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Deep Transfer Learning Models for Alzheimer's Disease Classification using MRI Images

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Abstract: Alzheimer's Disease (AD) is considered as a neurological brain ailment that leads to the irreversible destruction of nerve cells in the brain which are connected to the tasks of memory and thinking process in humans. Dementia is the result of this disorder which globally effects nearly 50 million of people worldwide. Various Machine learning approaches have been a topic of research for diagnosing Alzheimer's disease using brain images like Magnetic Resonance Imaging (MRI). Recent breakthrough of Deep Learning technologies in computer vision has advanced this field of study. Nevertheless, there exists certain limitations such as dependency on huge amount of training data and the need for appropriate optimization method in deep neural network models. In this paper, we endeavor to address these concerns with deep transfer learning models, where modern pre-trained CNN models like VGG, RESNET, Inception and Xception are set with pre-trained weights obtained from large sized standard benchmark datasets consisting of natural images. The fully-connected layer is then re-trained with trivial number of MRI images. Furthermore we employ the use of data augmentation approach for learning from imbalanced datasets which effectively rises the performance of the transfer learning models.

Keywords: *Alzheimer's disease, Dementia, MRI images, Deep Learning, Transfer Learning, Optimization, Resampling*

1. Introduction

Alzheimer's disease is termed as a degenerative neurological disorder that results in brain shrinkage and the death of nerve cells in brain. The symptoms of Alzheimer's are typically noticeable after age 60. However, some AD variations increase in humans with gene mutations at earlier ages [1-2].

The symptoms of Alzheimer's, commonly referred to as 5A's of Alzheimer's include: Amnesia, Apraxia, Agnosia, Aphasia, and Anomia are illustrated in Table 1.

Table 1. Symptoms of AD

S.No	5 A's of Alzheimer's	Symptoms
1	Amnesia	Amnesia is the loss of memory
2	Apraxia	Anomia is the inability to remember names of everyday objects
3	Agnosia	Apraxia is a disorder that is caused by damage to the brain, and patients with apraxia have difficulty with skilled movements and/or speech
4	Aphasia	Agnosia is characterized as the inability to recognize a familiar object, tastes, sounds, and other sensations.
5	Anomia	Aphasia takes away the person's ability to express themselves through speech

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The Alzheimer's disease damages the brain permanently, affecting cognition and memory. In the event of brain failure, the person may pass away. Due to the loss of nerve cells in the brain as a result of Alzheimer's, it can negatively affect the functionality of typical health activities like reading, writing, and speaking. Patients who are in cognitive stage are much more susceptible to abnormalities, whereas those who are in the last stages of AD suffer from heart failure. However, a patient's health can be improved by early diagnosis and treatment. Mild Alzheimer's, Mild Cognitive Impairment, Moderate Alzheimer's, and Severe Impairment are the four stages of AD that can be classified based on the extent of brain damage and the patient's state. MRI analysis for Alzheimer's patients is the most effective method in clinical research.

The number of AD patients worldwide is progressively rising each year. The scale for measuring the global worsening of mental disease is typically utilized. Seven phases of AD are based on this scaling and are dependent on the ranges of mental functioning. According to the grading system, phase 4 is the initial stage of mental disease, and phases 4 and 5 are the middle stages. This scaling technique is also used in the research because it makes it easy to get in touch with medical faculties. The scaling is based on a number of elements, including the patients' opinions, common behavior, reading, interests, and recollections [11].

A correct diagnosis of Alzheimer's disease (AD) is essential for patient care when the condition is still in its early stages because it enables patients to take

preventative measures before irreversible brain damage happens. Although there has been a recent increase in the use of computers to diagnose AD, the application of machine learning models are limited by congenital results. Diagnosis of AD in early stages is more possible rather than prediction [6].

In-depth studies on mental health have demonstrated the outstanding benefits of computational neuroscientific translational applications. The biological mechanisms responsible for the normal and abnormal states of the human brain can be modelled with the aid of multidisciplinary fields of study, which can then translate these mechanisms into observable clinical manifestations. Enhancing the initial exposure and completing the treatment plan for people at high risk of Alzheimer's disease are the goals of neuroscientific techniques.

