International Journal of Academic Health and Medical Research (IJAHMR)
ISSN: 2643-9824
Vol. 6 Issue 9, September - 2022, Pages: 35-44

A Novel Approach for classification of different Alzheimer's stages using pre-trained CNN Models with transferring learning and their comparative analysis

Gowhar Mohiuddin Dar*, Avinash Bhagat, Sophiya Sheikh

Department of computer applications, lovely professional university, Punjab, India

* Gowhar Mohiuddin Dar dargowhar123@gmail.com

Abstract: *Transfer learning has become extremely popular in recent years for tackling issues from various sectors, including the analysis of medical images. Medical image analysis has transformed medical care in recent years, enabling physicians to identify disease early and accelerate patient recovery. Alzheimer's disease diagnosis has been greatly aided by imaging (AD). Alzheimer's is a degenerative neurological condition that slowly deprives patients of their memory and cognitive abilities. Computed tomography and brain MRI scans are used to detect dementia in Alzheimer's patients. This research primarily aims to classify AD patients into multiple classes using ResNet50, VGG16, and DenseNet121 as transfer learning along with CNN networks on a large dataset as compared to existing approaches as hence improves classification accuracy. The different stages of Alzheimer's are early mental retardation, mild mental impairment, late mild mental impartment, and final Alzheimer's stage (AD). The novel approach gives results with an accuracy of 96.6%, significantly improved outcomes compared to existing models.*

Keywords: AD, EMCI, MCI, LMCI MRI, CNN, ResNet50, VGG16, DenseNet121

1 INTRODUCTION.

Nearly 50 million people worldwide have been diagnosed with Alzheimer's, a neurological condition [1]. The malady permanently affects the brain, diminishing comprehension, recall, and other capabilities. The patient succumbs in case of brain failure. By 2050, that estimate is projected to rise to 152 million[2]. As a result, in 2018, the expected global treatment expenses were established at almost $186 billion. In 30 years, this number is anticipated to increase by around four times[3]. Unfortunately, no precise treatment or prevention for Alzheimer's disease has yet been discovered by science. According to the established Clinical Dementia Rating (CDR) result, the disorder is split into four stages: early mild cognitive impartment, mild cognitive impartment, late mild cognitive impartment, and Alzheimer's (AD). Early diagnosis of dementia disorders is crucial for patient recovery and treatment expenses because the cost of treating patients with EMCI, and LMCI is different Diagnosis of Alzheimer's is best possible after the death of a patient since Alzheimer's pathology changes in patients could not be assessed early. The initial diagnostic criteria for Alzheimer's disease were created in 1984 and only relied on clinical symptoms. With the discovery of different biomarkers such as CSF, MRI, and PET data, the international working group devised a new approach in 2014, and this served as the Model for the National Institute on Aging and Alzheimer's Association's (NIA-AA) following set of standards. Biomarker data is used to connect the clinical condition of dementia or mild cognitive loss to intrinsic Alzheimer's pathologic changes with the high, moderate, or low risk in the NIA-AA criteria. [4-5]. Imaging biomarkers are used to assess Alzheimer's disease, such as CT, FMRI, MRI, and PET scans. The hippocampus and entorhinal cortex have shown extremely early changes in Alzheimer's disease that are consistent with pathology, but it is still uncertain which structure would be best for an early diagnosis. The physiology of dementia and its differential diagnosis have benefited greatly from structural and functional imaging, which also holds considerable potential for tracking the course of the disease [6]. Numerous articles are written regarding how various imaging methods can be used to detect Alzheimer's disease. In volumetric MRI, patterns of sick and healthy subjects were identified using feature-based morphometry (FBM) [7]. In computerized medical image processing, convolution neural networks (CNNs) have achieved major advancements. As a result, various CNN models, including VGG, MobileNet, AlexNet, and ResNet, are available for object detection and segmentation. Despite the fact that CNNs are a renowned deep learning technique, their effectiveness is hampered by the absence of an extensive medical imaging dataset. Transfer learning is among the efficient methods for building deep convolutional neural networks without overfitting when the amount of data is minimal. [8]. A pre-trained network is the foundation of transfer learning. The proposed method can learn the most useful features instead of training a specific CNN network without preparation. To categorize AD into five classes, the proposed research study has used four pre-trained networks, comprising VGG 16, ResNet, and DenseNet121.

