current non- automated methods such as Cognitive Impairment Testing, Mini-Mental State Examination (MMSE) and Clinical Dementia Rating (CDR) as well as Imaging techniques such as Magnetic Resonance Imaging (MRI), Positron Emission Tomography (PET) and Single-Photon Emission Computed Tomography (SPECT) are used to track abnormal changes in the brain and diagnose AD. In the proposed work, the detection of AD is done from MRI scans. The texture, area and shape features are extracted using Gray-Level Co-Occurrence Matrix

(GLCM) and Moment Invariants from the hippocampus which is selected as the Region of Interest (ROI). GLCM extracts the second order statistical texture features and Moment Invariants define the set of properties used for identification of shape. AD is then classified into various stages based on the features extracted from the ROI. using Artificial Neural Network (ANN) which trained using Error Back Propagation (EBP) Algorithm.

2. EXISTING METHODOLOGIES

Yanqing Zhang,et.al[1] proposed a method for Alzheimer's detection and classification where the input (T1-weighted MRI scans from OASIS dataset) is passed through a stem layer.This stem layer consists of several 3*3 convolutional layers,1*1 convolution layer and max pooling layer.Filter concatenation process is used where the input and output of all the above mentioned modules are passed through this.Based on the feature representation,the input MRI image is classified into four different output classes which are Non-demented,very mild,mild, and moderate AD.

David A. Wolk et. al [2] obtained the dataset from ADNI and AIBL cohorts,which consists of baseline MRI scans and Hippocampus extraction was done to this dataset.These hippocampal data were used to extract features to build the prognostic model.Informative feature extraction was done using deep learning model of convolutional neural networks.Prognostic model is a time-to-event model which estimates overall risk scores to progress to AD dementia for individuals.

Jun Chen et.al[3] proposed a method for Detection of Alzheimer's Disease using Narrative Speech.The first step consists of using 1585 input transcripts which are taken and Embedding layer will map each word from these into continuous vector.In the second step
GRU layer applies bidirectional GRU on top of word embedding layer for obtaining contextual word representations.In the third step CNN layer performs one dimensional convolution on embedded word sequence for extracting local n-gram patterns from transcript.In the fourth step Attention layer takes the input from the previous output layer and calculates the weight vector and computes the transcript level vector as a weighted sum of features.Finally the Output layer is the one that concatenates transcript-level vectors from CNN and GRU branches and the result is been feed to a fully-connected layer for softmax classification.

Kajal Kiran Gulhare,et.al[4] proposed a method for ALzheimer's Disease Detection by using DNN classification as a tool. The MRI data is obtained and stored in the database.Here softmax layer is used as an output layer which is superior to that obtained from SVM and back-propagation classifier and minimum error rate was obtained from three hidden layers of DNN.Data pre-processing technique is been used for removing irrelevant information and for better interpretation.Different features from the image data is been obtained from image segmentation.The attributes are extracted from the data and artificial neural network based classification method was applied on these extracted data.For segmentation process niblack-thresholding segmentation algorithm was used.

Kim-Han Thung,et.al[5] proposed a method for detection of AD and obtained the database from ADNI.They used multi-task deep learning of incomplete data where prediction tasks are done and associated with different modality combinations which are helpful for improving the performance of each task.Multi-Task Deep Learning (MTDL) framework is been used which contains two types of input one for each modality and three types of output one for each classification task.The architecture consists of basically three layers they are input layers,hidden layers and output layers.Multi-input and multi-output deep learning framework are been combined and trained a network by updating its weights based on the availability of modality data.

Nicola Amoroso,et.al [6] proposed a method in which they used Deep Neural Network and Random Forest feature selection for classification.Feature were selected from Hippocampal region and the selected features were used to train Deep Neural Network.Feedforward DNN was used which helped in feature representation of each patient in four aforementioned classes.The classification result obtained by DNN allowed the Bari Medical Physics Group(BMPG) to obtain most accurate prediction.

