A Detection Scheme of Cerebral Atrophy on Brain Computed Tomography Images Using a Deep-Learning Model

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***Abstract*—Pathological brain atrophy may arise from various neurological and systemic conditions, such as depressive disorders. In response to the clinical need for auxiliary diagnostic tools to detect brain atrophy in young individuals with depression, this study proposes a deep learning-based framework for the classification of cerebral atrophy using computed tomography (CT) images. The proposed approach leverages both convolutional neural networks (CNNs) to capture spatial structural changes of the brain. It also uses multilayer perceptron (MLP) to incorporate psychological risk factors to enhance diagnostic accuracy with a visual explanation for the classification. This integration allows for a more comprehensive representation of the patient profile. Experimental results demonstrate that the CNN model achieves an accuracy of 83.01%, while the multimodal model, which combines CT imaging data with psychological information, attains an improved accuracy of 87.25%. These findings underscore the effectiveness of multimodal data in cerebral atrophy classification, particularly in the context of depressive disorders. The visual explanation provides a heatmap to highlight key features influencing brain atrophy classification.**

***Index Terms*—cerebral atrophy, depression, suicidal thoughts, convolutional neural network, multimodal model.**

I. Introduction

In addition to age-related (or physiological) brain atrophy, pathological brain atrophy may occur as a result of various neurological and systemic diseases. Several neurological and psychiatric conditions, including Alzheimer's disease (AD) [1], traumatic brain injury, and major depressive disorder [2], are linked to accelerated or localized brain volume loss. Understanding the patterns and mechanisms of disease-associated brain atrophy is essential for improving diagnosis, monitoring disease progression, and developing targeted therapeutic interventions.

Numerous studies have also shown that volume loss in specific brain regions is associated with various neuropsychiatric disorders, particularly depression. A meta-analysis further confirmed significant reductions in brain volume among individuals with depression, specifically in the anterior cingulate cortex, orbitofrontal cortex, hippocampus, putamen, and caudate nucleus [3].

Most of the brain CT image research is related to intracranial lesion research while the research on cerebral atrophy mainly falls in AD diagnosis using magnetic resonance imaging (MRI). MRI provides excellent soft tissue contrast and is effective in distinguishing gray and white matter, making it suitable for assessing brain atrophy. However, its clinical use is limited by high cost, long scan time, and restricted accessibility, particularly for patients with metal implants or claustrophobia. Consequently, the clinical adoption of MRI-based biomarkers remains low despite their potential [4]. CT is faster, more accessible, and widely utilized in clinical settings, making it a practical alternative in regions where access to MRI is limited [5].

Research on brain morphology in depression has mainly focused on older or high-risk groups using small case-control studies. Large-scale or cohort studies involving younger individuals are lacking. Additionally, brain CT-based volumetric analysis has not yet been applied to psychiatric conditions like depression. However, promising findings in related fields indicate significant potential for developing predictive models of brain atrophy associated with depression and suicide risk using CT imaging.

In this paper, we propose a classification approach using CT images for cerebral atrophy related to psychiatric conditions based on a deep learning model. The proposed approach leverages both CNN and MLP to enhance diagnostic accuracy and also performs a visual explanation for the classification.

The remainder of this paper is organized as follows. Section II summarizes the related work about the cerebral atrophy

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research. Section III describes the dataset used in this cerebral atrophy classification prediction. Section IV presents the framework of the study, including data preprocessing, the classification model, and a visual explanation of the classification. Section V details the implementation of the study, including the experimental setup and evaluation metrics. Section VI evaluates the performance of the classification models. Lastly, Section VII concludes this paper along with future work.

II. Related work

Most brain analyses are based on MRI such as Alzheimer's disease diagnosis [1], and the CT-based brain analyses mainly focus on brain hemorrhage. Brain image studies conducted so far are mostly MRI-based brain volume evaluation studies. Gao et al. [6] used a deep learning network to perform the AD classification based on the CT. Some studies suggested that reduced hippocampal volume may be the most common structural neuroimaging findings associated with major depressive disorder (MDD) [2]. Additionally, research has compared regional gray matter (GM) volume differences between suicide attempters and non-suicidal individuals with MDD [7]. Lee et al. [7] investigated regional GM volume differences between suicide attempters and suicide non-attempters with MDD and examined their relationship with psychological risk factors for suicidality. Banasr et al. [8] indicated that depression is associated with structural alterations in limbic brain regions that control emotion and mood.

