

Alzheimer's Disease Detection and Severity Analysis using Deep Learning Methods

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Abstract—Alzheimer's Disease (AD) is a brain disorder that leads to memory loss and cognitive decline. Early detection is important to manage the disease effectively. In this study, deep learning techniques using Convolutional Neural Networks (CNNs) are applied to classify different stages of AD using brain MRI images. Two approaches are used: transfer learning with pre-trained models like DenseNet201, VGG19, and AlexNet, and custom CNN models with 8, 10, and 12 layers. The MRI images are taken from the OASIS dataset and undergo preprocessing, including resizing, normalization, and data augmentation. Models are evaluated using accuracy, precision, recall, F1-score, and confusion matrix. Results show that both transfer learning and custom CNNs perform well, with the 12-layer custom model achieving the best accuracy. This work shows the potential of CNNs for assisting in medical diagnosis of Alzheimer's Disease.

I. INTRODUCTION

Alzheimer's Disease is a progressive neurological disorder that causes memory loss, confusion, and behavioral changes, affecting millions of people worldwide. Early diagnosis is crucial to slow down its progression and improve patient care. However, traditional diagnosis methods relying on clinical tests and manual analysis of brain MRI scans are often time-consuming and prone to human error. Recent advances in artificial intelligence, especially deep learning, offer powerful tools to assist in medical diagnosis. Convolutional Neural Networks (CNNs), known for their ability to learn patterns from images, are widely used in medical imaging tasks. In this study, we apply CNN-based techniques to classify brain MRI images into four stages of Alzheimer's: Non-Demented, Very Mild Demented, Mild Demented, and Moderate Demented. We use both pre-trained models like DenseNet201, VGG19, and AlexNet, and custom CNN models with 8, 10, and 12

layers. The OASIS dataset is used for training and evaluation, and preprocessing techniques like resizing, normalization, and data augmentation are applied. By comparing the performance of different models using accuracy, precision, recall, F1-score, and confusion matrix, this work aims to build an efficient and reliable system that can support doctors in the early detection and severity assessment of Alzheimer's Disease.

II. LITERATURE SURVEY

Alzheimer's Disease Classification Using Pre-trained Deep Networks by Shanmugam et al. (2022)

This study used GoogLeNet, ResNet-18, and AlexNet on 6000 MRI images to classify five stages of Alzheimer's disease. Among the models, ResNet-18 performed the best with 98.63% accuracy. Its residual connections helped in better gradient flow and learning efficiency, especially for early-stage detection.

Alzheimer Disease Classification Using Transfer Learning by Acharya et al. (2021)

This paper evaluated VGG16, ResNet-50, and a modified AlexNet on a 4-class MRI dataset. The modified AlexNet achieved 95.7% accuracy and showed faster training and better generalization. Data augmentation and dropout helped reduce overfitting.

Classifying Alzheimer's Disease Stages Using CNNs on the OASIS MRI Dataset by Kumar and Nelson (2024)

This study developed 8-layer, 10-layer, and 12-layer custom CNNs and trained them on the OASIS dataset. The 12-layer CNN achieved the highest accuracy of 97.80%, showing that deep custom models can perform better than some pre-trained ones when designed for specific medical tasks.

Detection and Classification of Brain Alzheimer's Using CNN Model by Patki et al. (2022)

Using 5131 MRI images from the OASIS dataset, this work applied data augmentation and SMOTE for balancing classes. A CNN with Conv2D and dense layers achieved 93.7% accuracy. It emphasized the importance of preprocessing and balancing data.

Alzheimer Disease Early Detection Using CNNs by Farooq et al. (2017)

This research trained ResNet-152, ResNet-18, and GoogLeNet on ADNI data. GoogLeNet gave the best results (98.88%) due to its multi-scale feature extraction. The study showed that deeper architectures with skip connections are effective for MRI-based classification.

