ISSN 2616-5791 Vol.4, Issue 10: 57-60, DOI: 10.25236/AJMHS.2023.041009

Prediction and Visualization of Alzheimer's Disease Using Deep Learning Models

Mengyu Ge[1,*]

[1]*Brimmer and May School, MA, United States*
[*]*Corresponding author*

Abstract: *Symptoms of Alzheimer's disease are dullness, memory loss, and an inability to socialize. These symptoms of Alzheimer's disease are caused by the shrinking of the brain, which leads to the death of brain cells and prevents the patient from accessing his or her memories and making normal decisions. Alzheimer's disease affects about 10 percent of people over the age of 65 in the United States. But even with such a large number of patients, scientists still don't know much about Alzheimer's disease. Currently, scientists believe that the dominant causes of Alzheimer's are age and family history. The mainstay of diagnosing Alzheimer's disease is a combination of patient history, neuropsychology, and MRIs, as well as the use of medications to slow down the disease (Alzheimer's disease is not curable at the current state of medical care). However, as the United States and a growing number of countries around the world experience declining fertility rates and aging societies, the number of patients with Alzheimer's disease is beginning to increase. As a result, society's medical resources are becoming overwhelmed by the diagnosis of Alzheimer's disease. Society needs a more efficient way to diagnose Alzheimer's disease. Therefore, some scholars began to try to use AI deep learning to carry out the prediction of Alzheimer's disease. After validation, the network model trained using AI deep learning can now achieve a diagnosis of Alzheimer's disease accuracy better than that of ordinary neurologists. Thus, it can be seen that the direction of AI deep learning is feasible for the future to solve the problem of overloading the social healthcare system with Alzheimer's diagnosis. This paper is based on the FCN model in Development and Validation of an Interpretable Deep Learning Framework for Alzheimer's Disease Classification. We also used the same ANDI dataset as that paper. The model is an FCN and it randomly selects 3000 voxels of size 47x47x47 from each MRI scan for each training session #go back to the FCN section of the paper#. This FCN model is divided into six convolutional blocks. The first four convolutional blocks are 3D Convolutional Layer #explain more about these four convolutional blocks#. The remaining two convolutional blocks act as speedups for model efficiency #explain more about these two convolutional blocks convolutional blocks (speedups for model efficiency)# . After training, the final model that comes out can successfully predict the MRI images. After completing the reconstruction of this model and going through 3000 epochs of training, the model is slightly less accurate #To be completed#. But the model already has the ability to make predictions on MRI images.*

Keywords: *deep learning, Alzheimer's disease, MRI, FCN*

1. Introduction

Many families in the world are suffering from Alzheimer's disease. According to Alzheimer's Association, sixty-seven million people over the age of 65 in the United States suffer from Alzheimer's disease, which means that 1 in 9 people over the age of 65 is afflicted by Alzheimer's disease. Such a high prevalence of the disease means that a large number of diagnoses are needed to distinguish which patients actually have Alzheimer's. And the process of diagnosing whether or not a person has Alzheimer's can be tedious. Neurologists need diagnostic tools, patient history information, and other information to help make a more accurate diagnosis. These include brain imaging (MRI, CT, PET), CSF (a test of the cerebrospinal fluid), and blood tests, which can be seen as a burden on society's healthcare resources for a disease with such a high prevalence and a complicated diagnostic process.

Previously, some researchers have proposed a solution to the diagnosis of Alzheimer's disease by using AI deep learning to diagnose Alzheimer's disease.

In Development and Validation of an Interpretable Deep Learning Framework for Alzheimer's Disease Classification, researchers used the FCN model to predict Alzheimer's disease. Alzheimer's disease prediction. The authors used data from the ADNI for model training, internal validation and

ISSN 2616-5791 Vol.4, Issue 10: 57-60, DOI: 10.25236/AJMHS.2023.041009

testing, and then validated the model on the AIBL, FHS, and NACC to confirm the model's generalizability (ability to cope with data from other data sets).

In the end, the researchers tabulated the accuracy of all the models and could see that they were excellent at predicting Alzheimer's disease. They even exceeded the predictive accuracy of some neuroscientists. But the researchers also point out that the biggest problem is the "black box" problem, which means that doctors can't see exactly how the models work, or how they arrive at their results. As a result, although the model can maintain a high level of accuracy when validated against multiple datasets, it can't be used in the clinic[1-3].

