

# An Innovative Algorithm-Assisted Neuroimaging Technique for Calculating Brain Age

(Teknik Inovatif Pengimejan Neuro Berbantuan Algoritma untuk Mengira Usia Otak)

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## ABSTRACT

Brain scans and machine learning algorithms can now be used to determine a person's age. In this assessment, we discuss a brief summary of the multiple medicinal purposes of brain-age estimation in neuropsychiatry and general populations. This verified technique has created new opportunities for resolving clinical concerns in neurology. For the purpose of developing a framework for brain-age projection, we first give an overview of common neuroimaging modalities, feature extraction techniques, and machine learning models. In this study, we proposed a novel wild horse optimized multi-tiered convolutional neural network (WHO-MCNN) strategy for predicting brain age. We employed magnetic resonance imaging (MRI) to collect brain neuroimage data for this study. To retain edges and reduce noise in images, pre-processed data was exposed to a bilateral filter. The histogram of oriented gradients (HOG) was used to extract the features from the data to record shape and texture information that is valuable for object recognition. The proposed method is further compared to other machine learning algorithms. The results show the proposed method achieved better performance in MAE, RMSE, and  $R^2$ , such as 2.982, 3.925, and 0.537 for brain age prediction. Through early identification and treatment of age-related neurological diseases, this approach facilitates a greater understanding of brain aging processes. Finally, we offer some recommendations for future study approaches and talk about the real-world issues and difficulties that have been discussed in the literature.

Keywords: Brain age; magnetic resonance imaging (MRI); neuroimage; wild horse optimized multi-tiered convolutional neural network (WHO-MCNN)

## ABSTRAK

Imbasan otak dan algoritma pembelajaran mesin kini boleh digunakan untuk menentukan umur seseorang. Dalam penilaian ini, kami membincangkan ulasan ringkas tentang pelbagai tujuan perubatan anggaran usia otak dalam neuropsikiatri dan populasi umum. Teknik yang disahkan ini telah mewujudkan peluang baharu untuk menyelesaikan kebimbangan klinikal dalam neurologi. Bagi tujuan membangunkan rangka kerja untuk unjuran usia otak, pertama sekali kami memberikan gambaran keseluruhan modaliti pengimejan neuro biasa, teknik pengekstrakan ciri dan model pembelajaran mesin. Dalam kajian ini, kami mencadangkan strategi rangkaian saraf konvolusi berbilang peringkat (WHO-MCNN) yang dioptimumkan oleh kuda liar baharu untuk meramalkan usia otak. Kami menggunakan pengimejan resonans magnetik (MRI) untuk mengumpul data imej neuro otak untuk kajian ini. Untuk mengekalkan pinggir dan mengurangkan hingar dalam imej, data pra-proses didedahkan kepada penapis dua hala. Histogram berorientasikan kecerunan (HOG) digunakan untuk mengekstrak ciri daripada data untuk merekodkan maklumat bentuk dan tekstur yang penting untuk pengesanan objek. Kaedah yang dicadangkan ini dibandingkan dengan algoritma pembelajaran mesin yang lain. Keputusan menunjukkan kaedah yang dicadangkan mencapai prestasi yang lebih baik dalam MAE, RMSE dan  $R^2$ , seperti 2.982, 3.925 dan 0.537 untuk ramalan usia otak. Melalui pengenalpastian dan rawatan awal penyakit neurologi berkaitan usia, pendekatan ini memudahkan pemahaman yang lebih mendalam tentang proses penuaan otak. Akhir sekali, kami menawarkan beberapa cadangan untuk pendekatan kajian masa depan dan membincangkan isu dan kesukaran dunia sebenar yang telah dibincangkan dalam kepustakaan.

Kata kunci: Imej neuro; pengimejan resonans magnetik (MRI); rangkaian neural konvolusi berperingkat yang dioptimumkan oleh kuda liar (WHO-MCNN); usia otak

## INTRODUCTION

Brain age estimation is a captivating field, where scientists use images of the brain to evaluate how old it appears to be. This isn't always approximately calculating the number of years a person has lived, but rather computing the biological age of the brain (Baecker et al. 2021). The biological age can vary from the chronological age for several reasons, inclusive of genetics, lifestyle, and illness. Consider that the brain's age can provide treasured records regarding someone's specific brain fitness and potential risks for neurological ailments (Cole et al. 2019). Neuroimaging is critical equipment for assessing mental age. It includes capturing an inclusive image of the brain through the use of modern technologies like computed tomography (CT) and magnetic resonance imaging (MRI) (Franke & Gaser 2019). These images depict the shape and the traits of certain brain regions. By analyzing those pixels, scientists can discover patterns and versions associated with aging (Feng et al. 2019). Using machine learning is a common method for measuring brain age. It necessitates an emerging computer algorithm on large databases of brain images from many age groups of humans (Cole, Franke & Cherbuin 2019). The gathering of policies teaches to comprehend the features of the thoughts that exchange as people age, which include the shrinking of particular regions and the loss of mind quality (Elliott et al. 2021). After training, the set of standards can estimate the brain age of new images it has not seen earlier. Measuring brain age is crucial. First, it may help humans perceive if their brains age faster or slower than expected (Higgins-Chen, Thrush & Levine 2021). As an example, if a 60-12-month-old has a thought that looks lots older, they will be more liable to sicknesses like Alzheimer's (Trollor & Valenzuela 2001). In evaluation, if their thoughts seem younger, it suggests that they've got precise intellectual health. This information can be vital for early intervention and tailored remedy strategies (Jónsson et al. 2019). Furthermore, brain age evaluation can assist in examining how different factors affect brain health. Scientists can inspect the influence of lifestyle modifications, which include weight loss plans and exercise, in addition to the consequences of ailments and therapies (Miranda et al. 2019). This method allows for knowledge to promote healthy brain aging and save you from or postpone neurological sicknesses.