A Systematic Review on Deep Learning Techniques for Alzheimer's Diagnosis by Alsubaie et al. (2024)

This review summarized CNN, RNN, GAN, and hybrid models for Alzheimer's detection. It highlighted the success of multimodal approaches combining sMRI, PET, and fMRI for better accuracy. It also discussed the benefits of explainable AI and attention mechanisms.

III. DATASETS USED

Open Access Series of Imaging Studies (OASIS)

The OASIS (Open Access Series of Imaging Studies) dataset is a widely used collection of brain MRI scans designed to support research on aging and dementia. In this study, a subset of the OASIS dataset is used, containing T1-weighted MRI images categorized into four stages of Alzheimer's Disease: Non-Demented, Very Mild Demented, Mild Demented, and Moderate Demented. Each 3D MRI volume is sliced along the z-axis, and slices from index 100 to 160 are selected, as these contain the most relevant brain regions. The selected slices are resized to 224×224 or 227×227 pixels and converted to RGB format to match the input requirements of CNN models. The dataset is split into 70% for training, 15% for validation, and 15% for testing using stratified sampling to ensure balanced class distribution. This dataset is ideal for deep learning-based classification due to its high-quality scans and detailed labeling of dementia severity.

IV. METHODOLOGY

A. BLOCK DIAGRAM

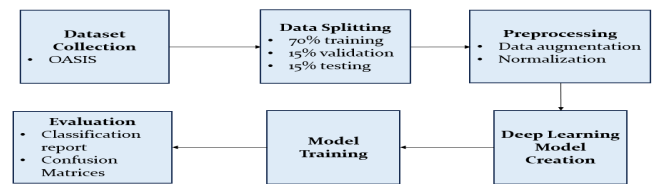


Fig. 1 Block Diagram

B. DATA PREPROCESSING

The MRI images used in this study are originally in grayscale format, as is typical in medical imaging. However, most pre-trained deep learning models such as VGG19, DenseNet201, and AlexNet are built to accept three-channel RGB images. To ensure compatibility with these models, each grayscale image is converted into a pseudo-RGB image by duplicating the single grayscale channel across three channels. All images are uniformly resized to either 224×224 or 227×227 pixels, depending on the architecture, which standardizes the input dimensions and helps reduce the computational load while maintaining important structural features of the brain scans.

Before feeding the images into the model, pixel values are normalized to a scale of 0 to 1. Normalization is essential because it allows the model to converge faster by ensuring consistent value ranges across the input data, which results in more stable and efficient gradient updates during training. This step is especially important when combining augmented data with the original dataset, as it helps maintain uniformity across all variations.

To improve the generalization capability of the model and reduce overfitting, real-time data augmentation is applied during the training process. This includes random image rotations within ± 20 degrees, zooming in and out up to 20%, horizontal flipping, shearing transformations within a 0.2 range, and brightness adjustments ranging between 0.8 and 1.2. These transformations create variations in the training images without altering their class labels, helping the model to learn robust features that are invariant to orientation, scale, and lighting changes. Any missing pixel areas generated during augmentation are filled using the nearest pixel value to preserve structural continuity.

The dataset is divided into training, validation, and testing subsets in the ratio of 70:15:15. To ensure that the distribution of the four Alzheimer's stages—Non-Demented, Very Mild Demented, Mild Demented, and Moderate Demented—is consistent across all sets, stratified sampling is employed. This prevents the model from being biased towards any one class during training and evaluation.

To address the issue of class imbalance, which is common in medical datasets, the number of samples in each category is analyzed before training. If necessary, techniques such as oversampling of minority classes or applying class weights during loss computation are considered. These strategies help

in balancing the learning process so that the model does not favor the majority class and is capable of accurately predicting all stages of dementia.

C. MODELS

1) CUSTOM 8 LAYERS CNN MODEL: The custom 8-layer CNN model is designed as a lightweight yet effective network for classifying Alzheimer's stages using MRI scans. It consists of three convolutional layers with filter sizes of 64, 128, and 256, each followed by a MaxPooling layer to reduce spatial dimensions and extract important features. After the convolutional layers, the output is flattened and passed through two dense layers of 512 and 256 neurons with ReLU activation. To prevent overfitting, dropout layers are applied after each dense layer. The final output is generated using a Softmax layer with four neurons corresponding to the four Alzheimer's categories. The model is trained using the Adam optimizer with a learning rate of 0.0001 and uses categorical cross-entropy as the loss function, along with early stopping based on validation loss.