An automated framework was developed by U. Rajendra et al. [9] to evaluate whether a baseline brain scan will detect any evidence of Alzheimer's disease. Lihua Wang et al. [10] integrated genomic data from six different brain areas using SVM machine learning techniques to find AD biomarkers. Martin Randles and Mohamed Mahyoub [11] proposed that relying on characteristics including lifestyle, medical history, demography, and other considerations, Alzheimer's is predicted at various stages. Rueda et al. suggested a fusion-based image processing technique that identifies discriminative brain patterns connected to the presence of neurodegenerative disorders [12]. The effectiveness of classification using a support vector machine (SVM) was assessed on several data sets once the discriminative patterns had been identified. A classification approach based on multilayer brain divisions was presented by Li et al. [13]. Using SVM, histogram-based parameters from MRI data were used to categorize various brain levels. Giraldo et al.[14] proposed an automated technique recently developed for identifying structural abnormalities in the thalamus, planum temporal, amygdala, and hippocampal areas. Hina Nawaz et al.[1] devised a framework based on the computer-aided system, which needs real-time AD diagnosis. They have suggested identifying the stages of AD. For certain deep feature modeling and extraction, researchers have used classification algorithms like KNN (K-nearest neighbour), RF (Random Forest), and SVM (Support Vector Machine). Large datasets were necessary for classification and extracting deep features to avoid overfitting problems. To attain the maximum accuracy in early Alzheimer's diagnosis, they have recommended on time the depth and propagation of learning techniques compared to previous approaches. There is currently no treatment for AD using any medical reasoning approaches, and early detection of Alzheimer's disease is complicated. To attain high accuracy, Ketki Tulpule et al. [16] focused on nonlinear SVM for the radial base purpose when developing a computerized machine learning approach for categorizing Alzheimer's phases. Muazzam Maqsood et al. [17] devised a transfer learning approach to identify Alzheimer's disease. They suggested breaking down the AD category among different divisions.

2 Transfer learning

A model created for one task is used as the basis for another using the machine learning technique known as transfer learning. Deep learning tasks in computer vision and natural language processing are built on pre-trained models. Compared to building neural network models from the beginning, they are both cheaper and faster, and they perform remarkably better on related tasks. Transfer learning is learning a new activity more effectively by applying what has already been learned about a related one [18]. For this approach to be practical, the features must be generic, i.e., applicable to both the base task and the target task [19]. Convolutional neural networks, often known as ConvNet, are a subset of Deep Neural Networks (DNN) and are most frequently applied to the processing of medical images. The fundamental structure of the CNN is shown in Figure 1.

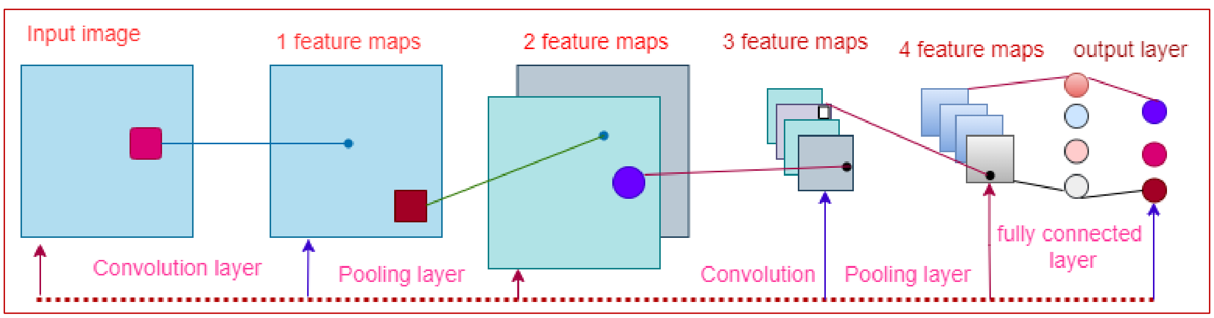


***Figure 1**: Basic CNN architecture*

Various Pre-trained deep learning models with transfer learning approaches have been put out in the research. VGG 16, ResNet 50, and DenseNet 121 were used in this study

2.1 VGG16

A convolutional neural network with 16 layers is called VGG-16. The ImageNet database contains a pre-trained kind of network that has been trained on more than a million images [20]. The pre-trained model can categorize images into 1000 distant object groups. The network has therefore acquired rich feature representations for a variety of images.

2.2 ResNet 50

A ResNet model version called ResNet50 contains forty-eight Convolution layers, one MaxPool layer, and one Average Pool layer. There are 3.8 x 10^9 floating-point operations available. It is a commonly used architecture, and we thoroughly examined the ResNet50 design [21].

2.3 DenseNet121

In densely connected convolutional networks, each layer is linked to every other layer. L(L+1)/2 direct connections between 'L' layers. DenseNet resolves the vanishing gradient problem by altering the typical CNN architecture and streamlining the connectivity between layers[22].

3 Experimental evaluation

MRI images from the ADNI dataset are used in this study. There are 2900 images in this dataset(580 images from each class), each measuring 224 × 224. The images from each AD stage are listed in Table 1.

AD stage	Total images in a Dataset			
	Training data	Test data	Validation data	Total
NC	400	90	90	580
EMCI	400	90	90	580
MCI	400	90	90	580
LMCI	400	90	90	580
AD	400	90	90	580

Table 1. *shows the images given inputs to the Model. 400 images from each class are used for training purposes, 90 from each class for validation, and 90 from each class for testing*

4 Data Balancing

Data balancing is essential for the Model to predict more accurately. Unbalanced data leads to overfitting and underfitting; thus, data needs to be balanced. Here in this study, we use upsampling techniques to balance the data. The figures below show the data before and after sampling