C.H.Suh, et.al [7] used deep learning based automatic brain segmentation and classification algorithm for accurate diagnosis of AD.The images used here are TI-weighted brain MRI images.The classification techniques used in this process are 5-fold cross-validation.A two-step DCNN is used here for performing brain parcellation along with three classifier techniques where XG-Boost method is used for disease prediction.This XG-Boost method was compared

with Support Vector Machine and logistic regression for calculating the areas under the curve for making the difference between AD from MCI and MCI from healthy brain.The author concludes that TI-weighted brain images are widely available and is best for prediction of Alzheimer's Disease.

Simeon Spasov et.al[8] proposed a method using Novel deep learning architecture and ad-hoc layer for 3D separable convolutions for identifying those people with MCI who have a high risk of developing Alzheimer disease. Alzheimer's Disease Neuroimaging Initiative (ADNI) database is used here and they have also combined Tensorflow and Keras for 3D implementation of 3D separable convolutions.Magnetic resonance imaging (MRI), neuropsychological,demographic and APOe4 genotyping data were combined as input measures where same network layers are used to extract representations from input biomarkers which are used for both MCI to AD conversion task and AD classification problem.

3. METHODOLOGY

MATLAB R2014a is used in the project execution. The OASIS dataset is used to perform experiments and training. From this downloaded dataset 235 scan images of MRI with various Alzheimer's disease phases were downloaded. The downloaded scans are used to train the network..There are two phases split in proposed approach is:

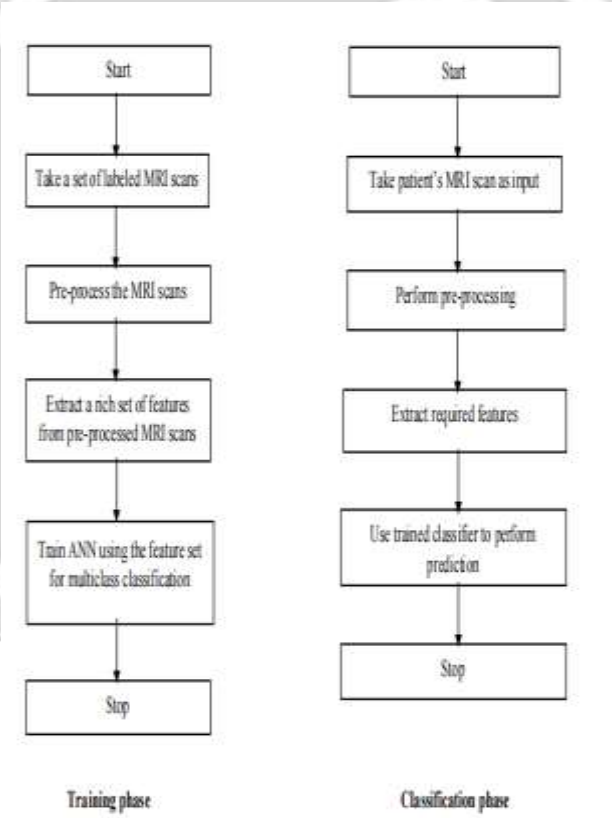

Fig-1: Flow chart of proposed method

A.Preprocessing

The pre-processing on the magnetic resonance imaging scans is completed using distinction(contrast) improvement.

B. ROI Extraction

The hippocampus is extracted because the region of interest because it is that the 1st region within the brain that gets affected in Alzheimer's illness.

C. Feature Extraction

The Texture, form, and space options are extracted from the Hippocampus region of the Brain for detection of AD. The Gray Level Co-occurrence Matrix is employed to extract the texture options and therefore the form, space options are extracted using seven-moment invariants. The options out there with the dataset like age, gender, education, socio-economic status, Mini-Mental Examination Score is extracted. These extracted are then accustomed to generate the feature vector.

