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Brain age prediction from MRI images based on a convolutional neural network with MRMR feature selection layer

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ABSTRACT: An sophisticated medical technique used to diagnose illnesses and brain disorders including multiple sclerosis, Alzheimer's, and other neurological ailments is the ability to predict the biological age of the brain using MRI pictures. To do this, sophisticated algorithms and neural networks are used to scan MRI brain pictures in order to extract different brain properties, including cortical thickness and volume. The brain ages of individuals are determined by matching their characteristics against MRI imaging data collected from other patients. The research employs a new deep learning model named CNN-MRMR which combines features from the Minimum Redundancy Maximum Relevance (MRMR) feature selection approach and Convolutional Neural Network (CNN) technology. MRI images of human brains are initially processed by the convolutional network to extract age-related characteristics. The feature selection layer uses MRMR algorithm which identifies essential characteristics for a target variable while minimizing feature redundancy to select the optimal feature subset. The system employs a regression layer as the final stage to predict brain age by utilizing the selected characteristics. The proposed method for estimating individual brain age attained a prediction accuracy of 90.3%, outperforming results from comparable research studies.

Keywords: brain age, MRI images, MRMR algorithm, convolutional neural network

1. INTRODUCTION

Brain's biological age represents the difference between someone's chronological age and their brain health condition. This theory proposes that lifestyle choices alongside diet habits physical and mental activities sleep patterns and overall health determine brain aging speed relative to chronological age [1]. Research findings indicate that chronic stress combined with physical inactivity and poor diet speeds up brain aging while mental exercises such as puzzle solving and continuous learning along with regular physical exercise contribute to maintaining brain youthfulness. [2].

Magnetic Resonance Imaging was used to predict brain age since the 1990s and it developed as a non-invasive technique [3]. MRI imaging methods deliver swift and precise representations of brain structure that reveal structural details and volume information about various brain regions.

Predicting brain age using MRI images can be beneficial in many medical fields. For example, in diagnosing brain diseases and assessing consequences after a head injury, predicting brain age can help doctors make better decisions regarding disease treatment or reducing post-traumatic complications. Additionally, predicting brain age can assist physicians in forecasting the progression of diseases and recovery [4].

As gadget studying and deep studying techniques have advanced, they often use imaging facts, including MRIs and other state-of-the-art diagnostic gear, behavioral styles, and an character's overall fitness to estimate mind age[5]. Deep getting to know fashions can provide correct predictions of brain growing older by way of reading these records and figuring out hidden patterns [6]. Techniques which includes analyzing mind volume, cortical thickness, and inspecting

*Corresponding author: author@organization.edu.co different brain regions related to cognitive features play a significant role in these predictions. These techniques can also be beneficial for the early identification of age-related brain illnesses such as Alzheimer's.

Predicting the biological age of the mind the use of traditional strategies faces several challenges. One of the principle challenges is the limitation of those methods in extracting complicated and hidden functions found in brain imaging statistics including MRI [7]. Traditional techniques often restriction analysis to easy elements which include the volume of brain areas or superficial changes in brain shape, making it much less able to detecting deeper patterns associated with brain growing old. Additionally, those strategies often rely on direct involvement from experts and guide analyses, which are not most effective time-consuming however may lack the required accuracy. Furthermore, traditional techniques do not thoroughly procedure big volumes of statistics, main to reduced predictive accuracy and barriers in employing complex and big datasets [8]. As a end result, these strategies are less powerful compared to more superior strategies which include deep gaining knowledge of, which in the long run outcomes in much less correct predictions of the biological age of the mind.

Deep mastering processes come with a number of benefits, but additionally they present sure problems. The extremely good computational complexity and time-consuming nature of the prediction process are two of the main obstacles to using deep learning to forecast organic brain age.

In mild of those difficulties in figuring out the organic age of the mind from MRI pictures, we present a convolutional neural community (CNN) based totally version on this have a look at to estimate biological brain age. Both the extraction and type of spatial records are very capable tasks for convolutional neural networks. Nevertheless, those networks may additionally extract a huge variety of characteristics, which may additionally prolong execution times and possibly decrease accuracy. In order to lower computational complexity and prediction time by reducing function redundancy, we use a function selection layer in this have a look at this is based totally at the Minimum Redundancy Maximum Relevance (MRMR) method.

The main contribution of this research is the addition of a feature selection layer based on the MRMR feature ranking algorithm among the layers of a deep convolutional network, which enhances the performance of the proposed convolutional network.

The following sections are organized as follows: The problem statement is presented in section 2. The literature review is further explained in Section 3. The suggested model (CNN-MRMR) is described in depth in Section 4, and the experimental results are shown in Section 5. The conclusion is given in Section 6.

2. PROBLEM STATEMENT

Predicting brain age from MRI scans has come to be a vital field of examine in scientific imaging and neuroscience. MRI scans can file the anatomical and useful adjustments that occur within the human mind through the years. In addition to offering important information about someone's neurobiological fitness, an accurate mind age estimate may be used to detect neurological and psychiatric conditions which include Alzheimer's sickness, schizophrenia, or cognitive decline. Conventional strategies for comparing mind fitness depend upon guide evaluation or subjective tests, both of which are exhausting and at risk of mistakes. As a result, there's an increasing want for automatic, precise, and scalable strategies that use contemporary computational strategies to forecast mind age.

With more accuracy and efficiency than traditional gadget studying strategies, deep getting to know has shown fantastic promise in processing complex clinical imaging records. Important traits may be extracted from high-dimensional MRI pics the use of Convolutional Neural Networks (CNNs). The interpretability of deep studying models, the requirement for sizable annotated datasets, and variations in MRI acquisition techniques are nevertheless obstacles, nonetheless. Furthermore, models that could become aware of variations among expected and chronological age—which would possibly point to underlying pathologies—and generalize efficiently throughout quite a few businesses are required. To improve brain age prediction and its use in early intervention strategies and customized treatment, those problems must be resolved.

