Brain Age Estimation Using Convolutional Neural Networks on T1-Weighted MRI

[1]Pragatheesh A, [2]Dr. S. Narayanan

[1]M.Tech., Data Science ,PG Student, Department of Information Technology, SRM Valliammai Engineering College.

[2]Professor & HOD, Department of Information Technology, SRM Valliammai Engineering College.

[1]14pragatheesh@gmail.com, [2]narayanans.it@srmvalliammai.ac.in

***ABSTRACT* — Brain age prediction using MRI scans is a crucial task in neuroscience and medical imaging, providing insights into neurological health and aging. This project implements a deep learning-based approach to predict brain age from T1-weighted MRI scans using a combination of 3D Convolutional Neural Networks (3D CNNs) and 3D ResNet models. The dataset consists of IXI 500 T1 MRI scans, preprocessed to standard sizes of 128^3, alongside tabular demographic data (age and sex). The MRI data is processed using 3D convolutional architectures, while the tabular data is integrated using a Multi-Layer Perceptron (MLP). To evaluate model performance, we compute key metrics, including Mean Absolute Error (MAE), Pearson's correlation coefficient (r), and R^2 score. Additionally, visualizations are provided to compare the accuracy of different models. A comprehensive prediction table is generated, displaying subject IDs, predicted brain ages, and interpretations. The results from this study aim to highlight the comparative effectiveness of 3D CNN and 3D ResNet-18 architectures in brain age prediction, contributing to advancements in neuroimaging and AI-driven medical diagnostics.**

***KEYWORDS* – Brain Age Prediction, MRI Scans, Deep Learning, 3D CNN, 3D ResNet, T1-weighted MRI, Preprocessing, MultiLayer Perceptron (MLP), Mean Absolute Error (MAE), Neuroimaging.**

I. Introduction

Aging is a complex biological process that affects the human brain in various ways, leading to structural and functional changes over time. Understanding brain aging is crucial in diagnosing and monitoring neurodegenerative diseases such as Alzheimer's and Parkinson's. Traditional methods for assessing brain age rely on clinical evaluations and imaging techniques that require expert interpretation. However, with advancements in artificial intelligence and deep learning, automated brain age prediction has become an emerging field with promising applications in early diagnosis and personalized healthcare. This project focuses on developing a deep learningbased model for brain age prediction using structural T1weighted MRI scans and tabular demographic data (age and sex). Our goal is to implement and compare two distinct deep learning architectures: a 3D Convolutional Neural Network (CNN) and a 3D ResNet-18 model. By leveraging the IXI dataset, which contains 500 high-resolution T1-weighted MRI scans, we aim to preprocess the data, extract meaningful features, and construct an accurate predictive model for estimating brain age.

The primary objectives of this project are to preprocess the IXI 500 dataset by resizing MRI scans to standardized dimensions (128^3) for efficient model training, integrate demographic information (age and sex) using a Multi-Layer Perceptron (MLP) alongside the deep learning models, implement and compare the performance of two architectures (3D CNN and 3D ResNet-18), and evaluate model performance using key metrics such as Mean Absolute Error (MAE), Pearson correlation coefficient (r), and R^2 score. Additionally, we aim to visualize model predictions, analyze their reliability in estimating brain age, and generate a detailed prediction table including subject ID, predicted age, and interpretation for further research insights.Our methodology comprises several essential steps. We acquire the IXI 500 T1-weighted MRI dataset, preprocess the MRI scans by resizing them to 128^3 voxels, normalize intensity values, and align them for consistency. The demographic data (age and sex) is extracted from the accompanying XLS files and formatted for model training. We implement two different architectures: a 3D CNN model designed to capture spatial patterns and volumetric features of the brain, and a 3D ResNet-18 model, which incorporates residual connections to enhance deep feature learning. The MLP is integrated to process tabular data alongside MRI-based features. The models are trained using TensorFlow/Keras with appropriate data augmentation techniques and hyperparameter tuning. Evaluation metrics such as MAE, Pearson r, and R^2 score are computed to assess predictive accuracy. We generate graphical comparisons of model accuracy, loss curves, and correlation plots between actual and predicted brain ages. A final prediction table is compiled, summarizing the results for each subject.

