Alzheimer's Disease Detection from MRI Dataset using Deep Learning

Ahmed Rafi Hasan 011191131, Ahmed Shabab Noor 011193024,
Raj Shekhar Karmaker 011193149, Md. Araphat Rahman Pial 011163089

***Abstract*—Many recent studies have applied Deep Learning (DL) algorithms to healthcare data. Convolutional neural networks (CNN) have success in categorizing image data. The deep neural network has been used in neuroimaging datasets, and the neuroscience community is interested in solving their domain problem. In this project, we solved Alzheimer's disease (AD) detection from magnetic resonance imaging (MRI) by using the 3D Convolutional Neural Network (3D CNN). In the elderly population, AD is the most common cause of dementia. There are four different significant stages of dementia. Our proposed method solved the binary classification where the classes are Alzheimer's Disease (AD) and Cognitive Normal (CN). The 3D deep convolutional neural network was used after the preprocessing pipeline. We used 3D ResNet-18 and ResNet-50 by transfer learning. Classification results evaluated by cross-validation prove that it can successfully detect AD and CN with reasonable accuracy.**

***Index Terms*—Alzheimer's disease, Magnetic Resonance Imaging, Deep Convolutional Neural Networks, Classification Analysis**

I. Introduction

Alzheimer's disease (AD) is the most frequent cause of dementia in older people and not only among older people, but it is also a reason for dementia cases among young people. Due to the increasing complexity and stress in life, AD is a common disease worldwide. The older population in developed nations suffers from AD, which may rise drastically in the next 50 years. It occurs as a result of an abnormal protein build-up in and around brain cells. It is a gradual neuro-degenerative disease associated with the synthesis and extracellular deposition of Beta-amyloid peptide, as well as the flame-shaped neurofibrillary tangles of the microtubule-binding protein named tau. This results in the loss of nerve cells, which shows as minor memory issues that progress to severe brain impairment over the duration. Unfortunately, there is no cure for Alzheimer's disease, and currently available medications can only assist in slowing the illness's progress temporarily. As a result, early detection is the best method to ensure effective therapy.

Researchers conducted several studies to detect different stages of AD using Deep Neural Network techniques. Christian et al. [1] prposed single-subject classification model after the feature extraction and selection techniques. An automated feature extraction approach was applied by them to MRI images in order to determine the most discriminative characteristics among groups of brain. Janani et al. [2] proposed Deep learning techniques to perform multimodel data fusion. They used stacked denoising auto-encoders and 3D convolutional neural networks (CNNs) for MRI images. Jyoti and Yanqing [3] proposed another method having faster framework for AD detection inspired by Inception-V4 network. They showed how hyper-parameters from a deep image classifier (CNNs) might improve feature learning from a small medical picture dataset.

Analyzing the studies, we found that the 3D Convolutional Neural network (CNNS) technique is recognized with several successes in recent years for brain MRI. We used 3D ConvNet and Fully Connected (FC) layers and 3D pretrained model called ResNet. We used different variations of ResNet. The spatial information was stored as we used 3D CNNs.

II. Methods

A. Pre-processing

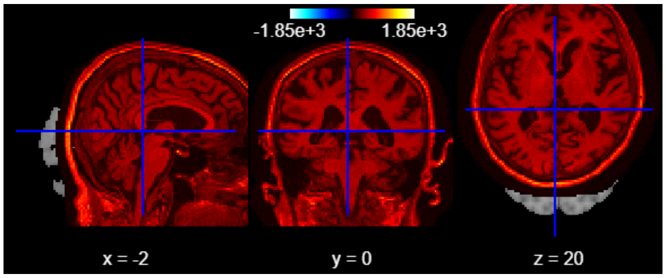
On the acquired images, as discussed in section III-A, we applied pre-processing techniques. First we took the raw data and co-registered them to a standard template for spatial normalization. The standard template we used was the MNI152 T1 1mm brain template. After normalization to the MNI space, we stripped the skull from the images. Preprocessing was done with the help of the FSL (FMRIB Software Library) [1] software. Figure 1 shows the original and pre-processing outcomes on the MRI scans.

B. Architecture

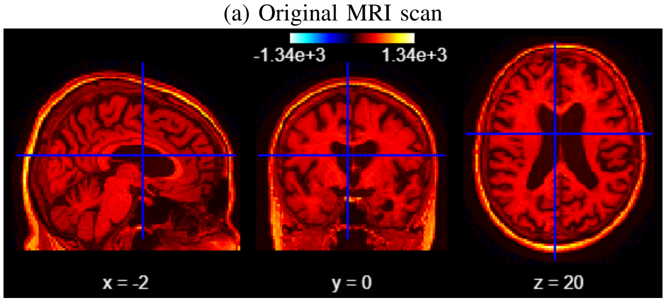
In this project, we used two types of architecture, namely, 3D ConvNet architecture and 3D ResNet architecture. Additionally, we experimented with three variations of the ResNet architecture, which are ResNet-18, ResNet-50, and ResNet-152.

