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# Transfer Learning for Detecting Alzheimer's Disease in Brain Using Magnetic Resonance Images

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**ABSTRACT**

Alzheimer's Disease (AD) is one of the most concerning diseases because the patients show very few symptoms at the earlier stages. Dementia is very common in patients who have suffered brain damage or those who have suffered from psychotic trauma. Patients who have a lot of age suffer the most from it. Magnetic resonance imaging (MRI) is widely used to clinically treat patients with Alzheimer's. Currently, there is no known remedy for the disease. We can only identify and try to give the proper medications to give some relief to patients. In this study, we have collected MRI data from patients with 4 different stages of Alzheimer's. The purpose of this paper is to build a model to securely detect these stages for the betterment of medical science. We implemented a transfer learning method with state-of-the-art models such as ResNet50, DenseNet121, and VGG19. We proposed our method with these models which have pre-trained weights of "ImageNet". The layers that we added are our novelty. We were able to achieve 97.70% accuracy on our best pre-trained model with an F1 score of 97% and a precision of 97% on our test data.



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## 1. INTRODUCTION

Alzheimer's disease is a slowly progressive neurodegenerative disorder that affects the basic cognitive ability of a person [1]. Millions of people around the world are affected by it, it is most commonly referred to as dementia [2]. In the beginning, it starts with a mild decline in cognitive abilities such as memory, intelligence, and other mental capacities and possibly leads to long-term effects that include a total loss of one's ability to communicate and feel emotion entirely. The most significant potential danger for developing dementia is considered to be age, due to the fact that the majority of patients are beyond the age of 65. Those who are before the age of 65 and are diagnosed with Alzheimer's disease are considered to be afflicted with "younger-onset Alzheimer's disease". A younger beginning of dementia is also known as early-onset Alzheimer's disease. Patients who have developed the disease at a younger age may be at any point of the disease's progression. Patients are most commonly afflicted with Alzheimer's and it is considered the most common form of dementia and those over the age of 85 and is considered the second most common cause of dementia overall. The Global Deterioration Scale (GDS) is commonly used to classify the level of severity of dementia [3]. Using a CDR scale may improve more effective coordination of care between medical professionals and loved ones. One hundred billion neurons (nerve cells) make up the human brain. Each nerve cell is linked to numerous others to create complex networks of communication. Some tasks are best handled by clusters of nerve cells. Some people's jobs include mental processes like deliberation and recall. The senses of sight, hearing, and smell are all aided by other people [2]. Brain cells are like mini-factories when it comes to getting the job done. They take in materials, produce energy, build apparatus, and dispose of byproducts. Information processing, storage, and cell-to-cell communication are all functions of a single cell. It takes a lot of coordination, not to mention a lot of fuel and oxygen, to keep everything going. Clinical criteria are routinely maintained in order to diagnose Alzheimer's disease; however, with only these criteria clinical experts are incapable of detecting the disease in its early, pre-clinical phases, and hence cannot provide an early diagnosis. Given this harsh reality, it is critical for the betterment of mankind to develop methods and techniques that can be incorporated into early diagnosis criteria, as this would allow patients afflicted with dementia to plan for their future care while still having the mental capacity to do so, as well as provide them with the access to available medications and non-drug therapies that may maintain their cognitive ability and ensure their quality of life.

We applied 3 models ResNet50, DenseNet121, and VGG19 for classifying the stages of Alzheimer's. We have been able to get 97% accuracy on our test data. The best model we were able to achieve this accuracy is VGG19. The contribution to our work is as follows.

- We proposed a tuned version of ResNet50, DenseNet121, and VGG19 with "ImageNet" as our pre-trained model to classify 4 different stages of Alzheimer's disease.
- We modified each model by adding two fully connected layers to the default model to learn more intricate features that the dataset represents.
- We conducted our study with three models, including ResNet50, DenseNet121, and VGG19, and compared the scores of these three models in a variety of datasets by adding data to show and compare the effectiveness of our proposed model.

The rest of the paper is described as follows. Section 2. provides a review of the literature to obtain complete knowledge about Alzheimer's disease classification using transfer learning models. We state our proposed methodology in Section 3.. In this section, we describe the dataset and the applied transfer learning models. In Section 4., we describe the environment setup and discussion of the results. Finally, Section 5. concludes the paper.