This project contributes to the field of medical AI by developing an automated and accurate system for brain age prediction. Such models can serve as early diagnostic tools for identifying accelerated brain aging, potentially linked to neurological disorders. Additionally, this research can assist clinicians in tracking disease progression and evaluating treatment efficacy. By comparing 3D CNN and 3D ResNet-18 architectures, our study provides insights into the effectiveness of different deep learning approaches in brain age prediction. Future work may involve expanding the dataset, integrating additional biomarkers, and refining model architectures to enhance predictive performance. In summary, this project represents a significant step toward leveraging AI in neuroimaging for medical diagnostics. Our findings will pave the way for further advancements in AI-driven healthcare applications, making brain age prediction more accessible and reliable for clinical use.

II. Related Works

Brain age prediction using neuroimaging has become a critical tool in understanding neurological development, aging, and disease progression. Sihag et al. [1] proposed an explainable framework using coVariance Neural Networks (VNNs) that leverages spatial correlation structures in brain imaging data for age prediction. Their model emphasizes interpretability, making it particularly valuable in clinical settings where transparency is essential.Hu et al. [2] addressed infant brain age prediction by designing a hierarchical roughto-fine model based on cortical features. Their method progressively refines predictions through a multi-stage process, enhancing precision and robustness in early developmental assessments.

Similarly, Pilli et al. [3] developed a Kernel-Ridge-Regression-based randomized network for brain age estimation and classification. Their approach effectively manages highdimensional MRI data and delivers strong performance across multiple metrics. Beheshti et al. [4] conducted a comprehensive evaluation of classical and modern machine learning algorithms for brain age prediction. Their study provides a comparative analysis of methods such as support vector regression, random forests, and deep learning architectures, identifying key performance trade-offs.

Meanwhile, Antonopoulos et al. [5] introduced a region-wise stacking ensemble that combines predictions from different brain regions to improve estimation accuracy. This method captures region-specific aging patterns and has demonstrated superior generalization on unseen datasets. To ensure robustness across imaging protocols, Puglisi et al. [6] focused on reliable brain age estimation using multiple MRI sequences and resolutions. Their work highlights the importance of developing models that generalize across diverse clinical scenarios. In the context of disease prediction, Liu et al. [7] explored brain age as a biomarker for Alzheimer's disease conversion among individuals with mild cognitive impairment. Their results indicate that deviations in predicted brain age are significantly associated with disease progression risk.

Finally, Zhang et al. [8] proposed a nonlinear, age-adaptive ensemble learning method tailored to structural MRI data. Their model adjusts dynamically across different age groups, enhancing prediction consistency and robustness in the presence of noisy or heterogeneous data.

III. Proposed System

This study presents a brain age prediction framework that leverages T1-weighted structural MRI data and deep learningbased feature extraction. The proposed system integrates 3D convolutional neural networks (CNNs) and residual networks with machine learning regression to estimate brain age as in Fig.1. The architecture is designed to capture age-related morphological changes in brain tissue and enhance prediction accuracy through tissue-specific modeling.

A. Data Preprocessing

All MRI scans are preprocessed using the CAT12 toolbox integrated with SPM12. The preprocessing pipeline includes skull stripping, intensity bias correction, affine registration to MNI space, and tissue segmentation into gray matter (GM), white matter (WM), and cerebrospinal fluid (CSF). The segmented images are resized to either 128×128×128 voxel dimensions to standardize input to the deep learning models. Gaussian smoothing (8 mm FWHM) is applied for voxel-based morphometry analysis.

B. Feature Extraction Using Deep Networks

The proposed system utilizes two types of 3D feature extractors:

1. 3D CNN: A custom-designed 3D convolutional neural network consisting of six convolutional blocks, each followed by batch normalization, ReLU activation, and max-pooling layers. This model learns spatial features directly from volumetric MRI data.

