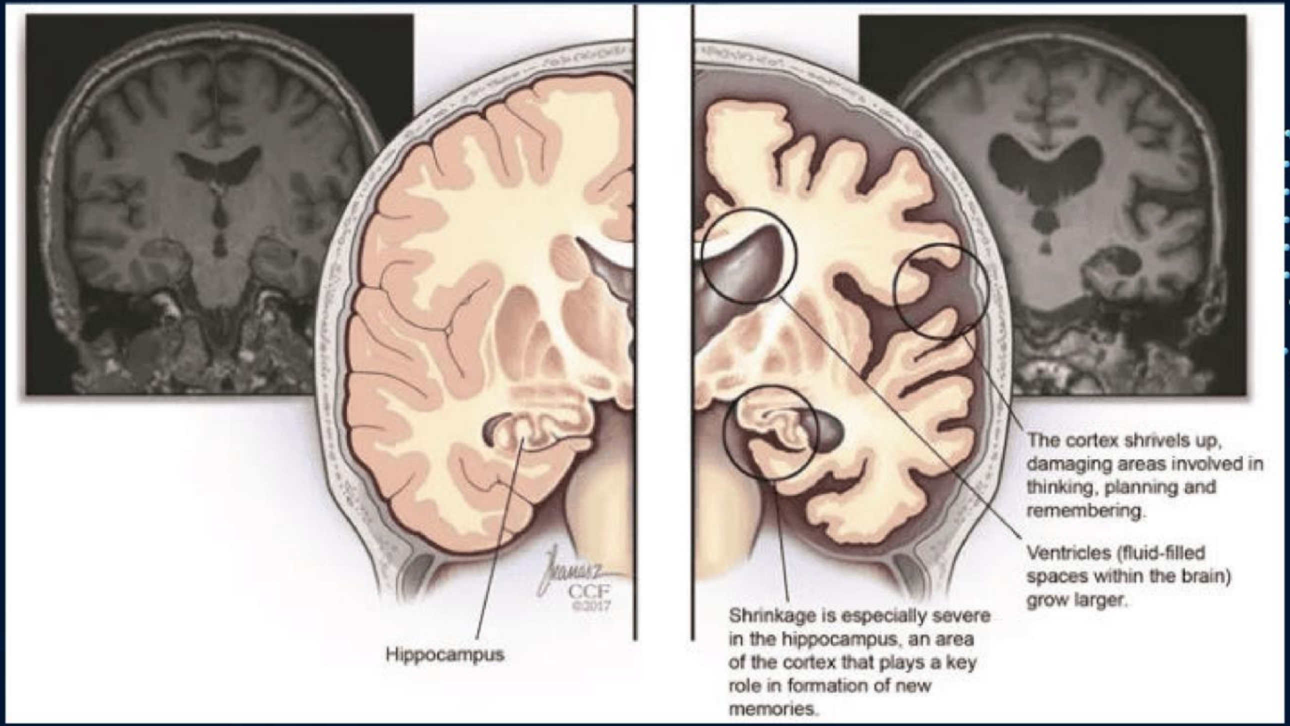
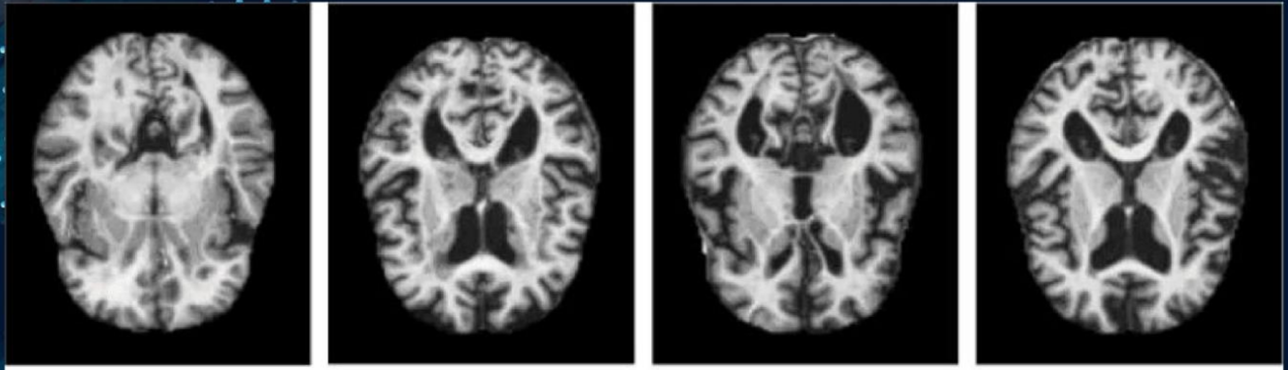
Enhancing Alzheimer's Prediction: Leveraging Pretrained Models ResNet50, DenseNet, and EfficientNet