## AIM OF THIS STUDY

The study proposes a novel WHO-MCNN strategy for predicting brain age using magnetic resonance imaging data.

## LITERATURE REVIEW

Using a large dataset of 839 patients, the study by Niu et al. (2020) assessed the precision of brain age estimation using 36 combinations of imaging markers and machine learning models, including deep learning. It suggested a fresh approach that takes behavioral performance, gender,

and chronological age into account, aiming to rectify the brain age difference's systematic bias. A study by Beheshti et al. (2019) provided a bias-adjustment strategy for brain age estimate with chronological age as a covariate. With a good  $R^2$  of 0.81 and a mean absolute error of 2.66 years, the method was applied to metabolic brain data from 675 persons without cognitive impairment issues. A growing body of research by Smith et al. (2019) was being done on brain age, or the apparent age of an individual deduced from brain imaging data. Factors such as sickness and cognitive decline were correlated with delta, the disparity between brain age and chronological age, which may indicate resistance or hastened aging. There has not been much research on the best methods for computing the delta. This technical note outlined potential improvements. The brain-age paradigm was becoming more and more helpful in forecasting future health outcomes and in understanding disorders associated with aging in the article (Cole 2020). To better anticipate brain age and increase sensitivity to lifestyle and biological variables that affect brain and cognitive health, multimodality neuroimaging can study the anatomy and function of the brain. To determine the brain ages of individuals with different types of epilepsy, the research by Sone et al. (2021) employed 1196 MRI images of healthy controls that are T1-weighted (magnetic resonance imaging). According to the results, brain-PAD (progressive age-related decline) levels significantly increased for all patients except those with extra-temporal lobe focal epilepsy. Epilepsy symptoms may be understood with brain-age prediction based on neuroimaging. A study by Cole, Franke and Cherbuin (2019) examined that brain age prediction has been transformed by machine learning, making it possible to analyze structural neuroimaging data. To forecast brain age, this technique entails building a regression model of age-related neuro-anatomical changes in healthy individuals. These 'brain-age gaps' could promote differential diagnosis, enable focused therapies, and help in the early detection of brain-based illnesses. Imaging markers of neuropathological processes linked to brain illnesses and deep learning have been used to simulate brain aging. Deep Brain Net, a deep neural network, was developed and assessed in research using MRI data from a varied group of subjects (Bashyam et al. 2020). In contrast to models that fit well, the model demonstrated stronger differentiation and provided robust brain-age estimations without specialized processing. The Simple Fully Convolutional Network (SFCN) might be utilized to estimate brain age from T1-weighted structural MRI data, a deep convolutional neural network model in research by Peng et al. (2021). Because it has fewer parameters, it can work with 3D volume data and tiny datasets. For brain age prediction, 2019 Predictive Analysis Challenge, SFCN earned the prize for achieving cutting-edge performance utilizing UK Biobank data. In order to estimate age in brain structures, the study by Jiang et al. (2020) used the Convolutional Neural Network (CNN). The front parietal, dorsal focus, and default mode

networks' best age prediction accuracy was found in CNN, according to data from 1,454 healthy participants ranging in age from 18 to 90. In terms of prediction accuracy, CNN outperformed relevance vector regression and Gaussian process regression. Comparing parous mothers to their nulliparous counterparts, De Lange et al. (2019) employed neuroimaging and machine learning, showing that the

former had fewer signs of brain aging. Common genetic variation or confounding factors were unable to explain the association between childbirths and a 'younger-looking' brain. Based on the findings, parity could be associated with neuronal alterations that affect women's brain aging in later life. Table 1 summarizes the studies, their main focuses, and key findings, facilitating easier comparison and analysis.