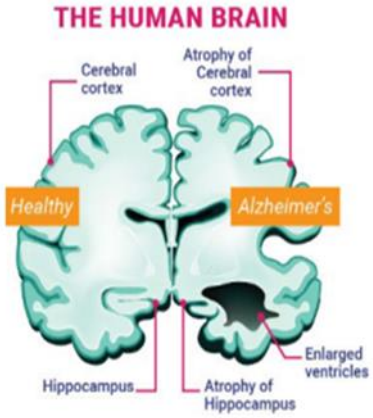

Fig 1. Progress of AD

The size of the brain's communication web system grows while the cerebral mantle and other brain structures get smaller. The network serves as the link between the body and the brain. Loss of brain nerve cells and damage to the junction between the two nerve cells and a neuron occur when the brain's structural size decreases as depicted in Figure 1. Due to neuron damage, communication disorders, behavioral disorders, and short term memory loss are prominent during the Alzheimer ’s Disease stages. Many computer-based methods for diagnosing AD have been developed by researchers, but none of them have been a practical success.

The early diagnosis of AD is now often performed using deep learning (DL) [7-8]. Recently, the researchers are developing DL techniques to extract features from clinical images like computed tomography, X-ray images and microscopic analysis[12]. These models can only reveal if the patient has AD or not; they do not reveal the precise stage of mental illness, which is necessary for accurate diagnosis and effective therapy. Because 15% of patients annually migrate from Mild Cognitive Impairment (MCI) stage to Alzheimer's disease (AD), the MCI stage is a very crucial stage .There is a good chance of recovery during Mild Cognitive Impairment phase so proper diagnosis with disease stage classification is significant [6].

The MRI imaging technique is an improved option for diagnosing AD since it is a less expensive method. MRI pictures accurately depict the structure and operations of the brain, making them suitable for medical applications [14].

2. Methodology

2.1. Dataset collection

The brain MRI scan pictures utilized in this study were collected from publicly accessible Kaggle archives as the dataset. All the images are resized into 128 x 128 pixels. The Dataset has four classes of images and consists of total 6400 MRI images as shown in Table 2.

Class I: Moderate Demented

Class II: Mild Demented

Class III: Non Demented

Class IV: Very Mild Demented

Table 2. Dataset statistics

Alzheimer Disease Stage	Number of images in Dataset		
	Train	Test	Total
Mild Demented	717	179	896
Moderate Demented	52	12	64
Non-Demented	2560	640	3200
Very Mild Demented	1792	448	2240

The sample MRI images of dataset is shown in Figure 2.

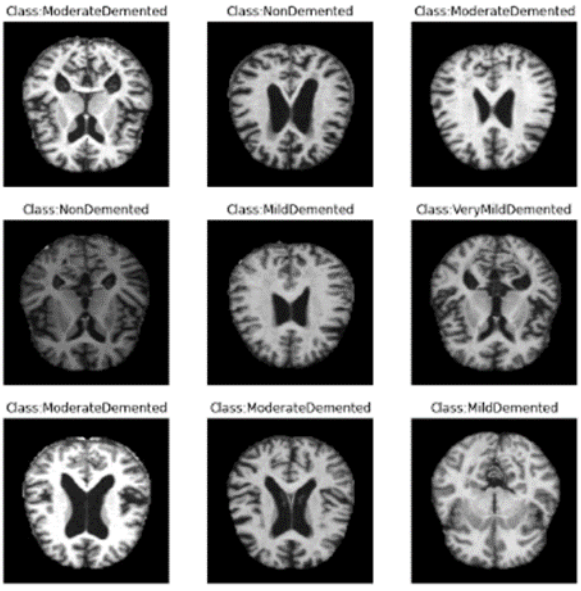

Fig 2. MRI Scans in Dataset

2.2. Data preprocessing

Anomalies could be seen in MRI brain pictures as a result

of MRI equipment limitations. Limitations in MRI image processing result in anomalies such inadequate image resolution, distortion, inhomogeneity, misinterpretation, and motion heterogeneity. While examining the brain MRI image, these incorrect image analyses may produce false positives. The patient's treatment options are further impacted by this incorrect diagnosis. Therefore data augmentation17 methods are employed to resample the images and further aids in improving the effectiveness of transfer learning models, by creating new and different examples to train datasets.