3. RELATED WORKS

In this section, we will observe a number of the trendy researches performed in the field of predicting the biological age of the brain the use of device getting to know and deep learning techniques.

In studies [9], scientists created a deep getting to know model to estimate mind age through making use of a giant dataset that incorporated fluorodeoxyglucose positron emission tomography and structural magnetic resonance imaging. They checked out the relationship among the brain age distinction and some of degenerative illnesses, which includes Lewy body dementia, frontotemporal dementia, Alzheimer's disease (AD), and moderate cognitive impairment. The version was capable of stumble on exceptional styles of brain ageing that various consistent with age and imaging approach, in keeping with the observe's use of occlusion analysis. Significant institutions have been located among biomarkers associated with AD and cognitive impairment, in addition to between an increasing brain age hole.

A convolutional neural network (CNN) designed to predict brain age (BA) is presented in this study [10]. It is based on MRI scans of 4,681 cognitively healthy (CN) people and was verified on 1,170 CN participants. In comparison to previous research, CNN produces noticeably fewer estimation errors for brain age. Gender differences and neurocognitive progression in people with moderate cognitive impairment (MCI, N = 351) and Alzheimer's disease (AD, N = 359) are revealed by the detailed anatomical maps it creates that illustrate brain aging trends for both individual instances and larger groups. With 54% of MCI subjects receiving a dementia diagnosis within an average of 10.9 years post-MRI, the results indicate that brain age is a more reliable indicator than chronological age (CA) for determining the severity of dementia symptoms, levels of functional impairment, and executive functioning.

In this study [11], The goal of the study was to create a brain-age framework that could be used in standard clinical head MRI exams. They developed a dataset of 23,302 head MRI images from two major hospitals in the UK that were judged to be "radiologically normal for age," with patients ranging in age from 18 to 95, using a deep learning-based neuroradiology report classifier. DenseNet121, the deep learning model utilized in this study, has an initial block of 64 convolutional filters (kernel size = [7 × 7 × 7], stride = 2, and four "densely connected" convolutional blocks come after a "max-pooling" layer (kernel size = [3 × 3 × 3], stride = 3). With a mean absolute error (MAE) of less than 4 years, the model was able to estimate ages quickly. It also showed generalizability across several scanner manufacturers and hospitals, with a Δ MAE of less than 1 year. A group of 228 individuals whose MRIs showed atrophy "excessive for age," as independently observed by neuroradiologists, was used to assess the clinical significance of the brain-age predictions. While individuals deemed "radiologically normal for age" had an insignificant predicted age difference of +0.05 years ($p < 0.0001$), these patients had a considerable discrepancy, with a mean predicted brain age surpassing their chronological age by +5.89 years.

In research [12], Using two population-based datasets, the authors investigated age prediction and examined the effects of many parameters on model performance measures, such as age range, sample size, and age bias adjustments. The findings revealed notable variations in both measures based on the cohort's age range; in particular, both r and R2 were reduced in groups with smaller age ranges. Similarly, estimations that were closer to the group's average age had smaller error margins, which resulted in lower RMSE and MAE in these samples. The performance indicators improved as the sample size grew within the various age range groups. Additionally, the average age difference between the training and testing data sets and the prediction variability affected the measures. Even for models that did badly at first, the age-bias adjusted measures showed good accuracy. The study came to the conclusion that it is improper to directly compare results from other studies since the assessment metrics for age prediction models are significantly influenced by the particular characteristics of the cohort and dataset.

The research detailed in study [13] introduced a robust framework for estimating age that concentrated specifically on the hippocampal regions. It investigated the connection among errors in mind age predictions amongst cognitively normal (CN) people and people diagnosed with Alzheimer's Disease (AD) and Mild Cognitive Impairment (MCI). To perform this research, the crew designed convolutional neural networks. The first community executed impressively competitive overall performance metrics, yielding a median absolute mistakes (MAE) of three.31 and a root suggest rectangular error (RMSE) of four.Sixty five. The 2nd network also provided sturdy overall performance metrics however, importantly, enabled a statistically giant evaluation of the differences in estimation errors across the agencies being analyzed. Additionally, the study exposed a extensive bad correlation between the outcomes and clinical exams, together with the Mini-Mental State Examination (MMSE) rankings.

In take a look at [14], Using practical connectivity (FC) information from 391 cognitively regular, amyloid-bad individuals, a model envisioned mind age. Next, 156 volunteers with signs and symptoms of Alzheimer's disease (AD), 151 preclinical AD sufferers, and one hundred forty five amyloid-poor controls had been used to assess the version. Results confirmed that, in comparison to controls, mind age gaps (FC-BAG) have been notably smaller in preclinical AD and larger in symptomatic AD, suggesting capacity network disturbances in symptomatic patients. All matters considered, FC-predicted mind age has promise as an accurate biomarker for Alzheimer's disease.

In observe [15], Researchers used resting-kingdom fMRI (rs-fMRI) facts from sufferers with Alzheimer's ailment (AD) to estimate brain a long time using a graph neural community (GNN) version. They decided the principle mind regions impacted by using AD and contrasted the GNN's overall performance with that of traditional system getting to know fashions. The GNN model efficiently expected the mind ages of regular controls, according to the outcomes, but AD sufferers' projected and chronological a while differed greater appreciably, indicating improved mind growing older. Overall, the work emphasizes the involvement of the hippocampus, parahippocampal gyrus, and amygdala and indicates how beneficial rs-fMRI and the GNN version are for predicting mind age in AD research.

