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DEEP LEARNING FRAMEWORK WITH ENHANCED RESNET50 MODEL FOR BRAIN AGE ESTIMATION USING MRI IMAGES

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Abstract
Human brain is an important organ that controls thought process and activities of a person. It is important to understand the patterns of brain including aging to have correlation of facts. In healthcare domain, MRI ss widely used modality for investigating brain related issues. With the emergence of deep learning models, medical image analysis for diagnosis of various problems has become easier. With respect to brain age estimation the existing research has witnessed some success. However, there is need for exploring enhanced deep learning models for leveraging estimation performance. Towards this end, in this paper we proposed a framework based on deep learning for brain age estimation. The proposed framework is made up of an enhanced ResNet50 model with an underlying algorithm known as Learning based Approach for Brain Age Estimation (LbA-BAE). Our experimental results using UK biobank dataset has revealed that the proposed framework is capable of estimating brain age with less error rate. The proposed algorithm is found better than many existing models with less MAE4.10.
Keywords –Artificial Intelligence, Deep Learning, ResNet50, Brain Age Estimation, Brain MRI Images

1. INTRODUCTION

Healthcare domain has been playing vital role to ensure health and wellbeing of humans.Appropriate and timely medical interventions could save lives of people besides increasing the span of human life. Human brain is an important organ which enables functionality of all parts of human body. If there is any abnormality in the brain, it has to be diagnosed in order to solve a specific health problem. Therefore, it is very important to have brain imaging modalities like CT scan and MRI.Recent research on brain age estimation has shown significant achievement besides providing other useful insights. An important observation from the literature is that Convolutional Neural Network (CNN) is the deep learning model which is widely used for computer vision applications. In fact,CNN model is found efficient in processing medical images[22,23,24,25,26,,27]. Out of different brain imaging modalities, we preferredMRI due to its capability in reflecting different kinds of brain ailments. Therefore, in this paper we focused aCNN based model for brain age estimation using brain MRI images.

Literature review many significant contributions in this research area.Enhanced the accuracy of brain age estimate, a bias-adjustment strategy lowers mistakes in clinical frameworks that use metabolic brain data [3]. To identifying anomalies and accelerated aging, machine learning algorithms reliably estimate brain age. In order to estimate brain age, this paper describes the function of deep learning, models, and future prospects [4]. Because brain age prediction accuracy is affected when faces are removed from MRI images due to privacy concerns, defacing techniques must be used with caution [5]. For simultaneous prediction of gestational age, brain type, and segmentation of the fetal brain, MTSE U-Net is suggested [13]. Although the idea of biological age (BA) is important, there isn't a clear benchmark for it. To mitigate aging aberrations, a novel system addresses organ-specific BA estimates using brain MRI [16].From the literature, it is observed that brain age estimation research needs further investigation on deep learning models for improving performance. Our contributions in this paper are as follows.

1. We proposed a framework based on deep learning for brain age estimation. The proposed framework is made up of an enhanced ResNet50 model.
2. We proposed an algorithm known as Learning based Approach for Brain Age Estimation (LbA-BAE).
3. We built an application to evaluate our framework and algorithm with UK biobank dataset.

The remainder of the paper is structured as follows. Review of recent literature is provided in section 2. Section 3 presents the proposed framework and the underlying algorithm. Section 4 provides observations made on experiments and results. Section 5 provides conclusions for future research.

2. RELATED WORK

The section presents review of literature made on the brain age estimation methods found recently. Dinsdale *et al*. [1] used data from the UK Biobank, a 3D CNN model forecasts brain age while displaying clinical correlations and possible predictions for health outcomes.Aging and disease-related brain alterations are multifaceted and intricate. Peng *et al*. [2] utilized T1 MRI data, SFCN, a lightweight neural network, performs exceptionally well in brain age prediction and sex categorization, adapting to different approaches to improve performance. Beheshti *et al*. [3] enhanced the accuracy of brain age estimate, a bias-adjustment strategy lowers mistakes in clinical frameworks that use metabolic brain data. Dular *et al*. [4]observed that, for a reliable assessment of brain age prediction models, the Brain Age Standardized Evaluation (BASE) technique and dataset are introduced. Tanveer *et al*. [5] purposed to identifying anomalies and accelerated aging, machine learning algorithms reliably estimate brain age. In order to estimate brain age, this paper describes the function of deep learning, models, and future prospects.

