Abstract

In recent years, research and various articles have demonstrated the wide-ranging applications of neural networks in detecting various diseases. Some diseases, such as Alzheimer's, for which there is generally no specific cure, and prevention relies on slowing down the progression, early diagnosis plays a crucial role in the disease's course.

In this project, an attempt has been made to create a model using pre-trained neural network models, utilizing various methods detailed in the text, to develop a model capable of detecting Alzheimer's disease in healthy individuals. Structural MRI data from the ADNI dataset was used in this project. The dataset included 294 Alzheimer's patients and 296 healthy individuals. It's worth mentioning that the latest MRI scans available in ADNI were used for each individual, and a ViT model achieved an accuracy of over 70%, which is considered good in medical tasks, especially with such a small dataset.

Problem Statement

In this project, we aimed to explore various input methods and experiment with different approaches to determine the best method for distinguishing between healthy and diseased individuals. Initially, we downloaded the data and preprocessed it using the widely renowned software, Fast Surfer, which specializes in MRI data preprocessing. This preprocessing involved normalizing images, smoothing them, skull stripping, and separating gray matter, white matter, and cerebrospinal fluid (CSF).

After preprocessing, we decided to employ different computational methods for classifying these 3D brain images. The most critical challenges we faced included selecting the model type, defining the input format, and choosing features for input. Since MRI images are inherently complex, we opted to use Deep Neural Networks (DNNs). Additionally, due to the limited amount of data available for training a neural network from scratch, we utilized pre-trained neural network models, a technique commonly referred to as transfer learning.

Selecting the appropriate model, determining the input format for 3D data (which differs from typical 3-channel RGB images), and tuning hyperparameters such as learning rate and data normalization methods were among the challenging aspects encountered in this project.

Research Methodology and Implementation

1-1 Model Design

The design of the model plays a crucial role in the outcome of the research. Given our limited computational resources and the inability to download more data, there were constraints to consider. In light of these conditions, the best choice was to use deep learning algorithms that had previously been trained on large datasets. Two popular model architectures, Vision Transformers and ResNet-18, were selected based on their research background.

In the ResNet-18 model, all layers were frozen to prevent their weights from changing during the

new training process. Additional layers were added at the end of the model, including three linear layers with input/output dimensions of 512/128, 128/2, and a softmax activation layer for classification. ReLU activation functions were used in between these layers. To mitigate overfitting issues, dropout layers with dropout rates of 20% and 10% were applied between each of the layers.

For the Vision Transformer architecture, all layers except the Multi-Layer Perceptron (MLP) layers were frozen during training.

1-2 Choice of Input Type

One of the most critical issues and challenges in this research was how to input MRI scans of patients into the designed models. The models are typically trained on data from ImageNet, which consists of 2D RGB color images. However, our patient MRI scans were all 3D with varying dimensions depending on the scanning equipment used. In this study, we sliced the patient MRI scans into different 3D sections and transformed them into 2D images as previously mentioned. The middle layers of these 2D images were considered as input. It's worth noting that in the preprocessing stage mentioned earlier, we normalized the weights of the MRI images, and in addition to skull stripping, we extracted three regions: Gray Matter (GM), White Matter (WM), and Cerebrospinal Fluid (CSF) from within the images. In this research, we used two specific types of input. In one type, we provided the extracted layers as color channels to the model. In the other case, we used only the Gray Matter (GM) as input, repeating its values three times and providing it to the model as R, G, and B channels (similar to giving a grayscale image to the model).

1-3 Dataset

The dataset used in this research was obtained from the Alzheimer's Disease Neuroimaging Initiative (ADNI), which is a publicly available neuroimaging database specialized in Alzheimer's disease research and is a subsidiary of the University of Southern California (USC). Access to the dataset was granted after submitting a request, and the data were downloaded and processed in multiple stages. It's worth mentioning that since each patient might have multiple MRI scans, we selected their latest MRI scan for inclusion in our research.

Patient Type	Number of data
Alzheimer Patients (AD)	294
Normal Person (Control group)	300
Sum	594

1-4 Evaluation Metrics

In this research, we used the widely recognized accuracy metric to evaluate the models. The formula for accuracy is as follows:

Accuracy = Accuracy = (True positives + True Negatives)/ (True positives + True negatives + False positives + False negatives)

Additionally, the F1 Score is another commonly used metric for evaluating models, especially when dealing with imbalanced datasets. We used both accuracy and F1 Score in each fold to comprehensively assess the models.

$$\frac{\textit{Number of True Positives(TP)}}{\textit{Number of True Positives(TP) + Number of False Positives(FP)}}$$

1-5 Analysis and Results

Our dataset was classified using two different models and two different input modalities in three different orientations. In total, we examined 12 different combinations of inputs and models, and each dataset was evaluated using a 5-fold cross-validation to prevent data bias.

Accuracy table for data:

Type of the cut of the MRI	GM with VIT model	VIT model	ResNet18 Model with GM	ResNet18 Model
Sagital	46%	47%	52%	44%
Coronal	71%	67%	56%	50%
Axial	62%	59%	59%	50%

F1-score table for data:

Type of the cut of the MRI	GM with VIT model	VIT model	ResNet18 Model with GM	ResNet18 Model
Sagital	53%	54%	48%	42%
Coronal	77%	73%	56%	42%
Axial	69%	66%	54%	42%

As observed, most of the informative data lies in the coronal and axial slices, which aligns with our research background. Notably, the vision transformer model that received Gray Matter (GM) layer data achieved an accuracy of 70%. These numbers are reported as the average of the executed folds.

Results:

Detecting Alzheimer's disease in healthy individuals is one of the most significant concerns, as early diagnosis can help prevent its widespread progression in various brain regions, making the timing of diagnosis crucial. In this research, we aimed to develop a program and project that could address this issue using innovative computational methods, including advanced deep learning algorithms. We successfully achieved desirable accuracy in this project through deep learning and MRI processing. It's worth noting that all processing was performed on a reliable server, ensuring the credibility of our results.

PS: In the university where I graduated having a thesis for your project isn't mandatory for being graduated but I wrote it down in Persian and this English version is summarized.

Also, you can see my codes here :

https://github.com/HediyeRaisy/MRI_Classification