The data augmentation method used for this study is Adaptive Synthetic Sampling Approach (ADASYN) where in the dataset is oversampled considering majority class. It is an enhanced technique of Synthetic Minority Oversampling Technique (SMOTE), which resamples the data by considering minority class observations.

2.3. Model Architecture

The input brain MRI dataset is further preprocessed using ADAYSN. Four transfer learning CNN models such as VGG-19, Inception-v3, ResNet50, Xception are used for Alzheimer's Disease classification purpose [3-5].

The VGG-19 features 138 million hyper parameters in total, 3*3 convolution kernels across the board, and 2*2 max-pool kernels. As a result, there are 44.9 percent fewer trainable datasets than there were before. Overfitting issues and a quicker learning rate are consequences of the less training data.

The Inception-v3 is made up of different Inception modules; where in each module that demonstrates four operations simultaneously aids in convolution layer's depth reduction.. A pre-trained CNN model called ResNet50 makes it simple in order to train the model with a large number of convolutional layers without raising the training error rate.

The Xception model, a 71-layer deep CNN based on an extreme interpretation of the Inception model, is inspired by the Inception model.

Pre-trained models are typically trained on large datasets like ImageNet, and the weights they provide are then applied to the Alzheimer Disease Dataset for fine-tuning [9-10] as illustrated in Figure 3.

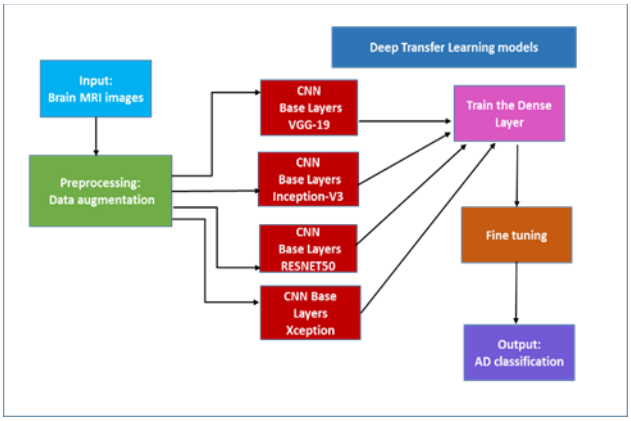

Fig 3. Architecture diagram for AD classification

3. Result Analysis and Discussion

The experiments are carried out using Python Keras and Tensor flow. CNN Pretrained Model, employs three layers of convolution which is applied to the input image size of (227x227) pixels. The image is then transformed into (128x128) pixels and the resultant feature matrix is 58 dense layer output13.

The optimization technique used in this experiment is Adam. It aids not only in minimizing the loss but also to adjust the weight and bias parameters. The graphs below show 100 epochs of data for each test predictive analysis, with each epoch represented by an x-axis and loss levels represented by a y-axis.

3.1 VGG-19 CNN Model

The model accuracy, obtained by applying VGG-19 model for AD classification is depicted in Figure 4. The training accuracy of the model increases slowly and attains a maximum value after 80th epoch, whereas the validation accuracy inclines after the 40th epoch reaching accuracy value of 0.90%. Figure 5 depicts the model loss curve where in the validation loss converges rapidly than the training loss and reaches to a steady state after 60th epoch. The performance of the VGG-19 model is articulated in a confusion matrix as depicted in Figure 6. Here we can deduce that the model can classify 89% of images in testing data.