Zhang *et al*. [6] opined that although systematic bias still exists, predicted age difference, or PAD, is thought to be a significant trait. The suggested age-level adjustment strategy works well. Cali *et al*. [7]found that, because brain age prediction accuracy is affected when faces are removed from MRI images due to privacy concerns, defacing techniques must be used with caution. Zhao *et al*. [8] explored and said that, with its effective feature learning, deep learning—particularly CNNs—dominates medical image processing, which is essential for cortical surface neuroimaging. Wood *et al*. [9] observed that, an essential tool for identifying neuro degeneration in clinical tests, CNNs reliably predict age from normal MRI scans. Zhang *et al*. [10] predicted brain aging is important for many biological domains. A combination of many algorithms results in a high accuracy ensemble model that facilitates the evaluation of illness risk.

Leonardsen *et al*. [11] focused on a trustworthy indicator of brain health which is the brain age delta. CNNs were trained on a sizable dataset, yielding excellent accuracy and practical significance. Engemann *et al*. [12] identified diseases is aided by population-level brain age modelling using machine learning. Broad-based examinations of brain health are made possible by M/EEG standards, which are useful instruments. Gangopadhyay *et al*. [13] observed that, for simultaneous prediction of gestational age, brain type, and segmentation of the fetal brain, MTSE U-Net is suggested. Milosevic *et al*. [14] found that with few mistakes, deep learning in forensic odontology for age prediction from dental x-ray pictures shows promise. Taylor *et al*. [15] explored and found that with

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a quicker transition from MCI to AD in affected patients, brain age gap (BAG) has promise as an Alzheimer's disease (AD) biomarker.
Armanious *et al*. [16] observed that although the idea of biological age (BA) is important, there isn't a clear benchmark for it. To mitigate aging aberrations, a novel system addresses organ-specific BA estimates using brain MRI. Jahanshiri*et al*. [17] used the unique aging patterns of brain imaging, brain age estimate is a critical tool for the early diagnosis of neurodegenerative illnesses. More than previous research, the ECNN model obtained an MAE of 3.57 years. Cheng *et al*. [18] studied with creative enhancements, deep neural networks, such as TSAN, that can reliably estimate age from neuroimaging and have the potential to be a biomarker for dementia risk. Mauer *et al*. [19] examined and found that with machine learning, age was automatically estimated from knee MRIs with a precision of 0.67 ± 0.49 years MAE, accuracy of huge, and sensitivity of 88.6%. Pardakhti*et al*. [20] debated subject in computer and medical sciences is Brain Age Estimation (BAE). A 3-year MAE is achieved using a 3D-CNN model with MRI data, indicating possibilities for resilient systems. From the literature, it is observed that brain age estimation research needs further investigation on deep learning models for improving performance.

3. PROPOSED SYSTEM

We proposed a deep learning framework for automatic detection of brain age from given MRI image. The framework exploits supervised learning approach in which an enhanced ResNet50 model is trained and then used for brain age estimation. The framework also supports transfer learning in order to retrain the ResNet50 model for improved capabilities. The given dataset is subjected to preprocessing where the MRI image samples are improved for quality. Afterwards the data set is divided into training on test sets. An enhanced ResNet50 model is trained with the training data.

