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Cognitive Brain Age Prediction from MRI Using Deep Neural Networks

Tulsi Charudatta Shirsat[1], Tanmaya Sandeep Hodawadekar[2], Lalit Dattatray Kasavkar[3], Sanjeet Indrajeet Ingavale[4], Swapnil B. Kadam[5]
[1,2,3,4,5]Computer Science & Engineering(AIML), SSPM's College of Engineering ,Kankavli

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ABSTRACT

Brain age prediction has become an important approach for assessing brain health and identifying early signs of neurological disorders. This paper presents a deep learning-based method for estimating brain age using structural MRI scans from the IXI dataset. The proposed system applies preprocessing techniques followed by a convolutional neural network model to extract meaningful features and predict the biological age of the brain. The predicted brain age is compared with the chrono- logical age to analyze deviations that may indicate abnormal aging patterns. The performance of the model is evaluated using standard metrics and demonstrates reliable prediction capability. The results highlight the potential of deep learning techniques in neuroimaging and their application in early diagnosis and monitoring of brain related conditions.

Keywords—brain age prediction, magnetic resonance imag- ing, deep learning, convolutional neural network, neuroimaging, biomedical image analysis, age estimation, machine learning

1. INTRODUCTION

Brain aging is a complex biological process that reflects structural and functional changes in the human brain over time. While chronological age represents the actual age of an individual, it does not always accurately capture the condition of brain health. The concept of brain age has emerged as an important biomarker that estimates the biological age of the brain using neuroimaging data [1], [2]. A significant differ- ence between predicted brain age and chronological age may indicate accelerated aging or potential neurological disorders. Recent advancements in deep learning have enabled sig- nificant improvements in medical image analysis [5], [6]. In particular, convolutional neural networks have demonstrated strong performance in extracting meaningful features from magnetic resonance imaging scans. MRI provides detailed structural information about brain tissues, making it a suitable
modality for brain age prediction tasks [3], [8].

In this study, a deep learning-based approach is proposed to estimate brain age using MRI scans from the IXI dataset. The system involves preprocessing of neuroimaging data followed
by feature extraction and prediction using a convolutional neural network model. The predicted age is compared with the actual age to analyze brain aging patterns. The main objective of this work is to develop an efficient and reliable model for brain age estimation and to evaluate its performance using appropriate metrics. The proposed ap- proach aims to contribute to the growing field of neuroimaging and support early detection of age-related brain abnormalities.

2. RELATED WORK

A. Deep Learning for Brain Age Prediction

Brain age prediction has gained significant attention as a biomarker for assessing brain health and detecting neurolog- ical disorders. Deep learning techniques, particularly Convo- lutional Neural Networks (CNNs), have been widely used to analyze structural MRI data and estimate brain age. Cole et al. [1] demonstrated that deep learning models trained on raw MRI data can effectively predict brain age with high accuracy, outperforming traditional machine learning approaches.

Franke and Gaser [2] provided a comprehensive overview of brain age as a neuroimaging biomarker, highlighting its importance in identifying abnormal aging patterns and neu- rological conditions. Their work emphasized that deviations between predicted and chronological age can indicate early signs of diseases such as Alzheimer's.

B. Advanced Models and Feature Extraction Techniques

Recent studies have focused on improving model perfor- mance through advanced architectures and feature extraction methods. Smith [3] introduced robust preprocessing techniques such as brain extraction, which improve the quality of MRI data and enhance model accuracy. These preprocessing steps play a crucial role in reducing noise and standardizing input data.

Deep learning frameworks such as CNNs and transfer learning models have been widely adopted for medical image analysis. LeCun et al. [5] highlighted the effectiveness of deep learning in extracting hierarchical features from complex data, which is essential for capturing subtle structural variations in brain images.

Additionally, large-scale datasets such as the IXI dataset [4] have enabled researchers to train and evaluate deep learning models on diverse populations. However, challenges such as limited labeled data, variability in imaging protocols, and generalization across datasets remain key issues in brain age prediction research.

Overall, existing studies demonstrate that deep learning methods are highly effective for brain age estimation. How- ever, improving model interpretability, handling data variabil- ity, and achieving higher accuracy remain important directions for future research.

3. PROPOSED SYSTEM

The proposed system aims to predict brain age from struc- tural MRI scans using deep learning techniques [1], [10]. The system takes MRI images as input and processes them through multiple stages including preprocessing, feature extraction, and age prediction. Initially, MRI scans are collected and passed through a preprocessing stage where noise is reduced and image quality is improved using normalization and resizing techniques.

