Alzheimer’s disease Detection: A deep Learning-based Approach

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Abstract - Mental health is an important part of a successful life for a person whether elderly, children, or young. Alzheimer’s is a fatal brain disease that severely damages the human brain, especially in the elderly. One way to prevent Alzheimer’s disease is by detecting it early. The proposed research employs a deep learning methodology using a 3D convolutional neural network (3D CNN) that has been proposed to detect Alzheimer’s disease at an early stage. The proposed model is primarily evaluated using three-dimensional brain images. A series of preprocessing have been applied that is an advanced normalization tool (ANT). The underlying pattern has a size of 128×128×64 and is passed to 17 layers of neural network that is 3D-CNN. Another contribution of this study is the conversion of a 3D Alzheimer’s image into a 2D image. A 2D convolutional neural network such that ResNET50 and VGG16 are proposed to be used for Alzheimer’s detection. The proposed model has attained the highest of 78.07% accuracy using 3D CNN.

Index Terms- ADNI dataset, Alzheimer’s disease, Brain MRIs, 3D-CNN, Classifier, Identification

1. INTRODUCTION

Alzheimer’s disease (AD), typically is a growing dynamic brain clutter, consequently, dementia is the disease’s most common occurrence in old age after 60. However, for people with gene mutations, Certain types of AD may manifest as early as between 35 and 55 years of age[1]. AD is such severe that it steadily tears down thinking ability and memory loss. As the condition progresses, it deteriorates gradually, causing conduct issues and a lack of self-care, eventually hindering the ability to carry out daily tasks [2] [3]. Essentially, Alzheimer’s disease results in the death of individual nerve cells and their interconnections in critical areas of the brain that play a crucial role in memory, like the entorhinal cortex and the hippocampal region [4]. The maturity of Alzheimer’s disease in AD patients from a healthy state takes several years [5]. The symptoms of mild cognitive impairment (MCI) initially grow, which convert into Alzheimer’s disease over the year [6]. Recent research has primarily concentrated on detecting Alzheimer’s disease at an early stage. Neurocognitive tests, brain imaging, and blood plasma spectroscopy are the current diagnostic techniques utilized for detecting AD [7][8]. However, these methods are expensive and are the time taken [9]. The expense of caring the AD patients is rising drastically, and there is a dire need of getting an automatic computerized system for prior and precise AD diagnosis. Pathophysologic agree that magnetic resonance imaging (MRI) demonstrates the utmost authentic and benchmark neuro-imaging [3]. As the brain consists of delicate soft and complex tissues, and its unconventional features, the MRI process is being used for scanning the brain’s internal structure for determining AD. Deep and machine learning algorithms are becoming more and more prevalent in all facets of life. In recent past years, many different machines and methods for deep learning have been put forth to use multi-view MRI images for Alzheimer’s disease [10] [11]. Deep learning has been demonstrated to perform better than traditional machine learning techniques in detecting intricate patterns within data that have many dimensions, particularly in the domain of computer vision. [12]. Due to the rapid advancement of neuroimaging techniques and the resulting large-scale multimodal neuroimaging data. A significant surge of fascination in applying deep-learning for AD diagnosis and classification by automated means at its early stages. According to reports, deep learning approaches are more efficient than traditional machine learning models for diagnosing AD. In this study [3], reviews the state-of-the-art for applying deep learning to diagnose AD. The investigation also examines different biomarkers and datasets that can be utilized of identifying or determining
the presence of Alzheimer's disease in an individual. The integration of AI in medical research has increased the precision and accuracy of predicting and detecting brain diseases. In [10], current machine & deep learning methods have extensively examined the detection of four brain disorders: Parkinson's disease, epilepsy, brain tumors, and Alzheimer's disease. With the popularity of ensemble methods, it is commonly used in the domain of computer vision and pattern classification. In [13] the author employed a local patch-based subspace ensemble technique. The author created a number of different classifiers each using a subset of local patches, followed by combing their results in a subsequent step.

In the proposed research, we suggest the utilization of deep learning algorithms for the initial stage detection of Alzheimer's disease. A detailed flow in visual representation or illustration of the proposed model is presented in Figure 1. We propose to use the Convolutional neural network (CNN) for handling the 2D and 3D MRI brain images. In this research, we have performed four experiments for early AD diagnosis using 3D-CNN on 3D-MRI brain images. The following is a summary of this paper’s significant contributions: (i) it is proposed to use the 3D-CNN17–Layers with an image size of 128 × 128 × 64 shown in Figure 2 (ii) The layers and size of images have also been observed using 3D-CNN14–Layers with the image size 64×64×32. (iii) A technique, conversion by an average of a 3D image into 2D is also proposed for the VGG16 neural network, and (iv) A latest CNN technique viz Resnet 50 is proposed to use for 3D converted the image into 2D.