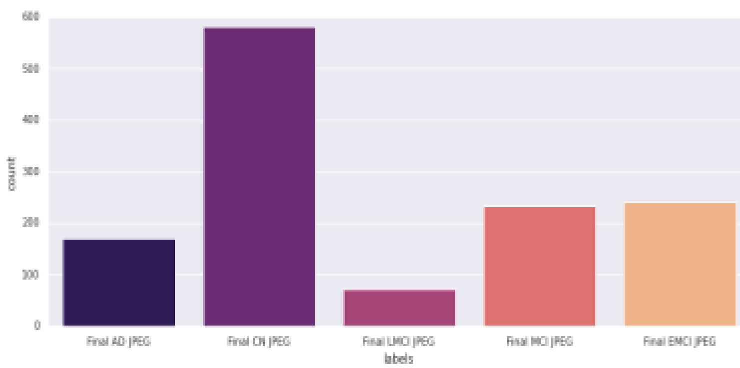


Figure 2(a) *shows the unbalanced data*

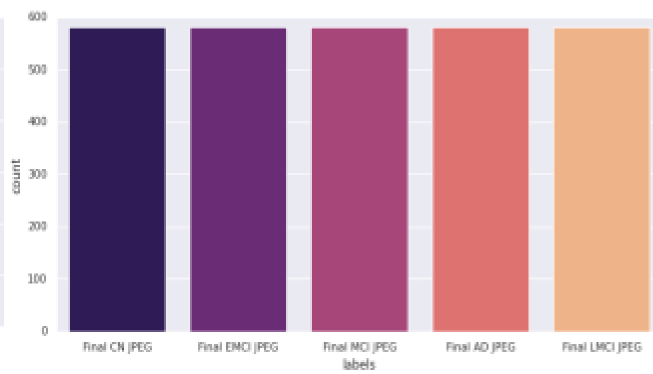


Figure** 2**(b) *shows the balanced data*

5 Data Augmentation

The size of the dataset is significant for deep learning models. These models predict more accurately and give better accuracy results on large datasets. The major drawback of image datasets is that they are not available in a large size. Therefore, it needs to be augmented to make the dataset larger for the models. We applied different data augmentation techniques to datasets, such as horizontal filliping of the images, rotation of images by 5 degrees, and width and shift in the images. in this study, we applied data augmentation with the help of an image data generator of Keras API. The figure below shows the effect of data augmentation techniques on brain MRI images.

International Journal of Academic Health and Medical Research (IJAHMR)
ISSN: 2643-9824
Vol. 6 Issue 9, September - 2022, Pages: 35-44

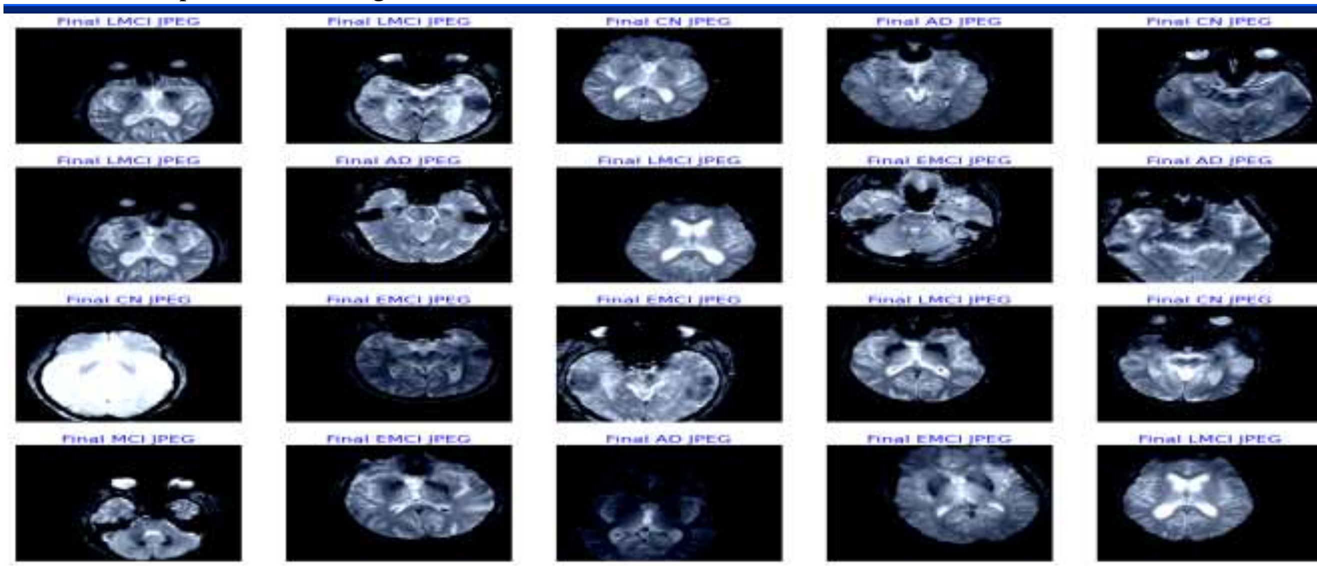


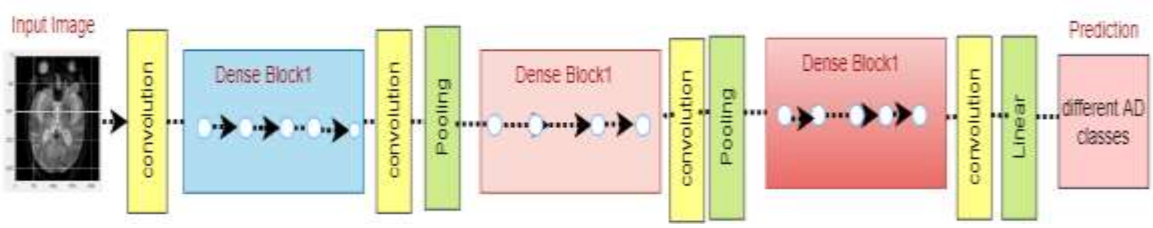
__Figure 3:__ shows the effect of data augmentation on images, some are flipped, rotated, or shifted.