Introduction

Alzheimer's disease is a **devastating** neurodegenerative disorder. Leveraging pretrained models such as *ResNet50*, *DenseNet*, and *EfficientNet* can significantly enhance the accuracy of early prediction. This presentation explores the potential of these models in improving Alzheimer's prediction.

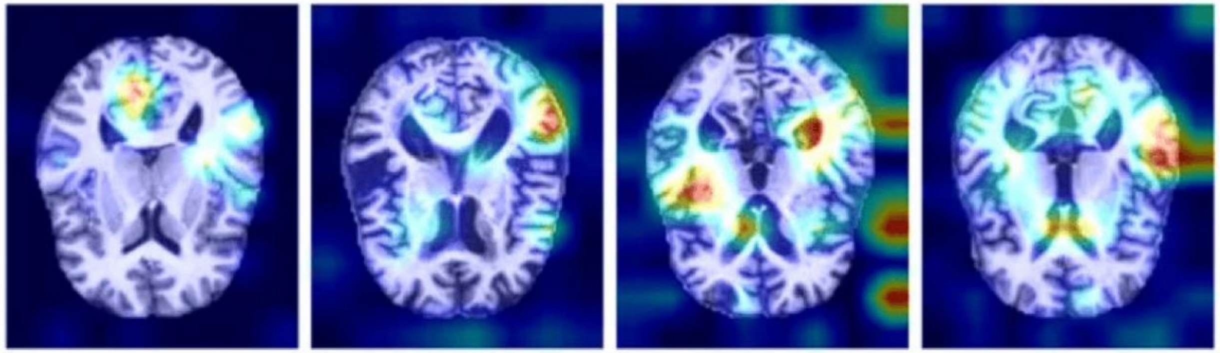


From left to right: Non-Demented, Very Mild Demented, Mild Demented, Moderate Demented

Understanding Alzheimer's

Alzheimer's is a **progressive** disease that impairs memory and cognitive function. Early detection is crucial for effective treatment. Pretrained models like *ResNet50*, *DenseNet*, and *EfficientNet* offer promise in accurately predicting the onset of Alzheimer's.

The goal of this project is to use pretrained models can categorize MRI images correctly into the classes of Alzheimer’s severity. This is especially useful between non-demented, early-stage Alzheimer’s, and mild dementia cases, where MRIs look very similar in order to help increase the accuracy of diagnosis by doctors and the efficiency of the treatment process to improve symptoms.



From left to right: Non-Demented, Very Mild Demented, Mild Demented, Moderate Demented