2) CUSTOM 10 LAYERS CNN MODEL: The custom 10-layer CNN model is a deeper architecture intended to learn more complex spatial patterns from MRI images. It includes five Conv2D layers arranged in three blocks: two layers with 32 filters, two with 64 filters, and one with 128 filters. Each block is followed by a MaxPooling layer to downsample the feature maps. The extracted features are flattened and passed to a dense layer with 512 neurons, followed by a dropout layer to enhance generalization. The final layer is a Softmax classifier with four outputs. The model is trained using the Adam optimizer, categorical cross-entropy loss, and early stopping to prevent overfitting.

3) CUSTOM 12 LAYERS CNN MODEL: The custom 12-layer CNN model is the deepest among the custom architectures, designed for handling high-dimensional MRI image features. It contains six convolutional layers with increasing filter sizes of 32, 64, 128, 128, 256, and 256. Each Conv2D layer is followed by a MaxPooling layer to reduce spatial complexity while retaining important features. The output from the final pooling layer is flattened and passed through two dense layers with 512 and 256 neurons respectively, both using ReLU activation. Dropout layers are placed after each dense layer to reduce the risk of overfitting. The model concludes with a Softmax output layer for four-class classification and is trained using the Adam optimizer with categorical cross-entropy loss and early stopping.

4) DENSENET201 MODEL: The DenseNet201 model is a transfer learning approach that leverages a pre-trained network originally trained on the ImageNet dataset. DenseNet201 is known for its densely connected layers that allow better feature reuse and improved gradient flow. The top layers of the model are removed and replaced with a GlobalAveragePooling2D layer followed by fully connected dense layers, ending in a four-class Softmax output. Selected

deeper layers of the base model are fine-tuned to improve performance on medical imaging tasks. The model is trained using the Adam optimizer and monitored using early stopping to avoid overfitting.

5) ALEXNET MODEL: The AlexNet model used in this study is a custom version inspired by the original architecture. It comprises five convolutional layers with ReLU activation functions and MaxPooling layers to downsample feature maps and reduce computation. These layers are followed by fully connected dense layers, ending in a Softmax classifier for four-class output. The model is lightweight, making it suitable for faster training with limited hardware. It is trained using the Adam optimizer and categorical cross-entropy loss function.

6) VGG19 MODEL: The VGG19 model is another transfer learning architecture employed in this project. Initially trained on the ImageNet dataset, the convolutional base of VGG19 is frozen to act as a fixed feature extractor. A new classification head is added, consisting of dense layers and dropout for regularization. After initial training, selected layers of the base model are unfrozen and fine-tuned to adapt the network to Alzheimer's classification. The final output layer is a four-class Softmax classifier. The model uses the Adam optimizer, early stopping, and validation loss monitoring to ensure optimal performance.

D. TRAINING PROCESS

The training process for all models was carried out using the Adam optimizer, chosen for its adaptive learning rate and efficient convergence during deep learning. The learning rate was typically set to 0.0001, and the loss function used was categorical cross-entropy, suitable for multi-class classification problems. The models were trained in mini-batches of 32 images over a maximum of 50 epochs. To avoid overfitting and ensure optimal performance, several training callbacks were employed. These included EarlyStopping, which monitors validation loss and stops training if no improvement is observed over a few epochs; ReduceLROnPlateau, which automatically reduces the learning rate when the validation loss plateaus; and ModelCheckpoint, which saves the best-performing model during training. Stratified data splitting was used to ensure balanced class distribution across the training, validation, and testing sets. Real-time data augmentation was also applied during training to expose the model to varied data samples, further improving its generalization ability. Overall, the training strategy focused on stability, performance, and preventing overfitting through dynamic learning adjustments and validation monitoring.