6 Result evaluation:

Dataset used in this paper is divided into testing, training, and validating data. A total of 2900 images are used in this research.2000 images for training(400 from each class), 450 for testing(90 from each category), and 450 for validating(90 from each type). We applied transfer learning by applying pre-trained CNN models such as Densenet121 and VGG16 with ImageNet weights. For multiclass classification, we are utilizing the RMSProp as our optimizer with a learning rate of 0.00001 and categorical cross-entropy as the loss metric while maintaining accuracy metrics that will provide training and validation results as well loss and accuracy values.

6.1 DenseNet121

DenseNet121 comprises one 7x7 Convolution fifty-eight 3x3 Convolution sixty-one 1x1 Convolution four AvgPool and one Fully Connected Layer. The performance of the classification models for a particular set of test data is assessed using a confusion matrix. The figures below show the basic architecture, confusion matrix, accuracy, and loss plot generated by the DenseNet121 model.



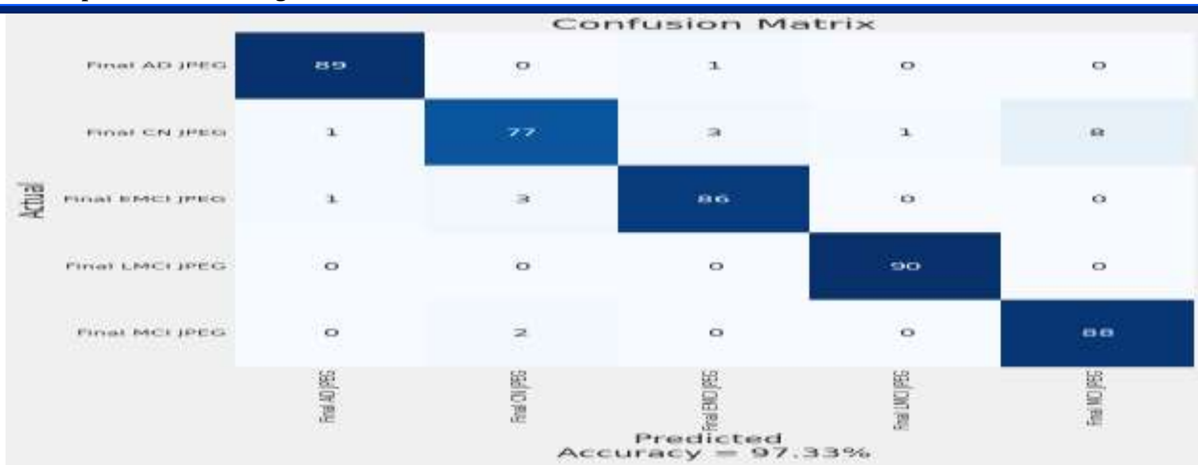
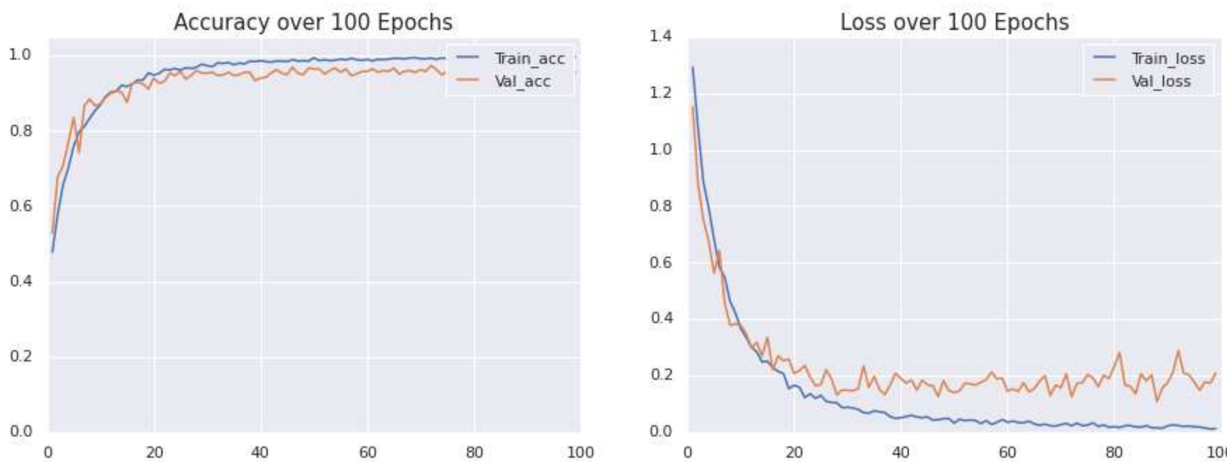