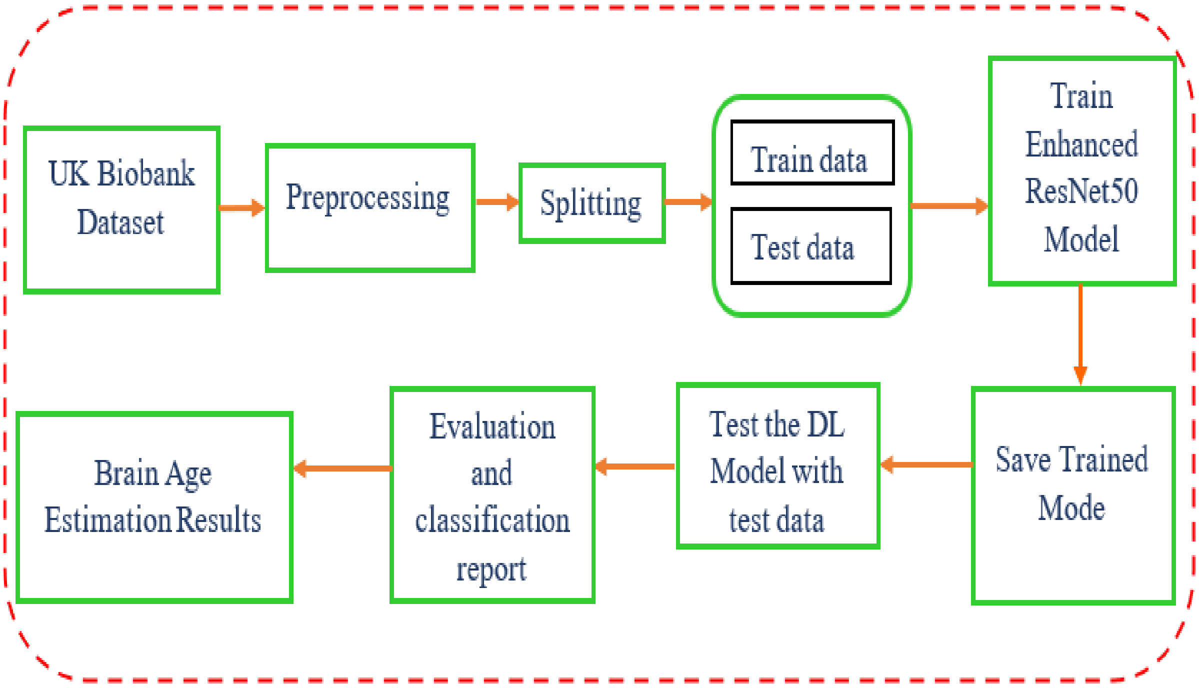

Figure 1: The proposed framework for brain age estimation

In the process of training, each sample is nothing but labelled data which is used by the model to gain the knowledge. Once the training is completed, the model is saved for future reuse. In the testing phase, the model gets loaded and used for brain age estimation with a given new sample. In the proposed deep learning framework, we used enhanced ResNet50 model as illustrated in Figure 2.

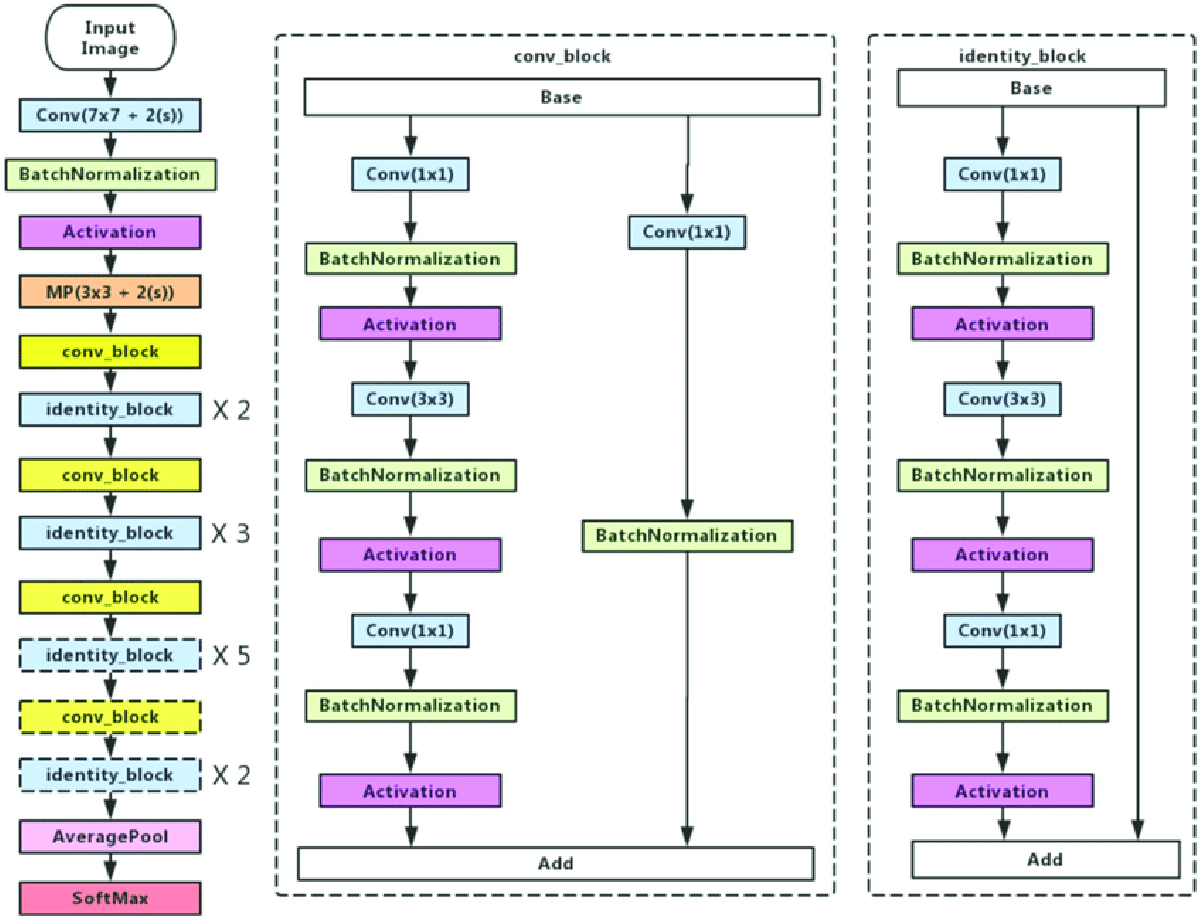

Figure 2: Enhanced ResNet50 model used in the proposed system

The ResNet50 model has convolutional blocks and identity blocks as presented in Figure 2. Each kind of block is repeated specified number of times. In the architecture some blocks are given with dotted line indicating the modified portions of ResNet50 model. This model is used for getting trained with training data and then estimate brain age for all the given test samples. We proposed an algorithm known as Learning based Approach for Brain Age Estimation (LbA-BAE).