## 2. LITERATURE REVIEW

Researchers all around the world have hypothesized that Alzheimer's disease disrupts the regular functions of some cells. They cannot pinpoint the exact origin of this problem. One cell can disrupt the operations of the other healthy cells, in turn, it may damage the whole system. Damaged brain cells become unable to perform their functions and die off, leading to permanent alterations in cognitive ability. Recent advances in machine learning and computer vision have led to some promising breakthroughs in the field of medical science [4]. In that regard, researchers have made a breakthrough in the diagnosis of Alzheimer's disease[5]. The development of convolutional neural networks (CNNs) has made a major impact on medical image processing. VGG19, DenseNet121, and ResNet50 are just a few examples of CNN architectures that have shown state-of-the-art performance in terms of image processing and classifications [6]. In [7], the authors examined the Alzheimer's disease classification using transfer learning models named AlexNet, VGG16, and ResNet50. They obtained the highest accuracy of 95.70%. In [8], the researchers proposed an Alzheimer's disease classification model based on transfer techniques. The highest accuracy is 96%. In [9], the researchers proposed transfer learning-based model classification for Alzheimer's disease on genome data, and their accuracy was only 89%. In [10], the authors examined transfer learning models named VGG19, ResNet 50, InceptionV3, and DenseNet169 for classifying Alzheimer's disease. Their highest accuracy is only 82.5%. In this paper [11], the researchers used three different transfer models named VGG16, InceptionV3, and Xception for classifying Alzheimer's Disease. The authors achieved a 75% accuracy only.

In this paper [12], the researchers proposed Densenet201, Resnet50, VGG16, and the Hybrid method models to classify Alzheimer's disease. The highest accuracy of 90% is obtained by the hybrid model. In [13], authors proposed a modified ResNet 50 model for classifying Alzheimer's disease and the model provided only 97.49% of accuracy.In [14], authors proposed a CNN CNN-based ResNet18 model for classifying Alzheimer's Disease. The limitation is that only one model is used and the accuracy is low which is 88.3%. In [15], authors proposed several CNN models named VGG19, ResNetv2, and ResNet152v2 for classifying

Alzheimer's disease. They also combined thrice with diverse combinations of the models to increase the result. This combined approach provides an accuracy of 96%. In [16], the authors proposed transfer learning based Alzheimer's Disease classification based on CNN models. Their highest accuracy is 96%.

## 3. PROPOSED METHODOLOGY

In this study, we proposed a transfer learning method to classify between 4 classes of Alzheimer's disease, namely four stages. This method used brain MRI images from various patients using pre-trained ResNet50, DenseNet121, and VGG19. A diagram for the proposed method is depicted in Figure 1. The dataset from Kaggle contains four classes named Alzheimer's Dataset (4 classes of Images). As the dataset only consists of 3200, the first task was to generate augmented images using the dataset. We chose a batch size of 6400 to train, validate, and test our method. The next task for us was to use the SMOTE (Synthetic Minority Over-sampling Technique) algorithm for oversampling imbalanced datasets by creating synthetic samples of the minority class [17]. We split the data randomly, with 20% of the data used for the test. We used the leftover 80% for the training and validation set.

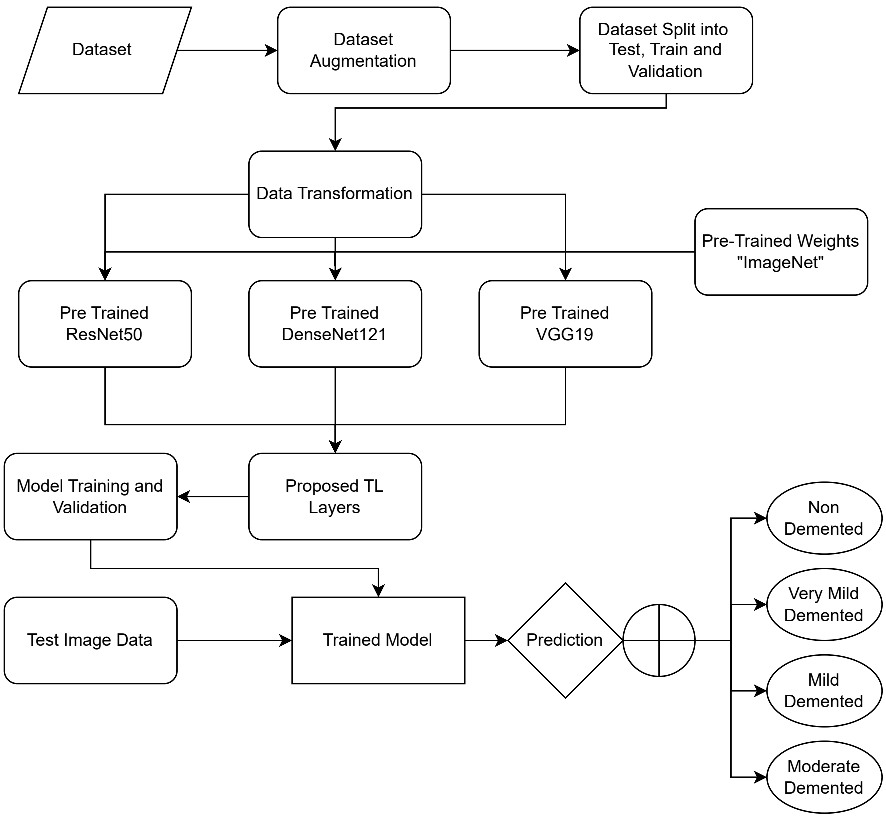



Figure 1. Proposed methodology

### 3.1. Dataset

This study is performed using a dataset obtained from Kaggle [18]. The data comprises brain images collected with the help of magnetic resonance imaging techniques at different stages of Alzheimer's disease (AD). These stages are non-demented, very mild demented, mild demented, and moderate demented.