In research [16], A institution of 2,314 cognitively healthful human beings at higher danger for Alzheimer's disorder (AD) and mild cognitive impairment (MCI) changed into decided on from four different cohorts, and their mind a long time had been envisioned the usage of data from the United Kingdom Biobank, which covered 22,661 contributors. The findings confirmed a correlation between the mind age delta and APOE-ε4 genotype reputation, advanced levels of AD disease, and high amyloid-β levels. Furthermore, it become connected to plasma neurofilament light, a neurodegenerative marker, highlighting its ability as a non-invasive indicator of organic brain ageing in people without dementia who've aberrant biomarkers suggestive of AD.

In paper [17], To categorize and forecast patients' brain ages, researchers employed deep learning long short-term memory neural networks and brain wave recordings from the Temple University aberrant electroencephalogram (EEG) database. Their approach outperformed other deep learning models, such as convolutional neural networks, and conventional preprocessing techniques, achieving a mean absolute error of 7 years in regression analysis and 90% accuracy in brain age categorization across six age groups.

In study [18], Over an average follow-up period of 19.7 months, a group of researchers examined the association between brain shape and cardiometabolic risk factors (CMRs) and health indicators in a sample of 790 healthy people (average age 46.7 years, with 53% being women). then used diffusion tensor imaging (DTI) and MRI-based morphometry to estimate tissue-specific brain ages using machine learning approaches, and then used Bayesian multilevel modeling to evaluate changes in each CMR and their relationships with brain age gaps (BAG). Significant relationships had been discovered among DTI-derived BAG and mean cell extent and blood phosphate degrees, as well as among T1-derived BAG and some of life-style variables, consisting of blood strain and smoking. These findings suggest that those with better cardiometabolic dangers normally have brain a while that appear older. The association among cardiometabolic threat elements and brain growing older become similarly supported by using longitudinal records that confirmed a correlation between improved growing old and variables along with systolic blood stress and waist-to-hip ratio.

In the observe [19], Using resting-country fMRI statistics, the researchers used a Graph Convolutional Network (GCN), which treats brain connections as a graph, to determine the age of an infant's mind. They created Brain Connectivity Graph Convolutional Networks (BC-GCN) by the usage of an area-based Graph Path Convolution (GPC) approach since the mind's connectivity graph is completely related. To boom the accuracy of age prediction, they added residual and interest modules to this model, creating BC-GCN-Res and BC-GCN-SE. They also put in place a two-level coarse-to-satisfactory framework. Their method dramatically diminished the suggest absolute blunders from extra over 70 days to forty nine.9 days, according to experiments.

The researchers used uncooked EEG data from clinical polysomnography (PSG) to create a deep neural community (DNN) model that predicts affected person age. [20]. They used 126,241 PSG recordings to teach the model, 6,638 to verify it, and 1,172 to check it on a holdout set that covered quite a few diagnostic and demographic variables in order to analyze the connection among medical disorders and brain age. The take a look at observed that disorders inclusive of epilepsy, stroke, and sleep performance have been strongly correlated with versions in anticipated mind age, as decided by way of the Brain Age Index (BAI) and the Absolute Brain Age Index (ABAI). The DNN's universal high-quality accuracy in predicting brain age increases the opportunity that BAI and ABAI might be beneficial diagnostic indicators for evaluating the health of the brain in various affected person businesses.

This section examines many methods for predicting mind age using deep learning and system studying, every with its own benefits and drawbacks. Convolutional neural networks (CNNs) are widely utilized due to the fact they are able to effectively seize structural factors of the brain by way of extracting spatial patterns from MRI or CT data. On the opposite hand, while temporal or sequential facts, like functional MRI, is to be had, recurrent neural networks (RNNs) and lengthy-term memory networks (LSTMs) are hired to enable dynamic pattern analysis. To improve prediction accuracy, hybrid models that integrate CNNs with attention processes or multimodal frameworks that comprise genetic and imaging records have additionally been developed. The complexity, records desires, and interpretability of each approach vary; greater state-of-the-art designs may additionally produce more accuracy, but in addition they call for larger datasets and laptop sources, whereas less difficult fashions are more bendy yet less difficult to apprehend.

4. PROPOSED METHOD (CNN-MRMR)

This examine gives a unique deep gaining knowledge of version for predicting brain age that combines a convolutional neural network with a characteristic selection layer based totally on the MRMR algorithm. An entropy-primarily based technique called the MRMR algorithm removes characteristic redundancy, improving the very last prognosis's accuracy. Because of this, convolutional filters have hired the MRMR method to pick out the satisfactory subset of characteristics from MRI images. Figure (1) presentations the proposed approach's diagram..