Algorithm: Learning based Approach for Brain Age Estimation (LbA-BAE)
Input: UK biobank dataset D
Output: Brain age estimation results, performance statistics P

1. Begin
2. D’←Preprocess(D)
3. (T1, T2)←DataSplit(D’)
4. Configure enhanced ResNet50 model m (Figure 2)
5. Compile m
6. Train m using T1
7. Save m for future reuse
8. Load m
9. R←Test(m, T2)
10. P←Evaluate(R, ground truth)
11. Display R
12. Display P
13. End

Algorithm 1: Learning based Approach for Brain Age Estimation (LbA-BAE)

As presented in Algorithm 1, it takes UK biobank dataset as input. The given dataset is subjected to pre-processing where images are resized and made suitable for supervised learning. The data is divided into training (T1) and test (T2) datasets in 80% and 20% respectively. Data augmentation techniques like rotation, flip, zoom, shear and centre shift towards training the model for better performance. The enhanced ResNet50 model presented in Section 3 is used in the training phase. In other words, enhanced ResNet50 model is trained with the 80% training data. The model learns from the training data and gains discriminatory knowledge. The model is persisted for future reuse with transfer learning. The trained model is tested with unlabelled data. The model performs its predictions and it results in predicted values pertaining to brain age estimation.

3.4 Dataset Details

UK biobank dataset [21] is used in the experiments of this paper. This dataset is widely used for brain age estimation research.

3.5 Evaluation Methodology

This research uses Mean Absolute Error (MAE) for evaluating performance of the proposed model and comparing it with existing methods.

$$MAE = \frac{\sum_{i=1}^{n} |y_i - x_i|}{n} \quad (1)$$

As expressed in Eq. 1, the actual and predicted values are compared in order to obtain the MAE value which is used for evaluation.

4. EXPERIMENTAL RESULTS

This section presents results of our empirical study with the proposed deep learning architecture where an improved ResNet50 model is used. The model also supports transfer learning in order to retrain with new training samples. The performance of enhanced ResNet50 model is compared against number of existing models in terms of main absolute error.

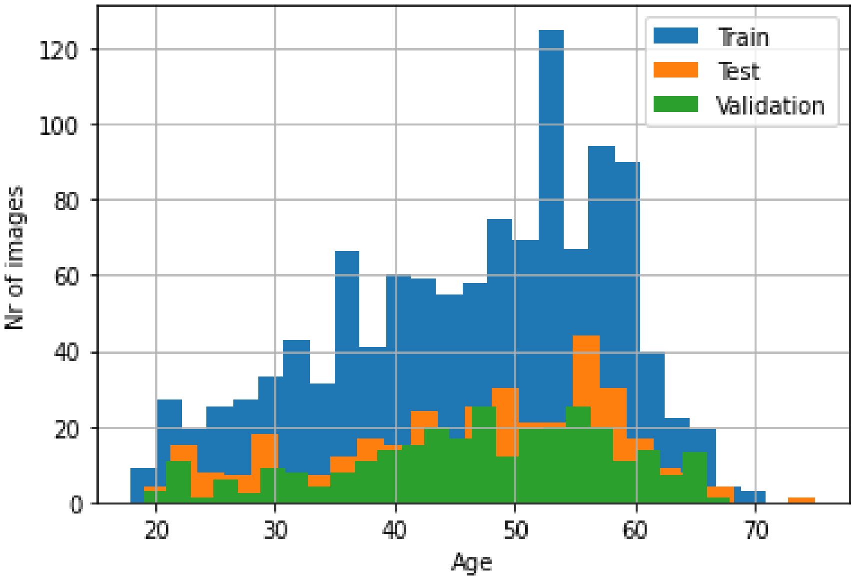

Figure 3: Shows data distribution dynamics in the dataset

As presented in Figure 3, it is observed that the dataset is divided into training set, test set and validation set appropriately for the purpose of supervised learning.

