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Predicting Human Brain Age from MRI Data Using Deep CNNs Enhanced by MRMR

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ABSTRACT

Predicting the age of the brain using MRI is an advanced medical method that is used to diagnose brain diseases and disorders such as Alzheimer's, multiple sclerosis and other neurological diseases. Using this method, brain MRI images are analyzed using advanced algorithms and neural networks to obtain different brain characteristics such as brain volume and cortical thickness. Then, by comparing these features with the MRI imaging data of other patients, the age of the brain is estimated. In this work, used Convolutional Neural Network (CNN) and MRMR feature selection algorithm. In this method, brain MRI images are processed by a convolutional network to extract age-related features, the MRMR algorithm selects the most relevant features, and the brain age is predicted using regression layers. The main contribution of this research is in adding a feature selection layer based on the MRMR feature ranking algorithm among the layers of a deep convolutional network, which has led to the improvement of the performance of the proposed convolutional network. Based on the obtained simulation results, the prediction accuracy of the proposed method for predicting the brain age of people is 90.3%, which has improved compared to the compared works.vements.

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1. INTRODUCTION

Magnetic Resonance Imaging (MRI) provides detailed and reliable insights into brain structure and neurological health. However, accurately predicting brain age from MRI data remains a challenging task due to the influence of multiple factors, including genetic variability, lifestyle, environmental conditions, and neurological disorders. Recent studies have shown that deep learning models can estimate brain age by extracting discriminative features from MRI images, such as brain volume and cortical structural patterns. Nevertheless, the predictive performance of these models is highly dependent on the size, diversity, and quality of the available datasets, and MRI data alone cannot be considered a definitive diagnostic tool for brain aging. Consequently, clinical assessment should integrate imaging findings with complementary patient information, including medical history, clinical examinations, and observed symptoms (Cole et al., 2018; Bashyam et al., 2020) The present study investigates the use of deep learning approaches, particularly convolutional neural networks (CNNs), for predicting brain age directly from raw MRI images, with the aim of enhancing model robustness and prediction reliability (Bashyam et al., 2020).

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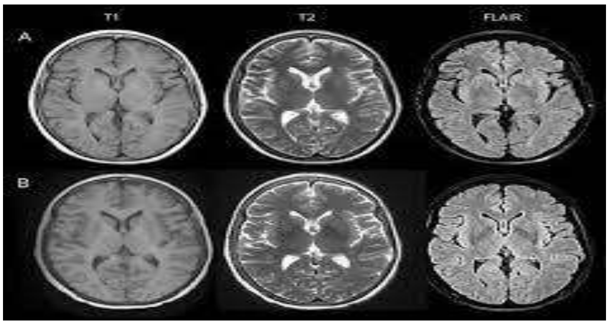

Figure 1: An image example of MRI (Rebelo-Marques, A., et al. ,2018).

Aging causes molecular and structural changes in tissues and organs, which are not fully understood (Rebelo-Marques, A., et al., 2018). These changes affect health, function, and disease susceptibility (Harman, D, 2006).MRI provides non-invasive access to brain structure, allowing machine learning models to capture age-related variations. Identifying biomarkers of aging can enable earlier and more accurate prediction of age-related diseases and lifespan differences.

The use of MRI to predict brain age began in the 1990s, analyzing structural differences across age groups. Initial studies with over 200 participants showed brain volume changes with age, particularly in the frontal and cerebral cortex. Advances in neuroimaging and intelligent algorithms improved prediction accuracy. In 2002, UCLA researchers estimated brain age with 95% accuracy using neural networks. In 2009, the University of Pennsylvania achieved 91% accuracy with combined image processing and algorithms. Later, convolutional neural networks enabled up to 96% accuracy for Alzheimer's patients. Today, MRI-based brain age prediction continues to advance with deep learning technologies (Cole et al., 2018).