TABLE 1. Comparison analysis

Study	Description	Key findings
Niu et al. (2020)	Examined the accuracy of brain age using 36 imaging indicators and machine learning models on 839 individuals	Suggested a way to address systemic bias in brain age differences by taking behavior, gender, and true age into consideration
Beheshti et al. (2019)	Created a bias-adjustment method for estimating brain ages in 675 individuals by utilizing chronological age as a covariate	Obtained a mean absolute error of 2.66 years and an $R^2$ of 0.81
Smith et al. (2019)	Investigated using imaging data to determine brain age as a proxy for apparent aging	Health issues and cognitive decline have been linked to delta, or the discrepancy between brain age and chronological age
Cole (2020)	Spoke about how the brain-age paradigm may be used to explain aging-related illnesses and predict health outcomes	Highlighted how multimodality neuroimaging may be used to evaluate the structure and function of the brain
Sone et al. (2021)	T1-weighted MRI scans of 1196 healthy controls were used to analyze brain ages in epileptic patients	Most patients had elevated brain-PAD levels, which has consequences for comprehending epilepsy symptoms
Cole, Franke & Cherbuin (2019)	Investigated how well machine learning predicts brain age from structural neuroimaging data	Proposed that brain-age gaps might improve early brain illness detection and differential diagnosis
Bashyam et al. (2020)	Created and assessed Deep Brain Net to estimate brain age using MRI data	Showed superior differentiation over traditional models and reliable brain-age predictions without the need for specialist processing
Peng et al. (2021)	Estimated brain age from T1-weighted MRI data using a Simple Fully Convolutional Network (SFCN)	SFCN won the 2019 Predictive Analysis Challenge with state-of-the-art brain age prediction capability
Jiang et al. (2020)	Used a dataset of 1,454 people using Convolutional Neural Networks (CNN) to estimate age in brain regions	In terms of age prediction accuracy, CNN fared better than Gaussian process regression and relevance vector regression
De Lange et al. (2019)	Compared the aging of the brains of parous moms and nulliparous women using neuroimaging and machine learning	Parous moms showed less indications of brain aging, indicating that parity may be related to aging-related neuronal alterations
Lu, Zhang & Yao (2025)	Discussed the difficulties in detecting Alzheimer's disease with CNNs and MRI	Lightweight Robust Alzheimer's Disease Vision Transformer (LRAD-ViT) was introduced to identify AD early and accurately (93.41% vs. CN)
Lu et al. (2025)	TB detection in CT and X-ray images using the CTBViT model	Presented the CTBViT model, which uses an independent classifier and Patch Reduction Block to detect tuberculosis in CT and X-ray images. Shown exceptional performance when validated on many datasets

CONTRIBUTION OF THIS STUDY

Brain age models help find neurodegenerative diseases early, customise medication, give researchers new ideas, test cognitive function, keep track of illness development, do non-invasive MRI scans, standardise tests, enhance risk assessment, work with other biomarkers, and promote public health. These models help individuals and healthcare systems by making it easier to learn about and take care of brain health. The new Wild-Horse-Optimized Multi-Tiered Convolutional Neural Network (WHO-MCNN) method for predicting brain age using MRI data makes predictions more accurate, faster, more flexible, able to handle changes, able to extract high-resolution features, able to scale up, able to process data in real time, able to use all available data, able to be understood, able to be generalised, and able to provide personalised healthcare. The model’s architecture lets doctors provide personalised therapies based on age predictions by letting them do brain health tests on each person and encouraging generalisation across groups. In general, brain age prediction models help individuals and healthcare systems get better knowledge about and take better care of their brains. The following discoveries are essential to this inquiry.

THE STUDY’S NOVELTY

a. *Advanced Prediction Framework* Introduces a novel WHO-MCNN strategy tailored for brain age

estimation using MRI data, addressing the issue of dimensionality in neuroimaging datasets.

b. *Image Pre-processing Enhancement* Implements a bilateral filter to enhance image quality with the aid of retaining edges and reducing noise, crucial for accurate feature extraction.

c. *Feature Extraction Innovation* Utilizes Histogram of Oriented Gradients (HOG) to capture shape and texture data from MRI statistics, which improves the illustration of neuro-image structures that are critical for object recognition.

d. *Evaluation Benchmarking* Compares the proposed WHO-MCNN approach with traditional machine learning algorithms, demonstrating superior overall performance in MAE, RMSE, and coefficient of  $R^2$  for brain age prediction.

These contributions highlight the methodological improvements, performance benefits, and scientific implications of the usage of WHO-MCNN for predicting brain age from MRI information.

METHODOLOGY

This section present data gathering, pre-processing using bilateral filter, feature extraction using histogram oriented gradient (HOG), a novel wild horse-optimized multi-tiered convolutional neural network (WHO-MCNN) strategy for estimating brain age. Figure 1 shows the flow of methodology.