The comparison result has been discussed in section V. Rest of the paper is distributed as: the state-of-the-art previous research has been discussed in section II, In section III brief explanation of tools and techniques that have been used in this research, the proposed methodology has been discussed in IV, and finally result and discussion section in V.

II. RELATED WORK

In today's environment, Alzheimer's disease (AD) is a prevalent cause of dementia. According to the report [14], a lot of people have Alzheimer's disease, and the prevalence of the condition is increasing daily. The cost of treating Alzheimer's disease has consequently skyrocketed. In order to effectively treat Alzheimer's disease, it is crucial to detect it early. Besides the clinical method, machine and deep learning methods are playing a vital role in the early detection of AD [15] [11]. Researchers frequently carry out AD identification utilizing favored methods include deep learning, ANNs, and support vector machines (SVM). For the identification of AD, a classification model based on an Enhanced Deep Recurrent Neural Network (EDRNN) with a built-in feature selection method was proposed in reference. [16]. An approach to deep learning that involves two sequential phases or stages. for AD early diagnosis is proposed in [17]. It incorporates data from multiple longitudinal multivariate modalities, comprising demographic information, cerebrospinal fluid biomarkers, cognitive scores, and neuroimaging data, as well as markers from the neuropsychological battery. In reference [18], a variant of the convolutional neural network approach called residual network 18 layers (ResNet-18) was employed. Essentially, the property of transfer learning of ImageNet was used to get around the requirement for a big, balanced dataset and equal weight was assigned to each class using weighting the loss function. Reference [19] presented a multi-task learning method for AD detection, which involved the use of EEC spectral images and a discriminative hybrid feature maps with high-order Boltzmann machine. In [11] author writes a review of some key works on AD disease early detection based on deep learning methods. He concluded that researchers mainly focus on two

![Fig. 1 Flow Diagram of the proposed model (a) 3D-CNN (b) converted 3D-image into 2D-image](image)
regions viz neuroimaging and biomarkers. In reference [20], The advantages of FSBi-LSTM, or fully stacked bidirectional long short-term memory, and 3D-CNN are used on the ADNI dataset in a framework based on deep learning.

Reference [21] The construction of Models for disease classification that are binary and ternary involved the integration of Magnetic Resonance Imaging (MRI) data with three-dimensional convolutional neural networks (3D-CNNs). A brief detail of Alzheimer’s disease is discussed in [22]. In [23], on the basis of combining the hippocampus ROI, Diffusion tensor imaging (DTI), and structural magnetic resonance imaging (sMRI) are geographical regions of the feature. The author described a technique for diagnosing Alzheimer’s disease. Information from the Neuroimaging Initiative for Alzheimer’s Disease (ADNI) database was used to compile this article. In [24] the author investigated the use of a convolutional neural network (CNN) for combining multi-modality data Images of the hippocampal region captured using T1 magnetic resonance imaging (MRI) and fluorodeoxyglucose-positron emission tomography (FDG-PET), to aid in the diagnosis of Alzheimer’s disease. The author suggested combining fMRI and deep learning, applying a quick yet precise method to resting-state fMRI data for feature extraction and Alzheimer’s disease classification using modified 3D convolutional neural networks (CNN) (AD) in [25]. The hippocampus area was automatically segmented from the patient’s brain MR images by comparing them to the author’s suggestion in [26].

III. MATERIALS AND TOOLS

The major problem facing the experts in the field is that no effective treatments are available for Alzheimer’s disease so far. Notwithstanding, the treatments currently available for AD are capable of mitigating symptoms or halting their advancement. As a result, detecting AD at an early stage, particularly during its prodromal phase, is of paramount importance. In this research, a deep learning-based algorithm has been proposed to use for in the early diagnosis of Alzheimer’s disease. A complete flow diagram of the proposed model is shown in Figure 1. We propose to use the Convolutional neural network (CNN) for handling the 2D and 3D MRI brain images. In this research, we have performed four experiments for early AD diagnosis using 3D-CNN on 3D-MRI brain images.