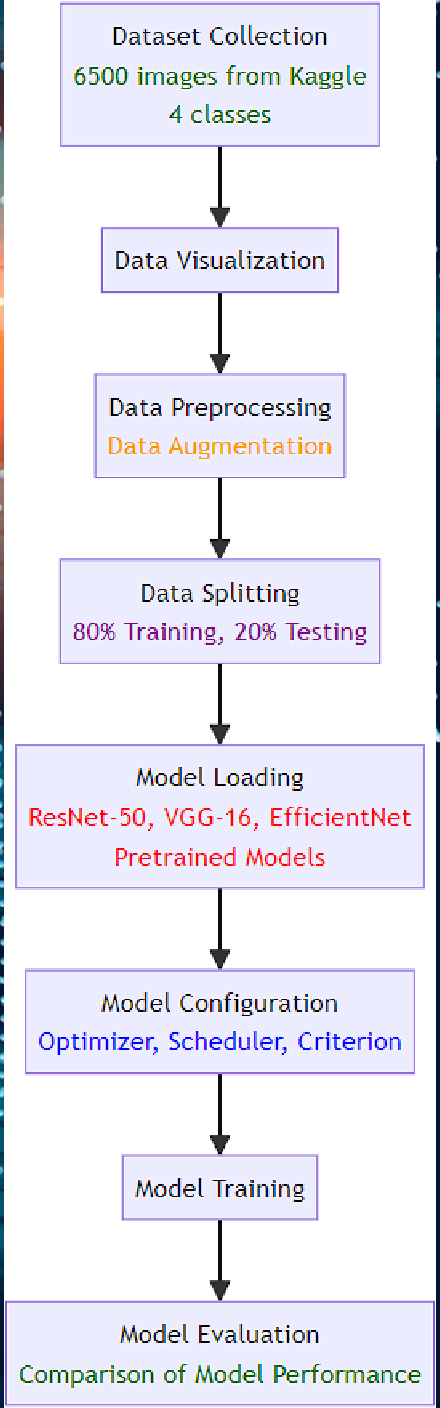
Data

The data used is taken fromKaggle. It contains brain MRI images on dementia that are classified into four classes: mild demented, moderate demented, non-demented, and very mild demented. The dataset is pre-split into a training set and a test set. The training set consists of 5121 MRI images and the test set consists of 1284 MRI images.

Here is the distribution of images from each class in the training and test set:

Pretrained Models

Utilizing pretrained models such as *ResNet50*, *DenseNet*, and *EfficientNet* provides a foundation for accurate prediction. These models have been trained on extensive datasets and can effectively extract **complex** features from medical images.



Methodology

we tried two different approaches when loading the images. The first few models we built were based on the images loaded in using the first method, and the transfer learning models and our best model were built based on the images loaded in with the second method.The first approach we took used TensorFlow image preprocessing. The images were loaded in as three-channel RGB images, and we performed an 80/20 split on the pre-split training set where images are separated into 80% training images and 20% validation images for cross-validation purposes. The test set was loaded in as-is with no modifications.For the second approach, we combined the pre-split training and test set into one dataset and the data are loaded in as one channel grayscale images. For data preprocessing, we normalized the images by dividing each image by 255. We performed an 80/20 split on the combined dataset where 80% of the images became training images and 20% of them became test images. From there, we conducted another 80/20 split on the training set with images split into 80% training images and 20% validation images for cross-validation purposes.

Preprocessing

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Number of images in training set: 5121
Number of images in testing set: 1279