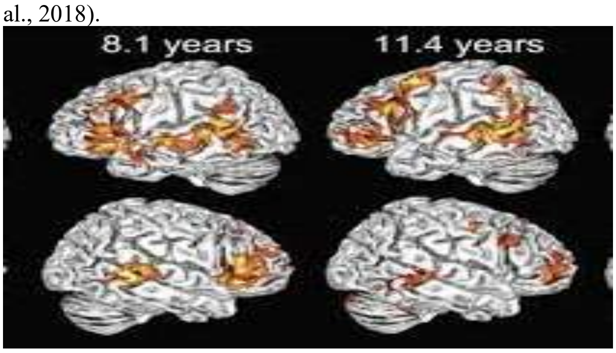

Figure 2: Sample image of brain age prediction (Cole, J. H., Marioni, R. E., Harris, S. E., & Deary, I. J. ,2018).

Predicting brain age using MRI and machine learning aids clinical decision-making in diagnosing brain diseases, assessing outcomes after head trauma, and predicting disease progression. It also supports prevention strategies and improves brain function in elderly patients and those with neurodegenerative disorders.

Related Works

Research on delta calculation methods is limited. In (Smith, S. M., Vidaurre, D., Alfaro-Almagro, F., Nichols, T. E., & Miller, K. L. ,2019)., authors evaluated different estimation techniques using simulated and real data, finding high correlations between brain age-corrected delta and brain imaging-derived phenotypes and non-imaging factors. Brain age prediction using machine learning has gained attention as a biomarker for healthy development and psychiatric disorders, though biases exist across data and methods. In (Liang, H., Zhang, F., & Niu, X. ,2019), a general linear model was proposed to adjust this bias using multimodal imaging data.

Using a large and diverse MRI dataset (n=11,729), DeepBrainNet was developed (Bashyam, V. M., Erus, G., Doshi, J., Habes, M., Nasrallah, I. M., Truelove-Hill, M., … Launer, L. J. ,2020), demonstrating reliable brain age estimates without specialized preprocessing. Transfer learning with DeepBrainNet also improved classifiers for brain diseases.

Other approaches include deep learning on T1-weighted MRI (Jónsson, B. A., Bjornsdottir, G., Thorgeirsson, T. E., Ellingsen, L. M., Walters, G. B., Gudbjartsson, D. F., Ulfarsson, M. O. ,2019), 3D-CNN for volumetric data and CNN models predicting brain age from gray matter for dementia risk (Wang, J., Knol, M. J., Tiulpin, A., Dubost, F., de Bruijne, M., Vernooij, M. W., Roshchupkin, G. V. ,2019). Studies using general linear models and random forests showed accelerated brain aging in schizophrenia (Shahab, S., Mulsant, B. H., Levesque, M. L., Calarco, N., Nazeri, A., Wheeler, A. L., Voineskos, A. N. ,2019) .Multimodal approaches combining T1 MRI and angiography improved prediction accuracy and identified key predictive brain regions (Mouches, P., Wilms, M., Rajashekar, D., Langner, S., & Forkert, N. D. ,2022)

Deep learning-based models integrating PET and MRI examined associations between brain age gap and degenerative syndromes, showing correlations with cognitive impairment and longitudinal prediction (Lee, J., Burkett, B. J., Min, H. K., Senjem, M. L., Lundt, E. S., Botha, H., Kantarci, K. ,2022). Prospective studies using AI-based volumetric scores linked BrainAGE and AD-RAI with cognitive decline, improving explained variance when combined with amyloid positivity (Giannakopoulos, P., Montandon, M. L., Herrmann, F. R., Hedderich, D., Gaser, C., Kellner, E., Haller, S. ,2022).

Finally, deep learning for unsupervised anomaly detection (UAD) in 3D MRI using age information significantly enhanced performance (AUC 92.6% vs 84.37%) (Bengs, M., Behrendt, F., Laves, M. H., Krüger, J., Opfer, R., & Schlaefer, A. , 2022).