A. Three Dimensional Convolutional Neural Networks

Comparable to customary significant learning structures, CNN models are dynamic models where a number of convolutional layers pile up on best of each other. Conventional CNNs are composed of two-dimensional convolutional components for two-dimensional image application. Due to the fact that 2D-convolutions CNNs can only record spatial information in two dimensions, and disregard the third-dimensional
information, it becomes extremely arduous to apply 2D-CNN to three-dimensional data. This research proposes the conversion of 3D images into 2D, followed by sending them to 2D CNN. Two fundamental properties of convolutional layers have partial connectedness and weight sharing [27]. Because it was connected to a nearby district of the input feature maps, an individual neuron within the convolutional layer is associated. This minimizes the number of variables, which makes building the CNN slightly more susceptible to being too snug (overfitting). Another important feature of this method is that the convolutional layer can store spatial plans with nearby neighbors that may be appropriate for tasks connected to images. The weights sharing attribute implies that weights in convolutional portions are shared over the entire spatial area covered by the feature maps, hence reducing the number of parameters and enhancing the organization’s generalization capability. In a CNN, a pooling layer will occasionally be inserted between active convolutional layers. The feature maps’ spatial evaluation and the number of parameters are reduced by the pooling operation. 2D-CNN is associated with two-dimensional attributes that project to extract spatial highlights, whereas in this case, three-dimensional kernels are included, adding three-dimensional feature shapes to identify three-dimensional spatial patterns as appeared in Figure 5. Specifically, in 3D-CNN, the points (x, y, z) are scattered on the jth in the outline of the ith layer in respect of the position as taken later. 2D and 3D convolutions are represented in equations 2 and 3 respectively.

\[
y_{x,y,z}^{i,j} = h\left((W_{e_{i,j}} * V_{e}^{(i-1)})_{x,y,z} + b_{i,j}\right) \quad (1)
\]

In this equation \(W_{e_{i,j}}\) is the weight of the neural network layer and the tendency for each jth highlight outline by \(b_{i,j}\), \(V_{e}^{(i-1)}\) signifies input feature map sets from the layer \((i - 1)\)th connected to the current layer. The star (‘∗’) represents a convolution operation and \(h\) is supposed to be a non-linear function. Inside the preparing procedure, the total weights of convolutional parts inside the \(W, CNN\) nearby the slant \(b\) is improved with respect to a provided loss function. 2D convolution:

\[
h_{1,1} = \sum_{x=1}^{3} \sum_{y=1}^{3} W_{x,y} V_{x,y} + b \quad (2)
\]

3D convolution:

\[
h_{1,1,1} = \sum_{x=1}^{3} \sum_{y=1}^{3} \sum_{z=1}^{3} W_{x,y,z} V_{x,y,z} + b \quad (3)
\]

where \(W_{x,y,z}\) is a kernel weight and \(b\) is a bias term. In the last layer, the feature map is represented by \(V\). A three-dimensional convolutional layer is particularly effective at evaluating spatial information over 3D input images and learning nearby designs [28]. The kernels counts of 3D convolutional inside the network is comparable to the complexity of trained adjacent patterns. As increasing the kernels, the network learns more noteworthy, successful, and useful highlights and features, but it will also be more vulnerable to overfitting. As a general rule, a network must have more convolutional layers to memorize more important characteristics and little to no feature maps in each layer to comply with its extremely high complexity [29].

B. Advanced normalizations tools ecosystem (ANTsx)

The Advanced normalizations tools ecosystem (ANTsx) is a collection of strong open-source computer program libraries used by scientists and researchers to prepare, and analyze data from natural biological and medical imaging sources all around the world [30]. The popular libraries Advanced normalizations tools ecosystem for language R and Python that use to create the models and their weight for applications like brain extraction, which are then released to the public. We have used one of the ANTsxPyNet’s utilities named Deep Atropos [30]. The utility Deep Atropos contains several functions of image preprocessing.