Dementia is characterized by significant memory deprivation and other cognitive declines severe enough to interfere with a person's daily life. Most cases of dementia are due to Alzheimer's disease [19][20]. In the very mild demented and mild demented stages, people may experience moderate alterations in their cognitive skills and recall [21]. In the intermediate stage of the condition, people become more confused and forgetful of different aspects. They need more assistance with their daily activities and self-care [22]. In the severe dementia stage, cognitive functions continue to decline; as the condition advances, a more significant toll on the patient's physical capabilities [21]. Figure 2 shows some images of the dataset.

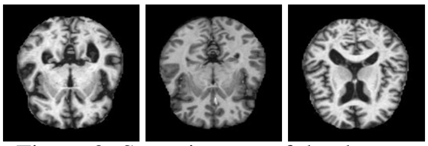


Figure 2. Some images of the dataset

MRI brain scans are available from the axial or horizontal plane in this dataset. A zoom range of 0.99 to 1.01 and a bright range of 0.8 and 1.2 is used for this study. As part of our image pre-processing, the targeted image size is $176 \times 176$. Since the dataset contains 3200 images divided into four classes, one includes only 64 images, the dataset is imbalanced. Under-sampling gives a smaller amount of data for efficient training. So, an oversampling method is used to validate the data correctly.

### 3.2. Transfer Learning Models

We used "ImageNet" as our pre-trained transfer learning model weights for our method. Then we trained the pre-trained models with our process as an add-on. The training was done with training and validation data. After training and evaluations, we compare the three transfer learning (TL) models to determine the best model for our methodology.

#### 3.2.1. ResNet50 Model

One of the well-known models for image data classification is ResNet50. This model is trained on many datasets consisting of various image categories [23]. In transfer learning techniques, this model can use pre-trained weights to solve different computer vision problems with limited datasets and computing resources.

On top of the base model, which is ResNet50 with "ImageNet" as pre-trained weights, we used layers such as dropout, batch normalization, dense, and Activation. After the data is trained on the base model, we used a dropout with a $50\%$ chance of dropout of weights. After that, all nodes were flattened to apply dense layers. Batch normalization was applied to address the internal covariate shift, which refers to the change in the overall distribution of neural network activations for nodes. A dense layer of 1024 was applied to train the trainable weights further. We used the activation function Relu for its ability to learn complex and non-linear relationships between inputs and outputs, in our case, the training data and validation data [24]. It is also a great choice to avoid issues such as vanishing gradients. At last, a dense layer with an output of 4 layers denotes the four classes of Alzheimer's disease in the dataset. The modified architecture is shown in Figure 3.

#### 3.2.2. DenseNet121 Model

DenseNet is another convolutional neural network model used for transfer learning. The data augmentation, oversampling, and splitting processes are the same as in ResNet50. The layers for our method are also identical. What differs is the base model. As for this base model, we use DenseNet, which works slightly differently from the previous model, as each layer is directly connected to every other layer in a feed-forward network [25]. The weight class is also identical to "ImageNet". The utilized architecture of the DenseNet121 is exhibited in Figure 4.

#### 3.2.3. VGG19 Model

Figure 5 shows a modified VGG19 architecture that keeps the core structure of the conventional VGG19 model [26], which includes convolutional layers, pooling layers, and fully linked layers. However, a significant change appears to be in the feature extraction process, where the architecture prioritizes structured downsampling with pooling layers (highlighted in green) after every two or four convolutional layers. The convolutional layers follow the standard VGG19 pattern of increasing filter sizes (64, 128, 256, and 512) as depth increases. The spatial resolution is gradually lowered, as denoted by width (W) and height (H) divisions at each pooling step (e.g., W/2, H/2 to W/32, H/32). In addition, the fully connected layers are reduced from three to one.

## 4. EXPERIMENTAL SETUP AND RESULT DISCUSSION

With GPU runtime, model training, evaluation, and testing are performed on Google Collaboratory. In this study, TensorFlow is used. TensorFlow is an open-source framework developed by Google researchers.

