An Investigation into the Correlation Between MRI Preprocessing and Performance of Alzheimer's Disease Classification CNN Model

Hyeon Sung Cho
Field Robotics Research Section
ETRI
Daejeon, South Korea
hsc@etri.re.kr

Jae-chan Jeong
Field Robotics Research Section
ETRI
Daejeon, South Korea
channij80@etri.re.kr

Hyo Bong Hong
Field Robotics Research Section
ETRI
Daejeon, South Korea
hb8868@etri.re.kr

***Abstract*—An irreversible degenerative neurological disease, Alzheimer's disease (AD) affects a large proportion of the elderly population. Due to the fact that there is no perfect treatment method yet for Alzheimer's disease, medical imaging such as MRI is currently the best method to diagnose mild cognitive impairment or early AD, as well as to respond early and treat it. Additionally, with the advancement of deep learning technology, research on AD reading automation through MRI data is receiving a great deal of attention. Numerous results have been published as a result of this research. Preprocessing of MRI data is a basic part of the automatic reading technology that uses MRI data. The purpose of this study is to compare the performance of MRI data preprocessing in the automatic AD reading technology using MRI with the results of the study.**

Keywords—Alzheimer's Disease, MRI, CNN, Preprocessing

I. INTRODUCTION

As a neurodegenerative disease, Alzheimer's disease (AD) affects a significant portion of the elderly population, and people with this illness face many challenges in maintaining independence. It is also associated with a lot of pain, not just for the patient but also for those around him or her.

Alzheimer's disease is still not completely treatable, so the best option is to detect the disease early via MRI or other means to slow down the progression of the disease.

On the other hand, with the recent development of deep learning technology, many studies have been reported that automatically decipher dementia using MRI data using CNN [6, 7, 8, 9].

The preprocessing of MRI data and the use of machine learning algorithms is a common practice in studies related to these topics. Preprocessing of MRI data also poses high technical challenges, as detailed research topics related to this have been published in a number of papers [10, 11, 12].

The purpose of this study is to examine how preprocessing technology impacts reading performance in the context of developing a deep learning model to read dementia based on MRI data. In this study to analyze the effect of preprocessing on performance, we compared performances of the deep learning model trained with unprocessed MRI data and the other model trained with preprocessed one.

II. DESIGN OF EXPERIMENTS

A. MRI Dataset

The data used to train the deep learning model for the diagnosis of Alzheimer's disease were public MRI data sets provided by ADNI[1], MIRAID[2], OSASIS-1[3], and OSASIS-3[4].

Among a total of 6,203 data obtained from four databases, 2,252 were randomly selected without overlapping subjects and used to train the CNN model.

B. CNN Training Enviroments

For the basic structure of the deep learning model, EfficientNet[5] was trained without a pretrained model, and tensorflow 2.11 was used as the framework used for deep learning. The CNN hyper-parameters for training were set as shown in Table I.

TABLE I. HYPER-PARAMETERS OF EFFICIENTNET

Parameters	**Setting Value**
Learning rate	0.001
Dropout rate	0.5
Loss function	Binary Crossentropy
Activation function	Relu

To check the effect of pretreatment on performance, we prepared two models. One is a model that learns by giving EfficientNet data that is not preprocessed as input, and the other is a model that learns by inputting data that has completed preprocessing.

C. MRI Preprocessing

Bias field correction, contrast enhancement, skull scriping, and registration are preprocessing techniques applied to MRI data taken at the earliest for Alzheimer's reading. The preprocessing method used in this paper performed MRI preprocessing in batches using the framework provided by ROBEX[6]. Fig. 1. shows an example of MRI data processed using the ROBEX tool.

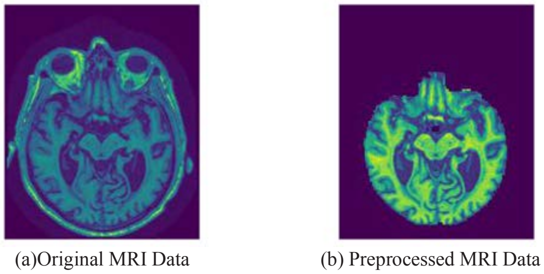

Fig. 1. Preprocessing results of MRI Data

D. Data Augmetation

Sufficient data is required to learn image data through CNN, but the data obtained from the four publicly available databases is in excess of the ceiling per class, so there is a somewhat insufficient part. In order to solve the problem of insufficient data, data augmentation was applied to expand the original 1,801 images to about 43,224 images. The techniques used here are image cropping, rotation, and shifting. Fig. 2. shows an example of augmentation of MRI data.