2. Dataset

This thesis uses data from Phase I and Phase III of ADNI. In phase I there were 852 data including MRI images but only about 400# interpreted number# of them were processed because the other half were labeled as MCI (moderate symptoms) but the model trained by the code could only produce two outcomes AD (with Alzheimer's disease) and CN (without Alzheimer's disease) therefore all the data for the MCI condition was not used. In contrast, in the Phase III data there are 600 data including AD and CN conditions. In addition to this, in the ADNI dataset, all subjects in Phase I had Subject ID, Status (Alzheimer's disease or not), Gender, Age, MMSE, and APOE scores. However, in Phase III, only Subject ID, Status, Gender, and Age were available, because the MMSE scores for Phase III were only recorded for a subset of the population and the APOE scores for Phase III were not successfully obtained for this thesis.

3. Environment Setup

Plugins downloaded using pip in the process of setting up the environment include:

1) PyTorch (1.1 or greater).

2) NumPy (1.16 or greater).

3) Matplotlib (3.0.3 or greater)

4) Tqdm (4.31 or greater).

4. Data preprocessing

After obtaining the data from ADNI the data is in .nii.gz format so the data needs to be decompressed to get the .nii file. Then we need to use FSL Flirt to open and linearly register the .nii images. Currently, FSL only supports Mac OS and Linux systems. This preprocessing is done on Mac OS. After obtaining the linearly registered .nii files, they are converted to .npy format and subjected to z-score voxel normalization, while the final step is to remove some outliers from the processed .npy files.

After the pre-processing of the data, the processed data and the code are transferred to a computer with a GPU via a USB flash drive for subsequent training.

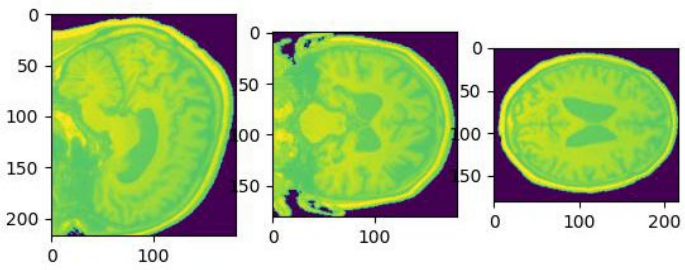

Figure 1: Data Output

After preprocessing, a .jpg image is generated that corresponds to the .npy image, thus allowing the training process to be visualized. As is shown in Figure 1.

ISSN 2616-5791 Vol.4, Issue 10: 57-60, DOI: 10.25236/AJMHS.2023.041009

5. Visualization of the training process

Training method

Since the number of datasets is not very large (639 .npy images), the code automatically splits the processed datasets into train set, test set, and valid set in the ratio of 46:39:13 after the preprocessing is completed, which is relatively small compared to the number of train sets in normal training. In addition, five splits of data between training and validation were performed to prevent overfitting.

Training model

The training epoch was set to 3000 but with subsequent rounds of training it was found that the accuracy before 2000 rounds was actually very close to the accuracy of the subsequent rounds of training #Figure #FCN The number of filters in the first layer of the FCN was set to 20. and the drop rate was set to 0.5 which means that for every 100 packets between neurons, 50 of them would be used. packets will be dropped thus reducing overfitting. Generally, the drop rate is set between 0.5 and 0.8. The patch size is set to 47x47x47 which means that a 47x47x47 square is randomly sliced from a 3D image to be processed and the batch size is set to 10 which means that 10 samples are processed before the model is updated.

Training results

The best model after the first training (using data from ADNI Phase I) was saved at generation 2660. This model achieved an accuracy of 0.79. Subsequent visualization of the project was done using this model.

After the second training (using ADNI III data), very strangely, the best saved model was the model from the 0th training. Its validation reached an accuracy of 0.89.

The third training (using ADNI III data) is more normal, and after 3000 rounds of training the best model is saved in the 1620th model. The validation accuracy is 0.79 as in the first training[4-5].