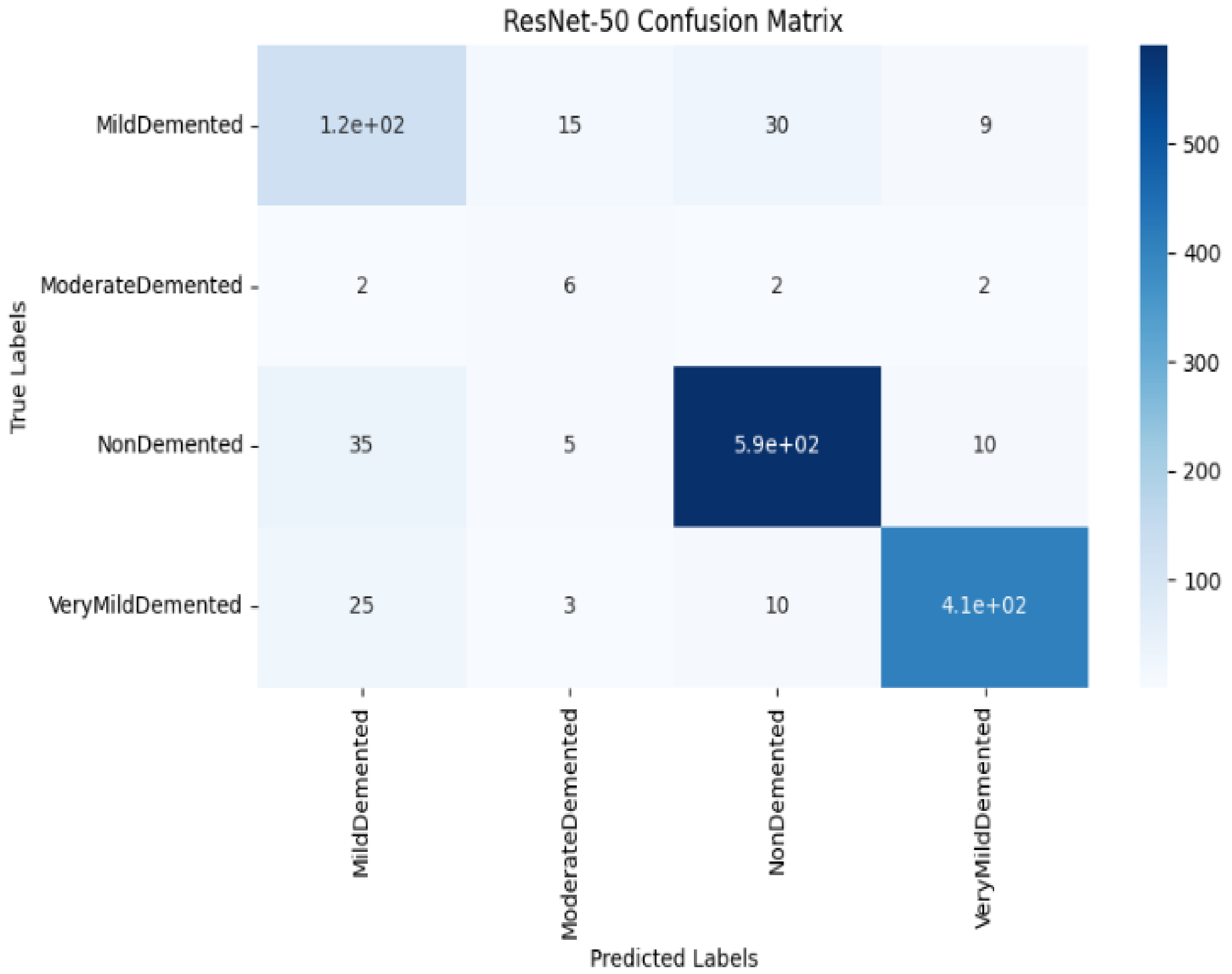
Number of images in each subfolder in the training set:
MildDemented: 717
ModerateDemented: 52
NonDemented: 2560
VeryMildDemented: 1792