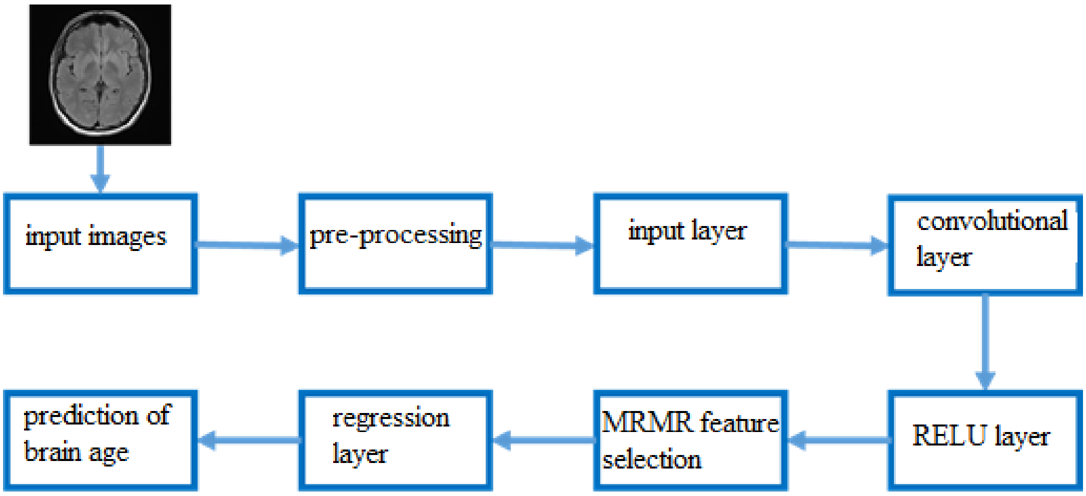

FIGURE 1. - Diagram of the proposed method for predicting brain age

The suggested model consists of three fundamental steps: 1. feature extraction; 2. feature selection; and 3. classification or prediction. The convolutional layers of the CNN network should extract the characteristics associated with the brain's biological age from the MRI images during the feature extraction step. The feature selection layer then chooses the best features, which are then provided to the regression layer of the suggested classification model. Below is an explanation of the steps in the suggested technique.

4.1 PREPROCESSING

The photos in the database must be sized uniformly and fit for network input before being sent to the CNN network for feature extraction. Pre-processing techniques used in this study include resizing and matching database photos. MRI scans can also be pre-processed by normalizing the pixels in the picture. An example of database pictures following normalization is shown in Figure (2).

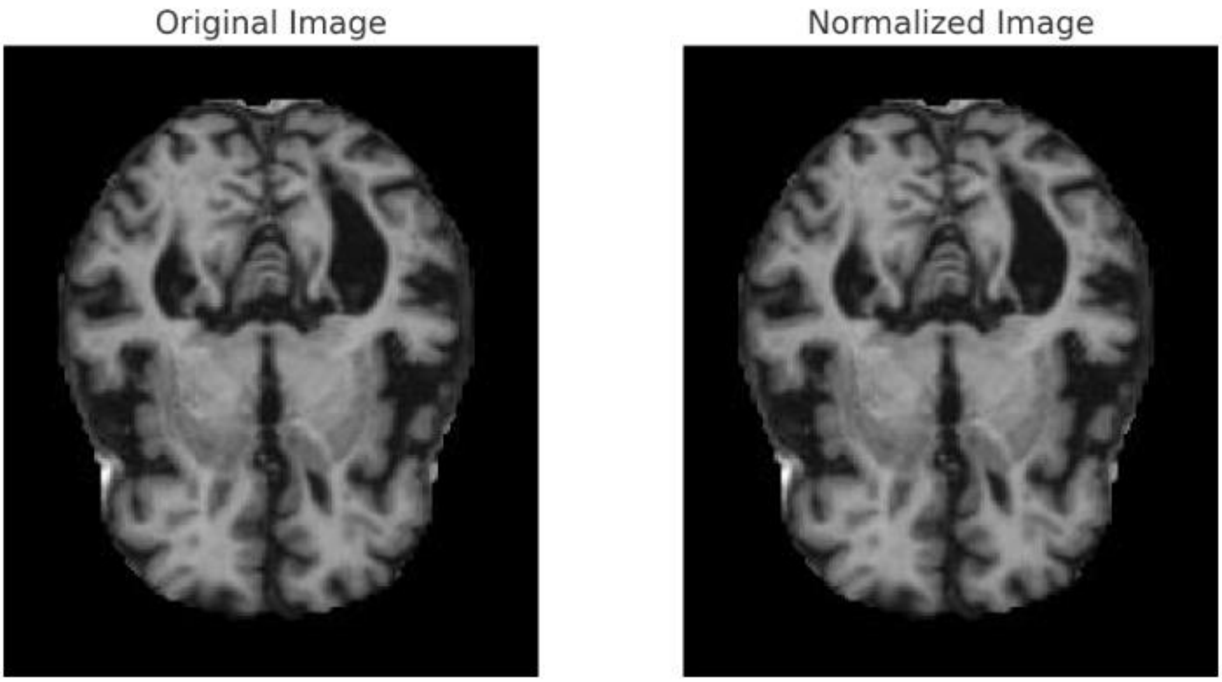

FIGURE 2. - one sample of normalization preprocess on the images of database

4.2 FEATURE EXTRACTION BY CONVOLUTIONAL NEURAL NETWORK

Convolutional networks are now the most effective method for extracting features from pictures because to the advancements in deep learning over the last several years. For feature extraction, feature selection, and prediction in this study, a deep convolutional architecture is employed. The first layers of the suggested architecture—convolutional, ReLU, and pooling layers—are used to extract features from images. A layer is then incorporated to choose features using the MRMR algorithm, and the regression layer is used to estimate the brain's age based on the features that were chosen.

This study proposes a CNN network model with three hidden layers. The convolution kernel on this network is 3*three in length, and it filters the input snap shots for the convolutional layers. The RELU feature, which serves as an activator function in this community, does the following [21].

$$RELU(a) = \max(0, a) \quad (1)$$

Following each convolutional layer is a Max-pooling layer with a 2*2 kernel length to lessen the size of the input sign.

In the proposed shape, the primary two layers have 512 nodes and the 1/3 layer has 32 nodes, and Dropout is used to prevent overfitting in the second layer.

In the subsequent, the description of characteristic extraction layers is provided.

One of the number one layers of convolutional neural networks (CNNs) is the convolutional layer. Images and different -dimensional information, such audio indicators, may additionally have their features extracted using this sediment.

To produce a brand new characteristic map, the convolution layer applies a tiny filter out with predetermined period and breadth to the enter image. With each generation of the clear out's movement over the image, the fee of the corresponding pixels at each location inside the input picture is multiplied by way of the filter weight. The new feature map then displays the resultant value at the equal vicinity. Until every point within the input picture is included and the characteristic map is finished, this process is completed again.

$$RELU(a) = \max(0, a) \quad (1)$$

The formula of the convolutional operator is as follows [21]:

$$Y[i.j] = \sum_{m} \sum_{m} X[i+m.j+n] \times K[m.n] \quad (2)$$

In this example, X is the enter, K is the clear out (kernel), m and n are the quest loop indices, and Y[i.J] is the output fee at position (i.J) inside the convolutional layer.