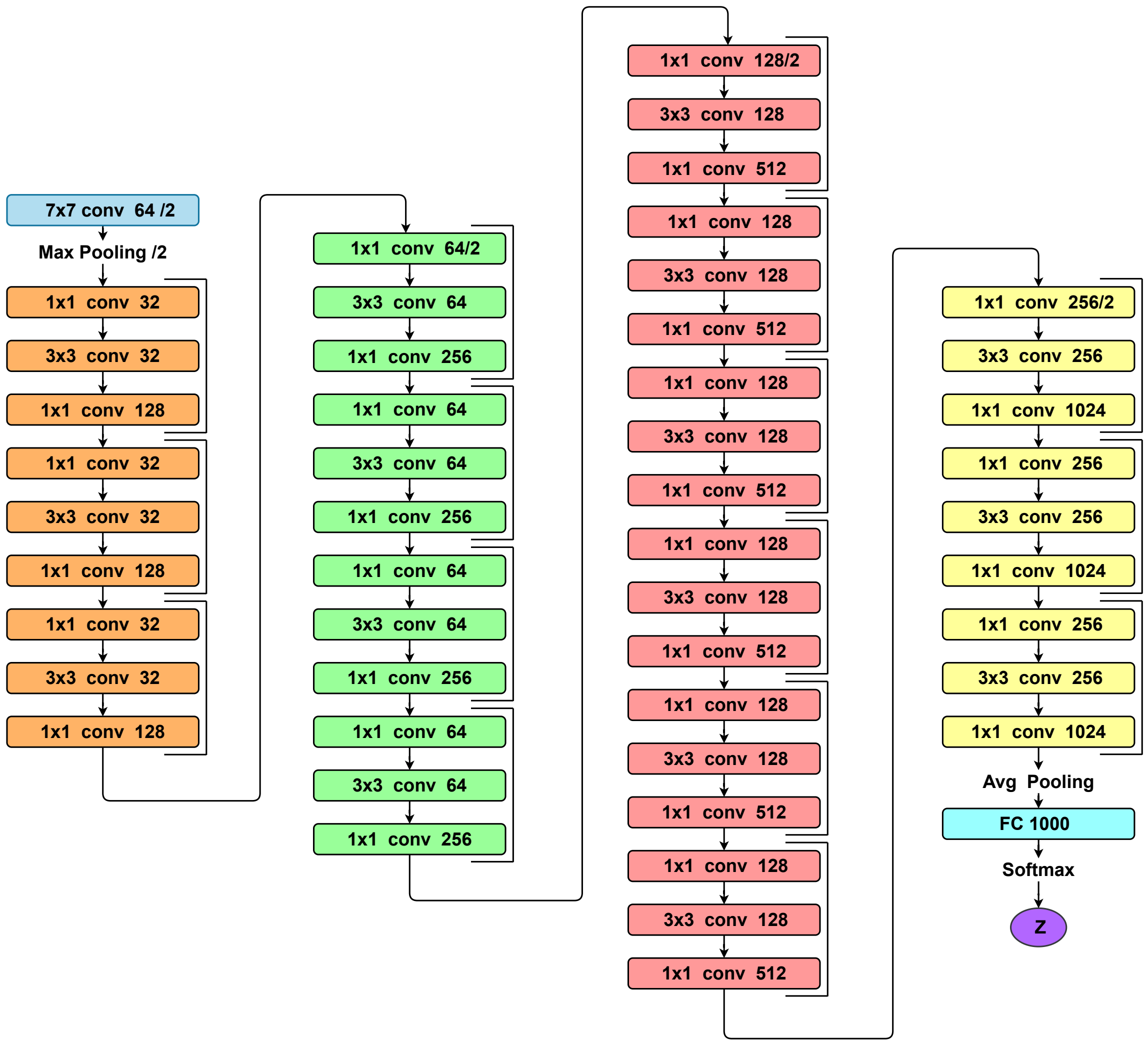



Figure 3. The modified architecture of ResNet50 model

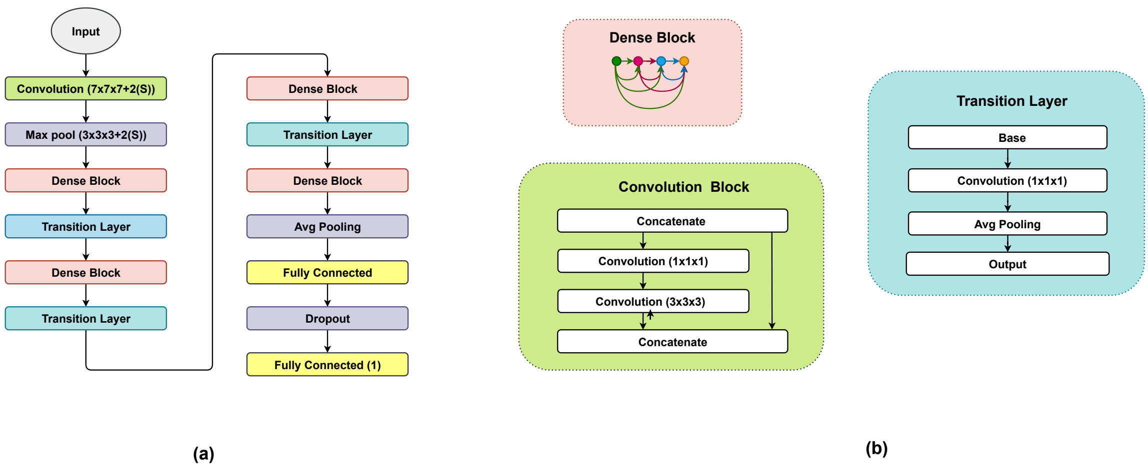



Figure 4. The modified architecture of DenseNet model

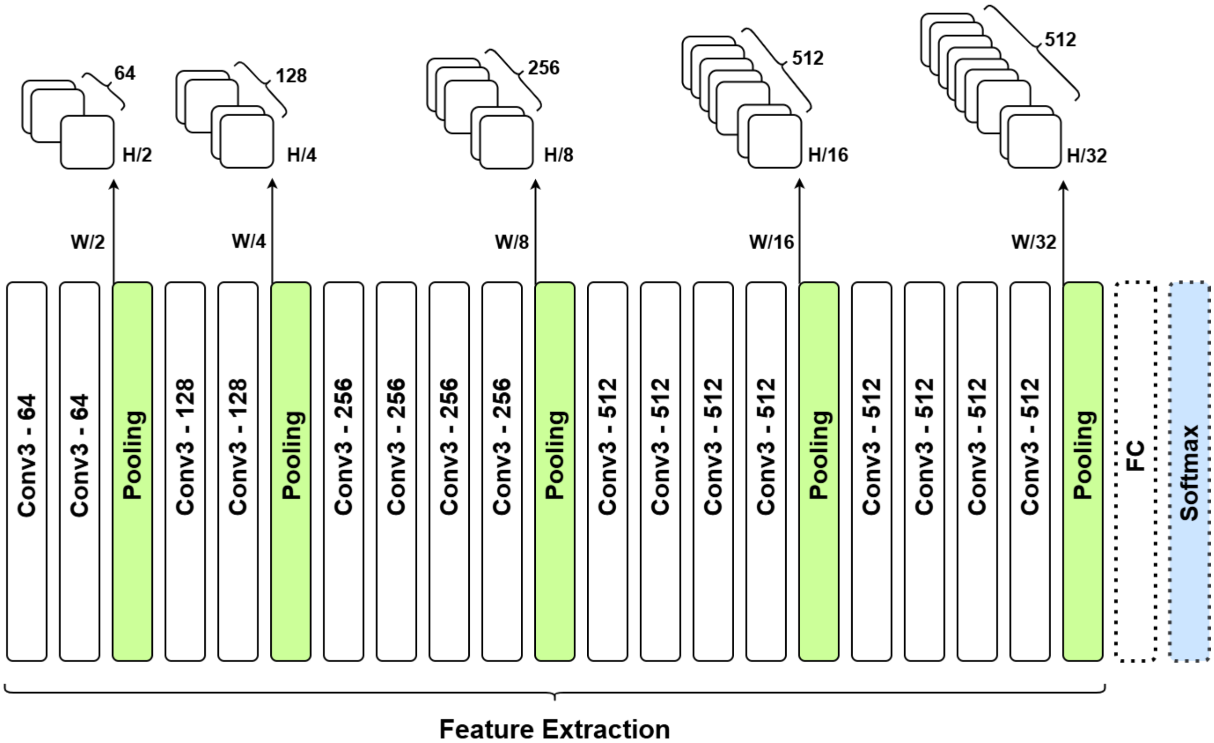



Figure 5. The modified architecture of VGG19 model

ImageDataGenerator from the Keras library of TensorFlow is used as a data loader and augmentation. We use the same configuration and the same dataset for all models.

Confusion matrix, precision, recall, F1 score, loss, and accuracy are the standard evaluation metrics used for the classification model. The Confusion Matrix provides a summary of the model's overall performance. It consists of four values, namely True Positive (TP), False Positive (FP), False Negative (FN), and True Negative (TN). Precision is a number that correctly identifies the positive cases among all predicted cases.

$$Precision = \frac{TP}{TP + FP} \tag{1}$$

Recall (R) denotes the correctly identified cases among all of the identified positive instances.

$$R = \frac{TP}{TP + FN} \tag{2}$$

AUC refers to the Area Under the ROC curve. The actual positive rate against the false positive rate is plotted as the threshold to classify positive and negative cases.

$$AUC = \sum_{i=1}^{n-1} (FPR_{i+1} - FPR_i) \times \frac{(TPR_{i+1} + TPR_i)}{2} \tag{3}$$

F1 score refers to the harmonic average of precision and recall.

$$F1 = 2 \times \frac{P \times R}{P + R} \tag{4}$$

Loss is the amount that quantifies the deviation between the predicted output and the actual output.

$$loss = -\Sigma(y\,true \times log(y\,pred)) \tag{5}$$

Accuracy defines the ratio of positive predictions to the total input samples.