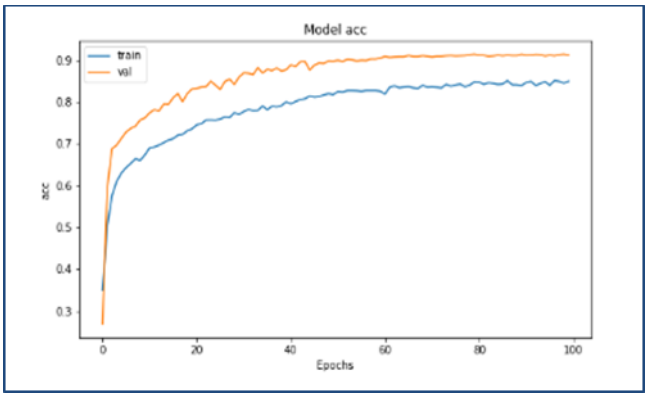

Fig 4. Accuracy curves of VGG-19 model

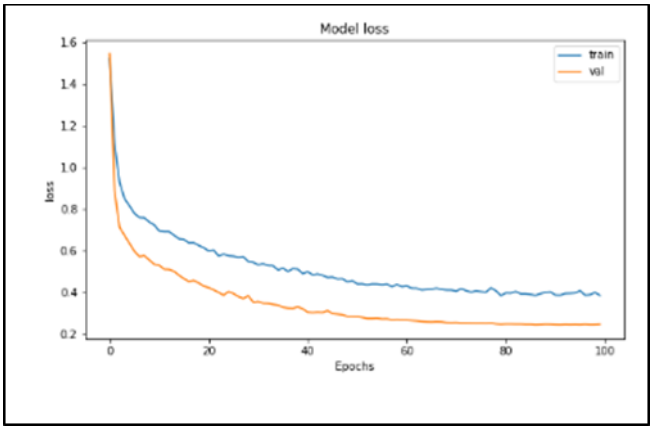

Fig 5. Loss curves of VGG-19 model

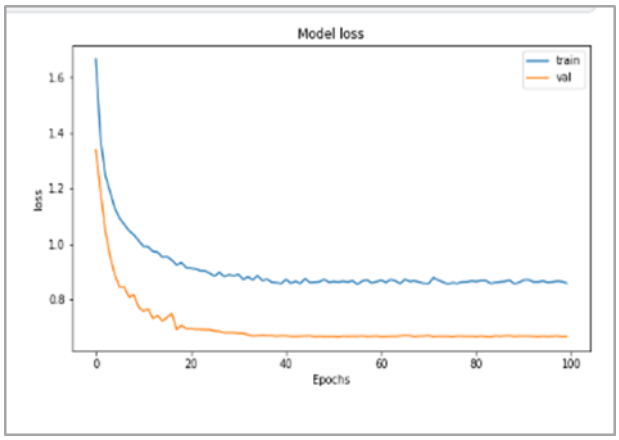

Fig 6. Confusion Matrix of VGG-19 model

3.2 RESNET50 CNN Architecture

The model accuracy, obtained by applying RESNET50 model for AD classification is depicted in Figure 7. In this experiment, the training accuracy reached to a stable value after 10th epoch, attaining accuracy of 0.60%, whereas the validation accuracy increases after the 5th epoch reaching accuracy value of 0.70%. Figure 8 depicts the model loss curve where in the validation loss converges rapidly than the training loss and reaches to a stable state after 20th epoch. The performance of the ResNet50 model is articulated in a confusion matrix as depicted in Figure 9. Here we can comprehend that the model can classify 68% of images of the testing data.