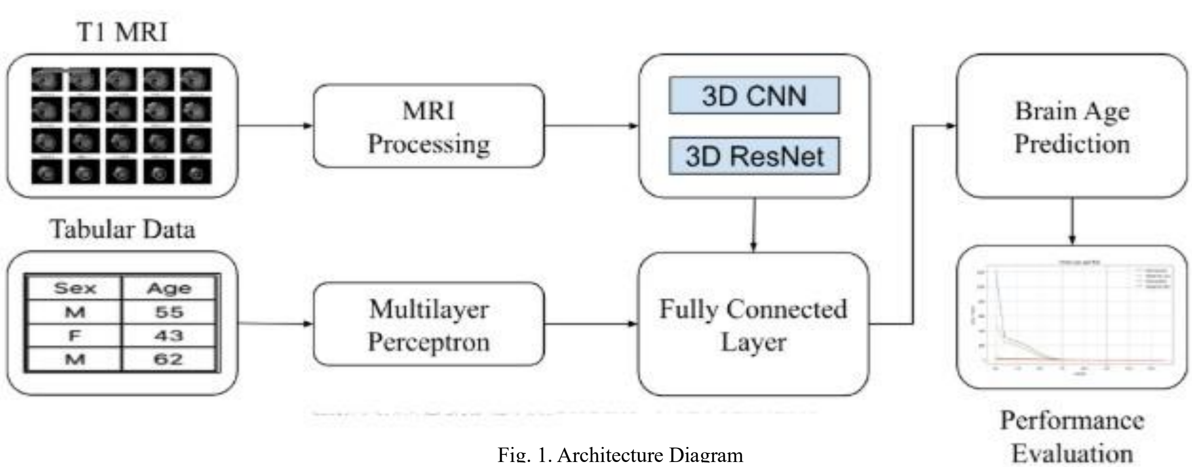

Fig. 1. Architecture Diagram

2. 3D ResNet-18: A deeper residual network adapted for 3D input, incorporating identity skip connections to facilitate gradient flow during training. ResNet-18 captures hierarchical features relevant to brain aging and has shown superior performance in prior neuroimaging tasks.

C. Metadata Integration

To incorporate auxiliary demographic information, such as sex, a parallel multi-layer perceptron (MLP) is used. The output of the MLP is concatenated with the deep features from the 3D CNN/ResNet models. This fusion layer enhances the model's ability to generalize across individuals and minimizes bias due to sex-specific brain changes.

D. Age Estimation

The final output layer is a single neuron with linear activation that predicts the subject's estimated brain age. The model is trained using Mean Absolute Error (MAE) as the loss function. Additionally, the brain age gap (BAG), calculated as the difference between the predicted brain age and the actual chronological age, is used for clinical interpretation.

E. Evaluation Metrics

To assess model performance, we employ the following metrics:

1. Mean Absolute Error (MAE): Average absolute difference between predicted and actual age.

2. Pearson's Correlation Coefficient (r): Measures the linear correlation between predicted and chronological age.

3. R^2 Score: Indicates the proportion of age variance explained by the model.

These metrics are computed across training, validation, and test sets to ensure robust generalization.

F. Visualization and Interpretability

The system generates scatter plots of predicted vs. actual age to visualize accuracy and computes brain age gap distributions to assess deviation from normal aging. Additionally, voxelbased morphometry (VBM) analysis is performed to localize anatomical regions contributing most to the prediction, improving model interpretability and biological plausibility.