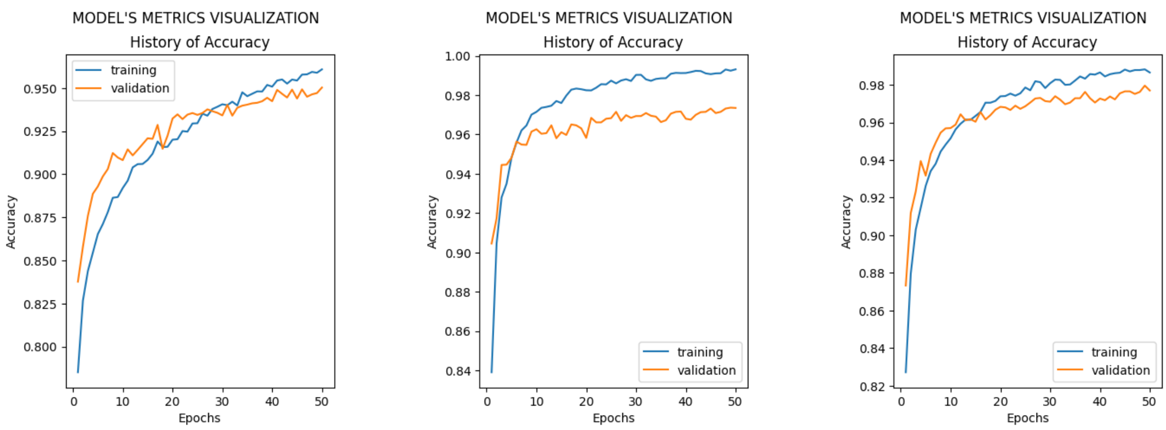
$$Accuracy = \frac{number\ of\ correctly\ classified\ instances}{total\ number\ of\ instances} \tag{6}$$

Figure 6 depicts the accuracy trends of three deep learning models during 50 training epochs. The training (blue) and validation (orange) accuracy curves provide information about each model's learning behavior and generalization capacity.

ResNet50 (6a): The model's performance is steadily improving, with validation accuracy closely tracking training accuracy, indicating high generalization. However, the final accuracy is lower than DenseNet121 and VGG19, implying that ResNet50 may require additional training epochs or hyperparameter adjustment for optimal performance.

DenseNet121 (6b): This model has the highest accuracy of the three, with rapid convergence in the first ten epochs. The validation curve remains nearly identical to the training curve, showing minimal overfitting. DenseNet's feature reuse method promotes efficient learning and accuracy.

VGG19 (6c): The model, like DenseNet121, achieves excellent accuracy but has modest oscillations in validation accuracy, which could imply mild overfitting. Despite this, VGG19 continues to perform well, displaying its capacity to extract deep features.

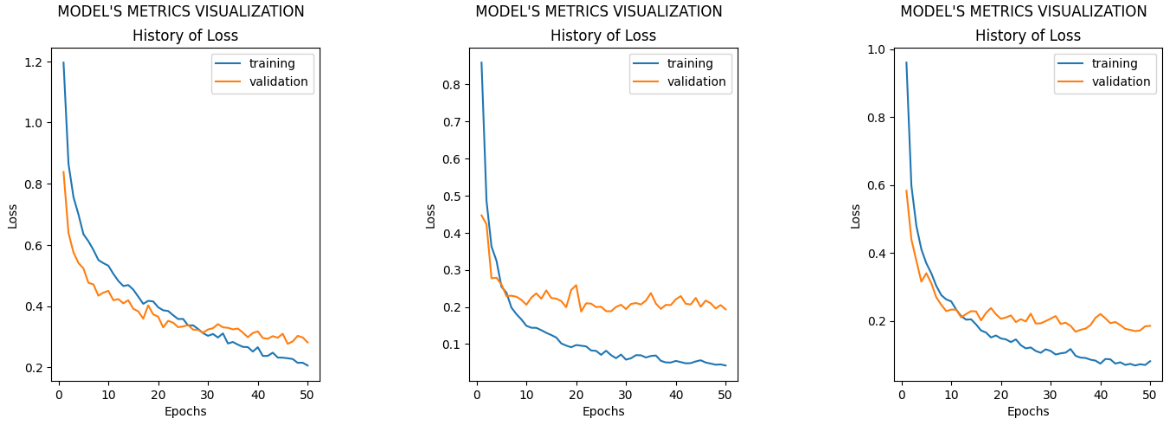



(a) (b) (c)