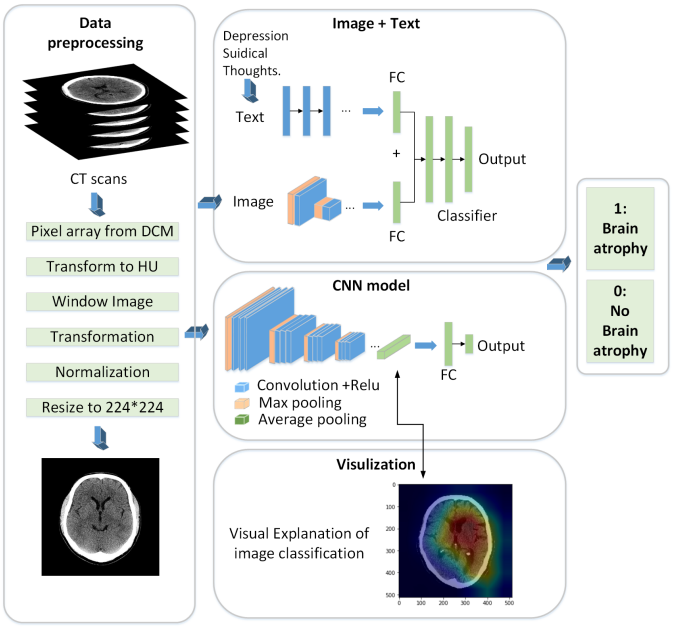


Fig. 1. The framework of cerebral atrophy classification

III. Dataset

The dataset was collected by the Kangbuk Samsung Hospital cohort for adults aged 18 years or older and undergoing health checkups. We performed the cerebral atrophy detection based on the CT scans and the psychiatric conditions. We totally selected 518 subjects' data to make up the dataset for doing the brain atrophy classification with 271 cases (with brain atrophy) and 247 controls (no brain atrophy). Every subject included 20 to 50 slices of CT scans. Since the number of slices for each subject was different, we could not use all the slices. In this study, we try to use three middle slices for the cerebral atrophy classification task. The morphological changes of the brain in the intermediate slice typically represent the cerebral atrophy, such as gray and white matter volume loss, ventricular enlargement, and sulcal widening.

The brain CT scans are in DICOM (digital imaging and communications in medicine) format, as an international standard used in medical imaging. Every DICOM data object consists of information like patient name, ID, patient birth date, institution name, physician information, and so on. This combination between the image information and the feature data can avoid the mistake when matching the detection data and subjects. In our study, to protect the patient's privacy, we replaced the personal information with anonymized and pseudonymized information.

IV. Method

Our study attempts to develop a deep learning model to predict brain atrophy as a clinical auxiliary diagnostic method related with psychiatric conditions in young groups. Fig. 1 illustrates the framework of the brain atrophy classification study. We investigate brain atrophy using readily available CT scan data and combined it with information on psychological risk factors to establish a diagnosis of brain atrophy that is convenient for clinical use. The framework includes four sections: data preprocessing, image classification model, image and text combined multimodal model, and the visualization heatmap in image classification.

At the first stage, one middle slice is selected from every patient's CT scan case for the cerebral atrophy classification. Then we select three middle slices of every subject's CT scan case and check whether the increase in the number of slices improves the performance or not. Then we combine the three slices of image data and psychological risk information to perform the classification task. Finally, we utilize the global average pooling layer of the CNN model to generate a rough location map of important features that affect the classification.

A. Data preprocessing

The image pixel data is extracted and preprocessed from brain CT scan. We transform the pixel array image data to Hounsfield Unit (HU)-scaled image data. Here, the CT scans provide information about different radiodensities of tissues that are scaled by the HU. According to the different radiodensity of the brain tissue, the brain tissue window scales are selected. After selecting the window of the brain tissue scaled in HU, the pixel array of the CT slice is transformed to a PIL (pillow) image for further transformation and normalization. Finally, each image data is resized to 224*224 tensor for further input.

B. CNN models

Two CNN models are used in this task. We construct a basic CNN model, which contain three convolutional blocks, followed by RELU activation and max pooling operations, and finally connect to the fully connected layer. We also use one pretrained CNN model (i.e., ResNet50) to perform the brain atrophy classification.

C. Multimodal model

We further developed a multimodal model to utilize a CNN model to process the CT scan image data and an MLP model to manage the psychological information data. The psychological information data includes depression information and suicidal thought information. The depression information is recorded as 1 if the subject has depression emotion problem; otherwise, the information is recorded as 0. The suicidal thought is regarded as the same.

D. Visual explanation

We utilize the gradient-weighted class activation mapping (grad-CAM) [9] to generate a rough location map for highlighting important features that affect the image classification. The CNN model uses convolutional layers to retain spatial information, while the last convolutional layer in CNN model has the best combination of semantics and spatial information features. Grad-CAM utilizes the last layer information to obtain the class-related localization map $L^c_{Grad-CAM} \in \mathbb{R}^{u \times v}$ of any class c. First, the neuron importance weights are computed in (1).

$$a^c_k = \frac{1}{Z} \sum_i \sum_j \frac{\partial y^c}{\partial A^k_{ij}}, \tag{1}$$

where A^k is the feature map activations of a convolutional layer. $\frac{\partial y^c}{\partial A^k_{ij}}$ is the gradient of the score for class c, which can be computed by the backpropagation process. Then, the gradient-weighted class activation map is generated in (2).

$$L^c_{Grad-CAM} = ReLU\left(\sum_k a^c_k A^k\right). \tag{2}$$

All the gradients are accessed from the global average pooling layer after the last convolutional layer. In (2), $L^c_{Grad-CAM}$ performs a weighted combination of forward activation maps followed by a RELU operation. The details of (2) can be accessed from the Grad-CAM [9].