E. PERFORMANCE EVALUATION

The evaluation process of an image classification model involves assessing how well the model performs on a given task of classifying images into predefined categories. It is essential to determine how accurate and

reliable the model is on both the training data (used for learning) and unseen test data (used for evaluation). Here's an overview of the key steps and metrics in the evaluation process:

1) **Precision:** Precision quantifies the accuracy of the model in predicting a specific emotion class. It is the ratio of true positive predictions to the total predicted positives for that class. High precision indicates a low rate of false positives.

$$\text{Precision} = \frac{\text{True Positives}(TP)}{\text{True Positives}(TP) + \text{False Positives}(FP)}$$

2) **Recall:** Recall measures the model's ability to correctly identify all instances of a particular class. It is the ratio of true positive predictions to the total actual positives for that class. High recall indicates a low rate of false negatives.

$$\text{Recall} = \frac{\text{True Positives}(TP)}{\text{True Positives}(TP) + \text{False Negatives}(FN)}$$

3) **F1-Score:** The F1-score is the harmonic mean of precision and recall, providing a balanced metric when there is an uneven class distribution. It combines both precision and recall into a single measure, where a value close to 1 indicates excellent performance.

$$\text{F1 Score} = 2 * \frac{\text{Precision} * \text{Recall}}{\text{Precision} + \text{Recall}}$$

4) **Support:** Support refers to the number of actual instances of each class in the dataset. It provides insight into the class distribution, which is crucial when interpreting the model's performance.

5) **Classification Report:** The classification report provides a detailed summary of model performance through key evaluation metrics: precision, recall, F1-score, and support for each Alzheimer's class. These metrics help assess how effectively the model differentiates among the four classes: Non-Demented, Very Mild Demented, Mild Demented, and Moderate Demented. The report is generally presented in tabular format, with each row representing a specific class and columns displaying metric values. Precision indicates how many of the predicted positives are actually correct, while recall measures how well the model captures all actual instances of a class. F1-score, the harmonic mean of precision and recall, provides a balanced view of both metrics. Support reflects the actual number of samples in each class and ensures fairness in model evaluation, especially when dealing with imbalanced class distributions. In the context of Alzheimer's stage classification, the report helps identify whether the model is performing equally across all stages or is biased toward more represented classes like non-Demented. It also highlights any difficulty the model has in identifying closely related stages such as Very Mild and

Mild Demented, which may present subtle structural differences in brain scans.

6) **Confusion Matrix:** A confusion matrix is a powerful evaluation tool used to analyze model predictions in multi-class classification problems like Alzheimer's stage detection. It provides a detailed count of both correct and incorrect predictions for each class, offering deeper insight into where the model succeeds and where it struggles. This matrix enables class-by-class performance analysis and is especially useful when class distributions are uneven. It not only reflects overall accuracy but also the types of errors made—such as confusing Mild Demented with Very Mild Demented due to their clinical similarity.

The confusion matrix provides the following components for evaluation:

- True Positives (TP): Number of samples correctly predicted as belonging to a specific class.
- False Positives (FP): Number of samples incorrectly predicted as belonging to a class they don't belong to.
- True Negatives (TN): Number of samples correctly predicted as not belonging to a specific class.
- False Negatives (FN): Number of samples incorrectly predicted as not belonging to their actual class.

This matrix helps reveal patterns of misclassification and supports model optimization by identifying which stages require better feature extraction or finer model tuning.

V. RESULTS AND DISCUSSION

The input requirements of the selected CNN models were carefully considered, and preprocessing steps were adapted accordingly to ensure optimal performance. MRI images from the OASIS dataset were originally in grayscale and were converted into RGB format to ensure compatibility with transfer learning models. All images were resized to either 224×224 or 227×227 pixels based on model input constraints. Data augmentation techniques such as rotation, horizontal flipping, zooming, shearing, and brightness adjustments were applied to artificially increase dataset size and improve model generalization while minimizing overfitting. This study evaluates the performance of both custom-built CNNs and transfer learning models using consistent preprocessing and data handling. The following sections provide a detailed analysis of the results obtained for each model, highlighting their classification performance and comparative strengths.