1) Gray Level Co-occurrence Matrix (GLCM):

GLCM is a technique used for extracting the second-order statistical texture features. it's a matrix within which the number of rows and columns are up to the number of gray levels within the image. GLCM of a picture is computed employing a displacement vector d(δ, θ). Six vital texture options are extracted mistreatment GLCM:

I. Entropy: It measures the complexness within the image

$$\mathbf{Entropy} = \sum_{i=0}^{N_g-1}\sum_{j=0}^{N_g-1} -P_{ij} * \log P_{ij}$$

II. Energy: it's a measure of total uniformity within the image

$$\mathbf{Energy} = \sum_{i=0}^{N_g-1}\sum_{j=0}^{N_g-1} P_{ij}^2$$

III. local Homogeneity: It can be defined as a measure of local uniformity within the image.

$$\mathbf{Local\ Homogeneity} = \frac{\sum_{i=0}^{N_g-1}\sum_{j=0}^{N_g-1} P_{ij}}{1+(i-j)^2}$$

IV. Contrast: It measures the intensity variation between a pixel and its neighborhood.

$$\mathbf{Contrast} = \sum_{i,j=0}^{N_g-1} P_{ij}(i-j)^2$$

V. Correlation: It is said as a measure of linear dependency between gray levels.

$$\text{Correlation} = \sum_{i,j=0}^{N-1} P_{ij} \left[\frac{(i - \mu_i)(j - \mu_j)}{\sqrt{(\sigma_i^2)\,(\sigma_j^2)}} \right]$$

VI. Variance: it is a measure of heterogeneousness.

$$\sigma_i^2 = \sum_{i,j=0}^{N-1} (i - \mu_i)^2 P_{ij}$$

$$\sigma_i^2 = \sum_{i,j=0}^{N-1} (j - \mu_i)^2 P_{ij}$$

2) Moment Invariants:

The moment invariants were initially introduced by Hu in 1962. The six absolute orthogonal invariants and a skew orthogonal invariant supported algebraical invariants were derived. These derived invariants were freelance of position, size, orientation also as parallel projection. These invariants outline the calculated set of properties of the region which will be used for sophistication identification in addition to the identification of form. Central Moment's are given by:

$$\mu_{p,q} = \sum_{x,y} (x - x_c)^p \, (y - y_c)^q$$

Where, (x_c , y_c) is the center of the object.

Central moments are often standardized to create them scale-independent,

$$\eta_{p,q} = \frac{\mu_{p,q}}{\mu_{0,0}^{\gamma}}$$

Where,

$$\gamma = \frac{p + q + 2}{2}$$

Hu brought forward seven moments freelance of translation, rotation and scaling supported these moments

$$\phi_1 = \mu_{2,0} + \mu_{0,2}$$

$$\phi_2 = \left(\mu_{2,0} - \mu_{0,2}\right)^2 + 4\mu_{1,1}^1$$

$$\phi_3 = \left(\mu_{3,0} - 3\mu_{1,2}\right)^2 + \left(\mu_{3,0} - 3\mu_{2,1}\right)^2$$

$$\phi_4 = \left(\mu_{3,0} + \mu_{1,2}\right)^2 + \left(\mu_{0,3} + \mu_{2,1}\right)^2$$

$$\phi_5 = \left(\mu_{3,0} - \mu_{1,2}\right)\left(\mu_{3,0} + \mu_{1,2}\right)\left[\left(\mu_{3,0} + \mu_{1,2}\right)^2 - 3(\mu\_2{,}1 + \mu\_0{,}3)^2\right]$$
$$+ \left(3\mu_{2,1} - \mu_{0,3}\right)\left(\mu_{2,1} + \mu_{0,3}\right).\left[3\left(\mu_{3,0} + \mu_{1,2}\right)^2 - \left(\mu_{2,1} + \mu_{0,3}\right)^2\right]$$

$$\phi_6 = \left(\mu_{2,0} - \mu_{0,2}\right)\left[\left(\mu_{3,0} + \mu_{1,2}\right)^2 - \left(\mu_{2,1} + \mu_{0,3}\right)^2\right] + 4\mu_{1,1}(\mu)\left(\mu_{2,1} + \mu_{0,3}\right)$$

$$\phi_7 = \left(3\mu_{2,1} - \mu_{0,3}\right)\left(\mu_{3,0} + \mu_{1,2}\right)\left[\left(\mu_{3,0} + \mu_{1,2}\right)^2 - 3\left(\mu_{2,1} + \mu_{0,3}\right)^2\right]$$
$$- \left(\mu_{3,0} - \mu_{1,2}\right)\left(\mu_{2,1} + \mu_{0,3}\right)\left[3\left(\mu_{3,0} + \mu_{1,2}\right)^2 - \left(\mu_{2,1} + \mu_{0,3}\right)^2\right]$$

All the extracted options are integrated to make a feature vector. The training set has the feature vectors extracted from the magnetic resonance imaging scans. every feature vector has eighteen options.