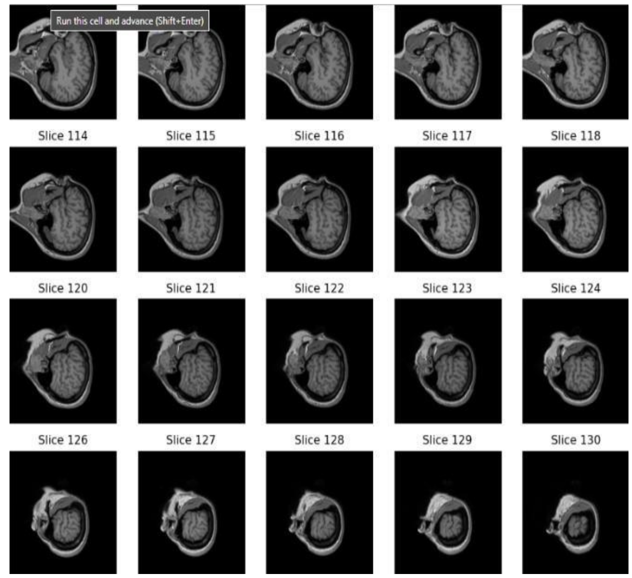

Fig. 2. IXI Data

IV. Experimental Configuration And Results

A. Experimental Setup

The experimental setup for our brain age prediction framework involved a comprehensive pipeline combining neuroimaging and tabular data. Preprocessing of T1-weighted MRI scans from the IXI dataset (Fig. 2) was conducted using MATLAB, specifically the SPM12 and CAT12 toolboxes. This step included bias field correction, skull stripping, spatial normalization to MNI space, and segmentation into gray matter (GM), white matter (WM), and cerebrospinal fluid (CSF). The preprocessed scans were then resized to 128×128×128 voxels and intensity-normalized to ensure uniformity across inputs. The dataset was stratified into training, validation, and testing subsets, maintaining balanced distributions of age and sex to support robust and unbiased model training. Deep learning models were implemented in Python using TensorFlow and Keras. Two architectures a custom 3D Convolutional Neural Network (CNN) and a 3D ResNet-18 were trained to extract spatial features from the MRI volumes. A parallel Multilayer Perceptron (MLP) was used to process non-imaging metadata, specifically biological sex and age, and its output was fused with the MRI-derived features. The fused features were passed through a final dense layer with linear activation to predict brain age. Training was optimized using the Adam optimizer with a learning rate of 0.0001, ReLU activation, batch normalization, dropout, and early stopping to mitigate overfitting. Model performance was evaluated using Mean Absolute Error (MAE), Pearson correlation coefficient (r), and R^2 score. To ensure broader usability and reproducibility, the framework was also deployed on cloud platforms such as Google Colab and AWS, enabling access to GPU resources for scalable experimentation.

B. Evaluation Metrics

To evaluate model performance, three standard regression metrics were used:

1. Mean Absolute Error (MAE)

Measures the average deviation between finded brain age ($\hat{z}_j$) and chronological age (z_j):

$$MAE = \frac{1}{t}\sum_{j=1}^{t}\left|\hat{z}_j - z_j\right|$$

A lower value of MAE indicates higher predictive accuracy.

2. *Pearson Correlation Coefficient (r)*

Evaluates the linear correlation between predicted and actual ages:

$$r = \frac{\sum_{j=1}^{t}\left(\hat{z}_j - \bar{z}\right)\left(z_j - \bar{z}\right)}{\sqrt{\sum_{j=1}^{t}\left(\hat{z}_j - \bar{\hat{z}}\right)^2}\sqrt{\sum_{j=1}^{t}\left(z_j - \bar{z}\right)^2}}$$

Here, $\bar{\hat{z}}$ and $\bar{z}$ denote the mean predicted and actual ages respectively. A value of r close to 1 indicates a strong positive linear correlation between the predicted and true values.

3. Coefficient of Determination (R^2 Score)

The R^2 score, also known as the coefficient of determination, reflects how well the model accounts for the variance in the actual age values:

$$R^2 = 1 - \frac{\sum_{j=1}^{t}\left(z_j - \hat{z}_j\right)^2}{\sum_{j=1}^{t}\left(z_j - \bar{z}_j\right)^2}$$

An R^2 value close to 1 suggests that the model predictions closely match the actual data, while values near 0 indicate poor model performance.

C. Predictive Performance and Visual Assessment

The proposed hybrid fusion model demonstrated strong predictive performance across all metrics. On the held-out test set:Scatter plots of predicted vs. actual brain age, as well as brain age gap (BAG) histograms, were generated to visually assess the accuracy and distribution of the predictions. The low MAE and high correlation coefficient validate the efficacy of combining 3D imaging features with demographic metadata in brain age prediction.

