Proceedings of the Second International Conference on Intelligent Cyber Physical Systems and Internet of Things (ICoICI 2024)
IEEE Xplore Part Number : CFP24VG0-ART ; ISBN : 979-8-3315-4066-1

2024 Second International Conference on Intelligent Cyber Physical Systems and Internet of Things (ICoICI) | 979-8-3315-4066-1/24/$31.00 ©2024 IEEE | DOI: 10.1109/ICOICI62503.2024.10696766

MRI Image-based Advanced Transfer Learning and Machine Learning Architectures for Classifying Alzheimer's Disease

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***Abstract*—Alzheimer's Disease (AD) is classified as a nerve disorder of the brain characterized by the irreversible degeneration of neurons responsible for computational functions and memory in humans. Exploratory investigations have been devoted to diverse Machine Learning methodologies in the context of AD diagnosis via brain images, such as Magnetic Resonance Imaging. There are several disadvantages to Deep Neural Network models, such as their dependence on large volumes of trained data and their need for a suitable optimisation technique. Here, an attempt is made to tackle these concerns by employing Deep Transfer Learning models. Specifically, previously trained current Convolutional Neural Network models used that have already been trained using large standard benchmark datasets of real-world photos, including Xception, RESNET, Inception, and VGG. Retraining the entirely connected layer with an insignificant number of MRI images ensues. Additionally, the data is augmented in order to facilitate learning from unbalanced datasets, thereby, significantly enhancing the performance of TL models.**

***Keywords*—Alzheimer's Disease, Deep Transfer Learning, Magnetic Resonance Imaging, Dementia, Optimization.**

I. INTRODUCTION

AD is classified as a degenerative nerve disorder characterized by neuronal cell death and brain atrophy. Typically, AD symptoms become apparent after the age of 60. Nonetheless, gene mutations at an earlier age increase the prevalence of certain AD variants in humans [1,2]. As shown in table 1, the symptoms of AD, also known as "5A's of Alzheimer's", consists of Anomia, Aphasia, Amnesia, Agnosia and Apraxia. AD causes irreversible brain injury, which impairs memory and cognition. A person with cerebral failure is at risk of dying. As a consequence of Alzheimer's, the degeneration of brain nerve cells can impair the ability of perform daily tasks such as reading, speaking, and writing. Individuals in the cognitive stage of AD are significantly more prone to experiencing abnormalities, whereas those in the terminal stages develop heart failure. However, early diagnosis and treatment can enhance the health of a patient. Moderate Alzheimer's Disease (Mod-AD), Severe impairment (AD), Mild Alzheimer's Disease (M-AD), and Mild Cognitive Impairment (MCI) are the four stages of the disease. The patient's state and the extent of brain damage differentiate these stages. The most effective technique in clinical research is to analyse Alzheimer's patients' MRIs.

An increasing number of AD patients are being identified annually on a global scale. With reference to this scale, seven stages of AD are distinguished, each with a unique spectrum of cognitive capacities. Fourth phase is the initial stage of mental illness, as designated by the grading system. Fourth and fifth phases comprise the intermediate stages. This scaling method is additionally employed in research due to its facilitation of communication with medical faculties. The scaling system is founded upon several factors, which encompasses the patients' perspectives, routine activities, reading habits, personal interests, and recollections [11].

In the early phases of AD, an accurate diagnosis is critical for patient care because it allows patients to implement preventative measures prior to the occurrence of irreversible brain injury. Despite recent surge in the utilization of computers for AD diagnosis, the implementations of ML models remain constrained by congenital outcomes. Early-stage AD is more amenable to diagnosis than to prognosis [6].

Extensive study on mental health has shown that using computational neuroscientific techniques has remarkable advantages. By using several interdisciplinary fields of research, it is possible to create models that depict the biological processes behind both normal and disordered states of human brain. These pathways may be then transformed into detectable clinical symptoms neuroscientific procedures seek to enhance the first exposure and ensure the completion of the treatment regimen for patients who have a high risk of developing AD. As the communication web systems grows, the cerebral cortex and other components decrease in size. The network serves as a agent, facilitating communication between the brain and the body. In Figure 1, the shrinking of the brain's structural volume is depicted along with the deterioration of synapses in the brain, or interconnections between two neurons. In the later stages, of AD, individuals often have communication impairments, behavioural issues and short-term memory loss as a result of neuronal destruction. Scientists have developed many computer-based techniques for diagnosing AD, but none of these approaches have been seen successful in practical applications.