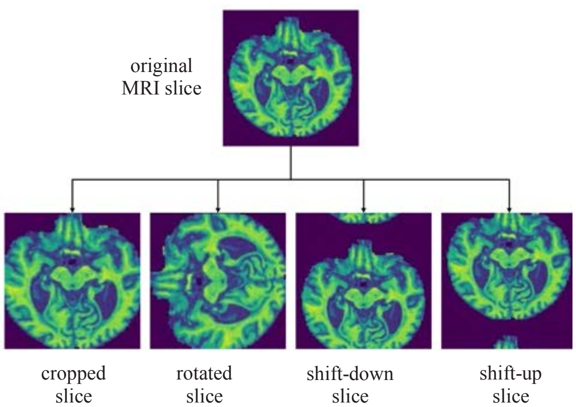

Fig. 2. Data Augmentation results of MRI data

Ten models were learned for each experimental setting using a 10-fold cross-validation method on 43,224 images to which data augmentation was applied. The data size used at each fold is shown in Table II.

TABLE II. COMPOSION OF DATA SET

Class		Training set	Validation set	Test set
Before Data Augmentation	**HC**	1,008	126	127
	AD	793	99	99
After Data Augmentation	**HC**	24,192	126	127
	AD	19,032	99	99

This work was supported by Electronics and Telecommunication Research Institute, Rep. of Korea (Grant No. 23-YS-1110).

III. RESULTS

The performance evaluation results of the two CNN models are reported in the Table III and the box plot is plotted in Fig. 3. The accuracy of the baseline model with test dataset was 67.79% (95% CI, 65.24%~70.34%) and the model which trained with preprocessed dataset was 68.76% (95% CI, 66.36%~71.16%), respectively.

TABLE III. PERFORMANCE OF TWO MODELS

Model	Accuracy (Mean)	Confidence Interval	Standard Deviation	Min	Max
Without preprocessing	67.79	65.24~70.34	0.034	61.95	71.68
With preprocessing	68.76	66.36~71.16	0.032	63.72	74.34

As a result of the performance analysis of the two methods, it was confirmed that there was no statistically significant difference ($P > .05$) in accuracy. The p-value of t-test was 0.414.

TABLE IV. STATISTICAL TEST RESULTS

Test Name	p-Value	t-Value
Shapiro-wilk test	0.451	0.93
T-test	0.414	-0.857

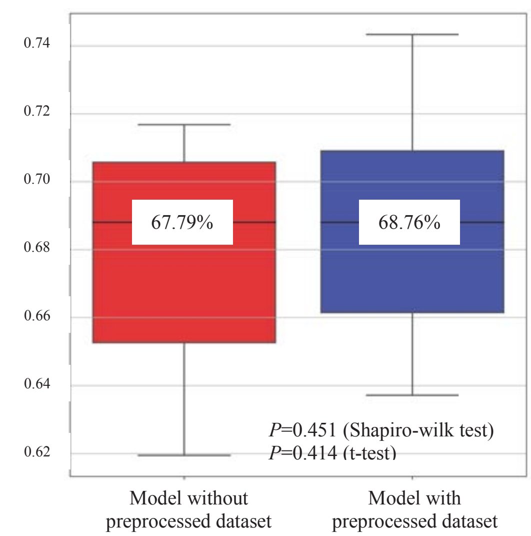

Fig. 3. Comparison of accuracy between the model without preprocessing and the model with preprocessed data.

IV. CONCLUSIONS

There have been many research results relating to deep learning models for Alzheimer's disease diagnosis using an MRI preprocessing technology. The purpose of this study was to compare the performance of two CNN models, one of which was trained using preprocessed datasets, and one of which was trained without preprocessed datasets. Tests of statistical difference indicate that there is no difference between the two models, although the average accuracy is slightly higher in the preprocessed model.

Performance analysis results are unusual from a conventional perspective. Based on the following experimental conditions, it can be estimated that preprocessing of MRI data had no significant effect on performance in this study. First of all, the amount of data used in this experiment is quite limited. There may also have been some impact from the part learned by extracting the Cerebral Sagittal Axis plane in the middle position from the 3D form of MRI data. Another reason is that EfficientNet, which has a simple structure and parameters, was used as a basic model due to the small size of the training data.