1) 3D ConvNet: A 3D ConvNet or 3D Convolutional Neural Network [4] is a 3D version of a regular 2D Convolutional Neural Network where the input may be an array of 2D images or a 3D volume. Ordinary Neural Networks and Convolutional Neural Networks are pretty similar. They are made up of neurons with weights and biases that can be learned. Each neuron takes some inputs, performs a dot product, and executes a non-linearity if desired. From raw picture pixels on one end to class scores on the other, the entire network reflects a single differentiable score function. On the last (fully-connected) layer, they have a loss function.

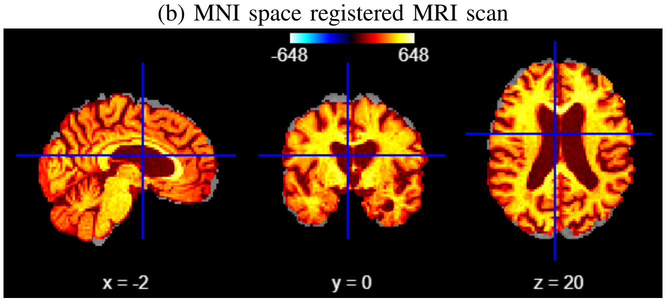
[1]FSL (https://fsl.fmrib.ox.ac.uk/fsl/fslwiki/)



(a) Original MRI scan



(b) MNI space registered MRI scan



(c) Skull stripped MRI scan

Fig. 1: Preprocessing on 3D MRI scans

A simple ConvNet comprises layers, each of which uses a differentiable function to translate one volume of activations to another. Convolutional Layer, Pooling Layer, and Fully-Connected Layer are the three primary types of layers used in ConvNet architectures, just as they are in standard Neural Networks. These layers are stacked to construct a complete ConvNet architecture.

The 3D ConvNet we used is built using convolutional layers, pooling layers, normalization layers, and fully connected layers. We built blocks that consist of a convolutional layer, max-pooling layer, and normalization layer. We used four such blocks, after which we stacked an average-pooling layer and three fully connected layers with dropout. In the first two block's convolution layers, we used 64 kernels and later increased them to 128 and 256. ReLU activation function was used for all layers except the output layer, where we used the Sigmoid activation function. Figure 2 illustrates the 3D ConvNet architecture we used.

2) 3D ResNet: ResNet, a new architecture presented by Microsoft Research in 2015, established a new architecture called Residual Network [5]. This architecture introduces the concept of the Residual Network to overcome the problem of the vanishing or exploding gradient. We employed a method called skip connections in this network. The skip connection bypasses a few stages of training and links directly to the output. Instead of letting layers learn the underlying mapping, we let the network fit the residual mapping. For this project, we used ResNet architectures of different depths. We used an 18-layer deep ResNet, a 50-layer deep ResNet, and a 152-layer deep ResNet. Increasing the depth has gradually improved the accuracy on the MRI dataset, which we further discuss in section III-B.

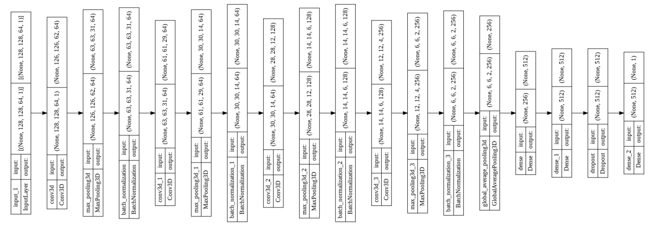


Fig. 2: 3D ConvNet Architecture

C. Loss Function

binary cross-entropy

A loss function is used by machines to learn. It is a way of determining how well a specific algorithm fits the data. If the forecasts are too far off from the actual findings, the loss function will return a vast number. The loss function learns to reduce estimation error over time with the help of some optimization function. Depending on the type of learning job we are dealing with, loss functions can be divided into two categories: regression losses and classification losses.

$$\text{loss} = -\frac{1}{N}\sum_{i}^{N}\sum_{j}^{M} y_{ij}\log\left(p_{ij}\right) \tag{1}$$

Cross-Entropy Loss, also known as Negative Log Likelihood, is widely used for classification. As the projected likelihood differs from the actual label, cross-entropy loss grows. Binary cross-entropy is used when we have only two classes. In binary cross-entropy, each projected probability is compared to the actual class output, which can be either 0 or 1. The score is then calculated, penalizing the probabilities based on their deviation from the predicted value. This refers to how close or far the value is to the actual value. Equation 1 shows the binary cross-entropy loss function, where M is the number of classes and N is the number of instances.