Contemporary practice increasingly employs DL to facilitate the early detection of AD [7-8]. Researchers, have recently developed DL approaches to extract information from clinical pictures, including X-Ray, computed tomography and microscopic inspection [12]. The identification of AD in a patient is the sole capability of these models; they fail to provide insight into the specific phase of the mental disorder, a critical factor in facilitating effective treatment and diagnosis. The MCI stage is crucial due to an annual progression rate of 15% from MCI to AD in individuals. Accurate identification via illness stage categorization in critical during the MCI stage due to high likelihood of recovery [6].

The utilization of the MRI imaging technique presents an enhanced alternative for the diagnosis of AD due to its reduced cost. Due to their ability to precisely depict the structure and functioning of the brain. MRI images are visible for medical purposes.

TABLE I. AD'S SYMPTOMS

5A's of AD	Symptoms
Anomia	Refers to the condition when individuals have difficulty in recalling the names of common things.
Aphasia	Impairs an individual's capacity to articulate their thoughts and communicate verbally.
Amnesia	Refers to the ability to recall or remember information or events.
Agnosia	Is a condition defined the inability to recognize familiar items, as well as the inability to perceive and identify senses such as taste and sound.
Apraxia	Is a neurological condition resulting from brain injury, characterized by impaired ability to perform skilful motions or articulate words.

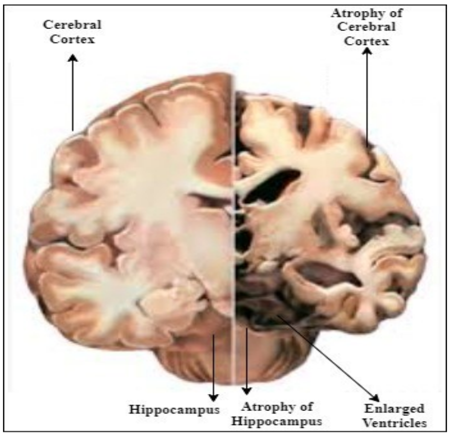

Fig. 1. Alzheimer's Progress

II. RELATED WORK

In this review looks at different approaches to use neuroimaging data to identify and diagnose Alzheimer's disease (AD). For the diagnosis of AD, which is characterised by brain deterioration, imaging techniques are essential. For the diagnosis of neurological conditions like dementia, brain MRI is an essential machine learning diagnostic tool. Studies have demonstrated the efficacy of integrating functional brain networks working within particular frequency ranges with magnetic resonance imaging (MRI) biomarkers for the diagnosis of Alzheimer's illness (AD) and for differentiating moderate cognitive impairments (MCI). Deep learning (DL) techniques that enable support vector machine learning (SVMs) have proven to be very precise and show promise for AD early detection [11-15]. For the purpose of diagnosing Alzheimer's disease (AD), algorithms using deep learning (DL) have shown to be superior than shallow learning techniques like convolutional and frequent learning in the classification of functional brain networks. Through medical image analysis, a unique DL model has shown how DL algorithms can be used to identify and classify various AD kinds [16-22].

Extensive research on mental health has shown the remarkable advantages of using computational neuroscientific translational applications. The physiological processes underlying both the typical and atypical conditions of the human brain may be simulated using interdisciplinary areas of research, which can then interpret these processes via observable clinical presentations. The objectives of neuroscientific procedures are to improve the first exposure and fulfill the treatment plan for those with a high susceptibility to Alzheimer's disease.