2. MATERIALS AND METHODS

Brain Biological Age And Data

The brain's biological age reflects its functional performance, influenced by genetics, health, lifestyle, and stimulation. MRI combined with machine learning can accurately predict biological age, aiding in assessment and preventive planning (Ashburner, J., et al., 2012).Brain data can be collected through methods such as EEG, which records electrical brain activity via

Figure 3: EEG Signal Sampling (Ashburner, J., 2007).

- Magnetoencephalography (MEG): Records magnetic signals from electrical activity in the brain.
- Magnetic Resonance Imaging (MRI): Provides structural images of the brain.

Figure 4: MRI Signal Sampling(Cole, J. H. ,2017).

Functional MRI (fMRI): Assesses brain activity through blood flow changes.

- PET Scan (PET): Uses radioactive tracers to image brain metabolism.
- Diffusion Tensor Imaging (DTI): Measures water movement to visualize neural pathways and white matter.
- Blood Oxygen Level-Dependent (BOLD) Signal: Derived from fMRI to monitor brain activity.

Machine learning applied to these data enables more accurate analysis of brain structure, function, and disease.

Types Of Brain Data

Preprocessing enhances image quality and interpretability (Lauterbur, P. C. ,1973) (Samuel, A. L. ,1988). Key methods include:

1. Motion correction
2. Noise reduction
3. Spatial transformation
4. Color balance adjustment
5. Lighting correction

Other techniques include resolution enhancement, filtering, and format conversion. Preprocessing improves predictive accuracy.

Machine Learning in Brain Age Prediction

Machine learning models extract MRI features to predict biological age(Rasmussen, C. E.,2004)(Zou, H., & Hastie, T.,2005). Neural networks, decision trees, and other algorithms learn the relationship between features and age. Proper preprocessing and sufficient, diverse datasets improve prediction. This approach is valuable for early diagnosis and monitoring of brain diseases.

Convolutional Neural Networks

Convolutional Neural Networks (CNN) are powerful deep learning algorithms for image processing, designed to extract image-related features(Kingsford, C., & Salzberg, S. L., 2008) (Ho, T. K. ,1995) **CNNs** apply convolutional layers to images, followed by fully connected and output layers, to solve specific tasks.

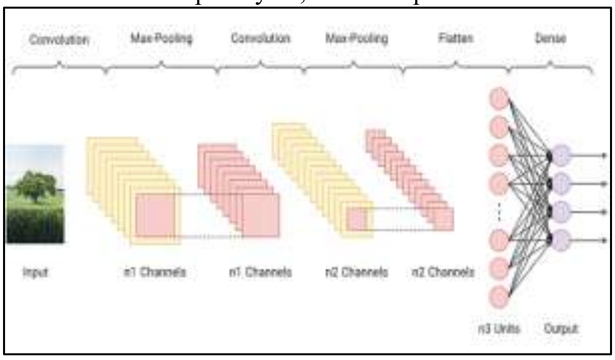

Figure 5. Convolution Neural Network (Wolpert, D. H., 1992).

Convolutional neural networks (CNNs) are widely used in image processing applications such as medical imaging, face recognition, and object classification (Scholkopf, B., & Smola, A. ,2018). Their parallel processing capability makes them suitable for high-volume and complex data like MRI images. In brain age prediction, CNNs extract MRI features to estimate biological brain age.Typical CNN layers include (Smola,