6. Conclusions

Because Alzheimer's disease is difficult to diagnose and consumes a lot of social and medical resources. Therefore, I would like to use the FCN model to predict the MRI map of a patient's brain in order to categorize the patient's Alzheimer's condition. I trained the FCN model using the ADNI Phase I and Phase III datasets to obtain and visualize a FCN model that can accurately predict Alzheimer's disease. The first training was done using the ADNI Phase I data. The FCN model from the last two training sessions was trained using ADNI Phase III data. The biggest difference between the two training sessions is that apart from the number of subjects (one session has about 200 fewer subjects than the three sessions), the three sessions do not have the MMSE and APOE scores. But this is what I wanted because then MMSE and APOE are scores that require a doctor's help to do the tests to get. My main goal is to reduce the amount of healthcare resources taken away from society so I would like to see if the accuracy of the FCN model decreases in the absence of MMSE and APOE scores.

Based on the FCN model from the former study I was able to get the model trained efficiently. Additionally another benefit of this model is that the SIZE of the inputs does not need to be consistent. After completing the training three times, the accuracy of the first model trained with one phase of data (0.79) was not as high as the accuracy of the last two models trained with three phases of data (0.89 and 0.79). This means that the MMSE and APOE scores do not have a significant impact on the accuracy of the model[6-8].

I have initially made the first trained model into a web page using HTML and support people to upload MRI images to the web page to classify the images. After a few tests, I think it is very feasible to make Alzheimer's tests this way in the future and use the model to make quick predictions. In the web page, the operator only needs to input age, gender, and MRI image in .nii format after Linear Registration, and the prediction is very accurate after comparison. However, the biggest problem with this web page is that the uploaded image must be a .nii image with Linear Registration. This can be optimized by adding a function to automatically perform Linear Registration.

ISSN 2616-5791 Vol.4, Issue 10: 57-60, DOI: 10.25236/AJMHS.2023.041009

References

[1] Acquarelli J; van Laarhoven T; Postma GJ; Jansen JJ;Rijpma A; van Asten S; Heerschap A;Buydens LMC; Marchiori E; "Convolutional Neural Networks to Predict Brain Tumor Grades and Alzheimer's Disease with Mr Spectroscopic Imaging Data. " PloS One, U. S. National Library of Medicine, pubmed. ncbi.nlm.nih.gov/36001537/.Accessed 12 Sept. 2023.
[2] Swapna. "Convolutional Neural Network: Deep Learning." Developers Breach, 25 Jan. 2022, developersbreach.com/convolution-neural-network-deep-learning/.
[3] Balachandran, Sandeep. "Machine Learning - Max Pooling with Color Images." DEV Community, DEV Community, 30 Mar. 2020, dev.to/sandeepbalachandran/machine-learning-max-pooling-with-color-images-2i21.
[4] "A Comprehensive Guide to Convolutional Neural Networks - the Eli5 Way." Saturn Cloud Blog, 17 June 2023, saturncloud.io/blog/a-comprehensive-guide-to-convolutional-neural-networks-the-eli5-way/.
[5] Gauriau R; Bizzo BC; Kitamura FC; Landi Junior O; Ferraciolli SF; Macruz FBC; Sanchez TA; Garcia MRT; Vedolin LM; Domingues RC; Gasparetto EL; Andriole KP; "A Deep Learning-Based Model for Detecting Abnormalities on Brain MR Images for Triaging: Preliminary Results from a Multisite Experience. " Radiology. Artificial Intelligence, U. S. National Library of Medicine, pubmed. ncbi. nlm. nih. gov/34350408/. Accessed 12 Sept. 2023.
[6] Gradient-Based Learning Applied to Document Recognition, ieeexplore.ieee.org/document/726791. Accessed 12 Sept. 2023.
[7] Krishnapriya, Srigiri, and Yepuganti Karuna. "Pre-Trained Deep Learning Models for Brain MRI Image Classification." Frontiers, Frontiers, 6 Mar. 2023, www. frontiersin.org/articles/10. 3389/fnhum. 2023. 1150120/full.
[8] Long, Jonathan, et al. "Fully Convolutional Networks for Semantic Segmentation." arXiv.Org,8 Mar.2015,arxiv.org/abs/1411.4038.