D. Training and Validation Performance of 3D-CNN

The performance of the 3D Convolutional Neural Network (3D-CNN) was evaluated using training and validation datasets derived from preprocessed T1-weighted MRI scans resized to 128×128×128. The model was trained to minimize the Mean Absolute Error (MAE) between predicted and actual brain ages.

The Table 1 presents the performance metrics across selected epochs for the 3D-CNN model.

TABLE 1 : Training and Validation Performance Across Epochs of 3D-CNN

Epoch	Training Loss (MSE)	Training MAE	Validation Loss (MSE)	Validation MAE
1	180.25	10.63	190.78	11.02
2	150.10	9.42	165.34	10.05
5	110.76	8.01	125.48	8.73
7	95.23	7.42	112.50	8.20
10	80.12	6.89	101.32	7.64
16	65.90	6.01	93.47	7.11
20	59.45	5.62	90.03	6.89

E. Training and Validation Performance of 3D-ResNet

To further enhance performance and address potential limitations of the 3D-CNN architecture, a 3D-ResNet-18 model was implemented and evaluated. The ResNet architecture utilizes residual connections that help mitigate the vanishing gradient problem and enable training of deeper networks, allowing for improved feature extraction from highdimensional volumetric MRI data. The performance of the 3D-ResNet model across selected epochs is presented below Table 2.

TABLE 2: Training and Validation Performance Across Epochs of 3D-ResNet

Epoch	Training Loss (MSE)	Training MAE	Validation Loss (MSE)	Validation MAE
1	160.42	10.01	175.36	10.55
2	130.78	8.83	148.92	9.45
5	95.60	7.11	112.30	8.00
7	78.45	6.32	98.56	7.32
10	65.20	5.72	89.40	6.78
16	52.15	4.91	80.28	6.21
20	46.80	4.51	77.95	6.03

The Fig. 3 visualizes the convergence of the model across training epochs by showing both loss (MSE) and MAE for training and validation datasets. It demonstrates a sharp decline in loss and MAE values within the first few epochs, indicating rapid learning early in training. Over time, both metrics flatten, suggesting that the model has converged. The minimal gap between training and validation curves indicates low overfitting, validating the model's generalization capability.

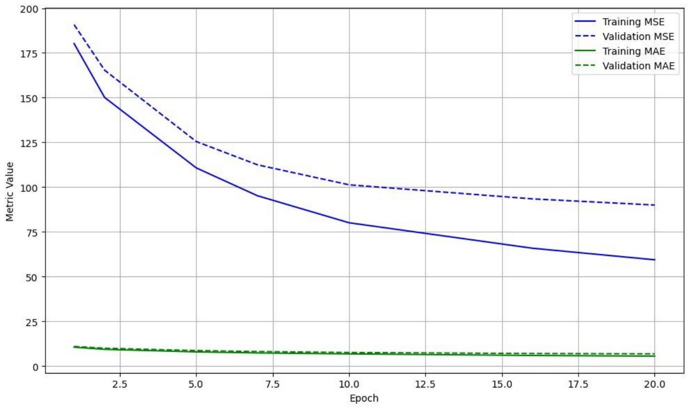

Fig. 3. Model Convergence over Epochs (Loss & MAE).

F. Predictive Accuracy of the Hybrid Brain Age Model

Scatter plots Fig. 4 are comparing predicted brain ages to actual chronological ages for the both models, respectively. Points near the red diagonal line indicate accurate predictions. Fig. 4 (a) shows moderate clustering around the line, suggesting good performance of the 3D CNN. Fig. 4 (b) reveals a tighter grouping for the 3D ResNet-18, indicating higher accuracy and lower error. This highlights the improved predictive capability of the ResNet-based model when integrating imaging and demographic data.