As a result, additional experiments and verifications related to the preprocessing and performance of MRI data related to the core subject of this study are needed. More rigorous verification through experiments using more data sets, CNNs of various structures, and pretrained models is needed in the future.

ACKNOWLEDGMENT

Data used in the preparation of this article were obtained from the Alzheimer's Disease Neuroimaging Initiative (ADNI), MIRIAD database, OASIS-1 database, and OASIS-3 database.

REFERENCES

[1] Petersen, Ronald Carl, Paul S. Aisen, Laurel A. Beckett, Michael C. Donohue, Anthony Collins Gamst, Danielle J. Harvey, Clifford R. Jack et al. "Alzheimer's disease neuroimaging initiative (ADNI): clinical characterization." Neurology 74, no. 3 (2010): 201-209.

[2] Malone, Ian B., David Cash, Gerard R. Ridgway, David G. MacManus, Sebastien Ourselin, Nick C. Fox, and Jonathan M. Schott. "MIRIAD—Public release of a multiple time point Alzheimer's MR imaging dataset." NeuroImage 70 (2013): 33-36.

[3] Marcus, Daniel S., Tracy H. Wang, Jamie Parker, John G. Csernansky, John C. Morris, and Randy L. Buckner. "Open Access Series of Imaging Studies (OASIS): cross-sectional MRI data in young, middle aged, nondemented, and demented older adults." Journal of cognitive neuroscience 19, no. 9 (2007): 1498-1507.

[4] LaMontagne, Pamela J., Tammie LS Benzinger, John C. Morris, Sarah Keefe, Russ Hornbeck, Chengjie Xiong, Elizabeth Grant et al. "OASIS-3: longitudinal neuroimaging, clinical, and cognitive dataset for normal aging and Alzheimer disease." MedRxiv (2019): 2019-12. LaMontagne, P.J., Benzinger, T.L., Morris.

[5] Tan, Mingxing, and Quoc Le. "Efficientnet: Rethinking model scaling for convolutional neural networks." In International conference on machine learning, pp. 6105-6114. PMLR, 2019.

[6] Arafa, Doaa Ahmed, Hossam El-Din Moustafa, Amr MT Ali-Eldin, and Hesham A. Ali. "Early detection of Alzheimer's disease based on the state-of-the-art deep learning approach: a comprehensive survey." Multimedia Tools and Applications 81, no. 17 (2022): 23735-23776.

[7] Tanveer, Muhammad, Bharat Richhariya, Riyaj Uddin Khan, Ashraf Haroon Rashid, Pritee Khanna, Mukesh Prasad, and C. T. Lin. "Machine learning techniques for the diagnosis of Alzheimer's disease: A review." ACM Transactions on Multimedia Computing, Communications, and Applications (TOMM) 16, no. 1s (2020): 1-35.

[8] Khojaste-Sarakhsi, M., Seyedhamidreza Shahabi Haghighi, SMT Fatemi Ghomi, and Elena Marchiori. "Deep learning for Alzheimer's disease diagnosis: A survey." Artificial Intelligence in Medicine 130 (2022): 102332.

[9] Gao, Shuangshuang, and Dimas Lima. "A review of the application of deep learning in the detection of Alzheimer's disease." International Journal of Cognitive Computing in Engineering 3 (2022): 1-8.

[10] Iglesias, Juan Eugenio, Cheng-Yi Liu, Paul M. Thompson, and Zhuowen Tu. "Robust brain extraction across datasets and comparison with publicly available methods." IEEE transactions on medical imaging 30, no. 9 (2011): 1617-1634.

[11] Kalaiselvi, T., T. Anitha, and P. Sriramakrishnan. "Data preprocessing techniques for MRI brain scans using deep learning models." In Brain Tumor MRI Image Segmentation Using Deep Learning Techniques, pp. 13-25. Academic Press, 2022.

[12] Isensee, Fabian, Marianne Schell, Irada Pflueger, Gianluca Brugnara, David Bonekamp, Ulf Neuberger, Antje Wick et al. "Automated brain extraction of multisequence MRI using artificial neural networks." Human brain mapping 40, no. 17 (2019): 4952-4964.