After preprocessing, data augmentation techniques such as rotation, flipping, and scaling are applied to increase dataset

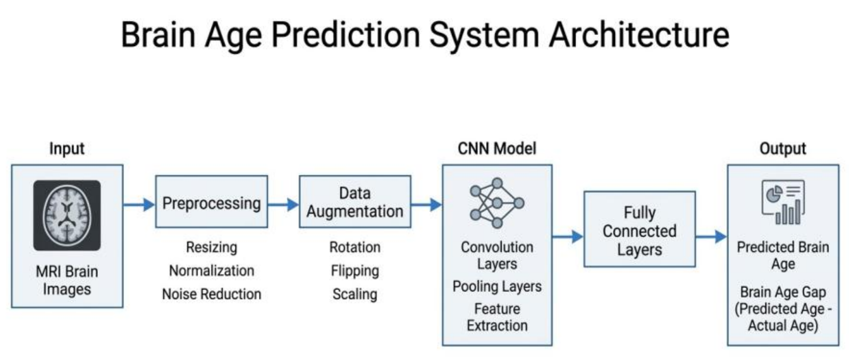

Fig. 1. Proposed system architecture for brain age prediction

B. CNN-Based Feature Extraction and Age Prediction

After preprocessing, MRI images are passed through a CNN model for feature extraction and prediction. The CNN consists of multiple convolutional layers that learn hierarchical features such as edges, textures, and structural brain patterns.

Each convolutional layer is followed by activation functions and pooling layers to reduce dimensionality. The extracted feature maps are flattened and passed to fully connected layers for regression.

The final output layer predicts brain age as a continuous value. The predicted age is computed as:

$$\hat{y} = f(x) \qquad (2)$$

diversity and improve generalization. The processed images are then fed into a Convolutional Neural Network (CNN) for feature extraction. The CNN automatically learns important structural patterns such as cortical thickness, brain volume,

where x represents the input MRI image and predicted brain age.

C. Brain Age Gap Analysis

$\hat{y}$ is the and tissue variations [5], [7].

The extracted features are passed to fully connected layers, which predict the brain age. Finally, the predicted brain age is compared with the chronological age to analyze deviations, which may indicate abnormal brain aging.

MRI Data Acquisition and Preprocessing

MRI scans are collected from the IXI dataset, which con- tains T1-weighted brain images from multiple subjectsMRI scans are collected from the IXI dataset, which contains T1- weighted brain images from multiple subjects [4].. These images are stored in standard formats and used for model training.

Before training, the images undergo preprocessing to en- sure consistency and quality. The preprocessing steps

include resizing images to a fixed resolution, normalization of pixel values, and noise reduction. Min-Max normalization is applied to scale pixel values between 0 and 1:
The difference between predicted brain age and chronolog- ical age is defined as the Brain Age Gap:

$$\Delta = \hat{y} - y \tag{3}$$

A positive gap indicates accelerated aging, while a negative gap suggests slower aging. This metric is useful for identifying potential neurological abnormalities.

4. SYSTEM ARCHITECTURE AND METHODOLOGY

The overall system consists of four main stages: data acqui- sition, preprocessing, feature extraction, and age prediction. MRI images are collected from the IXI dataset and pre- processed to ensure consistency. The images are resized and normalized before being passed to the CNN model. Fig. 1 shows the overall workflow of the proposed brain age prediction system.