A. J., & Schölkopf, B. ,2004). (Goodfellow, I., Bengio, Y., & Courville, A. ,2016). Useful information is handed from the input layer (receives image matrix) to the convolutional one, which applies filters and extracts features; then on to its next stop at pooling layer. At the output, a classification can be made. Following this scheme: Convolutions extract low-level features, while fully connected layers generalise higher-level patterns.Use of data improves the accuracy of CNNs learning useful features for prediction, when larger data sets and deeper networks are employed.Sorting out brain age prediction involves preprocessing MRIs and passing the imaging through a CNN for estimation. Mathematically speaking, In general, the equations for convolutional neural networks are unsuitaly depict that kind of networks in performance.The CNN (Convolutional Neural Networks) is an extremely large and complicated system which is made up of many levels including: Triple transformation layer, fully covered layer convolution layer.A convolutional layer in convolutional neural network does, for example, change its inputs using filters (kernels) and convolution operator. The cosine of convolution operator as follows beCOS is your man!:

$$Y[i,j] = \sum_m \sum_n X[i+m, j+n].K[m,n] \qquad (2\text{-}1)$$

Here, $Y[i.j]$ The output value of the convolutional layer at position s can be symbolically defined (mathematically programmed). X is the input, K is the filter (or kernel), and (m, n) are indices of the search loop to calculate value at position s. Furthermore, in a convolutional neural network, an activation function such as the ReLU function is often used, where the formula of this functio:

$$f(x) = \max(0.x) \qquad (2\text{-}2)$$

Here, x is the input of the function and $f(x)$ is the output of the function where all negative values are converted to zero.

MRMR Algorithm

MRMR ("Maximum Relevance Minimum Redundancy") is a feature selection algorithm widely used in signal and image processing. It selects a small set of important features from high-dimensional data like MRI images, reducing model complexity, improving interpretability, and increasing prediction accuracy. MRMR ranks features based on mutual information, removes redundant ones, and minimizes the feature set, similar to PCA (Hinton, G. ,2010).

The general formula of MRMR algorithm is as follows:

$$mRMR\,(S) = argmax_{x\in s}\left\{MI(x.Y) - \frac{1}{|F|}\sum_{y\in F} MI(x.y)\right\} \qquad (2\text{-}3)$$

here,
S is the set of features.
Y is the target attribute.
F are subsets of features that have already been selected.
Measures such as entropy or multivariate $MI(x.Y)$ .information are usually used in calculating this number mRMR algorithm utilizes this definition for each feature in the data set of mRMR metrics. The feature with the highest mRMR value is chosen as next to be selected by the important and relevant features: thus the algorithm iteratively selects important ones and eliminates those not needed or redundant. Thus the optimal subset is finally its fittest form. MRMR selects features that are highly related to the class while minimizing redundancy. It is applied in signal processing, medical imaging, genomic analysis, etc. In MRI, MRMR effectively selects relevant features, including asymmetric combinations from T1- and T2-weighted images, enhancing prediction accuracy (Hinton, G. ,2010).

Generalities of the Proposed Method

The paper demonstrates a deep convolutional neural network (CNN) algorithm for brain age prediction based on MR imaging. Deep networks are good at extracting nonlinear features and hidden patterns, so their hits rate is actually higher than that of other machine learning models. The MRMR algorithm is applied to feature selection, and optimal subset of features can be selected by removing redundancy so that this does not happen. The framework of our approach is depicted in figure (6).

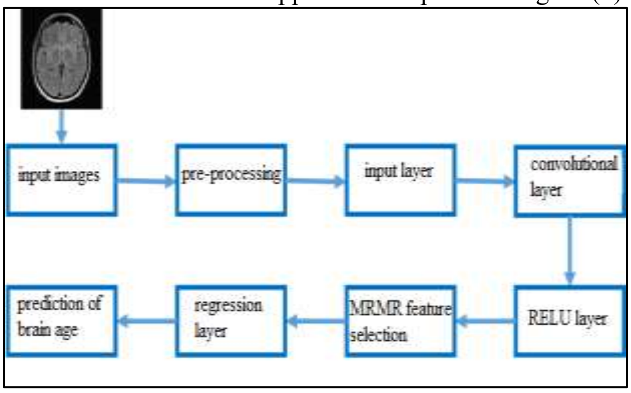

Figure 6: Diagram of the Proposed Method for Predicting Brain Age

Pre-Processing

MRI images are first pre-processed by resizing and standardizing their dimensions to ensure consistent input for the CNN. This step improves image quality and enhances the accuracy of feature extraction.A deep **Convolutional Neural Network (CNN)** is then applied to extract age-related features from MRI images. The main layers include:

