

Accurate Brain Age Prediction Through Advanced Preprocessing and 3D ResNet-50 Modeling

Ting-An Chang

Department of Electrical Engineering, National Yunlin University of Science and Technology, Yunlin, Taiwan

Chiang-Ming Yeh

Department of Electrical Engineering, National Yunlin University of Science and Technology, Yunlin, Taiwan

Chun-Liang Liu

Department of Electrical Engineering, National Yunlin University of Science and Technology, Yunlin, Taiwan

E-mail: changta@yuntech.edu.tw, M11212035@yuntech.edu.tw, clliu@yuntech.edu.tw

Abstract

Accurate brain age prediction from structural magnetic resonance imaging (MRI) holds significant potential for advancing our understanding of the aging process and its effects on neural structures. In this paper, a robust preprocessing pipeline and two state-of-the-art 3D convolutional neural network architectures, 3D ResNet-50 and 3D DenseNet-121, were employed to develop and evaluate a brain age prediction model. The preprocessing steps included skull removal, spatial normalization to the Montreal Neurological Institute (MNI) template, and brain tissue segmentation into gray matter (GM), white matter (WM), and cerebrospinal fluid (CSF). These steps ensured consistency and accuracy in the input data. The experimental results demonstrated that the 3D ResNet-50 architecture achieved superior performance, with a mean absolute error (MAE) of 3.9 for individuals over 50 years of age, surpassing the MAE of 4.1 achieved by the 3D DenseNet-121 model. These findings validate the efficacy of the proposed preprocessing pipeline and highlight the critical role of tailored deep learning architectures in brain age prediction. Future research could further enhance prediction accuracy by integrating multimodal imaging data and exploring hybrid model architectures.

Keywords: brain age prediction; magnetic resonance imaging; 3D ResNet; 3D DenseNet; preprocessing.

1. Introduction

The emergence of machine learning techniques has enabled the automatic prediction of diseases from medical imaging data [1], [2], [3]. With the recent advancements in deep learning, prediction accuracy has been elevated to levels that, in some scenarios, surpass human performance. These advancements have been recognized as valuable tools in assisting clinical diagnosis and treatment decision-making processes.

Structural magnetic resonance imaging (MRI) studies have demonstrated that profound neuroanatomical changes are experienced by the brain during normal development and aging. It has been observed that global gray matter volume decreases linearly with age, while regional gray matter is affected in a more heterogeneous manner. Significant reductions in gray matter volume have been identified in the frontal and parietal lobes, as well as in certain regions of the temporal lobe. However, non-linear patterns of age-related changes have been reported in specific subcortical regions, such as the caudate and hippocampus.

In addition, age-related alterations at the network level have been detected through structural MRI studies. More

recently, efforts to estimate brain age using structural MRI data have been increasingly pursued. These efforts are regarded as essential for advancing the understanding of the relationship between brain morphometry and brain-predicted age, offering deeper insights into the aging process and its effects on neural structures.

2. Datasets and Feature Statistics

In this paper, T1-weighted magnetic resonance images (MRIs) were collected from individuals with normal cognitive function to construct a comprehensive and representative brain age prediction model. To ensure a diverse and inclusive sample of healthy brain structures spanning multiple age groups, T1-weighted images were meticulously selected from three widely recognized neuroimaging databases: the Alzheimer's Disease Neuroimaging Initiative (ADNI) [4], Information eXtraction from Images (IXI), and Cambridge Centre for Ageing and Neuroscience datasets (Cam-CAN). Each of these databases contributed data that were critical to the creation of a model that could account for the structural nuances of the brain across a broad spectrum of life stages.

A total of 769 T1-weighted images were obtained from the ADNI database, comprising cognitively normal

elderly participants with a mean age of 72.46 years and a standard deviation of 6.89 years. These images were essential in providing insights into the normal aging process, allowing the study to explore structural changes in the brain that occur in older adults. Meanwhile, the IXI database contributed 275 T1-weighted images from healthy British adults, with an average age of 63.45 years and a standard deviation of 7.68 years. This set of data offered a crucial perspective on the structural characteristics of the middle-aged brain, bridging the gap between youthful development and the aging process. Additionally, the addition of the Cam-CAN dataset helps create a more continuous age range between these age groups. Cam-CAN provided T1-weighted images of 379 subjects with a mean age of 68.32 years and a standard deviation of 10.50 years. These scans proved invaluable for studying typical brain development during adolescence and early adulthood.