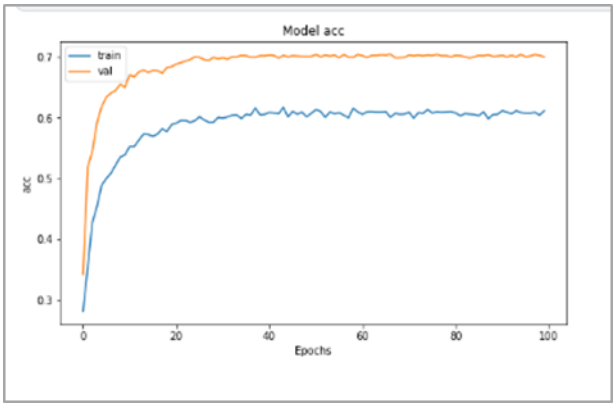

Fig 7. Accuracy curves of RESNET50 model

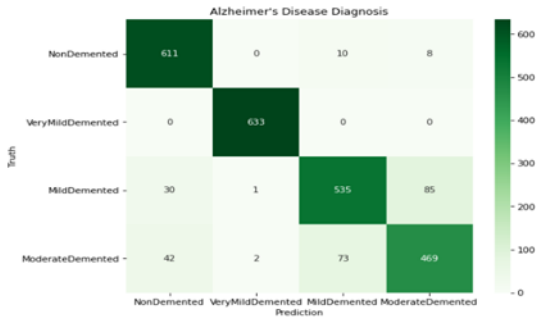

Fig 8. Loss curves of RESNET 50 model

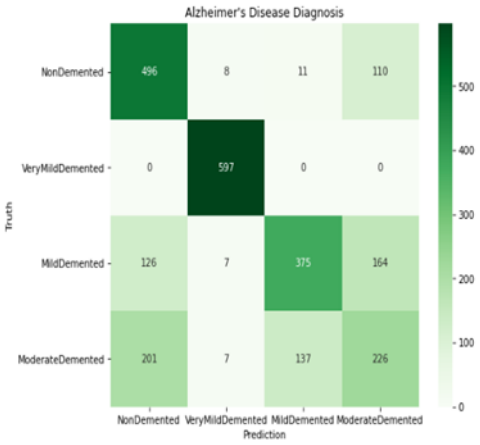

Fig 9. Confusion Matrix of RESNET50 model

3.3 Inception-V3 CNN Architecture

The model accuracy, obtained by applying Inception-V3 model for AD classification is depicted in Figure 10. In this experiment, the training accuracy reached to a stable value after 50th epoch, reaching accuracy of 95%, whereas the validation accuracy increase after the 40th epoch reaching accuracy value of 0.85%. Figure 11 depicts the model loss curve where in the training loss converges rapidly than the validation loss and reaches to a stable state after 50th epoch. The performance of the Inception-V3 model are articulated in a confusion matrix as depicted in Figure 12. Here we can deduce that the model can classify 89% of images from the testing data.