D. Classification

Artificial neural network using error-back propagation is done for multi-class classification. The Scaled Conjugate Gradient (SCG) algorithmic rule is employed to train the network. The neural network is trained on 235 magnetic resonance imaging scans. Their square measure are CDR0 scans, 69 CDR0.5 scans, 29 CDR1 scans, and a couple of CDR2 scans.Once the network is trained it's prepared for classification of AD's stages. The input layer consists of twenty-one neurons because it is that the length of the feature vector. 4 hidden layers are thought-about and therefore the output layer consists of four neurons that are wont to classify the topics into normal, mild, moderate, and severe class.

4. RESULTS

The Neural Network training performance is measured using Sum Squared Error (sse)

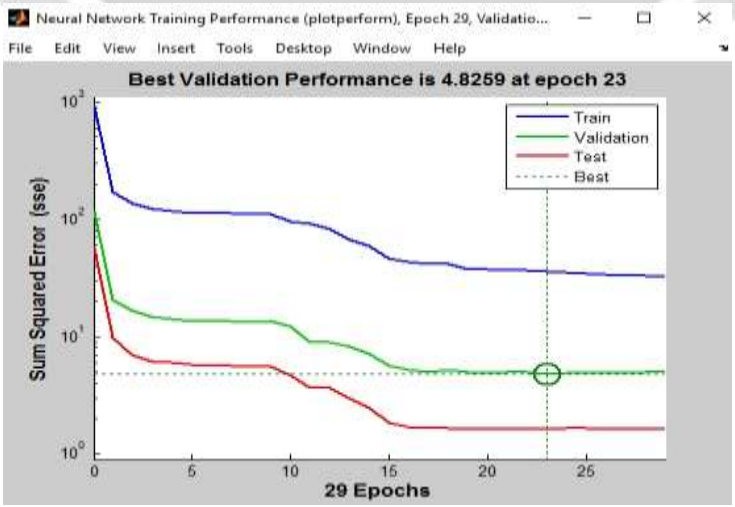

Fig-2: Neural Network Training Performance

The figure 2 illustrates the neural network training performance. The performance is shown for all of the training, validation, and x-axis sets. The coordinate axis shows the no. of epochs/iterations needed for training and therefore the y-axis shows the performance measured in terms of total sq. error (sse) that is shown in log scale. The ANN fits the most effective worth after fifteen epochs. sse of the ANN is diminished with the number of epochs. The ANN was well trained because it presents a very low sse at the last of the training section. The most effective validation performance found was 4.8259 at epoch twenty-three. The error bar chart was accustomed to get extra verification of network performance.

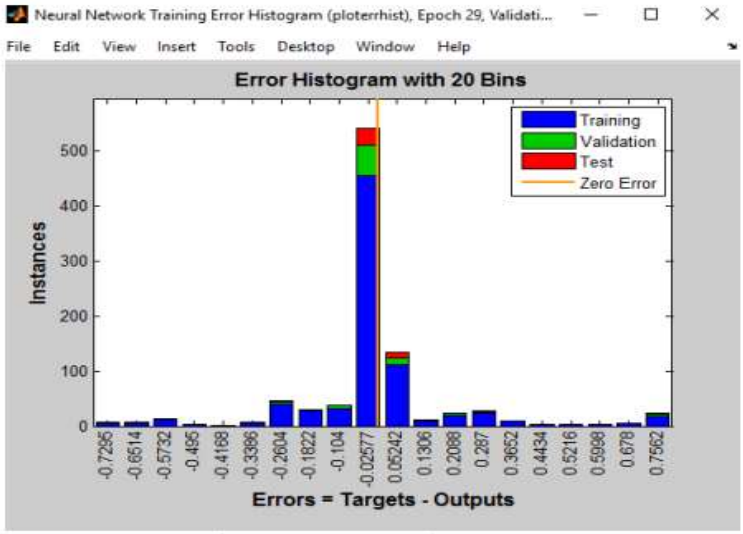

Fig-3:Error Histogram

The figure 3 depicts the error histogram. The x-axis represents various error values that occurred during the training, validation, and testing phases. The y-axis represents a number of times a particular error occurs. Most of the large amount of errors have occurred during the training phase.The overall accuracy of system found was 92% and the overall error rate was 8%.