Figure 4(a): *Basic architecture of the Densenet121 Model*

Figure 4(b): *shows the confusion matrix generated by the DenseNet121 model. The overall accuracy is 97.33%*



Figure(4c): *shows the accuracy and loss plot generated by the DenseNet121 model over 100 epochs*

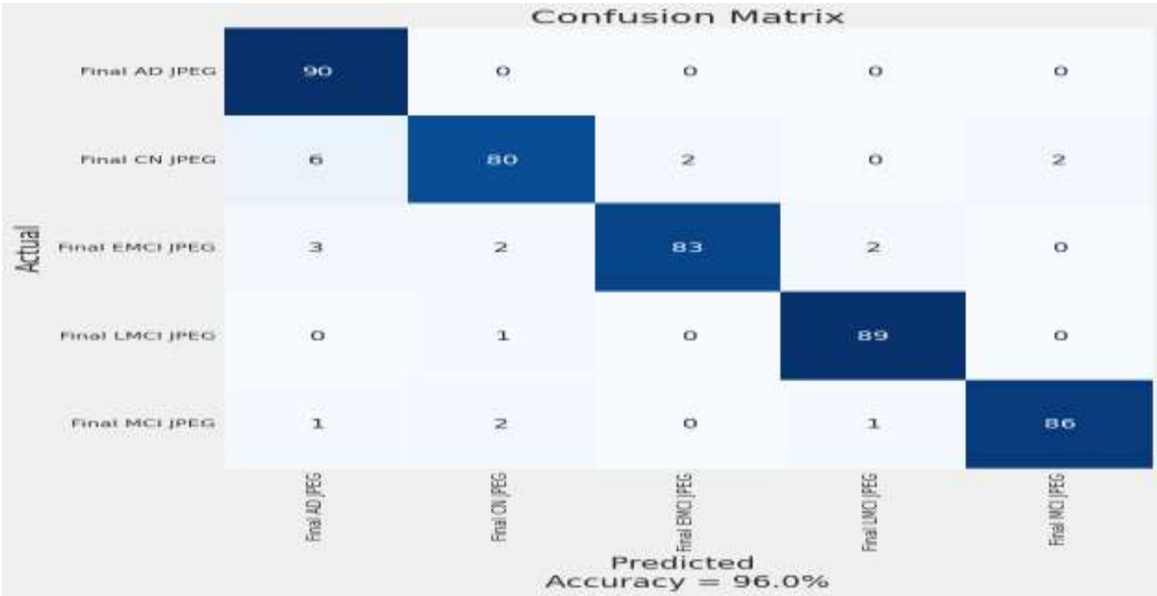
The classification reported generated by this model based on the different performance metric parameters is shown in table 2 below.

Table 2: *shows the classification report generated by the DenseNet121 model*

Classification Report	Precision	Recall	F1-score	support
Final AD JPEG	0.98	0.99	0.98	90
Final CN JPEG	0.94	0.86	0.90	90
Final EMCI JPEG	0.96	0.96	0.96	90
Final LMCI JPEG	0.99	1.00	0.99	90
Final MCI JPEG	0.92	0.98	0.95	90
Accuracy			0.96	450
Macro avg	0.96	0.96	0.96	450
Weighted avg	0.96	0.96	0.96	450

International Journal of Academic Health and Medical Research (IJAHMR)
ISSN: 2643-9824
Vol. 6 Issue 9, September - 2022, Pages: 35-44

6.2 VGG16



VGG16 Model comprises 16 layers and is implemented on an input image with dimensions(224x224) and converts it into (7x7) and five dense layer feature matrices as output. The overall accuracy of the model is 96.0 which is shown in the confusion matrix in figure 5(a). The loss and accuracy over 100 epochs are shown in figure 5(b).

Figure 5(a): *shows the confusion matrix generated by the VGG16 model. The overall accuracy is 96.0%*

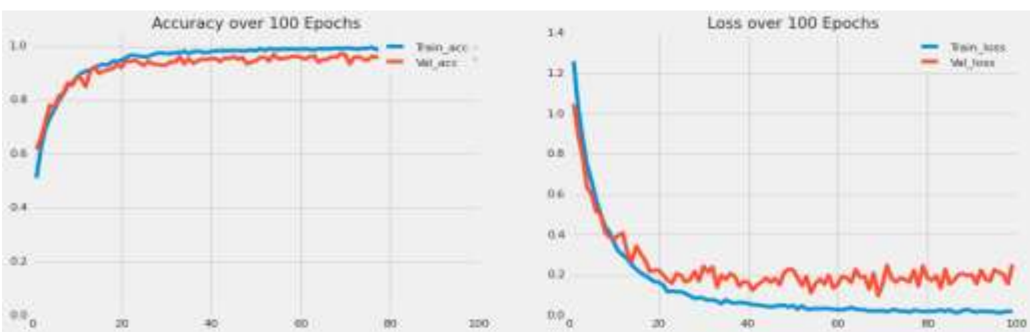


Figure 5(b) *shows the accuracy and loss plot generated by the VGG16 model over 100 epochs*