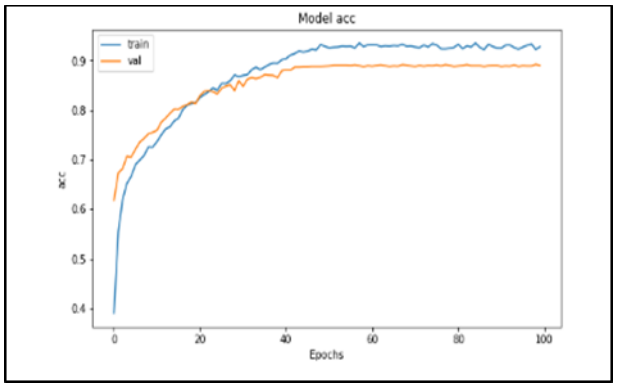

Fig 10. Accuracy Plot of Inception-V3 model

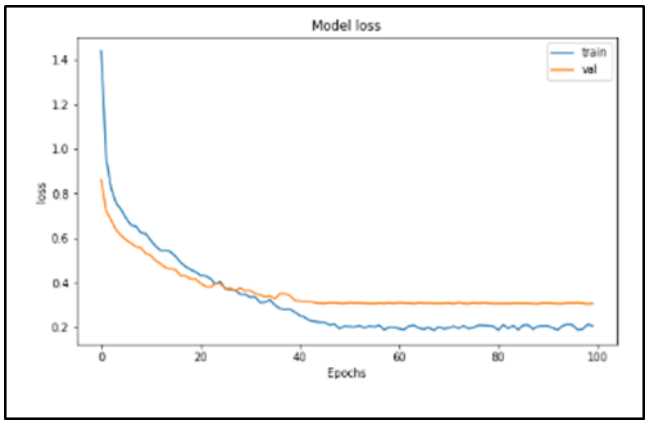

Fig 11. Loss plot of Inception-V3 model

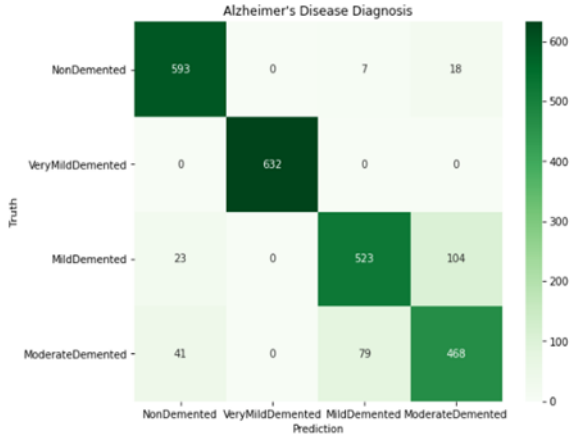

Fig 12. Confusion Matrix of Inception-V3 model

3.4 Xception CNN Architecture:

The model accuracy attained by applying Xception model for AD classification is depicted in Figure 13. In this experimentation, the training accuracy reached to a steady value after 40th epoch, reaching accuracy of 95%, while the validation accuracy tends to increase after the 20th epoch reaching accuracy value of 0.85%. Figure 14 depicts the model loss curve where in the training loss converges rapidly than the validation loss and reaches to a stable state after 25th epoch. The performance results of the Xception model are articulated in a confusion matrix as depicted in Figure 15. Here we can deduce that the model can classify 87% of images of the testing data.

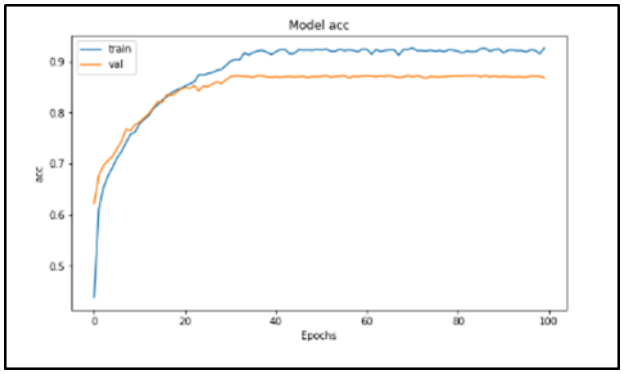

Fig 13. Accuracy plot of Xception model

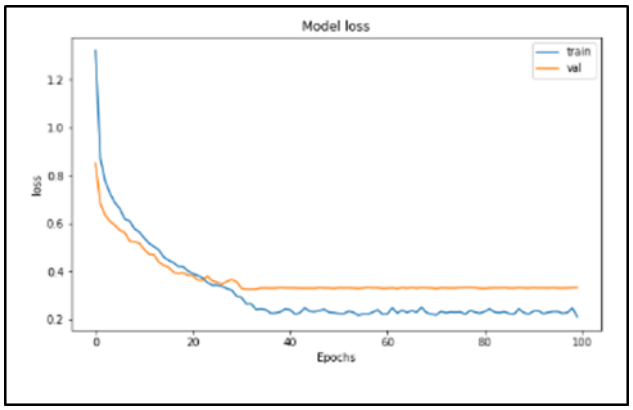

Fig 14. Loss plot of Xception model

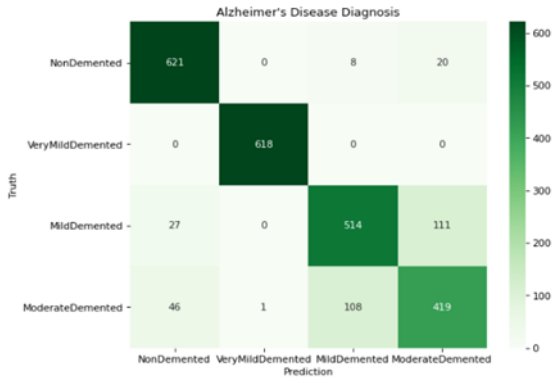

Fig 15. Confusion Matrix of Inception-V3 model

The performance of transfer learning models are assessed by using metrics such as Balanced Accuracy Score and Matthew's Correlation Coefficient in this experiment. These metrics incorporate the measues like True Positive (TP), False Positive (FP), True Negative (TN) and False Negative (FN).

Balanced accuracy score as represented by Equation-1 is particularly useful when the two classes are imbalanced – that is, one class appears much more than the other.

$$Balanced\ accuracy = (Sensitivity + Specificity)/2 \quad (1)$$

Where $$Sensitivity = \frac{TP}{TP+FN} \quad (2)$$

$$Specificity = \frac{TN}{TN+FP}$$

(3)

Matthew's Correlation Coefficient (MCC) [18] is the best single-value classification measure that aids to summarize the confusion matrix. It is calculated by using the formula as illustrated in Equation 4.

$$MCC = \frac{TN*TP-FN*FP}{\sqrt{(TP+FP)(TP+FN)(TN+FP)(TN+FN)}} \quad (4)$$

Balanced Accuracy Score [15] of transfer learning models by varying the optimization methods is depicted in Figure 16. VGG model with Adam optimizer outperforms the other models with Balanced Accuracy Score of 89.94%.