Figure 6. Accuracy of models (a) ResNet50, (b) DenseNet121, (c) VGG19

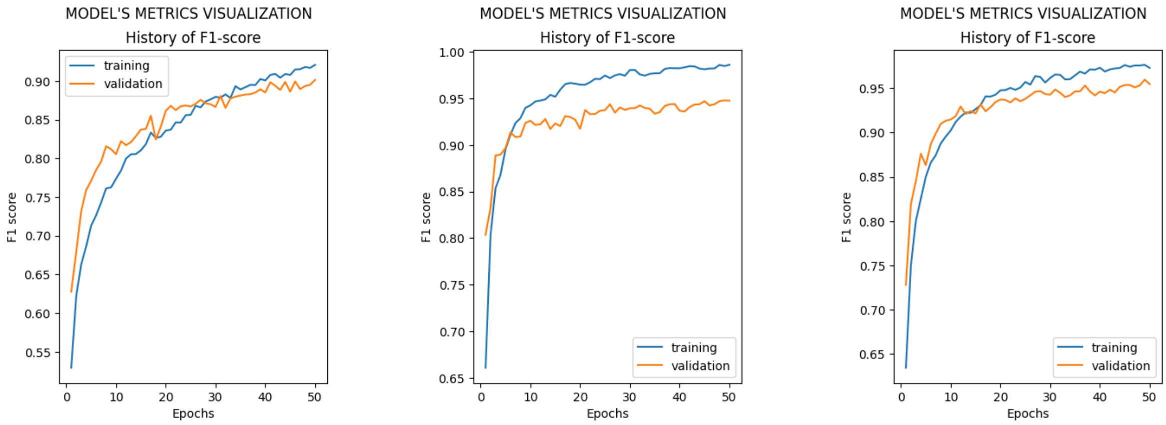
The Figure 7 depicts the loss curves for three deep learning models named ResNet50, DenseNet121, and VGG19 after 50 training epochs. The loss trends for the training and validation sets are shown. In all three examples, the training loss (blue line) is continuously decreasing, indicating effective learning. The validation loss (orange line) follows a declining trend but fluctuates, indicating varied generalization capabilities. ResNet50 and DenseNet121 exhibit smoother and smaller validation loss than VGG19, which has a bigger variance. This suggests that ResNet50 and DenseNet121 perform better than VGG19, which may be more prone to overfitting.

The Figure 8 shows the growth of F1-scores over epochs for three deep learning models as well as their training and validation performances. ResNet50 shows a consistent improvement in F1-score, with validation following training, showing good generalization. DenseNet121 has the greatest training F1-score, which approaches 1.0, but its validation score plateaus early, indicating mild overfitting due to its dense connection and greater feature reuse. VGG19, although being a traditional deep network, has a balanced training and validation curve that stabilizes above 0.95, indicating robust and smooth learning. The variances stem from architectural differences, ResNet50 uses residual learning to avoid vanishing gradients, DenseNet121 uses dense connections for rapid learning but risks overfitting, and VGG19 has a deep yet simple structure that ensures stable convergence. The overall comparison shows that ResNet50 and VGG19 provide superior generalization, whereas DenseNet121 learns aggressively. As a result, choosing a model depends on the particular trade-off between overfitting hazards and learning efficiency.



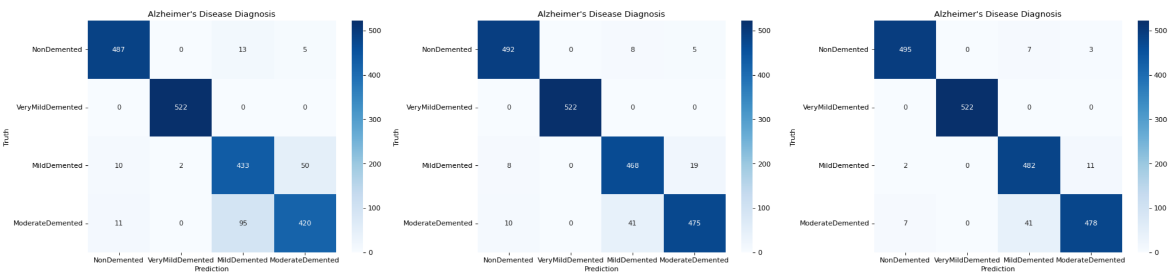

(a) (b) (c)

Figure 7. Loss of models (a) ResNet50, (b) DenseNet121, (c) VGG19




(a) (b) (c)

Figure 8. F1 score of models (a) ResNet50, (b) DenseNet121, (c) VGG19




(a) (b) (c)

Figure 9. Confusion matrix of models (a) ResNet50, (b) DenseNet121, (c) VGG19

Table 1. Various metrics calculation based on testing of all models named ResNet50, DenseNet121 and VGG19 where P=Precision, R=Recall, A=Accuracy.