TABLE II. COMPARISON OF PROPOSED MODEL VS. TRADITIONAL MODELS FOR ALZHEIMER'S DISEASE CLASSIFICATION

Criteria	Traditional Models	Proposed Model
Model Type	Basic Machine Learning (e.g., SVM, Random Forest)	Advanced Transfer Learning (e.g., ResNet, DenseNet)
Dataset Size and Diversity	Often Uses Smaller, Homogeneous Datasets	Utilizes Larger, More Diverse Datasets
Interpretability	Limited Interpretability	Enhanced with Attention Mechanisms
Preprocessing Consistency	Inconsistent Preprocessing Methods	Standardized Preprocessing Pipeline
Transfer Learning Utilization	Limited Exploration of Pre-trained Models	Fully Leveraged with Extensive Fine-Tuning
Evaluation Metrics	Primarily Accuracy	Comprehensive (e.g., Accuracy, Precision, Recall, F1-score, ROC-AUC)
Multi-modal Data Integration	Focused Solely on MRI Images	Integrates Additional Data Sources (e.g., Clinical Records)
Scalability	High Computational Requirements	Optimized for Clinical Deployment
Validation	Limited to Small Independent Cohorts	Validated on Large, Independent Cohorts

III. Proposed Method

A. Collection of Dataset

As the dataset for this investigation, brain MRI scan images were obtained from publicly accessible Kaggle archives. Every image has been resized to 128X128 pixels. The dataset comprises a grand total of 6400 MRI images, organized into four distinct classifications, as detained in table 2 and figure 2 shows a sample MRI images in dataset.

i. Extremely Mild Demetia
ii. Mildly cognitively impaired
iii. Moderately cognitively impaired
iv. Non-cognitively impaired

TABLE III. Dataset

Stages of AD	Total images in dataset		
	Train	***Test***	***Total***
Extremely M. D	1792	448	2240
M.CI	717	179	896
Mod.CI	52	12	64
N. CI	2560	640	3200

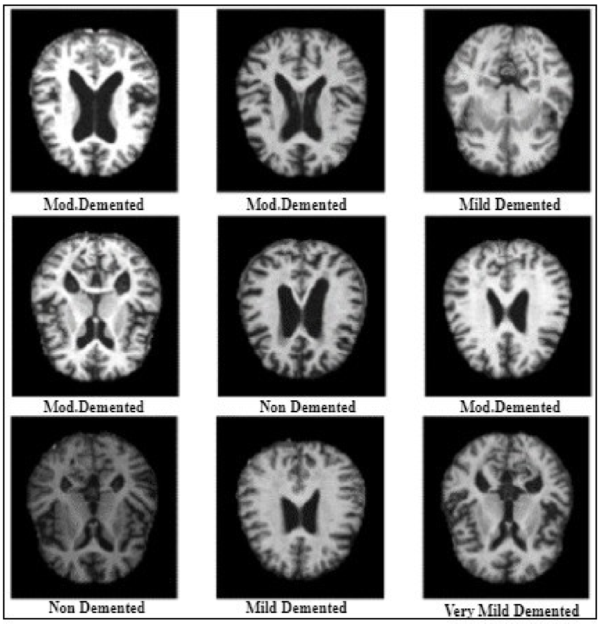

Fig. 2. MRI images in Dataset

B. Preprocessing of Data

Brain images captured with MRI technology may exhibit irregularities due to equipment limitations. MRI image processing constraints may rise to anomalies such as inadequate image resolution, inhomogeneity, motion heterogeneity, distortion and misunderstanding. During the examination of the brain MRI image, false positives may result from these erroneous image analyses. An inaccurate diagnosis further restricts the treatment options available to the patient. As a result, techniques for augmenting data are utilized for resampling the images and further enhancing the performance of TL models through the generation of novel and distinct instances for training datasets.

Here the Adaptive Synthetic Sampling Approach (ADASYN) is employed to augment the data augment the data by oversampling in consideration of the majority class. This method is an improved iteration of the Synthetic Minority Oversampling Technique (SMOTE), in which minority class observations are incorporated into the resampling process.

C. Model Architecture

ADASYN is utilized to further preprocess the input brain MRI dataset. Four CNN models utilizing TL, namely VGG-19, ResNet50, Inception-v3 and Xception are employed to classify AD [3-5].