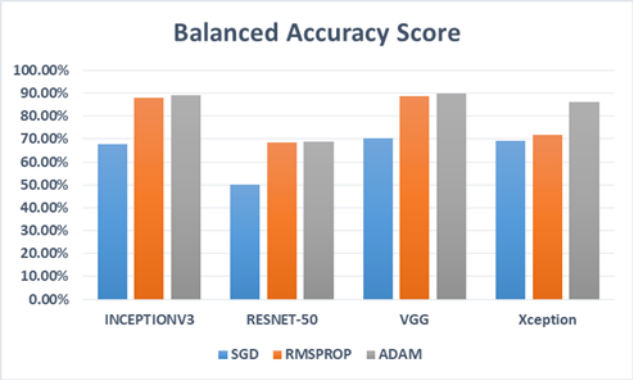

Fig 16. Balanced accuracy score comparison of transfer learning models

Matthew's Correlation Coefficient of transfer learning models by varying the optimization methods is depicted in Figure 17. VGG model with Adam optimizer outperforms the other models with Matthew's Correlation Coefficient of 86.64%.

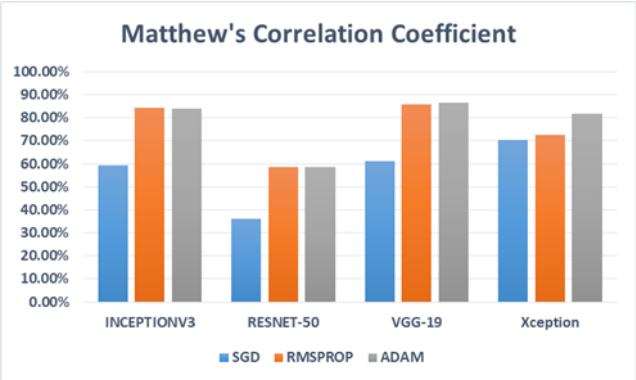

Fig 17. MCC of transfer learning models

4. Conclusions

This research presents a comparison of deep transfer learning models for classifying Alzheimer's disease. 6400 MRI images grouped into four classes are used in the study. Data preprocessing is performed using Adaptive Synthetic Sampling Approach (ADASYN). Transfer learning pretrained CNN models, including VGG16, Inception-V3, ResNet50, and Xception, are used to classify MRI images. If training accuracy and validation accuracy improve for each epoch, pretrained CNN model is believed to produce higher performance results. It is projected that the architecture would experience overfitting issues, particularly as training accuracy rises and validation accuracy falls. When the model is overfitted and is only able to focus on a specific collection of training data, it cannot produce accurate predictions for a new dataset. We draw the conclusion that VGG-19 performs better on the trained and tested datasets than Inception-v3, ResNet50, and Xception pretrained CNN models, based on the performance analysis of these models.

The research work can further be extended by employing the population based optimization algorithms for training the deep CNN based models in the predictive analysis of Alzheimer's disease.

References

[1] Sridevi Balne, Anupriya Elumal, "Machine learning and deep learning algorithms used to diagnosis of Alzheimer's: Review", Materials Today: Proceedings 47(2018), June 2021

[2] Mahendran N, Vincent PMDR, Srinivasan K, Chang CY. "Improving the Classification of Alzheimer's Disease Using Hybrid Gene Selection Pipeline and Deep Learning". Front Genet.;12 :784814, Nov 12 2021

[3] M. T. Abed, U. Fatema, S. A. Nabil, M. A. Alam and M. T. Reza, "Alzheimer's Disease Prediction Using Convolutional Neural Network Models Leveraging Pre-existing Architecture and Transfer Learning," 2020 Joint 9th International Conference on Informatics, Electronics & Vision (ICIEV) and 2020 4th International Conference on Imaging, Vision & Pattern Recognition (icIVPR), pp. 1-6, 2020

[4] Deekshitha Prakash1 , Nuwan Madusanka1 ," A Comparative Study of Alzheimer's Disease Classification using Multiple Transfer Learning Models", Journal of Multimedia Information System VOL. 6, NO. 4, (pp. 209-216): December 2019 ISSN 2383-7632.