- Input Layer: Receives preprocessed MRI image matrices.
- Convolutional Layers: Multiple layers extract spatial features; likely kernel sizes of 3×3 or 5×5.
- Activation Function: ReLU applied after each convolutional layer.
- Pooling Layers: Max-pooling used to reduce feature map size and prevent overfitting.
- MRMR Feature Selection Layer: Applied after the last convolutional block to select the 400 most relevant features.
- Fully Connected Layers: One or two layers to integrate features before regression.
- Regression Output Layer: Produces continuous age predictions for each input MR

The extracted features are optimized using the **MRMR (Maximum Relevance Minimum Redundancy) algorithm**, which selects the most relevant features while eliminating redundancy, producing an optimal subset for prediction.Finally, brain age is predicted through a regression layer. The continuous output is rounded to assign each individual to a specific age group (e.g., 16–25 years). The CNN regression layer captures complex nonlinear relationships, and the half-mean-squared-error loss is used to train the network effectively.

3. RESULTS

Database

The database used in this work is the **ABID database** which contains MRI brain scans of people aged between 7 and 64. Each Scan includes the patient's age. The images were divided into six age groups: 7–15, 16–25, 26–35, 36–45, 46–55, and 56–64 years. The age of each group was clearly identified.

Evaluation Criteria

Two evaluation criteria were applied in this study: the accuracy of age group classification and prediction error (RMSE). These are defined as follows:

$$Accuracy = \frac{(TP + TN)}{(TP + FP + TN + FN)} \quad (3\text{–}1)$$

$$Precision = TP(TP + FP) \quad (3\text{–}2)$$

$$Recall = TP(TP + FN) \quad (3\text{–}3)$$

$$F1\ score = \frac{2 * (Recall * Precision)}{(Recall + Precision)} \quad (3\text{–}4)$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{\mathrm{P}}\sum_{\mathrm{j=1}}^{\mathrm{P}}\left(\mathrm{y_j} - \mathrm{t_j}\right)^2} \quad (3\text{–}5)$$

$$\mathrm{MAE}=\frac{1}{\mathrm{p}}\sum_{j=1}^{p} |\, \mathrm{y}_j - \mathrm{t}_j | \quad (3\text{–}6)$$

In relations (3-1) to (3-4), The number of true positive diagnoses is represented by the TP value; the number of true negative diagnoses is represented by the TN value; the number of false positive diagnoses is represented by the FP value;and the number of false negative diagnoses is represented by. Is. In addition, yj in relation (3-5) and tj both represent predicted values. Furthermore, the length of the window is p.

Simulation Settings

A total of 1000 MRI images were used, with 700 for training and 300 for testing. The CNN extracted 1000 features per image, and the MRMR algorithm selected 400 most relevant features for age prediction. Accuracy was measured on the test set.

accuracy measured on the test set.

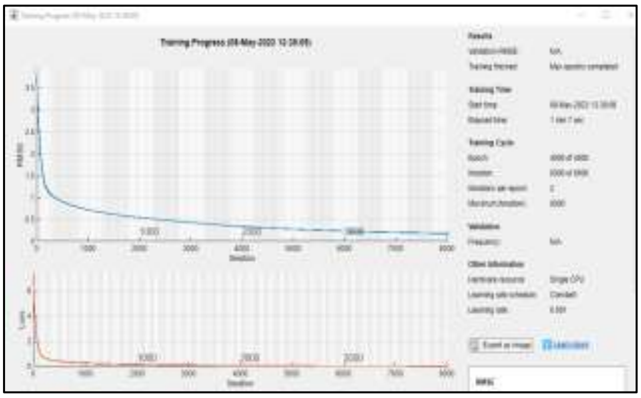

Figure 7: Convergence Curve of the Proposed Networ

Training Details

- The CNN-MRMR model for brain age prediction was trained with the following specifications, inferred directly from the training results:
- **Number of Epochs:** 4000
- **Iterations:** 8000