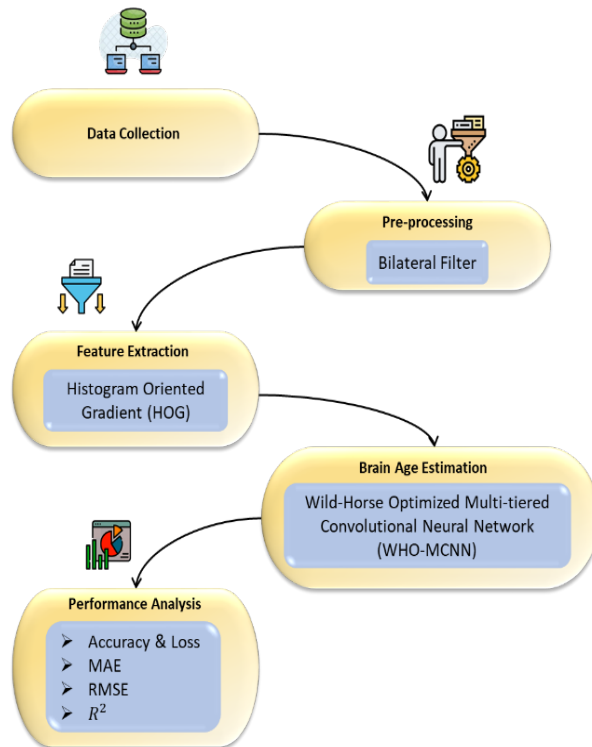


FIGURE 1. Overview of methodology

#### DATA GATHERING AND PRE-PROCESSING DATA

We used dataset sources from Kaggle in this investigation. This dataset has 416 cross-sectional participants, ranging in age from 18 to 96. Each patient receives three or four distinct T1-weighted MRI images taken during a single scan session. The subjects are all right-handed, including men and women. Very mild to moderate Alzheimer's disease (AD) has been clinically identified in 100 of the participants over 60.

[<https://www.kaggle.com/datasets/jboysen/mri-and-alzheimers>]

#### BILATERAL FILTER (BF) PRE-PROCESSING

BF is a non-iterative, nonlinear filter that removes noise without affecting edges. It considers the grey-level similarities between adjacent pixels as well as their geometric proximity. A local neighborhood's weighted sum of the pixels is determined by BF. Specifically, this pixel is replaced using the weighted average of each neighboring pixel. A pixel's spatial distance and intensity distance surrounding its neighborhood can be used to determine the weights in this computation. The coefficients of the spatial (domain) filters define the spatial distance within a pixel's neighborhood, while the intensity (or range) filter's coefficients are determined by the radiometric separation of that pixel from its neighboring pixels. At a pixel point  $x$ , the BF's output is computed as:

$$\underline{K}(y) = \left(\frac{1}{B}\right) \sum_{x \in M(y)} f\left(\frac{-\|x-y\|^2}{2\sigma_c^2}\right) f\left(\frac{-|K(x)-K(y)|^2}{2\sigma_s^2}\right) K(x) \quad (1)$$

where  $M(y)$  denotes  $K(x)$ 's spatial neighbourhood and two parameters control the level of intensity and spatial domain weight trade-off:  $\sigma_c^2$  and  $\sigma_s^2$ , respectively. This formula could be used to get the normalisation constant  $C$ .

$$B = \sum_{x \in M(y)} f\left(\frac{-\|x-y\|^2}{2\sigma_c^2}\right) f\left(\frac{-|K(x)-K(y)|^2}{2\sigma_s^2}\right) K(x) \quad (2)$$

In contrast to standard filters, BF may be acknowledged as an effective filter for edge preservation and noise elimination. Nevertheless,  $M(y)$ ,  $\sigma_c^2$  and  $\sigma_s^2$ , the filter parameters determine the BF's ideal performance. This dual-area weighting enables bilateral filtering to smooth the images while maintaining edges, making it effective for an obligation that includes denoising and enhancing snapshots while retaining critical details.

#### FEATURE EXTRACTION USING HISTOGRAM OF ORIENTED GRADIENTS (HOG)

The directed gradients histogram is a technique used in computer vision and image processing for item recognition. HOG is pivotal in brain age estimation, quantifying

gradient orientation in MRI scans. By binning orientations into histograms, it captures local structure and texture data crucial for age prediction, enhancing neuroimaging evaluation accuracy. Using this technique, the image is segmented into units called cells, which are connected tiny regions. The cells yield the histogram of directed gradients. Initially, the Sobel kernel is used to filter the image to create an image gradient in both directions.

$$|G(i, j)| = \sqrt{G_x(i, j)^2 + G_y(i, j)^2} \quad (3)$$

$$x, y_G = \left(\frac{G_y(i, j)}{G_x(i, j)}\right) \quad (4)$$

The visual gradient along the  $x$  and  $y$  directions is referred to as  $G_x, G_y$ . Equations (3) and (4) are used to establish each pixel in the gradient's angle and magnitude in the image. The rows and columns of the image are represented by the variables  $i$  and  $j$ , and the magnitude and angle of the gradient in these equations, respectively.

#### WILD HORSE OPTIMIZED MULTI-TIERED CONVOLUTIONAL NEURAL NETWORK (WHO-MCNN)

##### WILD HORSE OPTIMIZATION (WHO)

A unique algorithm in neuroscience utilizes Wild Horse Optimization (WHO) to evaluate the age of the brain. WHO, inspired by wild horse herd behavior, optimizes neural network parameters to increase the brain age prediction's accuracy using MRI data. This strategy combines evolutionary tactics with machine learning to provide promising advances in understanding brain development and aging processes.