[5] Oh, K., Chung, YC, Kim, K.W. etal. "Classification and Visualization of Alzheimer's Disease using Volumetric Convolutional Neural Network and Transfer Learning. Sci Rep 9, 18150 2019.

[6] Silvia Basaia, Federica Agosta . etal. "Automated classification of Alzheimer's disease and mild cognitive impairment using a single MRI and deep neural networks", NeuroImage: Clinical, Volume 21, 2019

[7] Jo, Taeho and Nho, Kwangsik and Saykin, Andrew,

"Deep Learning in Alzheimer's Disease: Diagnostic Classification and Prognostic Prediction Using Neuroimaging Data", Frontiers in Aging Neuroscience, 11, 2019

[8] U. Shah and A. Harpale, "A Review of Deep Learning Models for Computer Vision," IEEE Punecon, pp. 1-6, 2018,doi: 10.1109/PUNECON.2018.8745417.

[9] Suhad Al-Shoukry, Taha H. Rassem,"Alzheimer's Diseases Detection by Using Deep Learning Algorithms: A Mini-Review", IEEE ACCESS, 10.1109/ACCESS.2020.2989396

[10] Suhuai Luo, Xuechen Li, "Automatic Alzheimer's Disease Recognition from MRI Data Using Deep Learning Method", Journal of Applied Mathematics and Physics, 5, 1892-1898, 2017.

[11] B.Sudha, Dr.Kathiravan Srinivasan," Machinelearning And Deep Learning Techniques In Diagnosing Alzheimers Disease-A Review", International Journal of Advanced Science and Technology Vol. 29, No. 5s, pp. 1678-1688, 2020.

[12] Boureau, Y.-L., Ponce, J., and Lecun, Y. "A theoretical analysis of feature pooling in visual recognition," in Proceedings of the 27th International Conference on Machine Learning (ICML-10) (Haifa), 111–118, 2010

[13] Cheng, D., and Liu, M. "CNNs based multi-modality classification for AD diagnosis," in 10th International Congress on Image and Signal Processing, BioMedical Engineering and Informatics (CISP-BMEI) (Shanghai), 1–5, 2017.

[14] Cheng, D., Liu, M., Fu, J., and Wang, Y. "Classification of MR brain images by combination of multi-CNNs for AD diagnosis," in Ninth International Conference on Digital Image Processing (ICDIP 2017) (Hong Kong: SPIE), 5, 2017.

[15] Lin W, Gao Q, Yuan J etal. "Predicting Alzheimer's Disease Conversion From Mild Cognitive Impairment Using an Extreme Learning Machine-Based Grading Method With Multimodal Data", Front Aging Neurosci. Apr 1;12:77, 2020.

[16] Atif Mehmood, Shuyuan Yang, Zhixi Feng, etal,"A Transfer Learning Approach for Early Diagnosis of Alzheimer's Disease on MRI Images",Neuroscience,Volume 460, Pages 43-52, 2021

[17] Sitara Afzal, Muazzam Maqsood etal. "A Data Augmentation-Based Framework to Handle Class Imbalance Problem for Alzheimer's Stage Detection", IEEE Access, Vol. 7, 2019

[18] D. Chicco, V. Starovoitov and G. Jurman, "The Benefits of the Matthews Correlation Coefficient (MCC) Over the Diagnostic Odds Ratio (DOR) in Binary Classification Assessment," in IEEE Access, vol. 9, pp. 47112-47124, 2021.

[19] Kalyani, B. ., Sai, K. P. ., Deepika, N. M. ., Shahanaz, S. ., & Lohitha, G. . (2023). Smart Multi-Model Emotion Recognition System with Deep learning. International Journal on Recent and Innovation Trends in Computing and Communication, 11(1), 139–144. https://doi.org/10.17762/ijritcc.v11i1.6061

[20] Joseph Miller, Peter Thomas, Maria Hernandez, Juan González, Carlos Rodríguez. Machine Learning for Decision Support in Uncertain Environments. Kuwait Journal of Machine Learning, 2(3). Retrieved from http://kuwaitjournals.com/index.php/kjml/article/view/205