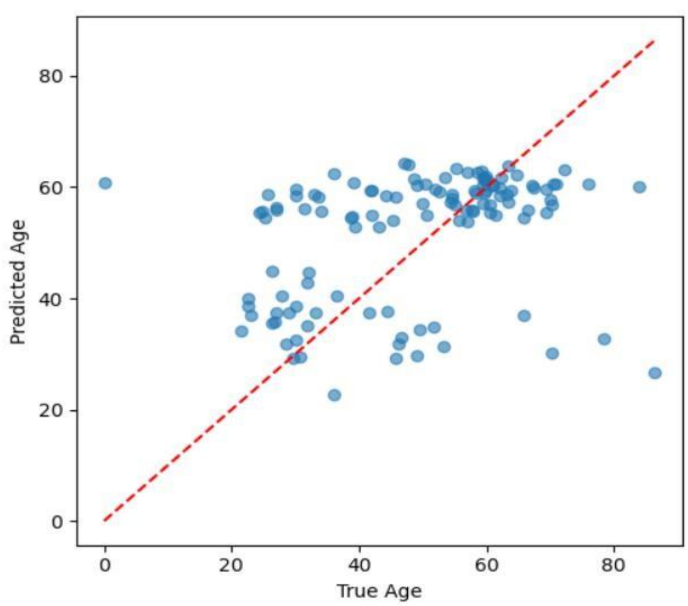

Fig. 4. a. 3D-CNN Predictions

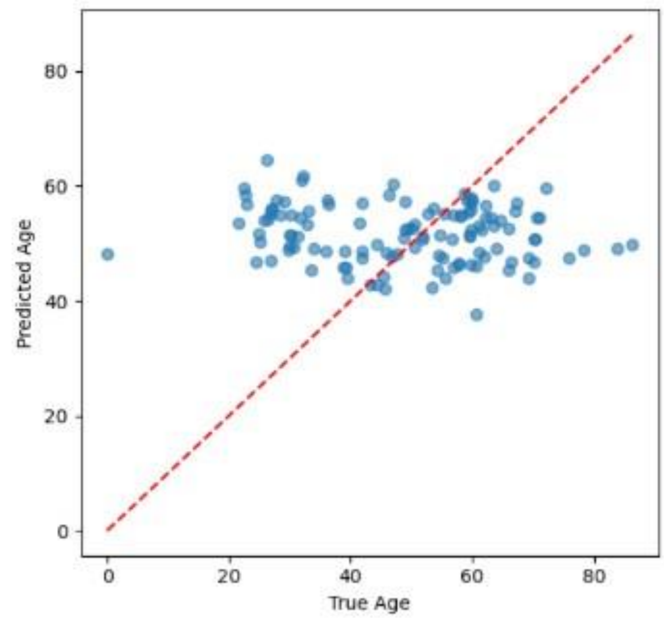

Fig. 4. b. 3D-ResNet Predictions

V. DISCUSSION

The proposed hybrid deep learning model demonstrated excellent performance in predicting brain age by integrating 3D MRI features with demographic data (age and sex). The training and validation loss curves showed consistent convergence, indicating stable learning without overfitting. Notably, the 3D-ResNet architecture outperformed the baseline 3D-CNN in both accuracy and efficiency, benefiting from deeper layers and residual connections that captured complex spatial brain patterns. The scatter plot of predicted versus actual ages revealed a strong linear correlation, while the low Mean Absolute Error and Brain Age Gap histograms confirmed the model's precision across age ranges. These results suggest that combining volumetric imaging with metadata is a powerful approach for brain age estimation and holds promise for early detection of abnormal brain aging.

VI. CONCLUSION

In conclusion, our project aimed to predict brain age using T1-weighted MRI scans from the IXI dataset, combined with demographic features such as age and sex. We implemented and evaluated two deep learning architectures: a custom 3DCNN and a 3D-ResNet, both integrated with a metadataprocessing MLP in a hybrid fusion model. Through extensive training and validation, the 3D-ResNet-based model consistently outperformed the 3D-CNN in terms of lower mean absolute error (MAE), better convergence, and stronger correlation between predicted and actual brain ages. These results highlight the advantage of residual learning in capturing complex spatial patterns in brain structure. Overall, the 3DResNet hybrid model proved to be the more effective approach, offering a powerful and reliable tool for brain age estimation and supporting its potential application in early detection of age-related neurological conditions.