We combine the grad-CAM and the image that is used for classification to generate a heatmap to visually display the parts of concern during the classification process.

V. Implementation

A. Experiment setup

In this section, we describe the implementation of the study. After data preprocessing, we first input the CT image to CNN models for image classification training. In the image classification part, we first use one slice from every subject to perform the classification task. Second, we used three slices from every subject to perform the classification task. Then, with the image classification performance, we combined the CNN model that processes the CT scan image with the MLP model that processes two psychological information for training a multimodal model to check whether or not the psychological information can improve the brain atrophy classification performance. At last, we utilized the global average pooling layer of the ResNet50 model to generate a heatmap to explain the image classification feature attention.

To prevent data leakage in our dataset training, we split the dataset at the subject level. We divided it into training set and test set, and used the KFold function from the scikit-learn library during the training process to implement the cross-validation strategy to prevent overfitting.

B. Evaluation metrics

In this study, we use accuracy, precision, recall, and F1_score to evaluate the performance of the brain atrophy classification task.

VI. Performance

We carried out brain atrophy classification with the CT image, and then performed the classification by combining the CT image with the psychological information. At last, we visualized the heatmap for explaining feature attention in brain atrophy classification. The performance of the classification model is listed in Table I.

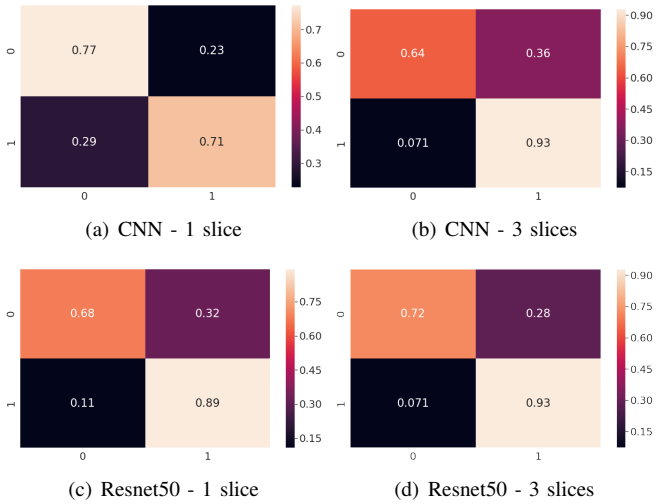
TABLE I
BRAIN ATROPHY CLASSIFICATION PERFORMANCE

Model	Input	Accuracy	Precision	Recall	F1_score
CNN	1	74.14%	74.25%	74.19%	74.13%
Resnet50	1	79.25%	80.38%	78.64%	78.76%
CNN	3	79.25%	81.58%	78.42%	78.48%
Resnet50	3	83.01%	84.39%	82.43%	82.62%
Multimodal	3 + 2 data	87.25%	91.58%	84.84%	88.08%

When we chose one slice from every patient case, the CNN model got 74.14% accuracy, while the ResNet50 pretrained model got 79.25% accuracy. When we chose three slices from every patient case, the model improved a lot. The pretrained ResNet50 model had better performance than the basic CNN model initiated from scratch. When we combined the CT image with the psychological information, such as depression status and suicidal thoughts, the multimodal model got the best performance, such as 87.25% accuracy.

A. Confusion Matrix

We checked the classification details by a confusion matrix. Fig. 2 presents the confusion matrices of the basic CNN model and the ResNet50 model. (a) shows the classification detail of the CNN model with one CT slice input. (b) shows the classification detail of the CNN model with three CT slices as input. (c) shows the classification detail of the pretrained ResNet50 model with one CT slice input. (d) shows the classification detail of the pretrained ResNet50 model with



(a) CNN - 1 slice (b) CNN - 3 slices

(c) Resnet50 - 1 slice (d) Resnet50 - 3 slices

Fig. 2. Confusion matrix

three CT slices as input. Here, the rows represent the true labels, while the columns represent the predicted values. A value of 0 indicates the patient does not have brain atrophy, and 1 indicates the presence of brain atrophy.