A completely unique set of rules in neuroscience utilizes Wild Horse Optimization (WHO) to evaluate the age of the brain. WHO, inspired by means of wild horse herd behavior, optimizes neural community parameters to boom the brain age prediction's accuracy using MRI records. This approach combines evolutionary techniques with gadget getting-to-know to provide promising advances in know-how mind improvement and getting older approaches.

WHO is a nature-inspired metaheuristic algorithm that uses wild horse herd behavior to efficiently solve optimization issues. Based on their social structure, horses may be broadly classified into two classes: territorial and non-territorial. Stallions, mares, and offspring are some of the age groups in which they live. Amidst their mutual grazing, mares and stallions coexist and engage in interactions. As they mature and form their own families, foals depart from their groups and join other groups. Stallions and siblings cannot mate because of this behavior. The WHO algorithm, which is a metaheuristic swarm-based algorithm, is inspired by the social structure of horses, including their mating, grazing, dominance, and leadership hierarchy.

THE FIVE STAGES THAT MAKE UP THE WHO  
ALGORITHM ARE AS FOLLOWS

*Forming Horse Groups, Establishing Initial Populations,  
and Selecting Leaders*

There are M–H non-leaders, such as foals and mares, and there are G leaders if there are N individuals and G groups. OS, or H/M is the definition for the proportion of stallions.

*Feeding behaviour*

Foals spend most of their lives grazing close to their group, as previously mentioned. To imitate the grazing period, it was expected that the stallion location would be in the middle of the grazing area. Use the following formula to allow other individuals to migrate.

$$W_{H,i}^j = 2Y\cos(2\pi RZ) \times (Stallion_{H,i} - W_{H,i}^j) + Stallion_{H,i} \quad (5)$$

where Z, as defined by Equation (5), is an adjustable parameter, R is an arbitrary integer in the range of -2 to 2, and where the stallion and the  $i^{th}$  group member are located is represented by  $W_{H,i}^j$  and  $Stallion_{H,i}$ , respectively.

$$O = \overline{Q1} < TDR, IDX = (O == 0), Y = R2\Theta IDX + \overline{Q3}\Theta(\sim IDX) \quad (6)$$

where Q2 is a random integer between 0 and 1, the random vectors  $1, \rightarrow \overline{Q1}$  and  $\rightarrow \overline{Q2}$ , and 0 and 1 make up the vector O, its dimension equal to the problem's size. Equation (6) computes TDR, a parameter that decreases linearly.

$$TDR = 1 - \frac{S}{S} \quad (7)$$

where S is the maximum number of iterations and S is the current number.

*The Behaviour of Horse Mating*

As previously said, one-way horses are unique from other animals in their behaviour is to separate their foals from their mother groups before they reach adolescence and mate. Using the following formula, one may mimic the behaviour of a horse mating:

$$X_{H,i}^o = Crossover(W_{H,i}^r, W_{H,i}^y), j \neq i \neq l, r = y = end \quad Crossover = Mean \quad (8)$$

And horse o's position in group l (made from the positions of horse r in group i and horse y in group j is represented by the symbol  $W_{H,i}^o$ . The crossover probability in Basic WHO is set to a constant known as PC.

*Leadership in groups*

The stallions who lead the group will guide the rest of the group to a waterhole or other appropriate location. The dominant group will use the waterhole first since group

leaders, or stallions, will fight for it. This behaviour may be simulated using the formula below:

$$\underline{Stallion}_{H,i} = \{2Y\cos(2\pi RZ) \times (WH - Stallion_{H,i}) + WH \text{ if } rand > 0.52Y\cos(2\pi RZ) \times (WH - Stallion_{H,i}) - WH \text{ if } rand \leq 0.5 \quad (9)$$

where WH denotes the location of the waterhole and  $Stallion_{H,i}$  and  $Stallion_{H,i}$ , respectively, represent the candidate and existing leader positions in the  $i^{th}$  group.

*Leadership Selection and Exchange*

Leaders are first chosen at random. On the basis of their fitness values, leaders are chosen. To simulate interactions between individuals in leadership roles and others, the formula below is utilised:

$$Stallion_{H,i} = \{W_{H,i}^j \text{ if } e(W_{H,i}^j) < e(Stallion_{H,i}) \text{ Stallion}_{H,i} \text{ if } e(W_{H,i}^j) \geq e(Stallion_{H,i}) \quad (10)$$

where the stallion and foal fitness values are represented by the variables  $e(Stallion_{H,i})$  and  $e(W_{H,i}^j)$ .

Wild Horse Optimization (WHO) is a revolutionary optimization approach that improves CNN layers in brain age estimation. Meanwhile, the activation function used in WHO is inspired by the behaviors of wild horses, allowing it to converge effectively and extract advantages in CNNs. By using this CNN, we were able to successfully learn and generalize from this common signal in the neuroimaging data, improving the accuracy of brain age prediction and efficiency.