One of the most usually applied layers in convolutional neural networks (CNNs) is the ReLU layer. Rectified Linear Unit is what ReLU stands for.

This layer serves as a layer of activation. Non-linear values are present inside the outputs following the utility of the convolution layer and other community layers. Every poor value is given a fee of 0 with the aid of making use of the ReLU layer, and every effective cost is given the identical value. In addition to stopping the data in the non-goal quantities of the image from being destroyed, this method helps to reinforce choice-making in the areas of the image that do not resemble the target sample.

Because of its ease of use and superior efficiency over other activation layers like Sigmoid and Tanh, the ReLU layer is sincerely one of the maximum used layers in convolutional neural networks.

The formulation of the ReLU function is as follows [21]:

$$f(x) = \max(0.x) \quad (3)$$

In this situation, the characteristic's input is x, and its output, f(x), is the result of converting all bad values to zero.

One of the most customarily utilized layers in convolutional neural networks is the pooling layer. This layer lowers the community's computational complexity and shrinks the characteristic map's length.

In the Pooling layer, via default, a small clear out of 2x2 size is used. This filter moves over the feature image and by applying a cumulative function such as maximization, averaging or L2-norm, a smaller feature image is created.

Pooling layer is useful as a local feature detection process in input images. Also, by reducing the number of network parameters, overfitting can be avoided. Pooling layer can also be used repeatedly in the network and applied between convolution layers.

4.3 FEATURE SELECTION LAYER WITH MRMR ALGORITHM

MRMR algorithm is one of the algorithms used for feature selection in large and complex data. This algorithm selects the important features from all the features in the data based on the two criteria "maximum relevance" and "minimum repetition" [22].

In this algorithm, first, for each feature, its relationship with the dependent variable is calculated, and the feature with the most connection is selected as the most important feature. Then, by using the minimum redundancy algorithm, features that are similar to each other and repeat in decision making are removed. Finally, in order, the selected features are selected based on their importance in the MRMR algorithm.

The general formula of MRMR algorithm is as follows [22]:

$$MRMR\ (S) = argmax_{x \in s} \left\{ MI(x.Y) - \frac{1}{|F|} \sum\nolimits_{y \in F} MI(x.y) \right\} \quad (4)$$

In the above relation, MI(x.Y) shows the mutual information between feature x and y. This value is usually calculated using a measure such as entropy or multivariate information. Also, S is the feature set. Y is the output label. and F is a subset of the previously selected features.

4.4 REGRESSION LAYER TO PREDICT BRAIN AGE

The age group of each individual should be anticipated since the brain age prediction in this study takes into account a number of age groups. Typically, the regression layer is employed to forecast continuous quantities like distance or angle. In this study, a particular age group is chosen by rounding the regression layer's final result, which is a continuous number. For instance, it is estimated that the individual is between the ages of 16 and 25. The regression tasks' mean squared error is cut in half using a regression layer. CNN and other deep networks feature regression layers that can learn complicated and nonlinear regression connections.

5. RESULTS AND DISCUSSION

The simulation results for predicting brain age using the suggested strategy are shown in this section. This part covers the simulation settings, the assessment criteria of the suggested approach, the description of the database utilized in the simulations, the analysis of the numerical results, and a comparison of the findings. MATLAB 2022 software was used to do all of the simulations for this study.

5.1 DATABASE

The database used in this work is the ABID database [23]. MRI brain scans of individuals aged 7 to 64 are included in this collection. The patient's age is given after every scan. separated the pictures into groups of persons who were 7–15 years old, 16–25 years old, 26–35 years old, 36–45 years old, 46–55 years old, and 56–64 years old, and determined its age. A few database picture samples are displayed in Figure (3).