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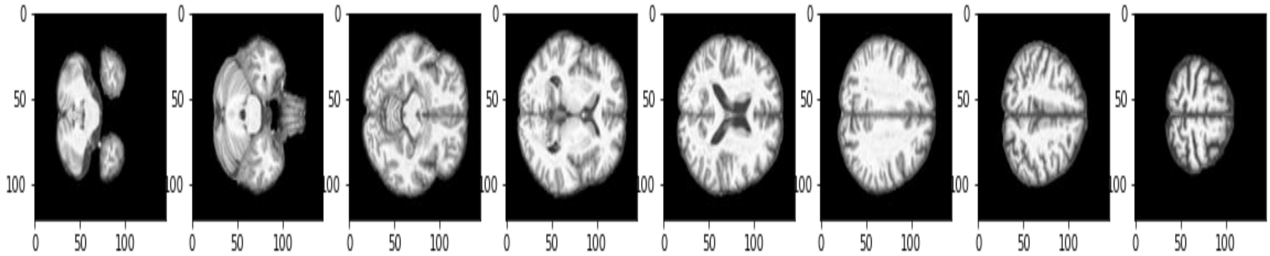

Figure 4: Shows an excerpt from brain MRI dataset

BrainMRI data set is preferred in this research because such modality has potential to reflect the brain aging patterns well.

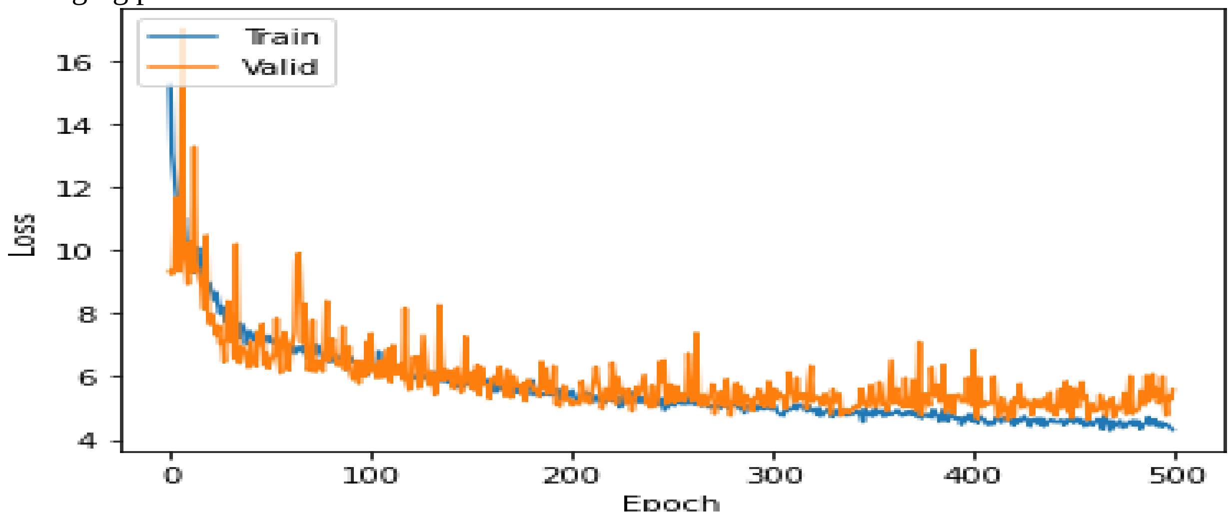

Figure 5: Loss value of the proposed model against number of epochs

As presented in Figure 5 the loss value is decreased gradually as the number of epochs is increased and it is converged at epoch 500.