| Model | Class | P(%) | R(%) | F1(%) | Sup | A(%) |
|---|---|---|---|---|---|---|
| ResNe50 | Non-Demented | 0.96 | 0.96 | 0.96 | 505 | 0.939 |
| | Very-Mild Demented | 1.00 | 1.00 | 1.00 | 522 | |
| | Mild-Demented | 0.80 | 0.87 | 0.84 | 495 | |
| | Moderate-Demented | 0.88 | 0.80 | 0.84 | 526 | |
| DenseNet121 | Non-Demented | 0.96 | 0.97 | 0.97 | 505 | 0.970 |
| | Very-Mild-Demented | 1.00 | 1.00 | 1.00 | 522 | |
| | Mild-Demented | 0.91 | 0.95 | 0.92 | 495 | |
| | Moderate-Demented | 0.95 | 0.90 | 0.93 | 526 | |
| VGG19 | Non-Demented | 0.98 | 0.98 | 0.98 | 505 | 0.977 |
| | Very-Mild-Demented | 1.00 | 1.00 | 1.00 | 522 | |
| | Mild-Demented | 0.91 | 0.97 | 0.94 | 495 | |
| | Moderate-Demented | 0.97 | 0.91 | 0.94 | 526 | |

The confusion matrix of all models is shown in Figure 9.

The repeated training of models is taken for multiple epochs. All models were trained for 50 epochs. We use training and validation sets for training the models. In each epoch, the loss is calculated with categorical cross-entropy. This loss is then propagated back. We used Adam as an optimization algorithm with a learning rate of 0.001. Table 1 shows the performance metrics calculation. All the models can accurately detect the four stages of Alzheimer's disease. Among them, the lowest accuracy, with 93% accuracy, is of ResNet50. The model that performed the most accurately is VGG19, with almost 98% leading only to a little difference from DenseNet121, which accurately predicts 97% of the test dataset. Table 2 shows the comparison among the ResNet50, DenseNet121, and VGG19 models. VGG19 achieves the highest average accuracy among them. Minimum accuracy is obtained in the first epoch number.

Table 2. Comparison result as per epochs among the models where E=epoch, Max. Acc.= maximum accuracy, Min. Acc.=minimum accuracy and Avg. Acc. average accuracy overall.

| Model | Set | Max. Acc. | Max. Acc. at E | Min. Acc. | Min. Acc. at E | Avg. Acc. |
|---|---|---|---|---|---|---|
| ResNet50 | Train | 0.960 | 50 | 0.785 | 1 | 0.939 |
| | Validation | 0.950 | 50 | 0.837 | 1 | |
| DenseNet121 | Train | 0.993 | 50 | 0.839 | 1 | 0.970 |
| | Validation | 0.974 | 49 | 0.904 | 1 | |
| VGG19 | Train | 0.988 | 49 | 0.827 | 1 | 0. 977 |
| | Validation | 0.969 | 33 | 0.873 | 1 | |

### 4.1. Comparison with existing works

Several studies on the classification of Alzheimer's disease using transfer learning models are compiled in Table 3. For every study, it provides a list of the models employed, the best accuracy attained, and important notes. Using extra fully connected layers to refine ResNet50, DenseNet121, and VGG19, our suggested method shows competitive performance with accuracies of 93.9%, 97.0%, and 97.7%, respectively. This demonstrates how well our adjustments and data augmentation strategies work to improve classification performance when compared to earlier approaches.

## 5. CONCLUSION

In this paper, we classified Alzheimer's disease into four classes, Non-Demented, Mild Demented, Very Mild Demented, and Moderate Demented, using three fine-tuned pre-trained models including ResNet50, DenseNet121, and VGG19. To validate the models, we modified the pre-trained models with our layers to further develop the architecture to detect Alzheimer's stages better on the Alzheimer's dataset collected on the Kaggle platform. The goal of this work is to broaden our knowledge and method to further test with more sophisticated models and optimize the proposed plan to build an optimized architecture for the detection of Alzheimer's disease. As performance metrics, we evaluated accuracy, precision, recall, and the the F1 score. VGG19 outperforms the accuracy by 97.70%. This will be beneficial for medical professionals.

Table 3. Comparison of Transfer Learning Models for Alzheimer's Disease Classification

| Study | Models Used | Highest Accuracy (%) | Remarks |
|---|---|---|---|
| [7] | AlexNet, VGG16, ResNet50 | 95.70 | Transfer learning-based |
| [8] | Transfer learning techniques | 96.00 | Transfer-based model |
| [9] | Transfer learning on genome data | 89.00 | Applied on genome dataset |
| [10] | VGG19, ResNet50, InceptionV3, DenseNet169 | 82.50 | Multiple CNN models used |
| [11] | VGG16, InceptionV3, Xception | 75.00 | Multi-model approach |
| [12] | DenseNet201, ResNet50, VGG16, Hybrid Model | 90.00 | Hybrid model performed best |
| [13] | Modified ResNet50 | 97.49 | Modified architecture |
| [14] | CNN-based ResNet18 | 88.30 | Used only one model |
| [15] | VGG19, ResNetv2, ResNet152v2 | 96.00 | Combined to improve results |
| [16] | CNN-based Transfer Learning | 96.00 | Transfer learning approach |
| **Our Proposed Model** | **Tuned ResNet50, DenseNet121, VGG19** | **97.70** | **Modified models with extra fully connected layers** |

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