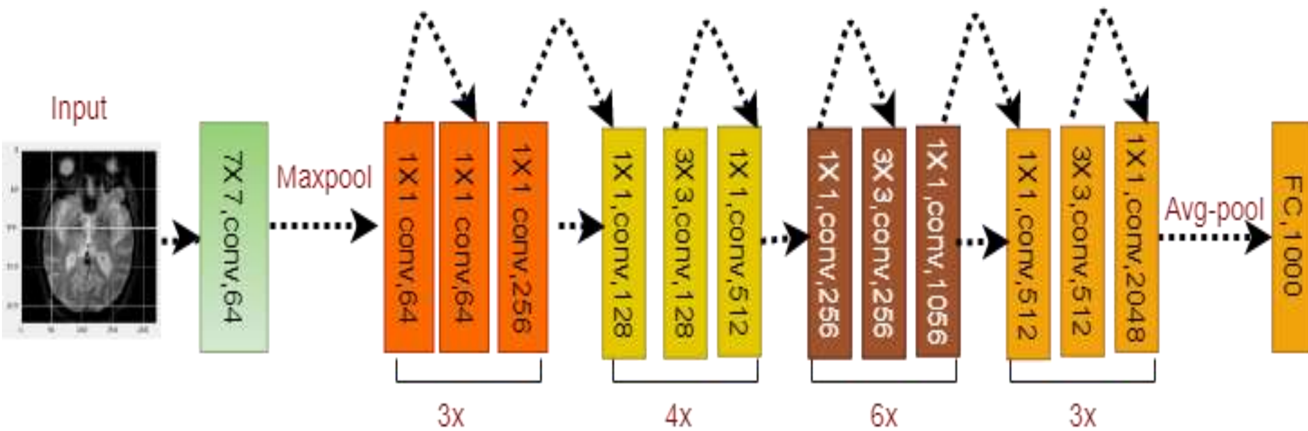
Classification Report	Precision	Recall	F1-score	support

Final AD JPEG	0.90	1.00	0.95	90
Final CN JPEG	0.94	0.89	0.91	90
Final EMCI JPEG	0.98	0.92	0.95	90
Final LMCI JPEG	0.97	0.99	0.98	90
Final MCI JPEG	0.98	0.96	0.97	90
Accuracy			0.95	450
Macro avg	0.95	0.95	0.95	450
Weighted avg	0.95	0.95	0.95	450

The classification report for the identification of different Alzheimer's stages generated by the model is shown in table 3 below. Classification is done as per different parameters such as recall, precision, f1-score, etc.

***Table 3**: shows the classification report generated by the VGG16 model*

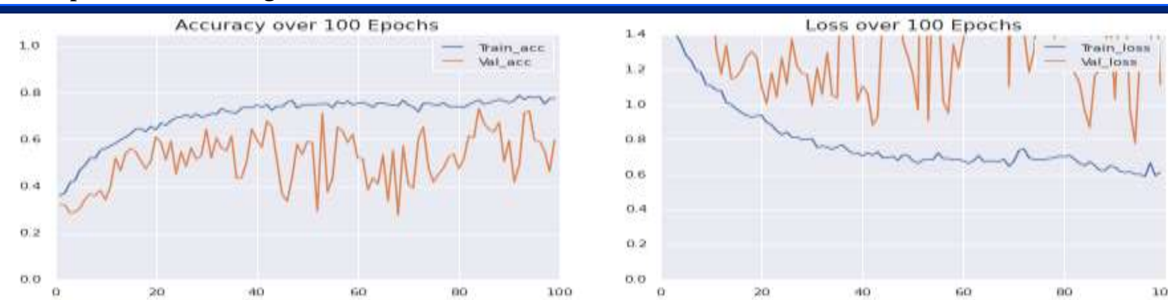
6.3 ResNet50



The input image size (224x224) is converted to (7x7) by applying the RESNET50 Model, which has fifty layers of coevolution, and the output feature matrix is five dense layers. The Model's accuracy is measured based on different parameters such as Recall, F1score, Precision etc. the basic architecture, confusion matrix, accuracy and loss plot are shown in figures below. Finally, the classification report generated by the model on the specified dataset is shown in table 4.

***Figure 6(a):** Basic architecture of the ResNet50 Model*

International Journal of Academic Health and Medical Research (IJAHMR)
ISSN: 2643-9824
Vol. 6 Issue 9, September - 2022, Pages: 35-44