A. CUSTOM 8 LAYERS CNN MODEL

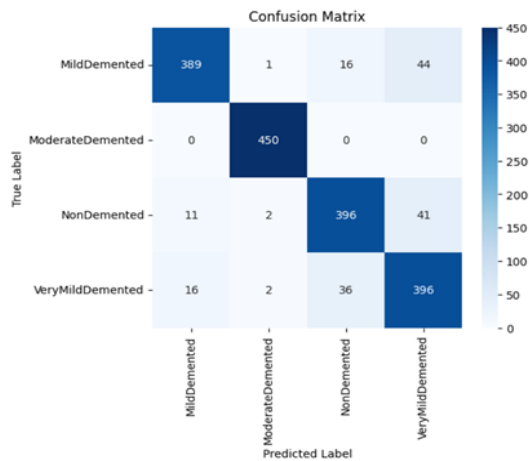


Fig. 2 Confusion matrix for custom 8 layer CNN model

	precision	recall	f1-score	support
MildDemented	0.94	0.86	0.90	450
ModerateDemented	0.99	1.00	0.99	450
NonDemented	0.88	0.88	0.88	450
VeryMildDemented	0.82	0.88	0.85	450
accuracy			0.91	1800
macro avg	0.91	0.91	0.91	1800
weighted avg	0.91	0.91	0.91	1800

Fig. 3 Classification report for custom 8 layer CNN model



Fig. 4 Accuracy plot for custom 8 layer CNN model

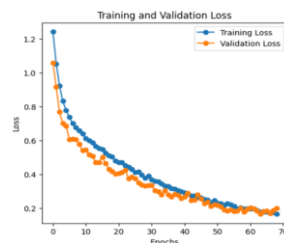


Fig. 5 Loss plot for custom 8 layer CNN model

The model achieved an overall accuracy of 91%, with macro and weighted averages for precision, recall, and F1-score also at 0.91, showing solid general performance across all classes. The model performed well in detecting Moderate Demented cases with 0.99 precision and 1.00 recall, indicating reliable identification of more severe stages. While recall remained high, the model showed slightly lower precision (0.82) and F1-score (0.85) for the Very Mild Demented class, suggesting some confusion in early-stage detection.

B. CUSTOM 10 LAYERS CNN MODEL

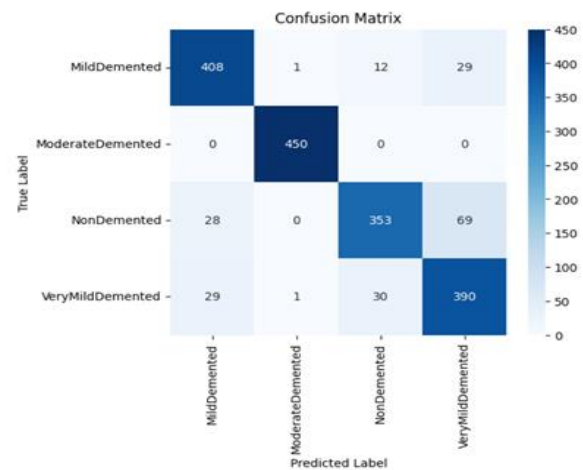


Fig. 6 Confusion matrix for custom 10 layer CNN model

	precision	recall	f1-score	support
MildDemented	0.88	0.91	0.89	450
ModerateDemented	1.00	1.00	1.00	450
NonDemented	0.89	0.78	0.84	450
VeryMildDemented	0.80	0.87	0.83	450
accuracy			0.89	1800
macro avg	0.89	0.89	0.89	1800
weighted avg	0.89	0.89	0.89	1800