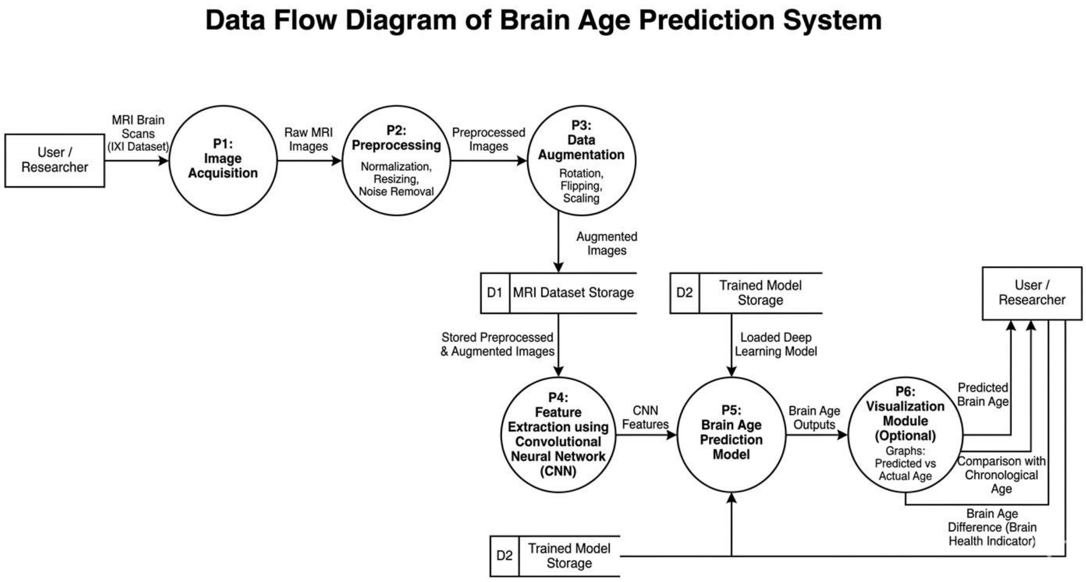

Fig. 2. Data Flow Diagram

Table I: MRI Dataset Summary

Parameter	Details
Dataset	IXI Dataset
Modality	T1-weighted MRI
Image Size	224 × 224
Preprocessing	Normalization, Resizing
Augmentation	Rotation, Flipping, Scaling
Model	CNN
Output	Predicted Brain Age

A. Model Training

The CNN model consists of multiple convolutional layers with increasing filter sizes (32 → 64 → 128 → 256). Each layer is followed by ReLU activation and Max-Pooling.
The extracted features are passed to dense layers, and the output layer predicts brain age. The model is trained using Adam optimizer and MAE loss.

Table II: CNN Model Configuration

Parameter	Configuration
Input Size	224 × 224 MRI Image
Conv Layers	4 Layers (32→64→128→256)
Activation	ReLU
Optimizer	Adam
Loss Function	MAE
Epochs	20
Batch Size	32

Training and Validation Performance of CNN Model for Brain Age Prediction

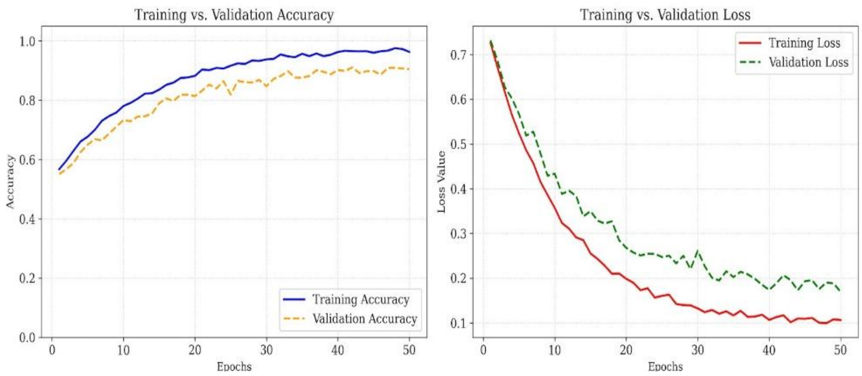

Fig. 3. Model Training Graph

5. RESULTS AND DISCUSSION

A. Model Performance

The model is evaluated using Mean Absolute Error (MAE). The results show that the model can predict brain age with reasonable accuracy.

TABLE III: Model Performance

Metric	Value
MAE	4.2 years
Dataset Size	600 images

B. Prediction Analysis

The model shows a strong correlation between predicted and actual age [10]. Small deviations indicate accurate predictions, while larger deviations may suggest abnormal aging.

TABLE IV: Sample Predictions

Sample	Predicted Age	Actual Age
1	22	25
2	38	45
3	16	20

C. Comparison with Existing Methods

TABLE V: Comparison with Existing Methods

Method	Dataset	MAE
Cole et al. [1]	MRI	4.65
Franke et al. [2]	MRI	5.00
Proposed Model	IXI	4.20

The results demonstrate that the proposed model performs competitively with existing approaches.