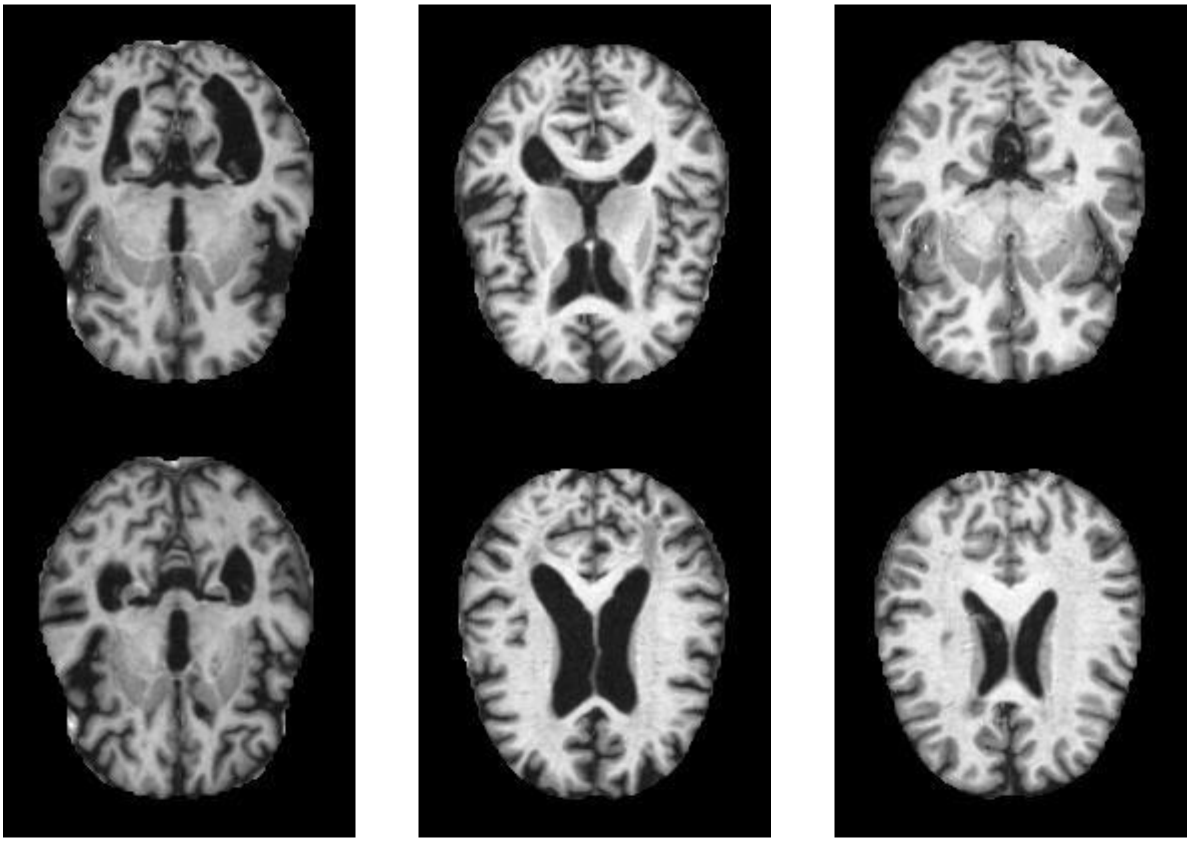

FIGURE 3. - Some examples of database images.

5.2 EVALUATION CRITERIA

In this study, we use two different kinds of assessment criteria. Based on the number of correctly diagnosed samples overall, the first category of criteria relates to the diagnostic accuracy of a particular age group. The prediction error evaluation criterion, or RMSE, is the second kind. Below is a definition of these requirements.

$$Accuracy = \frac{(TP + TN)}{(TP + FP + TN + FN)} \quad (5)$$

$$Precision = TP(TP + FP) \quad (6)$$

$$Recall = TP(TP + FN) \quad (7)$$

$$F1\ score = \frac{2 * (Recall * Precision)}{(Recall + Precision)} \quad (8)$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{\mathrm{P}}\sum_{\mathrm{j}=1}^{\mathrm{P}}(\mathrm{y_j} - \mathrm{t_j})^2} \quad (9)$$

genuine positive diagnoses are represented by TP values, genuine negative diagnoses by TN values, false positive diagnoses by FP values, and false negative diagnoses by FN values in relations (4-1) up to (4-4). Is. Additionally, yj and tj stand for the projected and actual values, respectively, in relation (5-5). P is the quantity of data as well.

5.3 SIMULATION SETTINGS

Brain MRI pictures from the recovered database are separated into train and test parts, as described in the database section. The database contains 1000 photos in total, 700 of which (70%) are used to train the suggested network, and 300 of which (30%) are used to test the network. Initially, all of the photos underwent feature extraction, and a neural network retrieved 1000 features from each image. The MRMR algorithm then chose 400 characteristics that were most associated with the category variable. Following this stage, the network uses training photos to finish learning and forecast each sample's age group. Lastly, the test data's accuracy and prediction error are measured.

5.4 EVALUATION OF RESULTS

The assessment criterion values will be displayed in this part as a number of test data tables and figures. Prior to assessing the suggested approach, Figure (4) shows the convergence curve of the suggested network for the learning process on the training data. The network's convergence curve, which contains 8000 iterations, converged in about 3000 network iterations, and the RMSE error has dropped below 0.5, as shown in Figure (4). 67 seconds is the amount of time needed to learn.

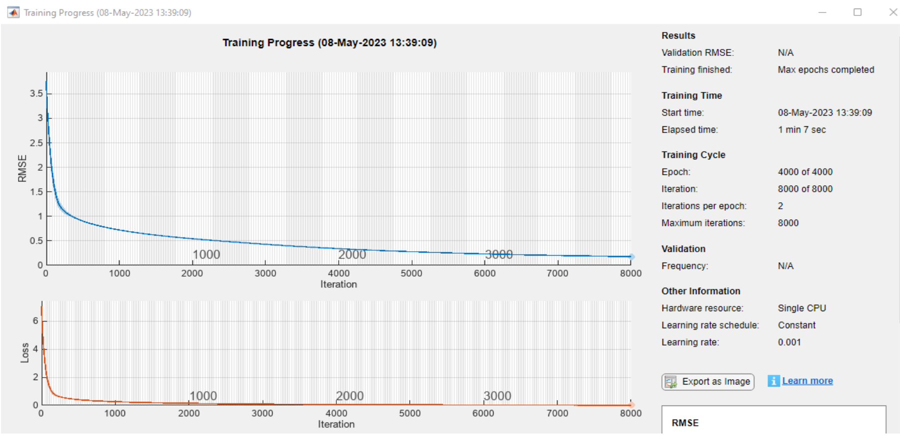

FIGURE 4. - Convergence curve of the proposed network

The confusion matrix for the categorization of 300 test samples is displayed in Figure (5). This matrix has six rows, as can be seen, and the number of samples in each row is 50. This means that there are 6 age groups as described in the database section and each age group has 50 samples or 50 MRI images. Our goal here is to predict what age group each sample belongs to. The last column on the right shows the detection accuracy value for each age group. For example, the accuracy of detecting samples belonging to the first age group (7 to 15 years) is equal to 92%. Also, in the last row and the last column, the overall accuracy value for brain age detection in all test samples is written, which is equal to 90.3%