The VGG-19 includes a total of 138 million hyperparameters 2*2 max-pool kernels, and 3*3 convolution kernels across the board. As a consequence, the number of trainable datasets has decreased by 44.9 % compared to its previous state. A reduced quantity of training data leads to overfitting concerns and an accelerated rank of learning. The utilization of ResNet50, a pre-trained CNN model, simplifies the process of training a model with a substantial number of convolutional layers while preventing an increase in the training error rate. Architecture for AD's classification is shown in figure 3.

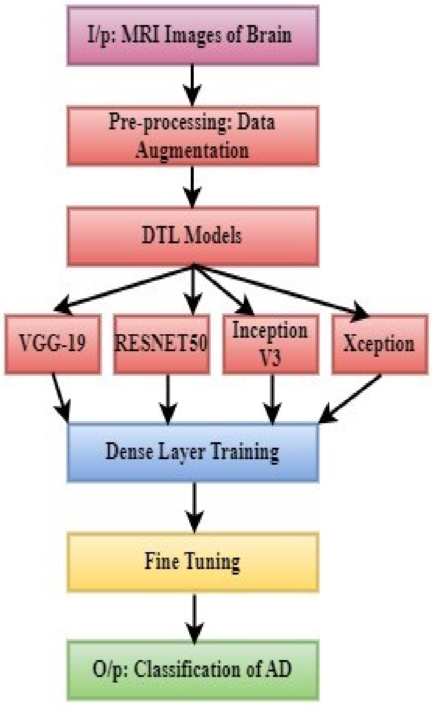

Fig. 3. AD Classification's Architecture Diagram

IV. Results and Discussion

Tensor Flow and Python Keras are used to carry out the studies. The CNN model that was previously trained analyses the initially captured image, which has 227x227 pixel size, using three convolutional layers. Following the conversion of the image to (128x128) pixels, the feature matrix output 13 consists of 58 dense layers.

Adam is the optimization method utilizes in this research study. In addition to aiding in the reduction of loss, it facilitates the adjustment of bias and weight parameters. The following graphs illustrates 100 epochs of data for each test predictive analysis. The y-axis represents loss levels, while the x-axis represents each epoch [9,10].

A. CNN Architecture: VGG-19

The model's training accuracy increases gradually and reaches its optimum values after 80 epochs; conversely, the validation accuracy begins to rise the 40th epoch and reaches 0.90%. An illustration of the model accuracy achieved in AD detection applying a modified VGG-19 algorithm design is shown in Figure 4. Figure 5 demonstrates how, after 60 epochs, the loss of validation achieves a constant state and converges more quickly than the training loss. In figure 6, a confusion matrix illustrates the effectiveness with the VGG-19 model. The model is capable of classifying 89% of the images in the testing data, as demonstrated here [13,14].