D. Model Output Visualization

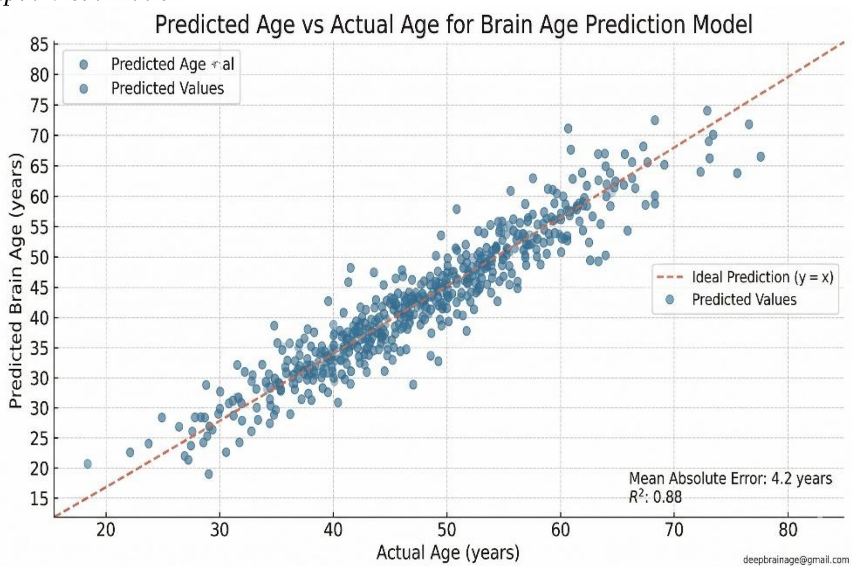

Fig. 4. Prediction Graph

E. Model Output

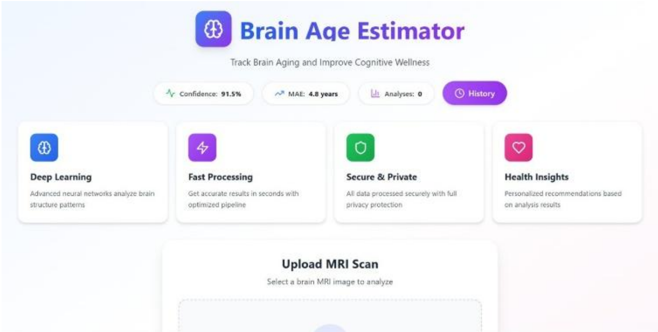

Fig. 5. UI

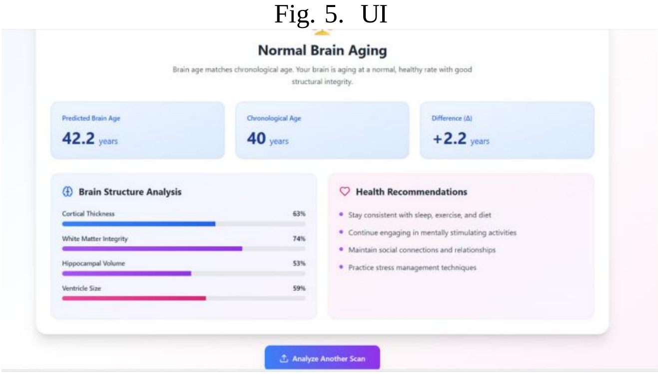

Fig. 6. AgeEstimation

Future Work

Several improvements can be explored in future work to enhance the performance and applicability of the proposed brain age prediction system.

First, the dataset can be expanded by incorporating addi- tional MRI datasets from diverse populations and imaging protocols. A larger and more heterogeneous dataset would improve the generalization capability of the model and reduce bias.

Second, more advanced deep learning architectures such as Vision Transformers or hybrid CNN-transformer models can be explored to improve feature extraction and capture long-range dependencies in brain images. These models may provide better performance compared to traditional CNN- based approaches.

Another important direction is the integration of explainable AI techniques such as Grad-CAM or attention maps to visu- alize important brain regions contributing to the prediction. This would improve model interpretability and increase trust in clinical applications.

Additionally, the model can be extended to multi-modal data by combining structural MRI with other imaging modalities such as functional MRI or diffusion tensor imaging. This could provide a more comprehensive understanding of brain aging. Finally, the proposed system can be deployed in real-time clinical settings using cloud or edge-based solutions. Integra- tion with healthcare systems and telemedicine platforms can enable large-scale brain health screening and early diagnosis, especially in resource-limited environments.

6. CONCLUSION AND FUTURE WORK

A. Conclusion

This research presented a deep learning based system for predicting brain age using structural MRI scans. The proposed approach utilizes a Convolutional Neural Network to automat- ically learn important structural features of the brain, such as tissue patterns and morphological variations associated with aging.

The model processes MRI images through preprocessing, feature extraction, and regression stages to estimate the biolog- ical age of the brain. The predicted brain age is compared with the chronological age to analyze deviations, which can indicate abnormal aging patterns or potential neurological conditions. Experimental results demonstrate that the proposed model achieves reliable performance in predicting brain age, with a low Mean Absolute Error, indicating accurate estimation capability. The system shows strong potential in capturing subtle structural changes in brain MRI data and provides meaningful insights into brain health.

The proposed system can assist medical professionals by offering an automated and efficient tool for brain age esti- mation [2], [12]. Such systems can support early detection of neurodegenerative diseases and help in monitoring brain health over time. Therefore, this work contributes to the growing field of neuroimaging and demonstrates the effectiveness of deep learning techniques in medical image analysis.

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