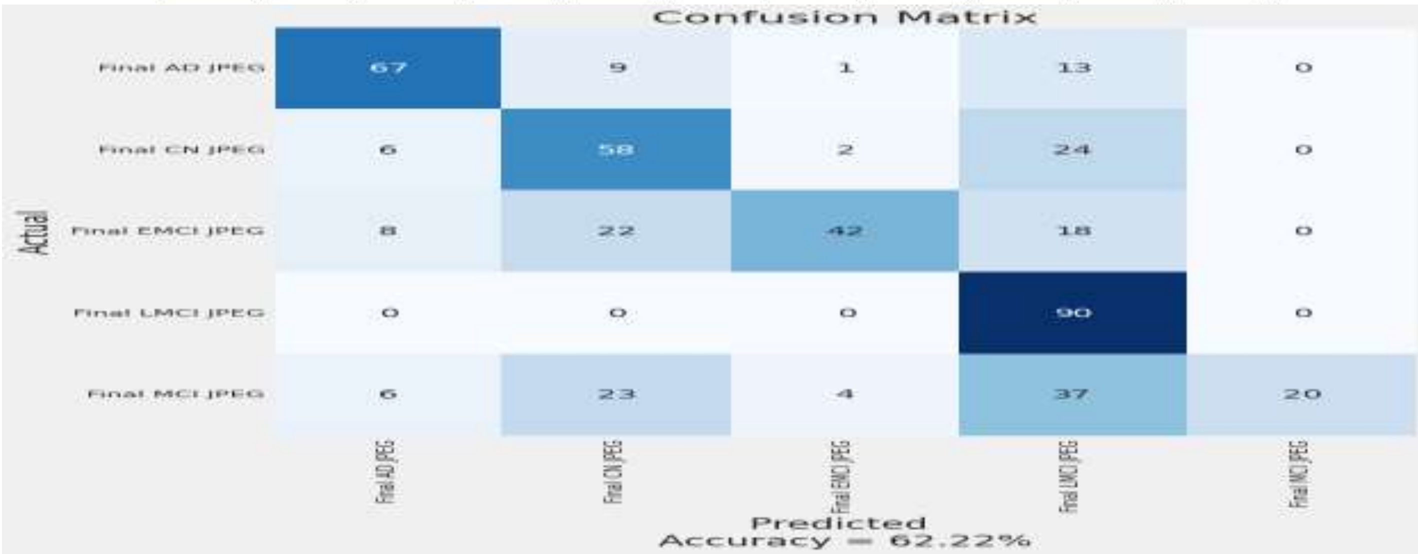


Figure 6(b): *shows the confusion matrix generated by the ResNet model. The overall accuracy is 62.22%*

Figure 6(c)*: shows the accuracy and loss plot generated by the ResNet model over 100 epochs*

Table 4*: shows the*

Classification Report	Precision	Recall	F1-score	support
Final AD JPEG	0.77	0.74	0.76	90
Final CN JPEG	0.52	0.64	0.57	90
Final EMCI JPEG	0.86	0.47	0.60	90
Final LMCI JPEG	0.49	1.00	0.66	90
Final MCI JPEG	1.00	0.22	0.36	90
Accuracy			0.62	450
Macro avg	0.73	0.62	0.59	450
Weighted avg	0.73	0.62	0.59	450

classification report generated by the ResNet50 model

7 Discussion:

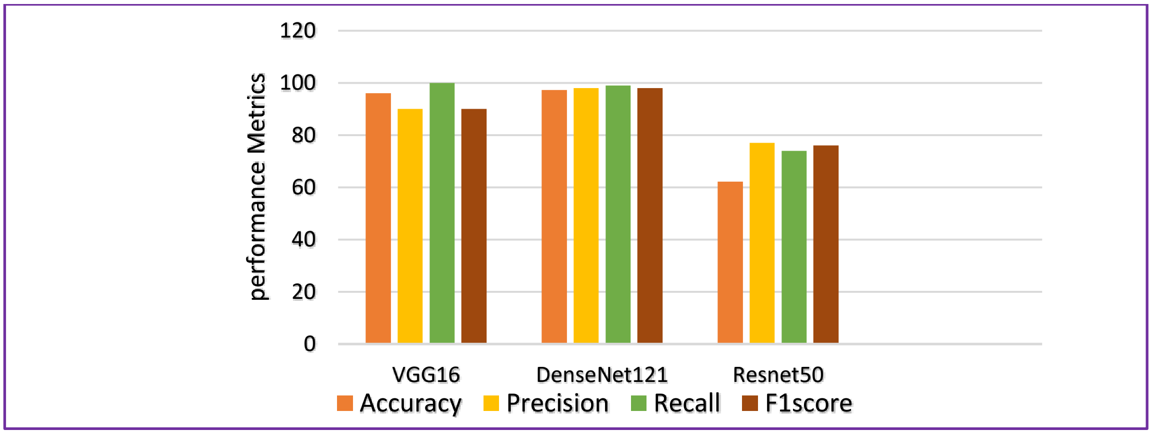
The proposed Model evaluates the efficiency of models in different performance metrics, such as the confusion matrix, accuracy, loss, F1 Score, precession, recall, ROC, and sensitivity. The general formulae to calculate different parameters are calculated by the following equations.

$$accuracy = \frac{TP}{TP+FN+TN+FP} \quad (1)$$

$$Precision = \frac{TP}{TP+FP} \quad (2)$$

$$Recall = \frac{TP}{TP+FN} \quad (3)$$

$$F1score = 2 \times \frac{precision \times recall}{precision + recall} \quad (4)$$



Where TP represents true positive, TN represents true negative, FP indicates false positive, and FN denotes false negative. For efficient classification results, precision and recall should always be high. In the present study, 2900 images from the ADNI dataset are split into groups based on the stages of Alzheimer's. For Evolution, the whole data is divided into training, testing, and validation(500,90,90 images from each class). The performance analysis comparison of the applied models is shown in the figure below.