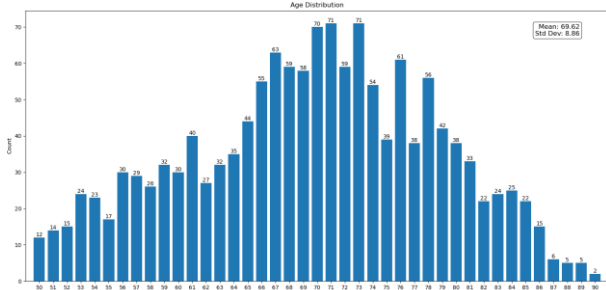


Figure 1. Age distribution of the collected datasets.

The combination of the ADNI, IXI, and Cam-CAN neuroimaging databases ensured that the sample focused exclusively on the older adult age range, capturing a comprehensive representation of late-life stages. This approach facilitated the inclusion of diverse brain structures across various life stages, significantly enhancing the robustness of the resulting brain age prediction model. In total, 1423 T1-weighted image datasets were sourced from these three databases as shown in Figure 1, providing a solid and diverse foundation for the modeling and analysis of brain development and aging trajectories.

3. Proposed System

3.1. Data Preprocessing

The initial step involved the removal of the skull from the original T1-weighted magnetic resonance images. This skull removal process was performed to eliminate non-brain tissue, which could interfere with the subsequent analysis, thereby increasing the accuracy and reliability of the study's results. After completing the skull removal, next use ANTs for rigid registration to align the images to the template `mni_icbm152_t1_tal_nlin_sym_09a.nii`. This template is a high-precision standard brain template designed for standardized processing in neuroimaging studies. This template originates from the Montreal Neurological

Institute (MNI) and was developed by the International Consortium for Brain Mapping (ICBM). It was generated based on T1-weighted MRI data from 152 healthy adult volunteers aged 20 to 50 years. The template has a resolution of 1 mm and dimensions of $189 \times 197 \times 233$, which helps ensure spatial consistency of brain images from different subjects. The use of rigid registration helps avoid unnecessary stretch deformation and aligns images more precisely, thereby improving the accuracy and stability of inter-individual comparisons.

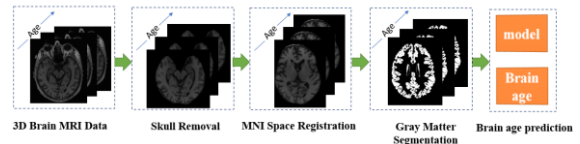


Figure 2. Proposed system flow chat.

Following the completion of spatial normalization, the Statistical Parametric Mapping version 12 (SPM12) software was employed to perform brain tissue segmentation. This step allowed the brain images to be precisely divided into three key tissue types: Gray Matter (GM), White Matter (WM), and Cerebrospinal Fluid (CSF). The segmentation process was carried out with high precision, enabling the extraction of distinct brain tissue components. This approach facilitated a more detailed and nuanced analysis, allowing for the independent investigation of different brain structures. By segmenting the brain into GM, WM, and CSF, more subtle neural structural information could be captured, providing deeper insights into the complexities of brain anatomy.

These Preprocessing techniques, including skull removal, spatial normalization, and tissue segmentation, laid the foundation for a more accurate and detailed analysis of brain structure. The input data were prepared in a way that maximized the reliability and precision of the brain age prediction model.

3.2. Accurate Brain Age Prediction Algorithm Design

Following the completion of Preprocessing and tissue segmentation of the brain images, we will focus on using gray matter (GM) images to train the 3D ResNet-50 model. The proposed system flow chat as shown in Figure 2. The reason for choosing the ResNet-50 architecture is that its effectiveness in processing high-dimensional medical imaging data has been widely proven. Its densely connected design not only facilitates the efficient transfer and reuse of features, but also effectively learns rich feature representations and captures complex spatial features inside the brain, thereby enhancing the performance capabilities of the model.

In the model training stage, the input gray matter image is extracted by 3D ResNet-50 [5], and then further processed through a fully connected layer, and finally a floating-point number is generated, representing the

model's predicted value of the subject's brain age. The loss function of the model is the Mean Absolute Error (MAE). This method can intuitively measure the accuracy of the model prediction by calculating the mean absolute difference between the predicted age and the actual age.

$$MAE = \frac{1}{N} \sum_{i=1}^N |y_i - \hat{y}_i| \quad (1)$$

Where N is the number of samples, y_i is the actual age, \hat{y}_i is the model predicted age.

During the model training process, the Adam optimizer is used for training. The final learning rate is 0.001, the weight attenuation is $1e-6$, and the epochs are 500. In terms of hardware configuration, the model is trained on the NVIDIA A100 GPU, ensuring high performance and efficiency of the operation.