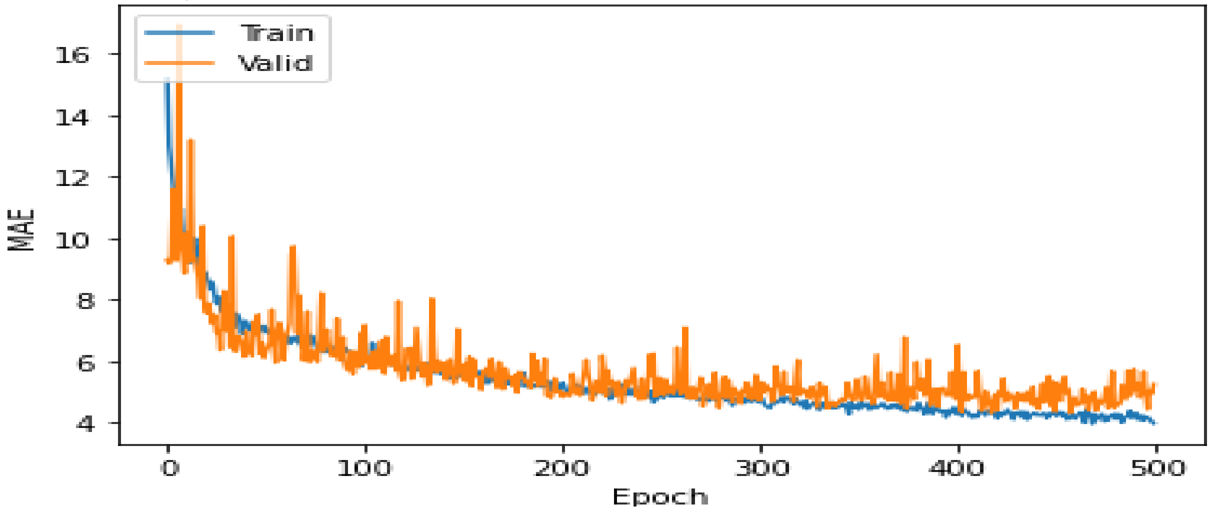

Figure 6: Shows mean absolute error against number of epochs

As presented in Figure 6, the mean absolute error exhibited by the proposal system is gradually reduced as the number of epochs is increased.

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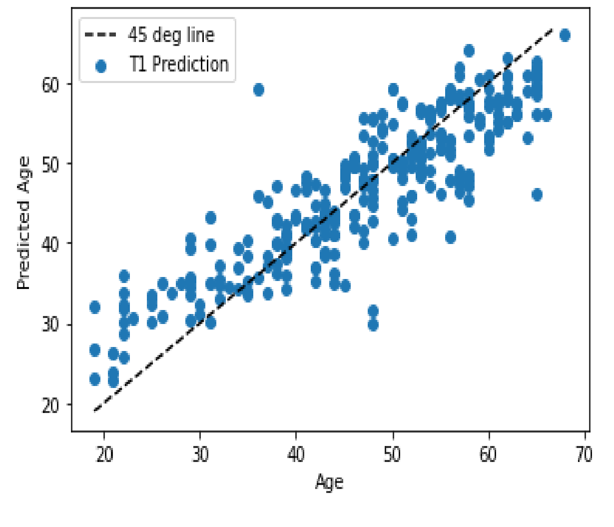
Validation prediction



Testprediction

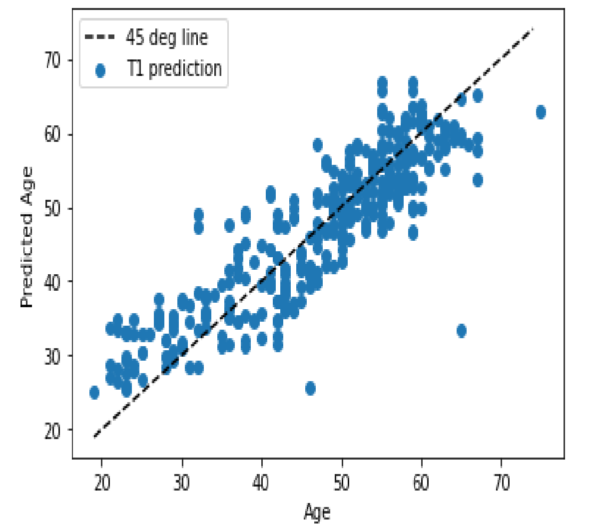


Figure 7: Shows the validation prediction and test prediction results reflecting brain ageestimation

As presented in Figure 7 the actual age and estimated edge are graphically provided for both validation and test results.

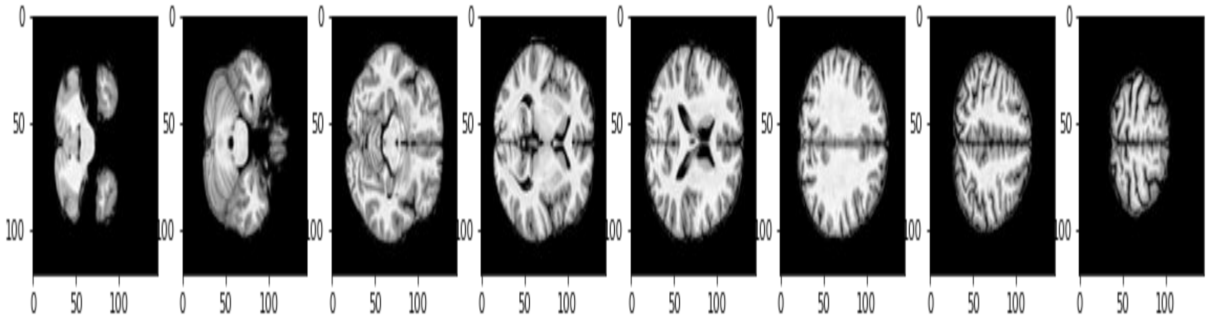
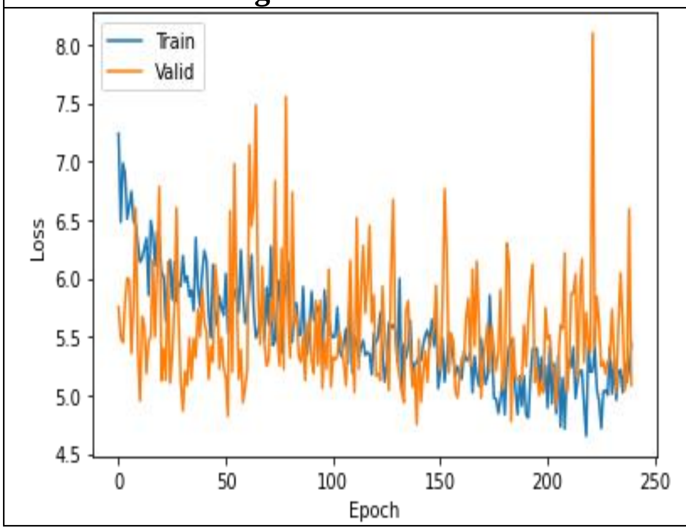