D. Optimizer

An optimizer is a function or algorithm that alters the characteristics of a neural network, such as its weights and learning rate. We must adjust each epoch's weights and reduce the loss function while training the deep learning model. As a result, the optimizer aids in lowering overall loss and increasing accuracy. Because a deep learning model typically has millions of parameters, finding the proper weights for the network is a complex issue. It necessitates the selection of an appropriate optimization algorithm for the given application.

Adam, or Adaptive Moment Estimation, is a method for gradient descent optimization. The method is quite efficient

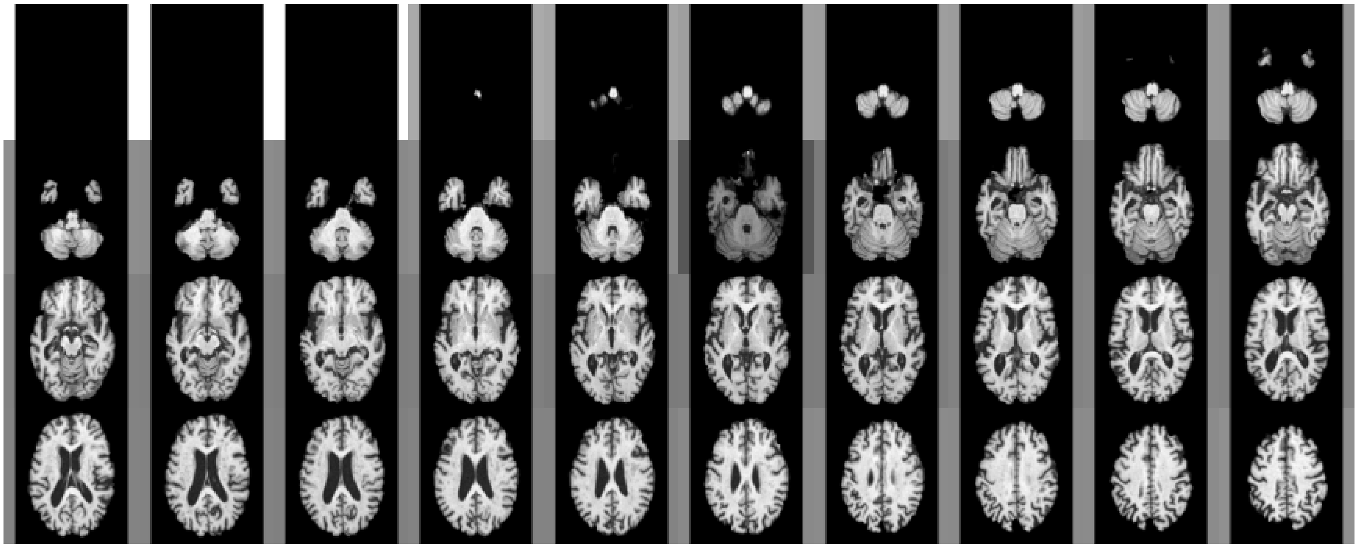


Fig. 3: Slice plot of 3D MRI sample.

when working with real problems with a large volume of data or parameters. Moreover, it is effective and takes minimal memory. It is mainly a hybrid of gradient descent with momentum and the RMSP algorithms. We used the Adam optimizer with a learning rate which has an exponential decay schedule. We started with an initial learning rate of 0.0001 and a 96% decay rate over 100000 steps.

E. Augmentation

There are a variety of preprocessing and augmentation methods available. We used simple data augmentation techniques. During training, the preprocessed MRI images were augmented by rotating at different angles. We added a dimension of size one at axis 4 to be able to execute 3D convolutions on the data because it was stored in rank-3 tensors of shape (samples, height, width, and depth). As a result, the new form was (samples, height, width, depth, 1). The training data was fed via an augmentation function randomly rotating MRI image volume at different angles. It was defined when we declared our data loader function.

III. Experiment

We have experimented with different deep learning models on an MRI dataset. We have discussed the dataset and the experimental results below.

A. Dataset

We acquired 3D MRI data from the ADNI (Alzheimer's Disease Neuroimaging Initiative) [2] database. We took samples of 75 patients with Alzheimer's diseade and 75 patients who were cognitively normal controls. We experimented on a total of 150 subjects.