4. Experimental results

To validate the accuracy of the proposed preprocessing method and model for predicting brain age, two 3D convolutional neural network architectures, 3D DenseNet-121 [6] and 3D ResNet-50, were selected for experimentation and comparative analysis. The selection of 3D ResNet-50 was informed by its residual learning capabilities, which have been demonstrated to effectively capture early age-related features of brain structure and enable the accurate learning of subtle, age-specific structural changes. The 3D DenseNet-121 architecture was chosen for its dense connection design, which facilitates the efficient transfer and reuse of features, providing notable advantages in detecting fine variations in brain structure.

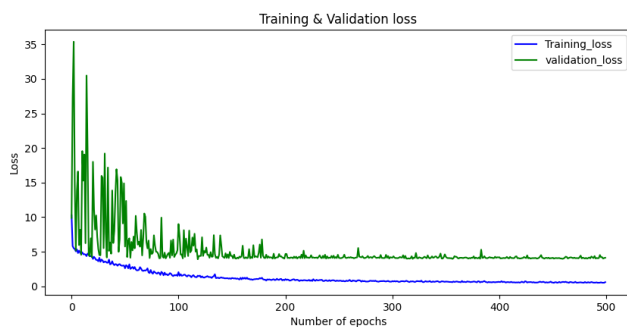


Figure 3. Mean absolute error performance of 3D ResNet-50

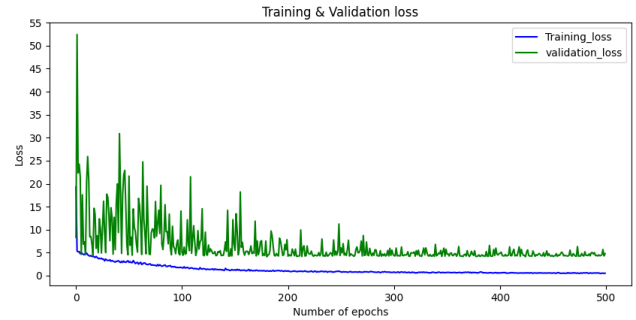


Figure 4. Mean absolute error performance of 3D DenseNet-121

The accuracy of the Preprocessing method and the 3D ResNet-50 architecture in predicting brain age was assessed through a series of experiments. For individuals over 50 years of age, it was observed that 3D ResNet-50 achieved a mean absolute error (MAE) of 3.9, indicating excellent predictive performance as shown in Figure 3.

To obtain a more comprehensive evaluation of the model's capabilities, a comparative analysis was conducted between 3D ResNet-50 and 3D DenseNet-121, another commonly used 3D convolutional neural network. For the same age group, 3D DenseNet-121 was found to achieve an MAE of 4.1 as shown in Figure 4. These experimental results demonstrated that 3D ResNet-50 significantly outperformed 3D DenseNet-121, exhibiting superior stability and accuracy in its predictions for individuals over 50 years of age.

5. Conclusions

In this paper, a comprehensive approach was developed and validated for brain age prediction using advanced preprocessing methods and two state-of-the-art 3D convolutional neural network architectures: 3D ResNet-50 and 3D DenseNet-121. The experimental results demonstrated the superior performance of 3D ResNet-50, particularly in predicting brain age for individuals over 50 years of age. The MAE of 3.9 was achieved by 3D ResNet-50, surpassing the MAE of 4.1 obtained by 3D DenseNet-121. These findings underscore the effectiveness of residual learning in capturing early and subtle age-related changes in brain structure, contributing to more stable and accurate predictions. This work provides a foundation for further research in brain age prediction, with potential applications in understanding the relationship between brain morphometry and biological aging. Future studies may explore integrating multimodal imaging data or employing hybrid deep learning models to enhance prediction accuracy and extend these findings to clinical and neurological applications.

Acknowledgment

The study was funded by National Science and Technology Council of Taiwan and National Yunlin University of Science and Technology, grant numbers: NSC 113-2221-E-224-042-.

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Dr. Chun-Liang Liu



He currently holds the position of Assistant Professor at the National Yunlin University of Science & Technology. His research interests include power electronics and battery management systems.

Authors Introduction

Dr. Ting-An Chang



He is an Assistant Professor of Electrical Engineering at the National Yunlin University of Science and Technology in Taiwan. He received his PhD degree in the Institute of Computer and Communication Engineering from National Cheng Kung University in 2018. His research interests smart healthcare and computer vision.

Mr. Chiang-Ming Yeh



He received his B.S. degree in Engineering in 2023 from Ming Chi University of Technology in Taiwan. He is acquiring an M.E. in National Yunlin University of Science and Technology.