Figure 7: *shows the comparative analysis of performance generated by pre-trained deep learning models on data set*

8 Conclusion

This study examined pre-trained strategies to predict the phase of Alzheimer's disease. The best accuracy of the Model achieved is 97.23 percent. The proposed Model works on ADNI data using Keras API, where the MRI image is divided into five categories: EMCI, MCI, LMCI, and AD. The analysis has looked at underfitting and overfitting problems, their solution, and the adjustment of the Model's impact on our application's performance. In this research, three advanced networks VGG16, DenseNet121, and RESNET50, were used, and results were compared. The suggested model outperformed the others significantly. In future studies, we will investigate applying the same Model to other disorders using the same data modality. Enhancement in classification results will be the primary priority while training and testing the data.

References

1. Nawaz, Hina, et al. "A deep feature-based real-time system for Alzheimer disease stage detection." Multimedia Tools and Applications 80.28 (2021): 35789-35807.
2. Maurer, Konrad, Stephan Volk, and Hector Gerbaldo. "Auguste D and Alzheimer's disease." *The lancet* 349.9064 (1997): 1546-1549.
3. Richards, Stephanie S., and Hugh C. Hendrie. "Diagnosis, management, and treatment of Alzheimer's disease: a guide for the internist." *Archives of Internal Medicine* 159.8 (1999): 789-798.
4. Jellinger, K., et al. "Clinicopathological analysis of dementia disorders in the elderly." *Journal of the neurological sciences* 95.3 (1990): 239-258.
5. Scheltens, P., et al. "Alzheimer's disease. Lancet (Lond Engl) 388: 505–517." (2016).
6.] O'Brien, J. T. "Role of imaging techniques in the diagnosis of dementia." *The British journal of radiology* 80.special_issue_2 (2007): S71-S77.
7. Toews, Matthew, et al. "Feature-based morphometry: Discovering group-related anatomical patterns." *Neuroimage* 49.3 (2010): 2318-2327.
8. Ting Xiao ,1,2 Lei Liu,1 Kai Li,3 Wenjian Qin,1,4 Shade Yu.[online]https://www.hindawi.com/journals/bmri/2018/4605191/2018.

9. Acharya, U. Rajendra, et al. "Automated detection of Alzheimer's disease using brain MRI images–a study with various feature extraction techniques." *Journal of Medical Systems* 43.9 (2019): 1-14.
10.] Wang, Lihua, and Zhi-Ping Liu. "Detecting diagnostic biomarkers of Alzheimer's disease by integrating gene expression data in six brain regions." *Frontiers in genetics* 10 (2019): 157.
11. Mahyoub, Mohamed, et al. "Effective use of data science toward early prediction of Alzheimer's disease." *2018 IEEE 20th International Conference on High-Performance Computing and Communications; IEEE 16th International Conference on Smart City; IEEE 4th International Conference on Data Science and Systems (HPCC/SmartCity/DSS)*. IEEE, 2018.
12. Rueda, Andrea, Fabio A. Gonzalez, and Eduardo Romero. "Extracting salient brain patterns for imaging-based classification of neurodegenerative diseases." *IEEE transactions on medical imaging* 33.6 (2014): 1262-1274.
13. Li, Tao, and Wensheng Zhang. "Classification of brain disease from magnetic resonance images based on multi-level brain partitions." *2016 38th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*. IEEE, 2016.
14. Giraldo, Diana L., et al. "Characterization of anatomical brain patterns by comparing region intensity distributions: Applications to the description of Alzheimer's disease." *Brain and behaviour* 8.4 (2018): e00942.
15. Gupta, Yubraj, et al. "Prediction and classification of Alzheimer's disease based on combined features from apolipoprotein-E genotype, cerebrospinal fluid, MR, and FDG-PET imaging biomarkers." *Frontiers in computational neuroscience* 13 (2019): 72.
16. Vickers, Neil J. "Animal communication: when I'm calling you, will you answer too?." *Current Biology* 27.14 (2017): R713-R715.
17. Maqsood, Muazzam, et al. "Transfer learning assisted classification and detection of Alzheimer's disease stages using 3D MRI scans." *Sensors* 19.11 (2019): 2645.
18. Olivas, E. S., et al. "Chapter 11: Transfer Learning, Handbook of Research on Machine Learning Applications." (2009).
19. Yosinski, Jason, et al. "How transferable are features in deep neural networks?." *Advances in neural information processing systems* 27 (2014).
20. Rayar, Frédéric. "ImageNet MPEG-7 Visual Descriptors-Technical Report." *arXiv preprint arXiv:1702.00187* (2017).
21. Fuse, Hiroki, et al. "Detection of Alzheimer's disease with shape analysis of MRI images." *2018 Joint 10th International Conference on Soft Computing and Intelligent Systems (SCIS) and 19th International Symposium on Advanced Intelligent Systems (ISIS)*. IEEE, 2018.
22. Huang, Gao, et al. "Densely connected convolutional networks." *Proceedings of the IEEE conference on computer vision and pattern recognition*. 2017.
23. Howard, Andrew G., et al. "MobileNets: Efficient convolutional neural networks for mobile vision applications." *arXiv preprint arXiv:1704.04861* (2017).