MULTI-TIERED CONVOLUTIONAL NEURAL  
NETWORK (MTCNN)

The Multi-Tiered Convolutional Neural Community (MTCNN) model is utilized for brain age estimation; this is a crucial feature in neuroscience and medical studies. This approach uses a multi-tiered structure to extract hierarchical features from neuroimaging data, along with MRI images. The convolutional neural network (CNN) layers that make up the essence of an MTCNN had been designed to extract more complicated and abstract data from the input data. These layers are regularly organized into stages, with lower tiers focusing on primary edges and texture recognition and higher tiers combining those characteristics to create more comprehensive shapes and samples associated with mind aging.

The MTCNN formulaic approach includes:

*Input layer* Preliminary layers' method process raw MRI data, extracting simple functions like edges and corners.

*Intermediate layer* subsequent layers integrate those primary functions to recognize more difficult pattern inclusive of shapes and precise textures to brain structures.

*Output layer* The very last layers' combination those discovered out functions to expect brain age, frequently the

usage of regression strategies to estimate chronological age primarily based on the extracted neuroimaging features.

This multi-tiered structure allows MTCNN to effectively analyze huge-scale datasets, adapting its parameters to accurately predict brain age through distinct populations and demographic factors. With the resource of focusing on local and global features of thoughts and images, MTCNN complements the precision of brain age estimation, facilitating more profound insights into neurological development, growing old tactics, and related medical programs. Algorithm 1 suggests the system of WHO-MCNN.

Algorithm 1: Process of WHO-MCNN

```

initialize_network_parameters()
for epoch in range(num_epochs):
    for batch in training_data_batches:
        input_data, labels = batch
        Forward pass
        conv_output1 = convolution_layer1(input_data)
        conv_output2 = convolution_layer2
        (conv_output1)
        maxpool_output = maxpooling_layer
        (conv_output2)
        flat_output = flatten(maxpool_output)
        fc_output = fully_connected_layer(flat_output)
        Compute loss
        loss = calculate_loss(fc_output, labels)
        Backward pass
        compute_gradients(loss)
        update_parameters()
    Evaluate on validation set
    validation_accuracy = evaluate_model
    (validation_data)

```

Print progress

```
print(f'Epoch [{epoch+1}]/{num_epochs},
```

Validation Accuracy:

```
{validation_accuracy}')
```

Test the final model

```
test_accuracy = evaluate_model(test_data)
```

```
Print(f'Final Test Accuracy : {test_accuracy}')
```

## EXPERIMENTAL FINDINGS

In this section, the outcome of age estimate for brain age prediction utilising a unique wild horse optimised multi-tiered Convolutional neural network (WHO-MCNN) technique is examined. Comparing our suggested method (WHO-MCNN) with existing approaches Bayesian ridge (BR), and vibrational Quantum circuit (VQC) (Jeon, Park & Baek 2024). The brain age estimation through Neuroimaging tested with 90% accuracy rate and 10% of loss rate. Figure 2 demonstrate the outcome of accuracy and loss.

Mean absolute error (MAE)

The mean absolute error (MAE) of a set of hard and fast forecasts is measured, without considering their path (whether or not they overestimate or underestimate the real values). Figure 3 and Table 1 depicts the MAE result. It shows that our suggested approach WHO-MCNN (2.982) outperforms the existing approaches BR and (3.310), and VQC (3.302).

$$MAE = \frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2 \quad (11)$$

Root mean square error (RMSE)

Although RMSE and MAE are comparable, RMSE gives higher errors in a greater significance. It is the average of the squared differences between the actual remark and the

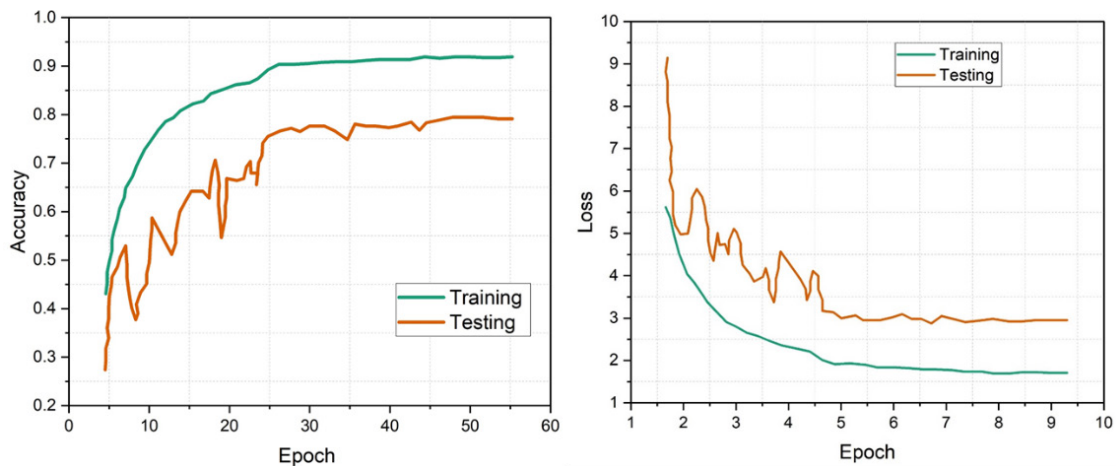


FIGURE 2. Outcome of accuracy and loss

forecast squared. Figure 4 and Table 2 depicts the result of RMSE. When comparing the suggested approach WHO-MCNN (3.925) with existing techniques BR and (4.280), and VQC (4.083), this method shows the superior result for estimating brain age.