Figure 7: Shows an excerpt from IXI dataset used for transfer learning

As presented in Figure 7, a new data set is used to get some samples of brain MRI images. ResNet50 model is retrained with these samples for improved performance towards better recognition of brain age with the help of transfer learning.

Transfer Learning Loss



Transfer Learning MAE

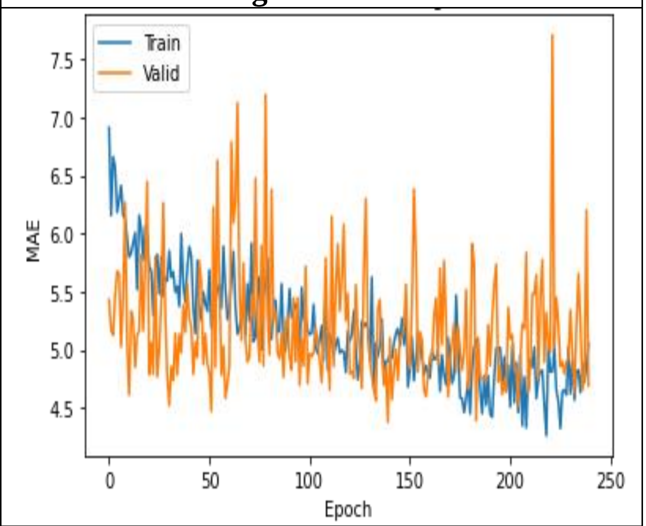


Figure 8: Shows loss and mean absolute error associated with transfer learning

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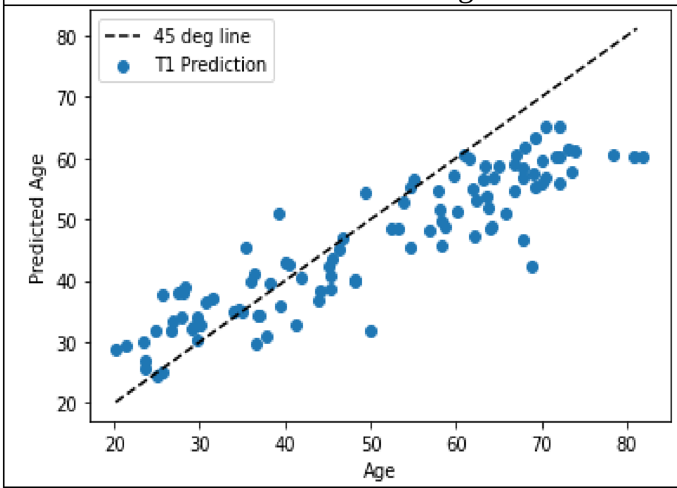
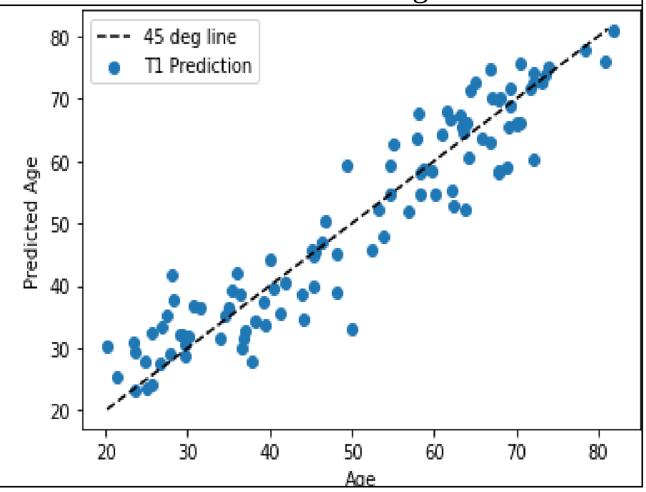
Prediction without transfer learning	Prediction with transfer learning
	

Figure 9: Shows the results before and after transfer learning

As presented in Figure 9 the experimental results are shown reflecting the importance of transfer learning in the process of brain age estimation.