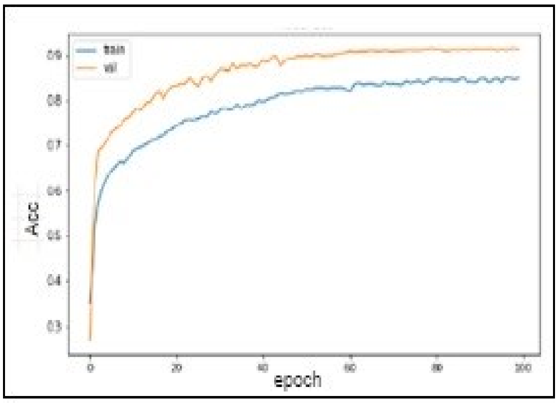

Fig. 4. Vgg-19 models' Accuracy Curve

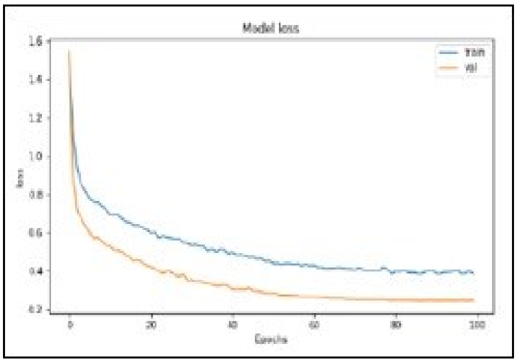

Fig. 5. VGG-19 models' Loss Curve

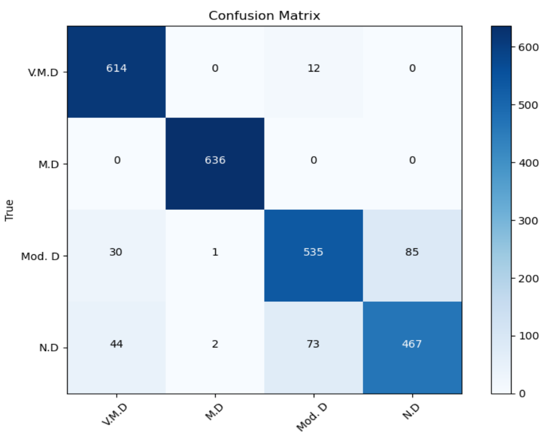

Fig. 6. VGG-19 model's Confusion Matrix

B. CNN Architecture: RESNET50

Figure 7 illustrates the model accuracy achieved through the application of the RESNET50 model for AD classification. The results of the experiment indicate that after its tenth epoch, training accuracy stabilised at.60%, whereas validation accuracy increased to.70% by the fifth epoch. A stable condition is reached after the 20th period, as figure 8 illustrates, when the validation loss meets the original training loss more quickly. Figure 9, a confusion matrix, shows the effectiveness of the RESNET50 model. This demonstrates that the model has the capability to classify 68% of the images in the testing dataset [16-20].

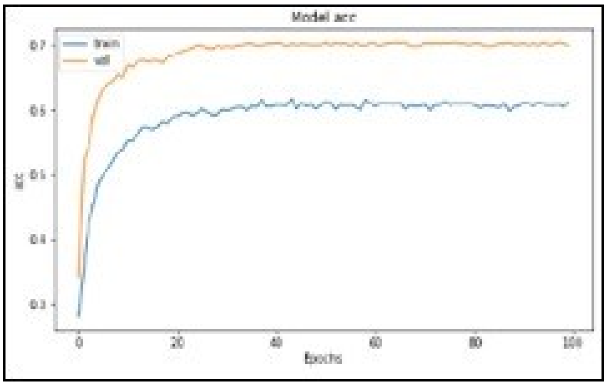

Fig. 7. ResNET50's Accuracy Curve

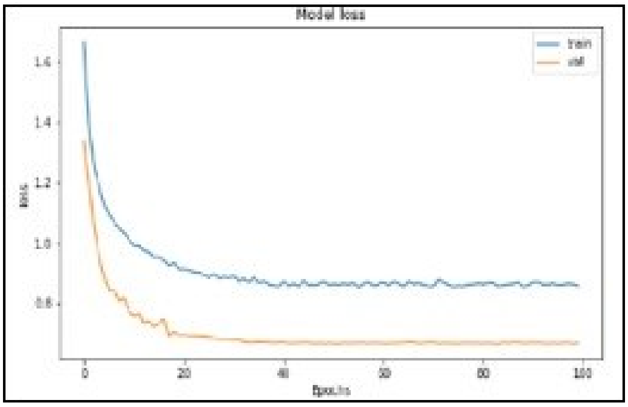

Fig. 8. ResNet 50's Loss Curve

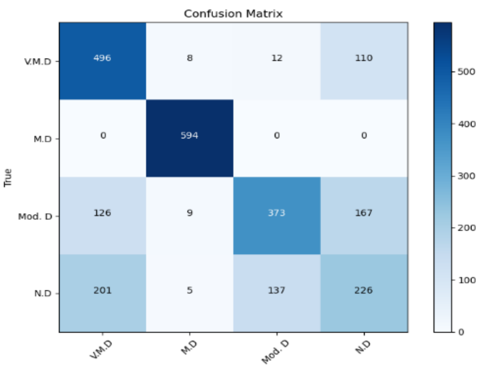

Fig. 9. ResNet50's Confusion Matrix

C. CNN Architecture: Inception-v3

The accuracy of the Inception-v3 model, which was utilized to classify AD, is illustrated in figure 10. The results of this experiment indicate that the training accuracy stabilized at

95% after the 50th epoch, where the validation accuracy increased to .85% at the 40th epoch. The model loss trajectory is illustrated in figure 11. The training loss exhibits faster convergence compared to the validation loss, ultimately stabilizing following the 50th epoch. The confusion matrix illustrates the efficacy of the inception-v3 model, as shown in figure 12. The model is capable of classifying 89% of the images in the testing data, as shown here.