B. Visualization of the prediction of Model

We utilized the Grad-CAM to generate a heatmap to visually explain the image positions that affect the classification result. Fig. 3 shows one example of the heatmaps generated by the Grad-CAM methods. The left image is the original scan image used for classification. The right image is a heatmap overlay that combines feature attention gradients with the original image, highlighting the regions that most influenced the classification result. The images are from a patient diagnosed with brain atrophy. The key features influencing the prediction in the heatmap include ventricular enlargement and widening of the cortical sulci, which are both the main characteristic indicators of brain atrophy.

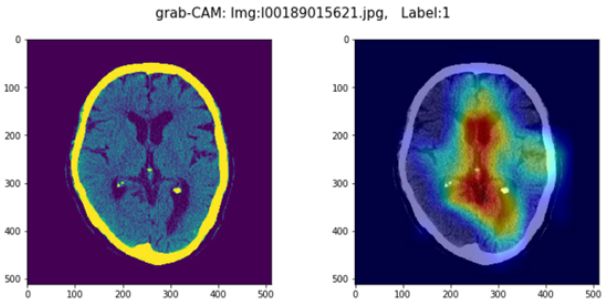


Fig. 3. Visual explanation

VII. Conclusion

This paper proposed a cerebral atrophy detection scheme for the clinical diagnosis of brain atrophy in a young group with depression using CT images. Both the CNN model and multimodal model could achieve a good performance for the brain atrophy detection. The visual explanation also supported the classification-capturing accurate characteristics. The brain atrophy detection scheme has strong potential for widespread clinical implementation. Due to their accessibility and routine use in clinical settings, utilizing CT images can address the limitations posed by the shortage of radiologists and enhance diagnostic efficiency. This approach may significantly improve the accuracy and practicality of brain atrophy diagnosis in everyday clinical practice. As future work, we will further validate our detection scheme using a larger and more diverse dataset. Additionally, we aim to optimize the model architecture to enhance its reliability and establish it as a robust reference for brain atrophy detection.

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References

[1] F. Zhang, B. Pan, P. Shao, P. Liu, S. Shen, P. Yao, and R. X. Xu, "An explainable two-dimensional single model deep learning approach for alzheimer's disease diagnosis and brain atrophy localization," 2021.

[2] N. Opel, R. Redlich, P. Zwanzger, D. Grotegerd, V. Arolt, W. Heindel, C. Konrad, H. Kugel, and U. Dannlowski, "Hippocampal atrophy in major depression: a function of childhood maltreatment rather than diagnosis?" *Neuropsychopharmacology*, vol. 39, no. 12, pp. 2723–2731, Nov 2014. [Online]. Available: https://doi.org/10.1038/npp.2014.145

[3] Koolschijn, P. C. M. P., van Haren N. E. M., Lensvelt-Mulders, G. J. L. M., H. E. H. Pol, and Kahn, "Brain volume abnormalities in major depressive disorder: A meta-analysis of magnetic resonance imaging studies." *Human Brain Mapping*, vol. 17, no. 30, pp. 3719–3735, 2009.

[4] Z. LQ, W. JY, Y. SY, W. GG, W. Q, D. YB, W. XL, C. XW, and D. CF, "Artificial intelligence in medical imaging of the liver." *World J Gastroenterol*, vol. 10, no. 25, pp. 672–682, 2019.

[5] A. Kaipainen, J. Pitkänen, F. Svärd, O. Jääskeläinen, H. Jokinen, S. Melkas, T. Erkinjuntti, R. Vanninen, A. Koivisto, J. Lötjönen, J. Koikkalainen, S.-K. Herukka, and V. Julkunen, "A novel ct-based automated analysis method provides comparable results with mri in measuring brain atrophy and white matter lesions," *Neuroradiology*, vol. 63, pp. 1–12, 12 2021.

[6] X. W. Gao, R. Hui, and Z. Tian, "Classification of ct brain images based on deep learning networks," *Computer Methods and Programs in Biomedicine*, vol. 138, pp. 49–56, 2017. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0169260716305296

[7] Y. J. Lee, S. Kim, A. R. Gwak, S. J. Kim, S.-G. Kang, K.-S. Na, Y.-D. Son, and J. Park, "Decreased regional gray matter volume in suicide attempters compared to suicide non-attempters with major depressive disorders," *Compr Psychiatry*, vol. 67, pp. 59–65, Mar. 2016.

[8] M. Banasr, J. M. Dwyer, and R. S. Duman, "Cell atrophy and loss in depression: reversal by antidepressant treatment," *Curr. Opin. Cell Biol.*, vol. 23, no. 6, pp. 730–737, Dec. 2011.

[9] R. R. Selvaraju, M. Cogswell, A. Das, R. Vedantam, D. Parikh, and D. Batra, "Grad-cam: Visual explanations from deep networks via gradient-based localization," *International Journal of Computer Vision*, vol. 128, no. 2, p. 336–359, Oct. 2019. [Online]. Available: http://dx.doi.org/10.1007/s11263-019-01228-7