Model	MAE
GPR	6.16
SVM	5.8
SVR	5.08
ResNet50	4.78
VGG	4.67
Enhanced ResNet50 (Proposed)	4.1

Table 1: Shows different models under their performance

As presented in Table 1 the mean absolute error observed in the experiments against each model is provided.

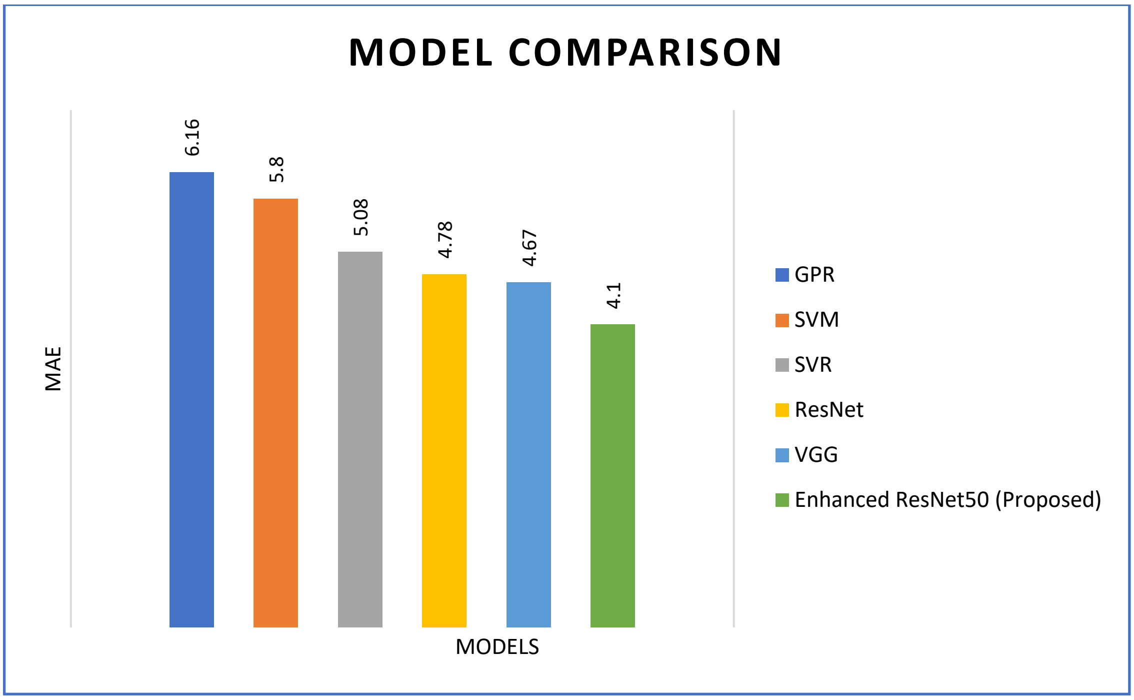


Figure 10: Shows the results of experiments exhibited by different models

As presented in Figure 10, different models are provided with their performance in terms of mean absolute error. The lesser in mean absolute error indicates better performance. The mean absolute error is nothing but the difference between actual age and predicted age. Therefore, the value of this metric should be less in order to consider that the model performance is better. The proposed enhanced ResNet50 model is compared against baseline ResNet50 model along with many existing models. From the empirical study it is observed that the proposed model achieved highest performance with 4.1 as been absolute error.

5. CONCLUSION AND FUTURE WORK

In this paper, we proposed a framework based on deep learning for brain age estimation. The framework exploits supervised learning approach in which an enhanced ResNet50 model is trained and then used for brain age estimation. The framework also supports transfer learning in order to retrain the ResNet50 model for improved capabilities. The proposed framework is made up of an enhanced ResNet50 model with an underlying algorithm known as Learning based Approach for Brain Age Estimation (LbA-BAE). Our experimental results using UK biobank dataset has revealed that the proposed framework is capable of estimating brain age with less error rate. The proposed algorithm is found better than many existing models with less MAE 4.10. The proposed framework uses only one pretrained model which has been enhanced. In our future work, we intend to improve other pretrained models like AlexNet, VGG19 and InceptionV3 for exploring deep learning models further.

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