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2} \quad (12)$$

*R-square (R<sup>2</sup>)*

The ratio of the unbiased variable (predicted age) to the established variable (actual age) that can be predicted is known as R<sup>2</sup>. Figure 5 and Table 3 depicts the R<sup>2</sup>. When comparing the suggested technique WHO-MCNN (0.537) BR and (0.300), and VQC (0.425) with existing approach, this method shows the superior result to predicting brain age.

$$R^2 = 1 - \left( \frac{RSS}{TSS} \right) \quad (13)$$

where RSS is a square residual and TSS is a sum of squares.

*Significance Testing*

To accurately interpret the effectiveness of WHO-MCNN approach compared to traditional algorithms (e.g., Bayesian Ridge and Vibrational Quantum Circuit):

*Hypothesis Setting:* a) Null Hypothesis (H<sub>0</sub>): There is no significant difference in brain age prediction accuracy between WHO-MCNN and other algorithms and b) Alternative Hypothesis (H<sub>1</sub>): There is a significant difference in accuracy.

*Statistical Tests:* a) Use a t-test or ANOVA, if comparing multiple algorithms, depending on their distributions, b) Ensure assumptions (e.g., normality, homogeneity of variances) are tested (e.g., using Shapiro-Wilk and Levene’s tests) and c) Set a significance level (α) at 0.05.

*Confidence Interval Calculation:* a) For parameters like MAE, RMSE, and R<sup>2</sup>, calculate 95% confidence intervals and b) Use bootstrapping or the t-distribution to account for small sample sizes in MRI data.

DISCUSSION

Brain age estimation has potential; however, it has some drawbacks, along with the ‘curse of dimensionality’, which

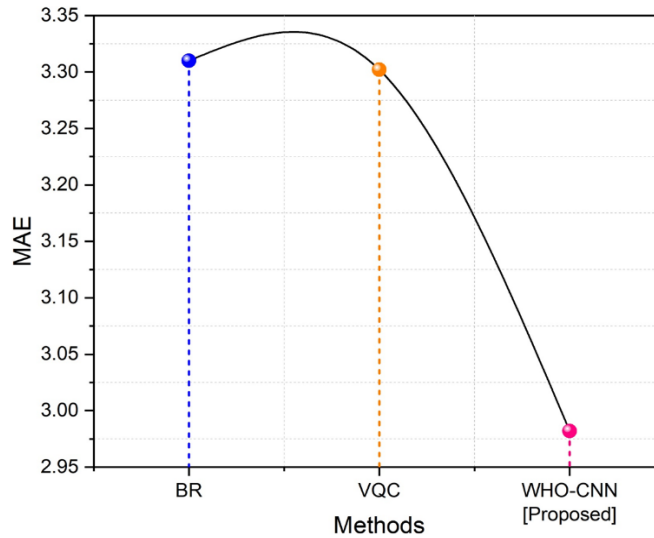


FIGURE 3. Outcome of MAE

TABLE 1. Value of MAE

Methods	MAE
BR	3.31
VQC	3.302
WHO-CNN [Proposed]	2.982

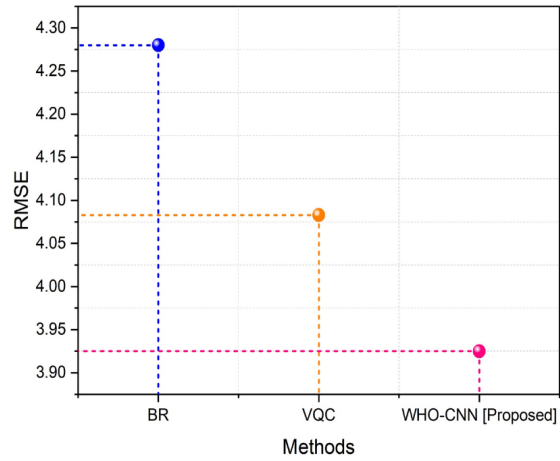
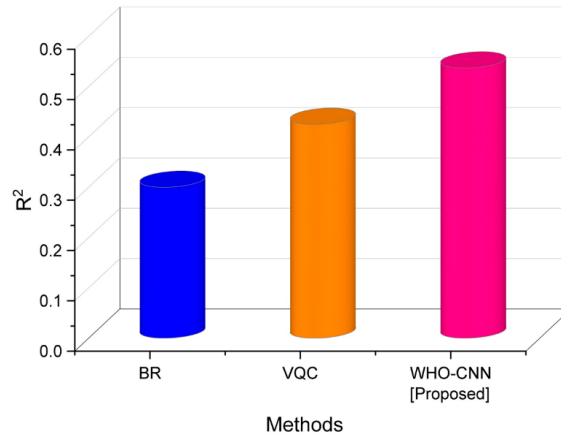