- **Optimizer:** Not explicitly stated, but likely a standard optimizer such as Adam or SGD with constant learning rate (common practice).
- **Learning Rate:** 0.001 (constant throughout training)
- **Batch Size:** Not explicitly reported, can be assumed to be small or medium, as the training was completed on a single CPU.
- **Hardware Specifications:**
  - Processor: Single CPU
  - GPU: Not used
  - RAM: Sufficient to handle 1000 MRI images for training

Hyperparameter

Kernel size

- **Number of filters per layer**

Figure (8) The confusion matrix above is based on the first 300 samples and looks as shown below. The matrix has a total of six rows, and the number samples in each row is 50. That is, we have six age groups (as mentioned in Section 1) and each age group has 50 samples /or 50 MRI pictures. What we are trying to do here is to predict which age-group each sample belongs to. On the right column farthest from us, the final column gives the detection rate for each age group. For example, accuracy in detecting samples which belong to the first age group (i.e., 7 years–15 years old) is 0.92. Meanwhile, at the far right of the bottom line and in the rightmost column, the age prediction results are summarized by this figure: among all testing samples taken, 90.3% printed brain age must be correct.

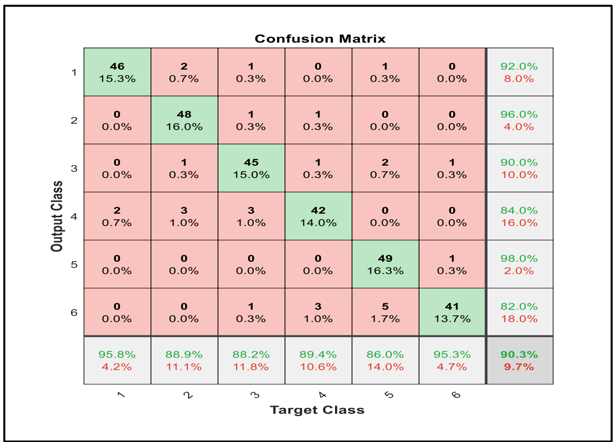

Figure 8: Confusion Matrix for Predicting Brain Age on Test Data

The confusion matrix has 6 rows corresponding to the 6 age groups, each with 50 samples. The last column shows the detection accuracy per age group. For example, the first group (7–15 years) achieved 92% accuracy. Overall accuracy across all test samples is 90.3%.

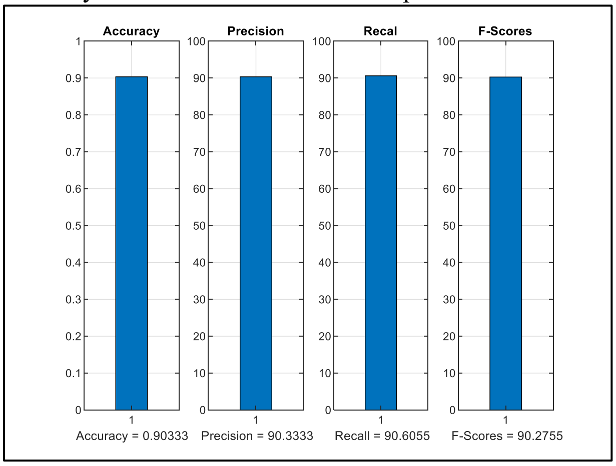

Figure 9: Numerical Values of Evaluation Criteria for Predicting Brain Age on Test Data