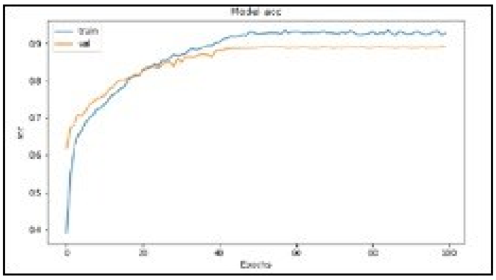

Fig. 10. Inception -v3 model's Accuracy Curve

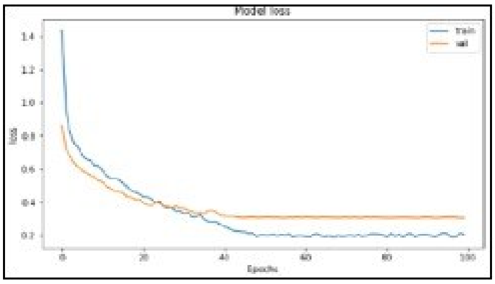

Fig. 11. Inception -v3 model's Loss Curve

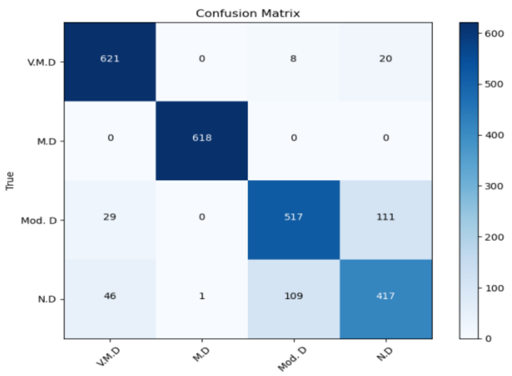

Fig. 12. Inception -v3 Confusion Matrix

D. CNN Architecture: Xception

Figure 13 illustrates the achieved model accuracy while using the Xception model for AD categorization. During the experiment, the training accuracy reached a stable level of 95% following the 40th epoch. In contrast, the validation accuracy exhibited a tendency to increase following the 29th epoch, eventually reaching a value of 85%. The predicted curve loss is shown in figure. 14, which indicates the simulated loss converges more quickly than the validation loss. The 25th epoch marks the stable state for the training loss. As demonstrated in figure. 15, the Xception model's performance results are displayed as a confusion matrix. From the above information, it can be inferred that the model has the ability to accurately categorize 87% of the images in the testing dataset [21-28].

This experiment involves assessing the performance of TL models using measures like as Matthew's Correlation Coefficient and Balanced Accuracy Score. These metrics include measures such as True Positive (TP), True Negative (TN), False Positive (FP) and False Negative (FN).

Equation 1 represents the balanced accuracy score, which is especially valuable when there is a significant imbalance between the two classes, with one class being significantly more prevalent than the other.

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

where,

$$Specificity = {}^{TN}\!/_{TN+FP} \quad \ldots (2)$$

$$Sensitivity = {}^{TP}\!/_{TP+FN} \quad \ldots (3)$$

The MCC (Matthew's Correlation Coefficient) is a classification measures that provides a concise summary of the confusion matrix and is considered the most effective single-value metric for this purpose. The calculation is performed using the procedure shown in equation 4.

After modifying the optimisation processes, the Balanced Accuracy Score [15] of the TL models is displayed in the figure 16. The VGG model performs better than the other models when trained with the ADAM optimizer, attaining a balancing Accuracy Score of 89.94%.

The figure 17 illustrates MCC of TL models as it varies with different optimization strategies. The VGG model, when trained using the ADAM optimizer, achieves superior performance compared to other models, with a MCC of 86.64%.