C. Dataset

All dataset images included in this research were gathered from the Alzheimer’s disease neuroimaging initiative (ADNI) database with their tested outcomes and imaging results including patient details like age, sex, and visit covering at slightest three to four years of monitoring. ADNI database has different types of a group like ADNI1, ADNI2 or ADNI Go. For this study, we considered the dataset ADNI1 which originally included three different groups: normal control (CN), mild cognitive impairment (MCI), and Alzheimer’s disease (AD). Also, in the ADNI1 dataset, there is a penalty of groups like ADNI1 annual 2 years 3T, ADNI1 Baseline 3T, or ADNI1 Standardized 1.5T. All groups have a different number of MRI images. We used ADNI1 Standardized 1.5T weighted dataset which has 1075 MRI samples. According to ADNI procurement protocol, the examination and diagnosis of every MRI sample were taken from a knowledgeable radiologist. We haphazardly doled out the samples agreeing to the extent of 80% within the group of training and 20% within the approved bunch of patients and guaranteed that the extent of patients within the two bunches is comparative. Our focus is on precisely AD and NC
slices, we sorted out only AD and NC samples from the whole dataset consisting of 1075 MRI samples so the total number of sample MRIs we are using is 555 where 248 samples for AD and 357 samples for NC as shown in Table I. Remaining 520 MRI samples which belong to MCI were cut out from this study. So, out of the total number of MRI samples, 441 (AD = 196 and CN = 245) MRI samples were used for the training group while 114 (AD = 52 and CN = 62) MRI samples were designated as the validation testing group.

### IV. PROPOSED METHODOLOGY

In this study, we have proposed to use a powerful deep learning-based 3D-CNN for AD early detection using a full range of ANDI 3D brain images shown in Figure 3. The flow diagram of the proposed model is shown in figure 1(a & b). Essentially, a variety of image sizes and layers of the neural net have been used and proposed. It has also been proposed that to convert the 3D images into 2D before applying the deep learning model. The underlying 2D image structure is sent to CNN technique such that RESNET 50.

<table>
<thead>
<tr>
<th>Table I AD AND NC COUNTS</th>
<th>ADNI I 1.5T Group</th>
<th>MRI Samples</th>
</tr>
</thead>
<tbody>
<tr>
<td>AD</td>
<td>248</td>
<td></td>
</tr>
<tr>
<td>NC</td>
<td>357</td>
<td></td>
</tr>
</tbody>
</table>

### A. Normalization and Brain Extraction

Essentially, the structural magnetic resonance imaging (sMRI) is used in a deep learning model that learns the discriminative patterns that are invariant to various types of transformation. Advanced normalization tools (ANTs) [32] have been proposed to use for the normalization and extraction the brain images. The following footsteps are involved for normalization and extraction: Preprocessing, brain segmentation with spatial tissue priors comprising the cerebrospinal fluid (CSF), brain extraction, denoising, and bias correction, white matter (WM), gray matter (GM), deep gray matter, brain stem, and cerebellum. After the process of brain extraction and normalization as shown in Figure 4, the dimensions of the extracted image will be the same (i.e., 256 × 256 × 161). Basically, our focus is only the brain so skull things are not necessary for our research so this step allows us to focus on the area of interest.

### B. Re-size Images and Normalization

We have re-sized the images as our proposed 3D-CNN model takes the 3d image which has the dimension of 128 × 128 × 64. After resizing the image, the image has been normalized to get better results and clean noise from the image. After getting all images data, we separate it into training and testing data by 80:20 ratio. 80% of AD and NC images are used for training the model while the rest 20% of AD and NC images are used to testing the model.

### C. 3D-Convolutional Neural Network

Most CNN structures include convolutional layers, pooling layers, fully connected layers, and classifiers. The layer of convolution was utilized to extricate image features that may produce a feature map. The layer of pooling was utilized to diminish most of the features from the convolution layer. We reduced the feature maps and replaced them with columnar feature maps after minimizing feature maps in pooling layer. This streamlines the parameters to the ideal number. At this point, the classifier was ultimately used for ad recognition. This section describes the adopted CNN architectures and the changes made to each. Originally developed for 2D color images, these networks deal with 3D grayscale MRI. Hence, the foremost normal adjustment was to change over all 2D operations like pooling and convolution to 3D. In 2D CNN, the full set of MRI expectations is initially obtained one by one, but the convolutional kernel performs important slice measurements of size and width to allow classification. Overall, 2D CNN can use a single slice as input, so to speak. It is not possible to provide settings from related slices. From this, we can conclude that predictions for MRI scans can be achieved through voxel data using relevant slices. 3D CNN with 17 layers solves this problem by classifying volume patches from scans using a 3D convolutional kernel. Leveraging inter-slice data speeds up execution, but these CNNs use plenty of parameters, which increases the amount of computation. For our experiment, processed MRI imaging is placed on the initial layer as an input layer, as shown in Figure 2. Afterward we extracted features from MRI images by using a large 3x3x3 convolution kernel. Then we used a large 2x2x2 maximum pooling to reduce the parameters of the feature map. Batch normalization (BN) is placed and the maximum pooling layer made sure a simplified computational process and the most effective steepest descent method after the layer of convolution. Repeated these steps four times to get an optimized feature map. To diminish the feature maps output dimensionality, we then used the global average pooling layer. Lastly, feature maps are compatible with layers that are fully connected by the rectified linear unit (ReLU) and dropout features and finally, we used the sigmoid classification as we have binary classification problem. Sigmoid function has a feature of mapping any input information to an output which extends from 0 to 1. For
any values which is less than and equals to 5, sigmoid returns a zero closest value, and for the values which is greater than 5, the result of the function gets near to 1. Sigmoid is comparable to a two element of SoftMax, where the second component is accepted to be zero. Subsequently, sigmoid is generally utilized for binary classification.