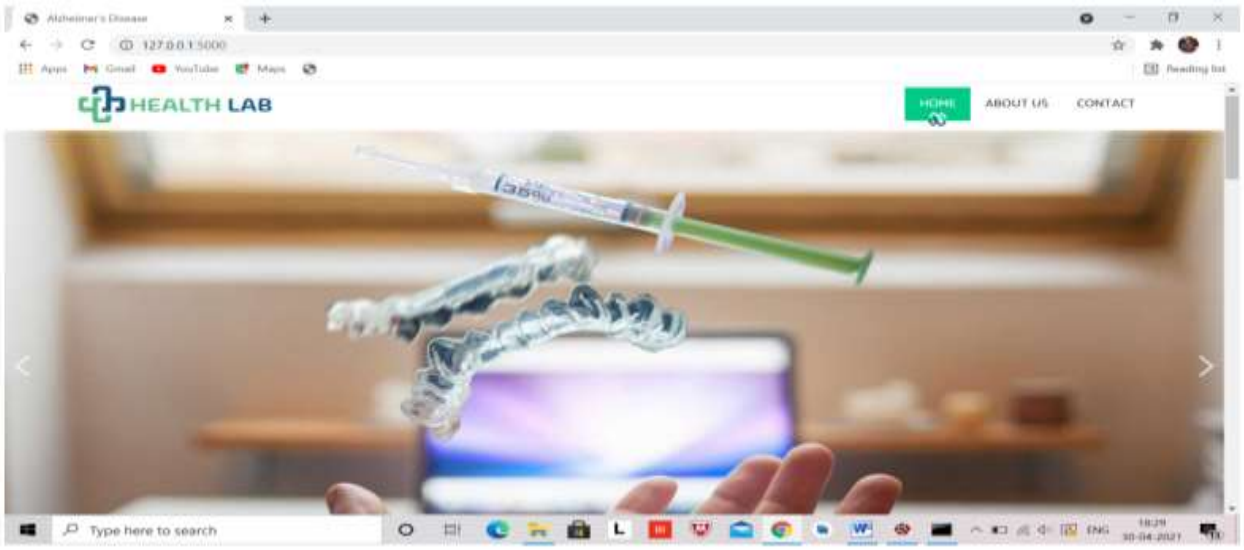

Fig-4: Home Page

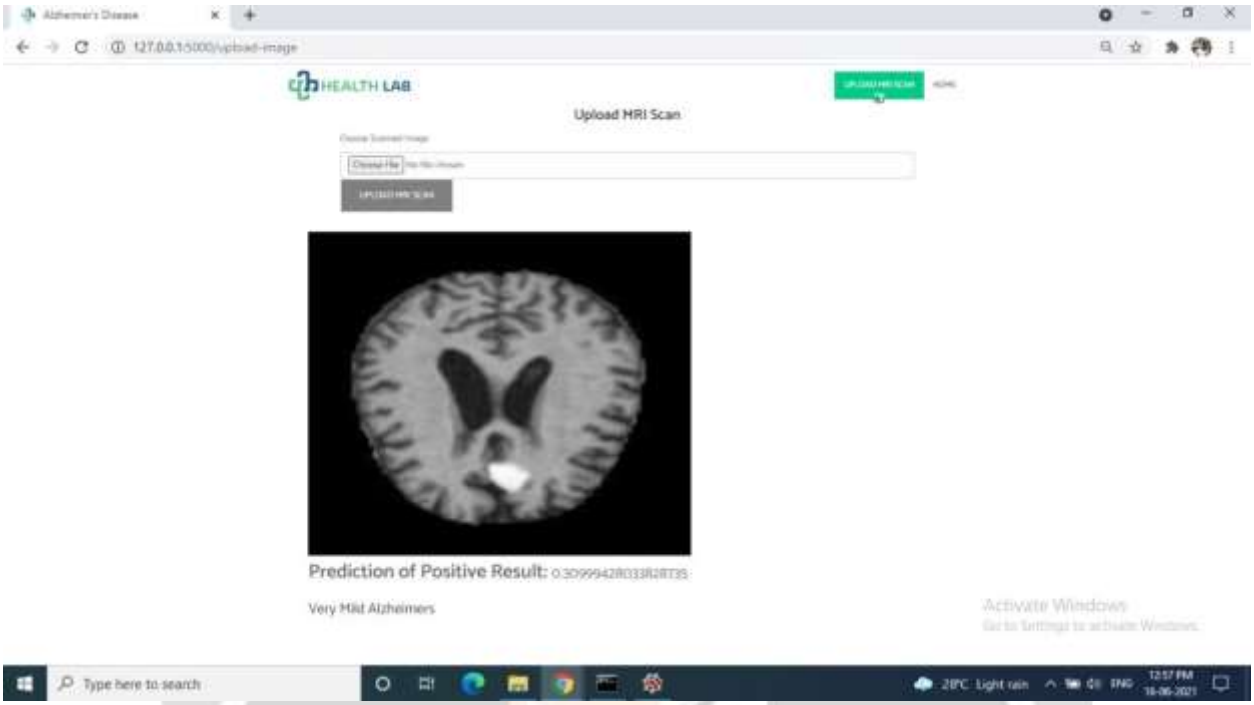

Fig-5: Very Mild Alzheimer's

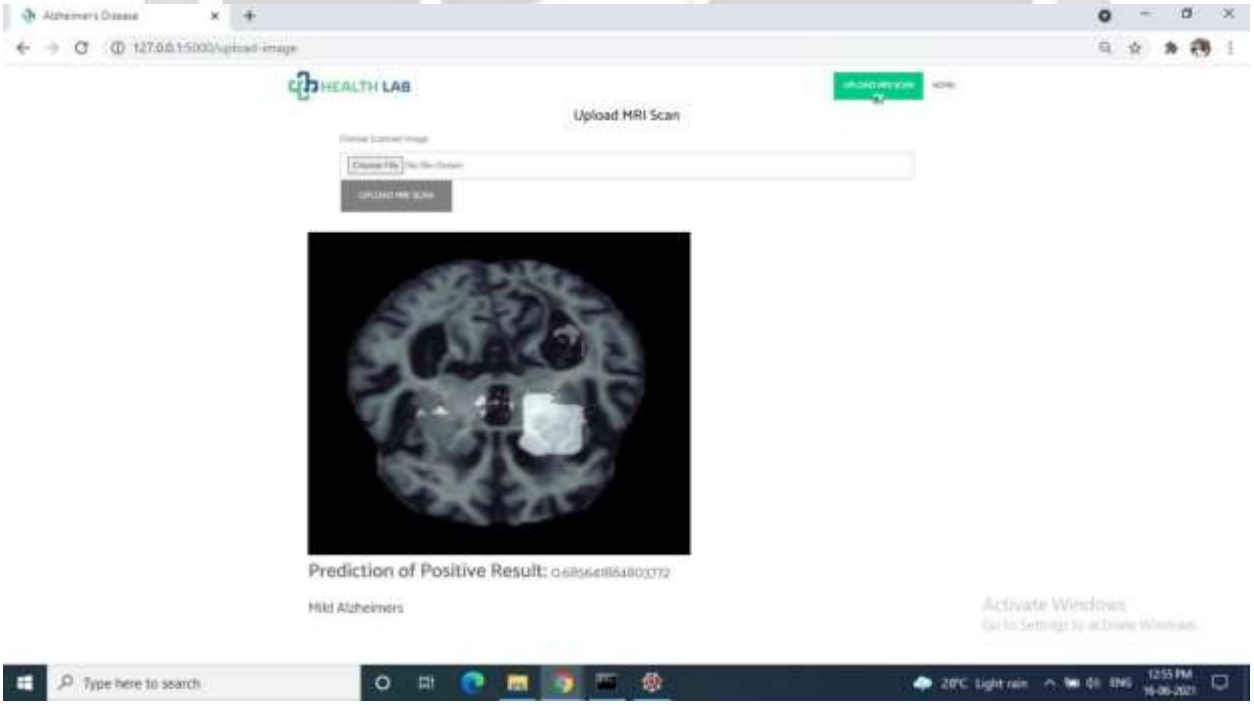

Fig-6: Mild Alzheimer's

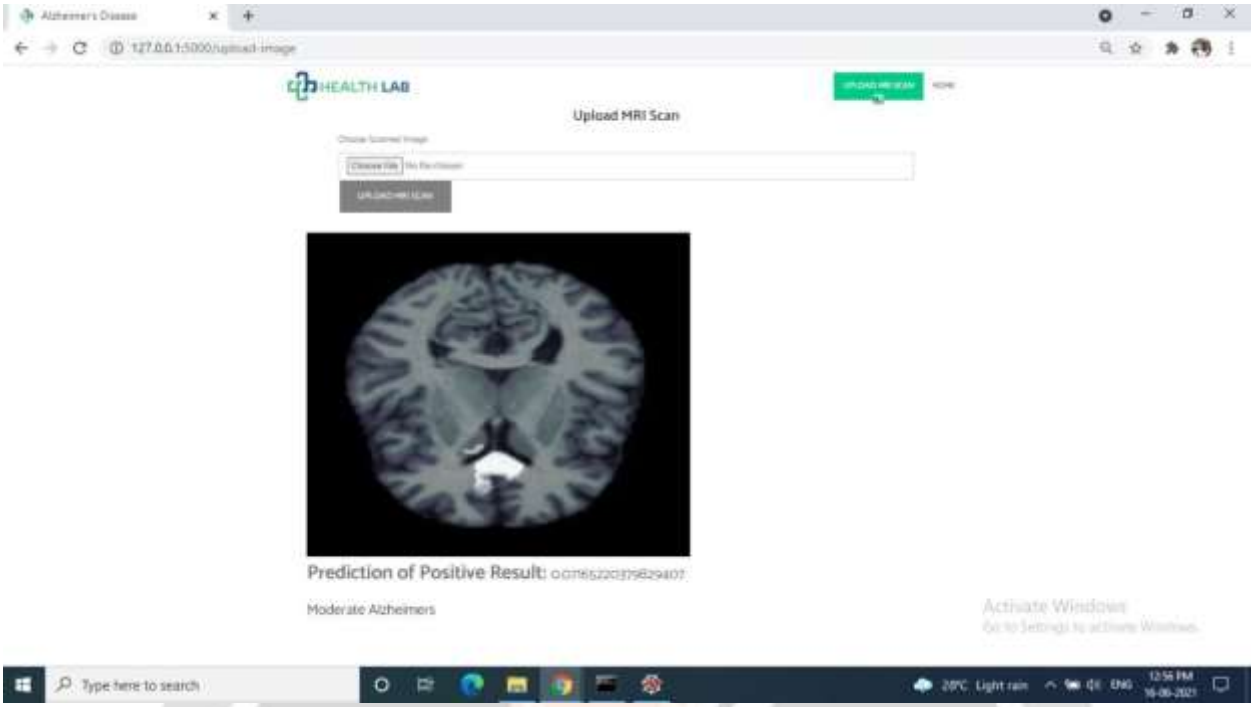

Fig-7: Moderate Alzheimer's

5. CONCLUSIONS

In this work, a machine learning primarily based approach for detection of Alzheimer's disease is projected. The OASIS dataset was used for experiments. the texture, area, and shape features from the hippocampus region of the magnetic resonance imaging scan are extracted. The matter features from OASIS were additionally extracted. These options were accustomed to training the neural network with error back propagation for classification. The proposed system has a mean accuracy of 92 %.

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