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

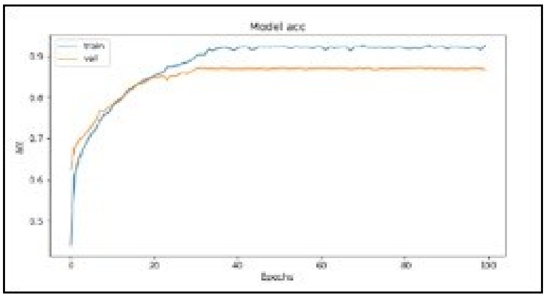

Fig. 13. Xception model's Accuracy Curve

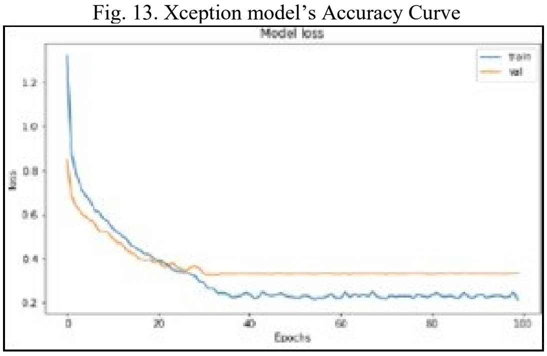

Fig. 14. Xception Models' Loss Curve

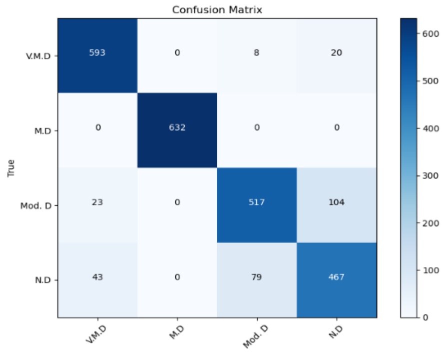

Fig. 15. Xception Models' Confusion Matrix

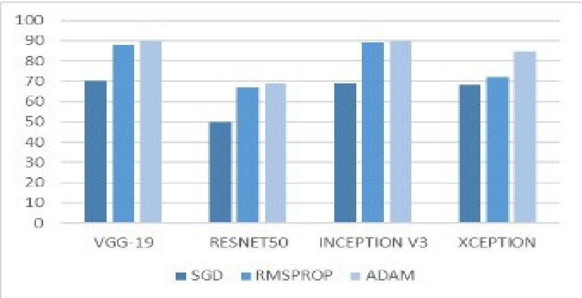

Fig. 16. TL Models' Balance Accuracy Score Comparison

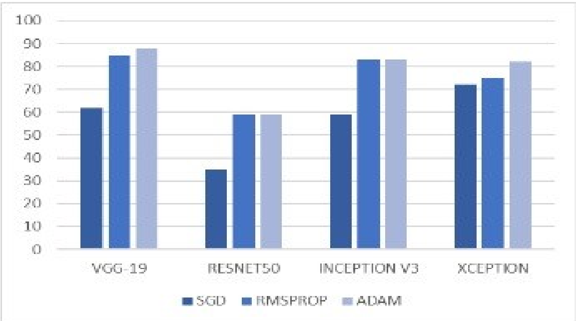

Fig. 17. TL Model's MCC

V. Conclusion

In this study, a comparison of DTL models is used for the classification of AD and utilizes a total of 6400 MRI images that have been categorized into four distinct classifications. The process of data preparation is carried out with the ADASYN. If the accuracy of training and validation improves with each epoch, it is expected that the pretrained CNN model would provide superior performance outcomes. In particular, when training accuracy rises and validation accuracy falls, overfitting issues are predicted to arise on the design. When a model is overfitted, it becomes too specialized to a particular set of training data, resulting inaccurate predictions for new datasets. According to the performance research, it can be concluded that VGG-19 performs better than ResNet50, Xception and Inception-v3 pretrained CNN models on the trained and tested datasets. One way to further the study is to use population-based optimization techniques to train deep CNN models for more predictive analysis of AD.

Acknowledgement

This paper was supported by KIIT Deemed to be University Library and Dr. Gopabandhu Sahu (Librarian), India, as well as the staff of SCB, Medical college, for their invaluable assistance and contributions to this study. Their dedication and support were integral to the successful completion of our study.

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