FIGURE 4. Outcome of RMSE

TABLE 2. Value of RMSE

Methods	RMSE
BR	4.28
VQC	4.083
WHO-CNN [Proposed]	3.925

FIGURE 5. Outcome of  $R^2$ TABLE 3. Value of  $R^2$ 

Methods	$R^2$
BR	0.3
VQC	0.425
WHO-CNN [Proposed]	0.537

could bring about overfitting and incorrect predictions. The quality and consistency of neuroimaging records can affect accuracy. The complexity of the brain, along with genetic, environmental, and lifestyle factors, may lead to an oversimplified understanding of aging. More rigorous validation across multiple businesses and life ranges was required for generalizability. Statistical strategies are nonetheless limited in their capacity to properly capture brain-growing-old mechanisms in the examination (Cole et al. 2019), probably leading to gaps in understanding and application.

In a study by Deary et al. (2009), age-related cognitive decline has barriers due to small impact sizes, bad replication, the chance of reverse causation, the issue of separating precise influences from genetics, health situations, lifestyle factors, and the high cost of useful resources - in-depth nature of brain imaging and genome-extensive scans. Those hazards lessen the dependability of effects and might limit their use in large-scale investigations.

The proposed 2D slice-based Recurrent Neural Network (RNN) model gives reduced parameters and quicker training in comparison to standard 3D convolutional neural networks in the article (Lam et al. 2020). However, it could lose three-dimensional spatial context due to sequential processing of 2D slices, probably affecting characteristic extraction and interpretation. Moreover, the model's reliance on sagittal slice ordering might introduce variability and sensitivity, doubtlessly impacting predictions' consistency and robustness.

Harmonization techniques in neuroimaging aim to reduce biases from multi-website data, but they can introduce website-unique record loss, affecting sensitivity to detect differences among organizations like controls and individuals with autism spectrum disease (Jeon, Park & Baek 2024). Harmonization could introduce variability or errors, undermining the robustness and generalizability of findings across distinctive datasets and medical applications. Therefore, careful attention and validation are crucial to ensure the blessings outweigh those drawbacks in neuroimaging research.

To overcome these barriers, our method, the WHO-MCNN, an optimized multi-tiered convolutional neural network, uses advanced MRI data preprocessing strategies and HOG for feature extraction. This approach captures significant form and texture data for accurate brain age forecasts and representative superior inclusive performance in accuracy metrics. This innovative technique permits initial detection and remedy of age-associated neurological circumstances.

#### CONCLUSION

This study presents a unique approach, the WHO-MCNN, for forecasting brain age using MRI statistics. Through addressing the paper on dimensionality in brain-age

assessment, the WHO-MCNN leverages innovative methods along with bilateral filtering and HOG for feature extraction from neuro-images. The comparative evaluation with distinctive device mastering algorithms establishes superior inclusive performance in MAE (2.982),  $R^2$  (0.537) and RMSE (3.925) parameters for brain age forecast. The innovative approach improves early detection but also enriches comprehension of intricate age-related neurological diseases. This method holds promise for growing focused interventions and personalized health maintenance strategies geared toward maintaining cognitive features and their prevalence throughout the life duration.

#### STUDY LIMITATIONS AND FUTURE SCOPE

There are significant issues and limitations associated with brain-age assessment technologies, primarily concerning interpretability, reliability, and clinical utility. Ethical concerns arise regarding the use of AI in healthcare, alongside worries about privacy related to neuroimaging data in therapeutic contexts. Abnormal brain age could indicate pathogenic processes or increased risk of cognitive decline, yet the sensitivity and specificity of these assessments remain untested. Healthcare professionals may also unintentionally favor patients with a positive brain age result, affecting professional choices and patient relationships. The variability of age-related brain changes complicates the accurate determination of brain age across diverse demographic groups, influenced by genetic, environmental, lifestyle factors, and disease pathology.

Moreover, poorly understood biological mechanisms contributing to brain aging - such as oxidative damage and protein accumulation - raise questions about whether neurological diseases cause an aged brain appearance or whether accelerated brain aging leads to increased disease susceptibility. Addressing these complex interactions calls for comprehensive multimodal longitudinal studies that evaluate various biological and environmental aspects, with the integration of machine learning algorithms potentially clarifying the connections between brain aging and neuropathological conditions.

Technological challenges hinder many clinical settings from effectively employing brain age assessment methods, compounded by the lack of standardized practices for validating these computational approaches. Inconsistent neuroimaging datasets and protocols further complicate accuracy and reliability, as variations in imaging conditions could bias predictions. While some regions have established regulatory frameworks, substantial barriers remain due to the absence of robust protocols for algorithm evaluation as medical devices. Additionally, logistical concerns such as resource availability could restrict the widespread application of brain age estimations, as funding may be allocated to more pressing healthcare priorities.

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