Fig. 7 Classification report for custom 10 layer CNN model

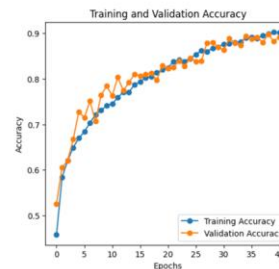


Fig. 8 Accuracy plot for custom 10 layer CNN model

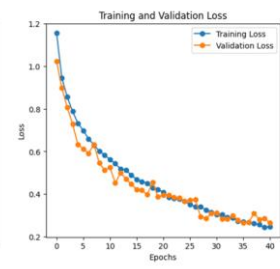


Fig. 9 Loss plot for custom 10 layer CNN model

The model achieved an overall accuracy of 89%, with consistent macro and weighted averages for precision, recall, and F1-score (all 0.89), indicating balanced performance across all classes. The model performed perfectly on the "Moderate Demented" class with 100% precision, recall, and F1-score, suggesting that this class is well-learned and easily distinguishable. The Non Demented class had a lower recall (0.78), and Very Mild Demented had lower precision (0.80). This might imply some confusion between these and other classes, possibly due to subtle feature differences.

C. CUSTOM 12 LAYERS CNN MODEL

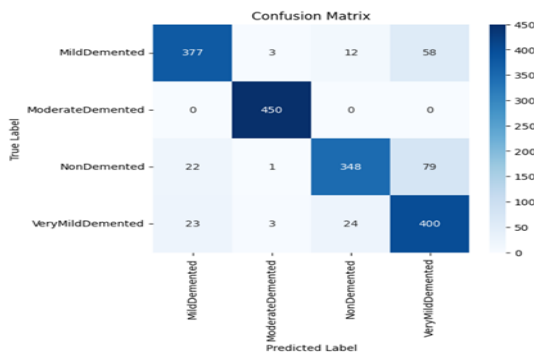


Fig. 10 Confusion matrix for custom 12 layer CNN model

	precision	recall	f1-score	support
MildDemented	0.89	0.84	0.86	450
ModerateDemented	0.98	1.00	0.99	450
NonDemented	0.91	0.77	0.83	450
VeryMildDemented	0.74	0.89	0.81	450
accuracy			0.88	1800
macro avg	0.88	0.88	0.88	1800
weighted avg	0.88	0.88	0.88	1800

Fig. 11 Classification report for custom 12 layer CNN model

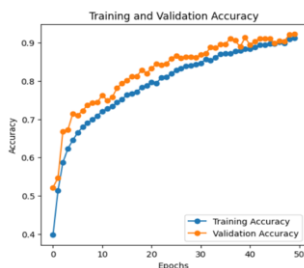


Fig. 12 Accuracy plot for custom 12 layer CNN model

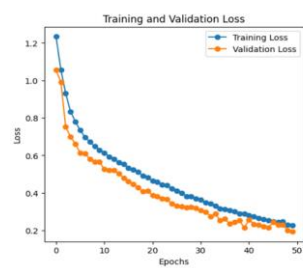


Fig. 13 Loss plot for custom 12 layer CNN model

The model achieved 88% accuracy, with macro and weighted averages of 0.88 for precision, recall, and F1-score—indicating consistently good classification across all categories. The model maintained high performance for the "Moderate Demented" class, with precision of 0.98, recall of 1.00, and F1-score of 0.99, showing near-perfect classification. Very Mild Demented had a relatively low precision (0.74) but high recall (0.89), meaning it captures most cases but also misclassifies others as this class. Non Demented had strong precision (0.91) but lower recall (0.77), indicating it misses some actual Non Demented cases.