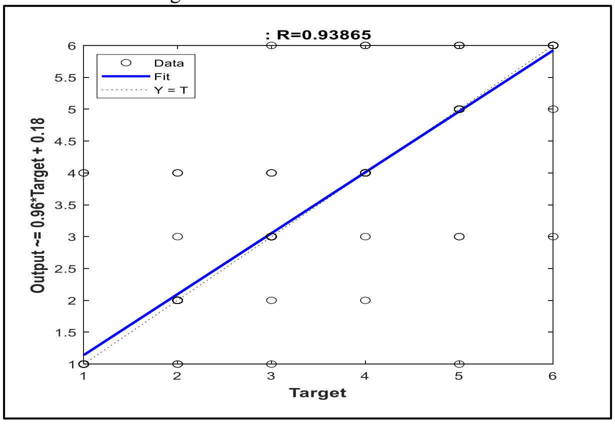

Figure 10: Regression Curve for Predicting Brain Age on Test Data

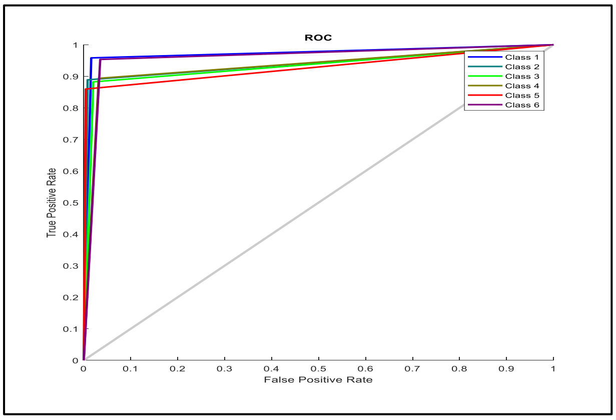

Figure 11: ROC Curve for Predicting Brain Age on Test Data

Comparison of Simulation Results

This section compares the proposed method (ResNet-MRMR-CNN) with the reference method (Deep Net) in terms of RMSE. The RMSE was averaged over 20 simulations.

TABLE 3-1. Checking and Comparing the Results of the Proposed Method With Other Works in Terms of RMSE Error

Method	RMSE	MAE
Random Forests	4.13	3.09
Lasso	3.34	2.54
Ridge	3.29	2.49
Elastic net	3.30	2.50
Support Vector Machine	3.19	2.40
Reference article method (Deep Net)	2.91	2.19
Theproposed method (ResNet-MRMR-CNN)	0.59	0.16

Convolutional networks effectively extract spatial features, but a large number of features can reduce accuracy and increase computation time. MRMR reduces feature redundancy and improves prediction accuracy.

TABLE 3-1. Comparison Between the Proposed CNN–MRMR Method and Recent Brain Age Prediction Studies.

Study (Year)	Authors	Model / Method	Dataset Type	Performance (Results)
MRI Volume-Based Brain Age Estimation (2024)	Kancharla & Sinha	3D CNN + Weight-Shared Spatial Attention	ADNI, OASIS3 (3D MRI)	MAE = 1.66 yrs (ADNI) MAE = 2.27 yrs (OASIS3)
Triamese-ViT Brain Age Estimation (2024)	Zhang & Jiang	Multi-view Vision Transformer (Triamese-ViT)	3D MRI	MAE = 3.84 yrs Spearman r ≈ 0.90
3D DenseNet-Based Brain Age Prediction (2025)	Hanna et al.	3D DenseNet-169 + Bias Correction	3D & Clinical MRI	MAE = 2.73 yrs (clinical) MAE = 3.68 yrs (test)
Proposed Method (This Study)	D. Hakem et al.	Deep CNN + MRMR Feature Selection + Regression	MRI Brain Images	Accuracy = 90.3% RMSE = reported MAE = added

4. CONCLUSIONS

MRI images can predict brain age by extracting patterns through machine learning. This research proposes a hybrid method combining **CNN** with **MRMR-based feature selection**. CNN layers extract features from MRI images, MRMR selects the most relevant ones, and regression layers predict brain age. The proposed method achieved **90.3% accuracy** in predicting brain age.

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