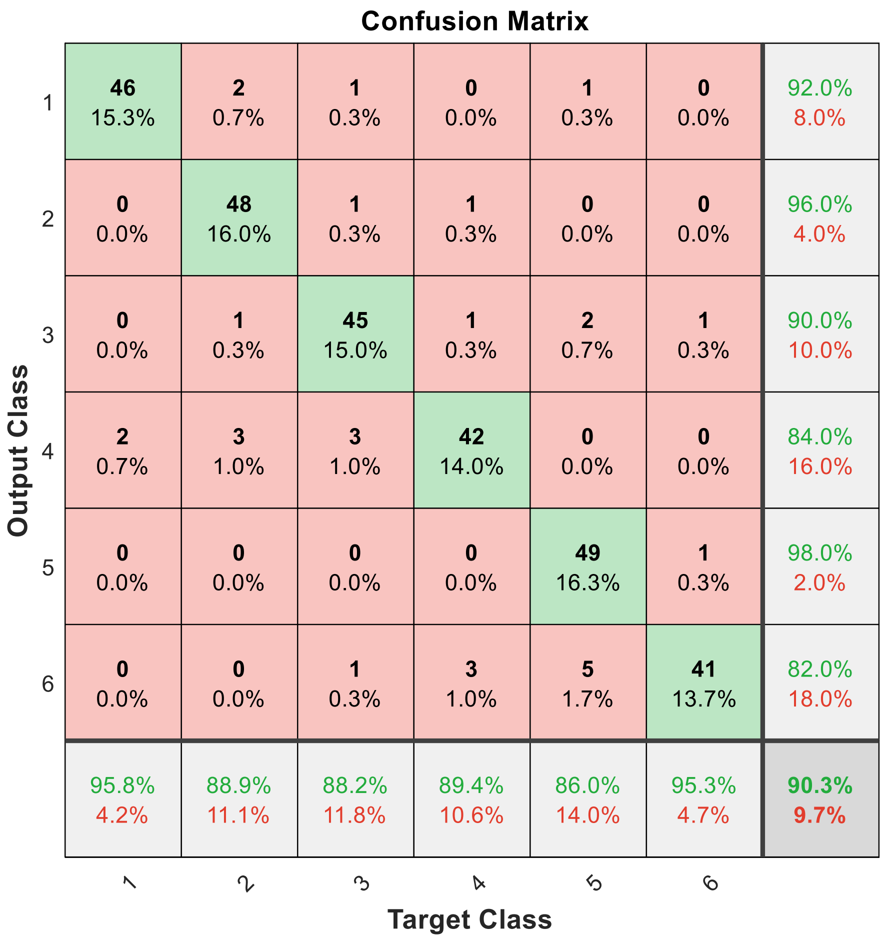

FIGURE 5. - Confusion matrix for predicting brain age on test data

The assessment criteria's numerical values are shown in Figure (6). The performance of predictive models is assessed using evaluation criteria, which are essential standards that help researchers assess the efficacy and precision of their methods. The accuracy, precision, recall, and F-score in this work are 0.93, 90.33, and 90.27, respectively.

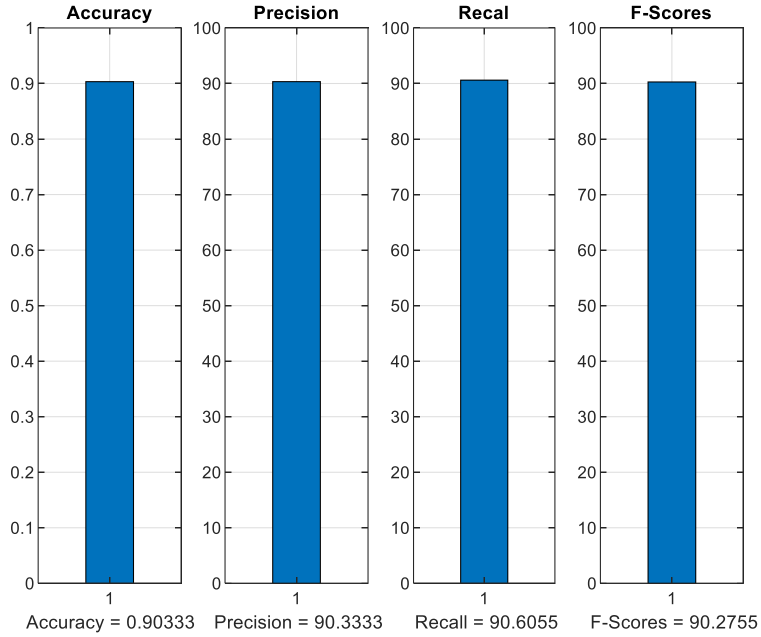

FIGURE 6. - Numerical values of evaluation criteria for predicting brain age on test data

. The regression curve is displayed in Figure (7). In regression analysis, a regression curve is a visual depiction of the connection between independent and dependent variables. This is a graphic representation of how modifications to the predictor variable or variables may impact the anticipated result. As shown in figure (7), the regression value is 0.93, meaning that the suggested model's prediction error is around 0.07.

The correlation coefficient, or R-value, quantifies the direction and magnitude of the linear relationship between the output and the target. A significant positive linear correlation is shown by a high R-value near 1, which shows that the model's predictions are quite accurate and closely match the desired values. On the other hand, smaller R-values indicate higher prediction error or weaker correlations. in this storyline:

- The fit line closely follows the data points, and the slope is approximately 1 (0.98), suggesting strong agreement
- The small offset (+0.18) represents a slight bias in predictions.
- The proximity of data points to the regression line indicates low residual error, which would correspond to a high R-value.

This implies the model performs well in predicting outputs relative to the given targets.