D. DENSENET-201 MODEL

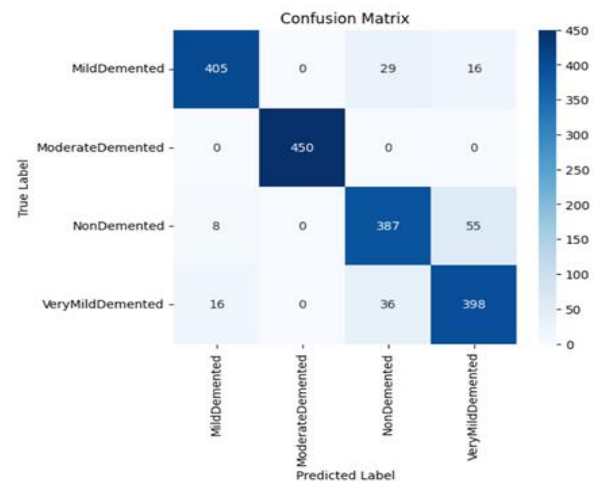


Fig. 14 Confusion matrix for Densenet-201 model

	precision	recall	f1-score	support
MildDemented	0.94	0.90	0.92	450
ModerateDemented	1.00	1.00	1.00	450
NonDemented	0.86	0.86	0.86	450
VeryMildDemented	0.85	0.88	0.87	450
accuracy			0.91	1800
macro avg	0.91	0.91	0.91	1800
weighted avg	0.91	0.91	0.91	1800

Fig. 15 Classification report for Densenet-201 model

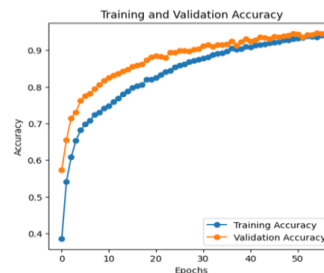


Fig. 16 Accuracy plot for Densenet-201 model

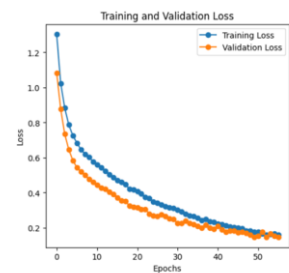


Fig. 17 Loss plot for Densenet-201 model

The model achieved perfect precision, recall, and F1-score (1.00) for the Moderate Demented class, indicating flawless identification of this stage. With an accuracy of 91% and balanced macro and weighted averages (all 0.91), DenseNet-201 shows strong and consistent performance across all classes. The model performs slightly lower for Very Mild Demented and Non Demented cases (F1-scores: 0.87 and 0.86), highlighting the challenge in distinguishing early-stage and normal conditions.

E. Alexnet Model

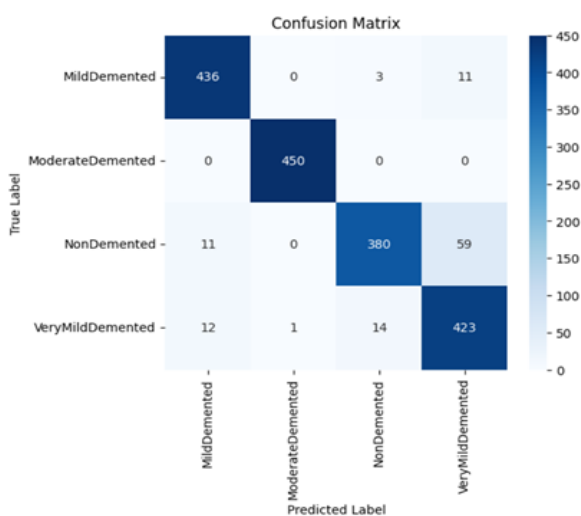


Fig. 18 Confusion matrix for Alexnet model

	precision	recall	f1-score	support
MildDemented	0.95	0.97	0.96	450
ModerateDemented	1.00	1.00	1.00	450
NonDemented	0.96	0.84	0.90	450
VeryMildDemented	0.86	0.94	0.90	450
accuracy			0.94	1800
macro avg	0.94	0.94	0.94	1800
weighted avg	0.94	0.94	0.94	1800