Fig. 4. Image Preprocessing - Brain extraction and Normalization [31]

Fig. 5. Typical images of 2D and 3D convolution process
V. RESULTS AND DISCUSSION

In this study, we have applied multiple experimental steps to test and betterment for the results to be improved. For this purpose, our research methodology has verified which is primarily based on the comparisons: NC vs AD. Total 555 number of images are being used for all experiments in which 307 number of images were related to NC and 248 images were refers to AD. All experiments include 3D-CNN 17 Layers, 3D-CNN 14 Layers, ResNet50 and VGG16 were executed by utilizing Python 3 technology along with the Keras. The machine we used has a single google computer engine backend (GPU) using google colab which allows to use 12 GB of GPU. Amid the preprocessing, ADNI dataset images have been downloaded manually. For image preprocessing which includes brain extraction and normalization, ANTs pipeline has been used as we discussed earlier on paper. At long last, we compared our research findings along with the predominant results while classifying AD. Our strategy was primarily approved for early conclusion of AD (i.e., NC vs. AD). The following measures has been utilized for the evaluation of classification of the proposed methodology: accuracy, recall, specificity, the area under the curve (AUC), F1 score and precision. These measures are reviewed as takes after:

\[
\text{Accuracy} = \frac{TP + TN}{TP + TN + FN + FP}
\]

\[
\text{Sensitivity} = \frac{TP}{TP + FN}
\]

\[
\text{Specificity} = \frac{TN}{TN + FP}
\]

\[
\text{Precision} = \frac{TP}{TP + FP}
\]

where FP, TN, TP, and FN are false positive, true negative, true positive, and false negative respectively. The AUC calculation relies on all sensible sets of sensitivity and specificity by altering the rating score limits provided using the systems developed.

A. Experiment-1

In this experiment, our proposed model 3D-CNN with 17 layers has been used primarily. Images has been resized to 128 × 128 × 64 for the training and testing purpose. For training purpose, 80% data is used and remaining 20% is used for testing.

In the proposed model experiment, first 13 layers are used as convolutional and pooling layers and remaining layers are used as fully connected layers. Our experiment utilized the Adam optimizer [33] to train the model; we set the learning rate of 0.0001 at the starting as mention in most of the studies. The loss function we used is binary cross entropy and the estimate of minibatch was initialized as 2. By using our proposed 3D-CNN 17 layers model, we got 78.07% accuracy, 74.55% recall, 81.35% specificity, 78.84% precision, 78.13% AUC and 76.63% F1 score as mention in Table II.

Then we resize the images to 64×64×32 and used 3D-CNN but this time we minimize the number of layers from 17 to 14. We remove top 3 convolutional and pooling layers due to small size of images. Same number of divisions has been used for training and testing as we used in the last experiment. The optimizer, learning rate, loss function and the estimate of minibatch are also similar to our proposed model. By using this 3D-CNN 14 layers model, we got 57.01% accuracy, 51.64% recall, 78.26% specificity, 90.38% precision, 59.70% AUC and 65.73% F1 score as mention in Table II. As compare to previous results, this model performs not very good in the same scenarios. Our proposed 3D-CNN model with 17 layers performed better in all aspect whether its accuracy or F1 score despite that we have resources and GPU limitations. A good preprocessing method may improve the overall results.