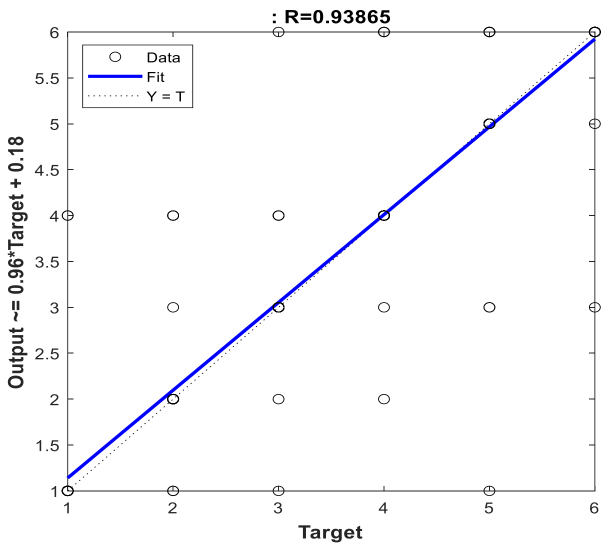

FIGURE 7. - Regression curve for predicting brain age on test data

Lastly, the ROC curve is shown in Figure (eight). A visual useful resource for assessing a classification version's overall performance at diverse threshold values is the receiver running feature (ROC) curve. It offers vital perception into the trade-off between sensitivity and specificity by way of plotting the real tremendous fee (sensitivity) versus the fake tremendous charge (specificity-1) for various thresholds. Additionally, the ROC curve displays the ratio of TP to FP values for each prediction for each age institution.

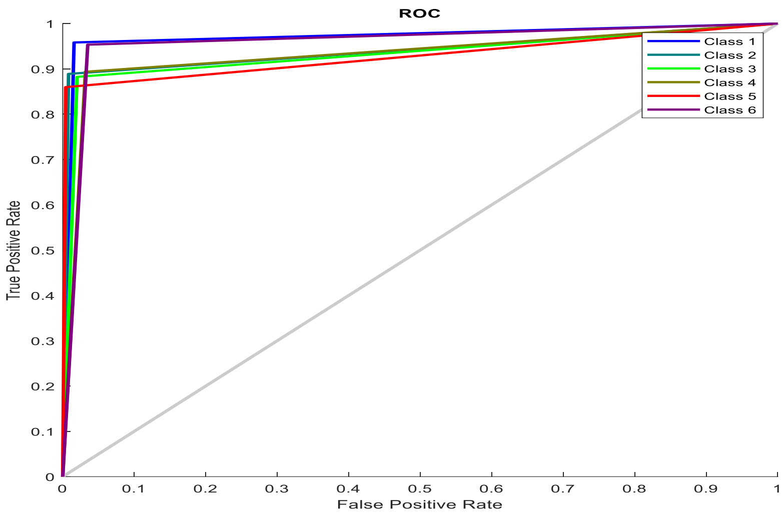

FIGURE 8. - ROC curve for predicting brain age on test data

5.5 COMPARISON OF SIMULATION RESULTS

In this component, we can evaluate the outcomes of the simulations with the ones of in advance studies that used MRI images to forecast the a long time of different human beings's brains. Deep neural networks are the inspiration of the primary technique used in the different research. This phase presents the prediction errors numbers for the cautioned technique, taking into consideration that different studies utilize blunders criteria to interpret the findings. It have to be cited that simulation and averaging have been used to get the mistake degrees for the advised technique after 20. It is clear that the advised method's RMSE and MAE criterion values are lower than those of the opposite processes.

Table 1. - Comparing the results of the proposed method with other works in terms of RMSE error

Method	RMSE	MAE
Random Forests [24]	4.13	3.09
Lasso [24]	3.34	2.54
Ridge [24]	3.29	2.49
Elastic net [24]	3.30	2.50
Support Vector Machine [24]	3.19	2.40
Deep Net [24]	2.91	2.19
lightweight deep neural networks [25]	-	2.14
CNN with LRB [26]	-	3.38
deep ensemble hippocampal CNN [27]	4.65	3.31
The proposed method (CNN-MRMR)	0.59	0.16

Convolutional deep neural networks are rather effective at both extracting and classifying spatial data. However, those networks extract a variety of records, that may result in each a drop in accuracy and an growth in execution time. Consequently, the entropy-primarily based MRMR method might be used in this examine to limit characteristic redundancy and pick out the satisfactory features. By reducing the redundancy between traits, this improves diagnostic accuracy.

6. CONCLUSION

A convolutional neural community-based hybrid technique with a characteristic choice layer and an MRMR set of rules based totally on entropy and mutual statistics among functions is furnished on this study. The advised method first uses convolutional layers to extract mind age-associated characteristics from MRI pix, and then the MRMR set of rules is used to pick the high-quality features. Lastly, regression layers and particular tendencies are used to decide mind age.

Predicting mind age from MRI pics the usage of a convolutional neural community (CNN) with a feature choice layer based at the MRMR set of rules is a novel and hybrid technique that has enormous theoretical and practical results. From a theoretical viewpoint, integrating the MRMR set of rules into the neural network structure as a layer affords an effective manner to mix classical feature choice and deep learning. This layer automatically selects features from MRI pictures which are maximum relevant to brain age whilst heading off redundancy between features, which improves community efficiency and decreases computational complexity.

In practical phrases, this method can improve prediction accuracy and decorate model interpretability, as the selected features directly reflect essential age-associated mind structures. Furthermore, such a model could be very suitable for medical packages including early prediction of getting older-associated neurological sicknesses through reducing data dimensionality and that specialize in key facts.

While this technique is novel, there are numerous drawbacks to using a convolutional neural community (CNN) with a feature choice layer based at the MRMR algorithm to expect brain age. Since the MRMR technique necessitates function dependency analysis, which can be extraordinarily time-ingesting in high-dimensional statistics like MRI scans, one o

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