Fig. 19 Classification report for Alexnet model

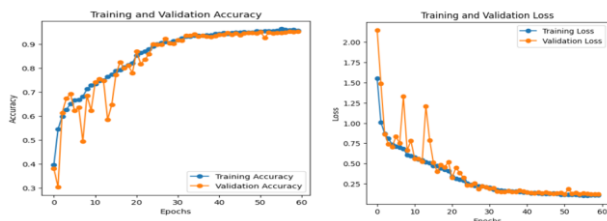


Fig. 20 Accuracy plot for Alexnet model

Fig. 21 Loss plot for Alexnet model

F. Vgg19 Model

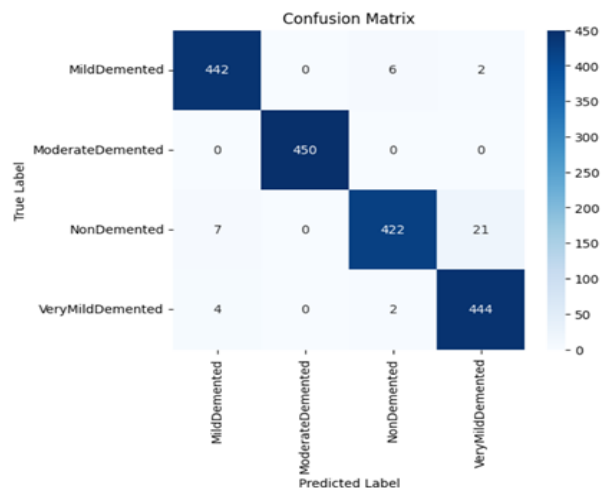


Fig. 22 Confusion matrix for VGG19 model

	precision	recall	f1-score	support
MildDemented	0.98	0.98	0.98	450
ModerateDemented	1.00	1.00	1.00	450
NonDemented	0.98	0.94	0.96	450
VeryMildDemented	0.95	0.99	0.97	450
accuracy			0.98	1800
macro avg	0.98	0.98	0.98	1800
weighted avg	0.98	0.98	0.98	1800

Fig. 23 Classification report for VGG19 model

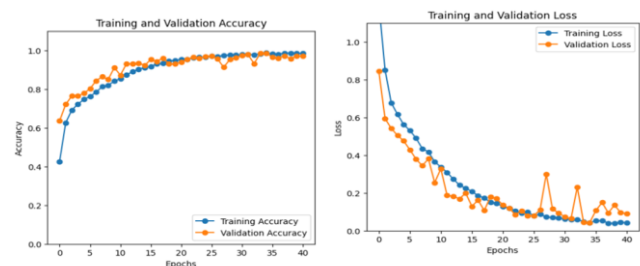


Fig. 24 Accuracy plot for VGG19 model

Fig. 25 Loss plot for VGG19 model

VGG19 achieved an impressive overall accuracy of 98%, with macro and weighted averages for precision, recall, and F1-score also at 0.98, indicating exceptional and consistent performance. The model showed perfect classification (1.00 precision, recall, and F1-score) for the Moderate Demented class, demonstrating its effectiveness in identifying more severe stages. With F1-scores ranging from 0.96 to 1.00, VGG19 accurately classified all four stages, including early ones like Very Mild Demented (F1-score: 0.97), highlighting its reliability in comprehensive Alzheimer's stage detection.

VI. FUTURE SCOPE

The current study can be further enhanced by developing lightweight and efficient CNN models that can be deployed on edge devices, enabling real-time Alzheimer's detection in portable medical systems. Future work can also focus on integrating multimodal data such as PET scans, EEG signals, or clinical reports along with MRI images to improve diagnostic accuracy and provide a more holistic understanding of the disease. Implementing explainable AI (XAI) techniques like Grad-CAM or LIME can help visualize model predictions, making the system more transparent and reliable for clinical use. Additionally, creating a web-based or mobile application to deploy the trained model can facilitate remote screening, particularly in rural or resource-limited areas. The use of 3D CNNs or spatio-temporal models can be explored to capture the full volumetric information of MRI scans rather than relying on selected slices. Synthetic data generation using GANs may also be incorporated to address class imbalance and enhance the robustness of the model. Moreover, using transfer learning models pre-trained on medical imaging datasets or applying self-supervised learning on large-scale unlabeled MRI data may improve feature extraction and performance. Finally, incorporating longitudinal data of patients can help in predicting the progression of Alzheimer's over time, supporting proactive treatment planning.

VII. REFERENCES

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