The ADNI was established in 2003 as a $60 million, 5-year partnership between different public and private institutions including the National Institute on Aging (NIA), the National Institute of Biomedical Imaging and Bioengineering (NIBIB), the Food and Drug Administration (FDA), etc. The major purpose of ADNI was to see if serial MR, PET, other biological markers, and clinical and cognitive assessments could be used to track mild cognitive impairment and early Alzheimer's disease progression. According to the incorporation criteria of this initiative, all patients were between the ages of 55 and 90 and spoke either or both English and Spanish. The Mini Mental State Examination score requirement for all subjects were between 24 to 30, however the Clinical Dementia Rating (CDR) differed for the two categories. For CN subjects the CDR had to be zero and for AD subjects the CDR had to be 0.5. Figure 4 shows the MRI sample of an AD and a CN subject.

t1-weighted MRI samples were taken from the database for this project. For the sake of uniformity, we only took samples that had undergone 3D gradwarp correction and B1 non-uniformity correction. For non-uniformity intensity correction is performed by the B1 non-uniformity correction method. MRI scans were performed on the baseline and screening visits at 1.5 tesla. The acquired data was in 3D NIfTI format. Figure 3 shows a sliced plotting of 3D MRI sample after it has been pre-processed.

[2]Alzheimer's Disease Neuroimaging Initiative (https://adni.loni.usc.edu/)

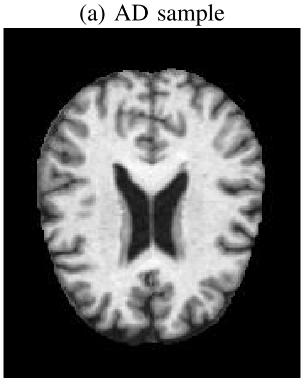
B. Results

We achieved results on the various deep learning models that we have applied on the MRI dataset. Table **??** illustrates these results.

Model	Validation Accuracy
3D ConvNet	65.22%
3D ResNet-18	73.91%
3D ResNet-50	73.91%
3D ResNet-152	71.74%

TABLE I: Model validation accuracy

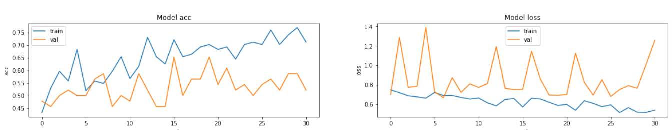
(a) AD sample



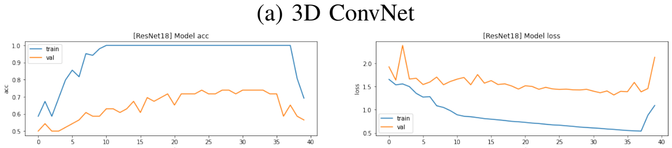
(b) CN sample

Fig. 4: Sliced MRI scans of the brain

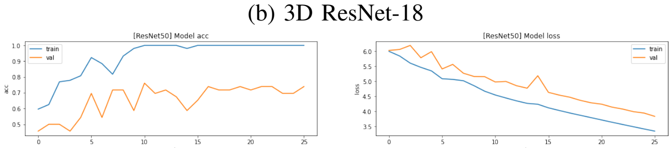
Figure 5 shows the model accuracy and loss curves for the different models.



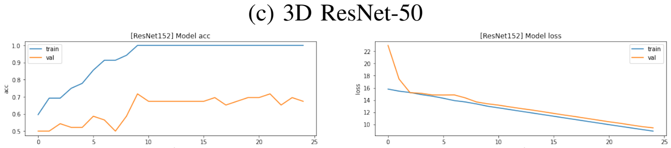
(a) 3D ConvNet



(b) 3D ResNet-18



(c) 3D ResNet-50



(d) 3D ResNet-152

Fig. 5: Model accuracy and loss curve

IV. CONCLUSION

For the early identification and treatment of Alzheimer's disease patients, an automated Alzheimer's disease detection and classification system are essential. As a result, we have presented a deep 3D CNN model for Alzheimer's disease diagnosis and classification which is automated. We have demonstrated the model's performance measurement on the ADNI dataset. We used data augmentation as we have a small dataset, but we achieved a good result. We got better accuracy in 3D ResNet compared with 3D ConvNet. The proposed method might be improved in several ways. First, we want to work with more MRI AD datasets in the future, such as OASIS, to get comparable or better results. We want to use transfer learning to see if it is more effective than our proposed method. We want to use state-of-the-art models such as ConvNeXt, DOLG to get better accuracy. We can increase accuracy using Generative Adversarial Networks (GAN) and Ensemble Learning (EL). [6]

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