References

[1] Saurabh Sihag, Gonzalo Mateos, Corey McMillan, Alejandro Ribeiro, “Explainable brain age prediction using coVariance neural networks,” arXiv preprint arXiv:2305.18370, May 2023.

[2] Dan Hu, Zhengwang Wu, Weili Lin, Gang Li, and Dinggang Shen, “Hierarchical Rough-to-Fine Model for Infant Age Prediction Based on Cortical Features,” IEEE Journal of Biomedical and Health Informatics, vol. 24, no. 1, pp. 214–225, Jan. 2023.

[3] Raveendra Pilli, Tripti Goel, M. Tanveer, R. Murugan, and P. N. Suganthan, “Kernel-Ridge-Regression-Based Randomized Network for Brain Age Classification and Estimation,” IEEE Transactions on Cognitive and Developmental Systems, to appear, Aug. 2024.

[4] Iman Beheshti, M. A. Ganaie, Vardhan Paliwal, A. Rastogi, Imran Razzak, and M. Tanveer, “Predicting Brain Age Using Machine Learning Algorithms: A Comprehensive Evaluation,” IEEE Journal of Biomedical and Health Informatics, vol. 26, no. 4, pp. 1432–1440, Apr. 2022.

[5] Georgios Antonopoulos, Shammi More, Simon B. Eickhoff, Federico Raimondo, Kaustubh R. Patil, “Region-wise stacking ensembles for estimating brain-age using MRI,” arXiv preprint arXiv:2501.10153, Jan. 17, 2025.

[6] Lemuel Puglisi, Alessia Rondinella, Linda De Meo, Francesco Guarnera, Sebastiano Battiato, Daniele Ravì, “Reliable brain age estimation across multiple MRI sequences and resolutions,” IEEE Trans. Med. Imaging, to appear, Jul. 2024.

[7] Weijia Liu , Qunxi Dong , Shuting Sun, Jian Shen and Bin Hu , Kun Qian “Risk prediction of Alzheimer’s disease conversion in mild cognitive impaired population based on brain age estimation,” IEEE Trans. Neural Syst. Rehabil. Eng., vol. 30, pp. 2146–2156, 2022.

[8] Zhaonian Zhang , Richard Jiang Paul Chazot , Ce Zhang , Bryan Williams , Nicola Pavese, Ahmed Bouridane and Azeddine Beghdadi, “Robust brain age estimation based on sMRI via nonlinear age-adaptive ensemble learning,” IEEE Trans. Neural Syst. Rehabil. Eng., vol. 30, pp. 2146–2156, 2022 .

Pragatheesh A. was born in Cumbum, Tamil Nadu, India, on September 14, 2002. He received the B.Tech. degree in Artificial Intelligence and Data Science from Karpagam Academy of Higher Education, Coimbatore, India, in 2024. He is currently pursuing the M.Tech. degree in Data Science at SRM Valliammai Engineering College, Chennai, India. His major field of study is data science and artificial intelligence. He has completed internships in SOC Analyst Training and Android App Development. During his undergraduate studies, he worked on a project titled A Sentimental Approach Towards Emotion-Based Music Recommendation System Using Hybrid Model. His current areas of interest include machine learning, and data science. Mr. Pragatheesh has participated in academic and project-based activities throughout his academic career. He actively contributes to research discussions and technical forums within his institution.

Dr. S. Narayanan is a researcher and academic in the field of Information and Communication Engineering. He completed his Ph.D. from Anna University, Chennai, in 2017. He also holds an M.Tech in Computer and Information Technology from Manonmaniam Sundaranar University, Tirunelveli (2005), and a B.E. in Electronics and Communication Engineering from the University of Madras, Government College of Engineering, Bargur (2000). His research interests include the development of new technologies using Data Science Algorithms, IoT, communication systems, and smart solutions to address real-world challenges.