### TABLE II
A DETAILED RESULTS OF 3D-CNN

<table>
<thead>
<tr>
<th>Model</th>
<th>Image Size</th>
<th>Train Test Ratio</th>
<th>Accuracy</th>
<th>Recall</th>
<th>Specificity</th>
<th>AUC</th>
<th>Precision</th>
<th>F1 Score</th>
</tr>
</thead>
<tbody>
<tr>
<td>3D-CNN 17 Layers</td>
<td>128x128x64</td>
<td>80/20</td>
<td>78.07%</td>
<td>74.55%</td>
<td>81.35%</td>
<td>78.13%</td>
<td>78.84%</td>
<td>76.63%</td>
</tr>
<tr>
<td>3D-CNN 14 Layers</td>
<td>64x64x32</td>
<td>80/20</td>
<td>57.01%</td>
<td>51.64%</td>
<td>78.26%</td>
<td>59.70%</td>
<td>90.38%</td>
<td>65.73%</td>
</tr>
</tbody>
</table>

### TABLE III
A DETAILED RESULT OF 2D CNN

<table>
<thead>
<tr>
<th>Model</th>
<th>Image Size</th>
<th>Train Test Ratio</th>
<th>Accuracy</th>
<th>Recall</th>
<th>Specificity</th>
<th>AUC</th>
<th>Precision</th>
<th>F1 Score</th>
</tr>
</thead>
<tbody>
<tr>
<td>ResNet50</td>
<td>224x224x3</td>
<td>80-20</td>
<td>46.84%</td>
<td>55.25%</td>
<td>63.42%</td>
<td>50%</td>
<td>56.84%</td>
<td>56.03%</td>
</tr>
<tr>
<td>VGG16</td>
<td>224x224x3</td>
<td>80-20</td>
<td>53.15%</td>
<td>54.25%</td>
<td>53.15%</td>
<td>50%</td>
<td>55.42%</td>
<td>54.82%</td>
</tr>
</tbody>
</table>
B. Experiment-2

In this experiment, ResNet50 [34] has been used primarily. For this experiment, images have been converted from 3D to 2D by using mean function. Images have been resized to 224×224 and add one more dimension for RGB channel by repeating the dimension 3 times because ResNet50 supports 224 × 224 × 3 input size images so images were converted into 224×224×3. For training purpose, 80% data is used and remaining 20% is used for testing. This experiment utilized the Adam optimizer to train the model; we set the learning rate of 0.01 at the starting as mention in most of the studies. We used the loss function of binary cross entropy and the estimate of minibatch was initialized as 32. By using ResNet50, we got 46.84% accuracy, 55.25% recall, 63.42% specificity, 56.84% precision, 50% AUC and 56.03% F1 score as mention in Table III. This result seems to be non-acceptable results due to less number of data that is 555 images only used and for betterment of result if we are using ResNet50, we had to have large amount of data images. During the conversion 3D to 2D, the major information was lost.

After using ResNet50 and getting poor results, one more experiment has been performed with VGG16 [35]. Same configuration has been used of training and testing data. The size of images, optimizer, learning and loss function were also some as we are used in ResNet50. By using VGG16, we got 53.15% accuracy, 54.25% recall, 53.12% specificity, 55.42% precision, 50% AUC and 54.82% F1 score as mention in Table III. Only we got the better accuracy as compare to ResNet50 but overall the performance results are not good.

VI. CONCLUSION

We redone the 3D-CNN utilizing complete image of brain and finished the great accuracy and F1 score with an orchestrate network design utilizing ADNI MRI dataset. Our strategy is completely mechanized (i.e., no assist data input or administrator interaction is required) and has better speed despite that the limited resources and GPU. Importantly, our strategy did not utilize any domain-specific information from Ad, though all other entries included earlier illness data (e.g., statistic data or hippocampus volume). As an outcome, we are convinced that it may be utilized to treat other diseases that can be benefitable by using MRI data as input. We trust that our methodology can be used to distinguish critical patterns, affirm prior expert results, help in diagnosing scenarios, and ultimately help to recognize the patterns for diseases other than Alzheimer’s. In the future, it may be possible to apply the Artificial Intelligence (XAI) approach to better understanding the internal parts of the brain that are involved in decision making. In addition, it helps to understand cross-matching highlighted locales with expert information to see how each can help improve the procedure. At last, utilizing history information of patient to enhance the data contained in MRIs, drive the choice handle, and tie it to foundations of patient would be charming.

REFERENCES