Number of images in each subfolder in the testing set:
MildDemented: 179
ModerateDemented: 12
NonDemented: 640
VeryMildDemented: 448
```

Preprocessing Steps:

Step	Value
Image Dimensions	224 x 224
Batch Size	32
Rescaling	1./255
Rotation Range	20 degrees
Width Shift Range	0.2
Height Shift Range	0.2
Shear Range	0.2
Zoom Range	0.2
Horizontal Flip	True
Validation Split	0.2

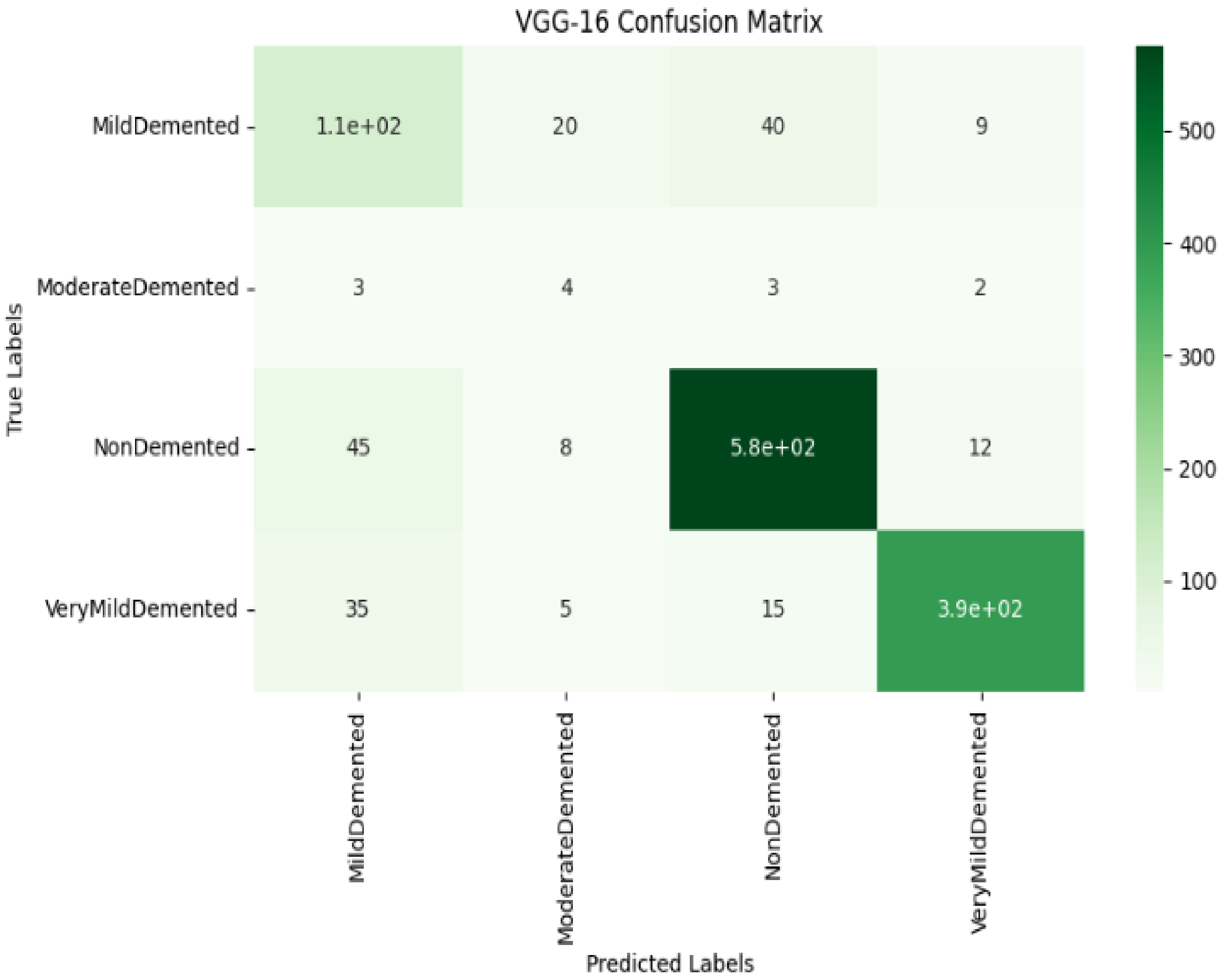
Parameter	Value
Activation	softmax
Optimizer	adam
Loss Function	categorical crossentropy
Metric	accuracy
Epochs	20



ResNet-50 Classification Report

	precision	recall	f1-score	support
0	0.73	0.70	0.71	179
1	0.50	0.50	0.50	12
2	0.92	0.92	0.92	640
3	0.95	0.92	0.93	448
accuracy			0.85	1279
macro avg	0.77	0.76	0.77	1279
weighted avg	0.87	0.85	0.86	1279

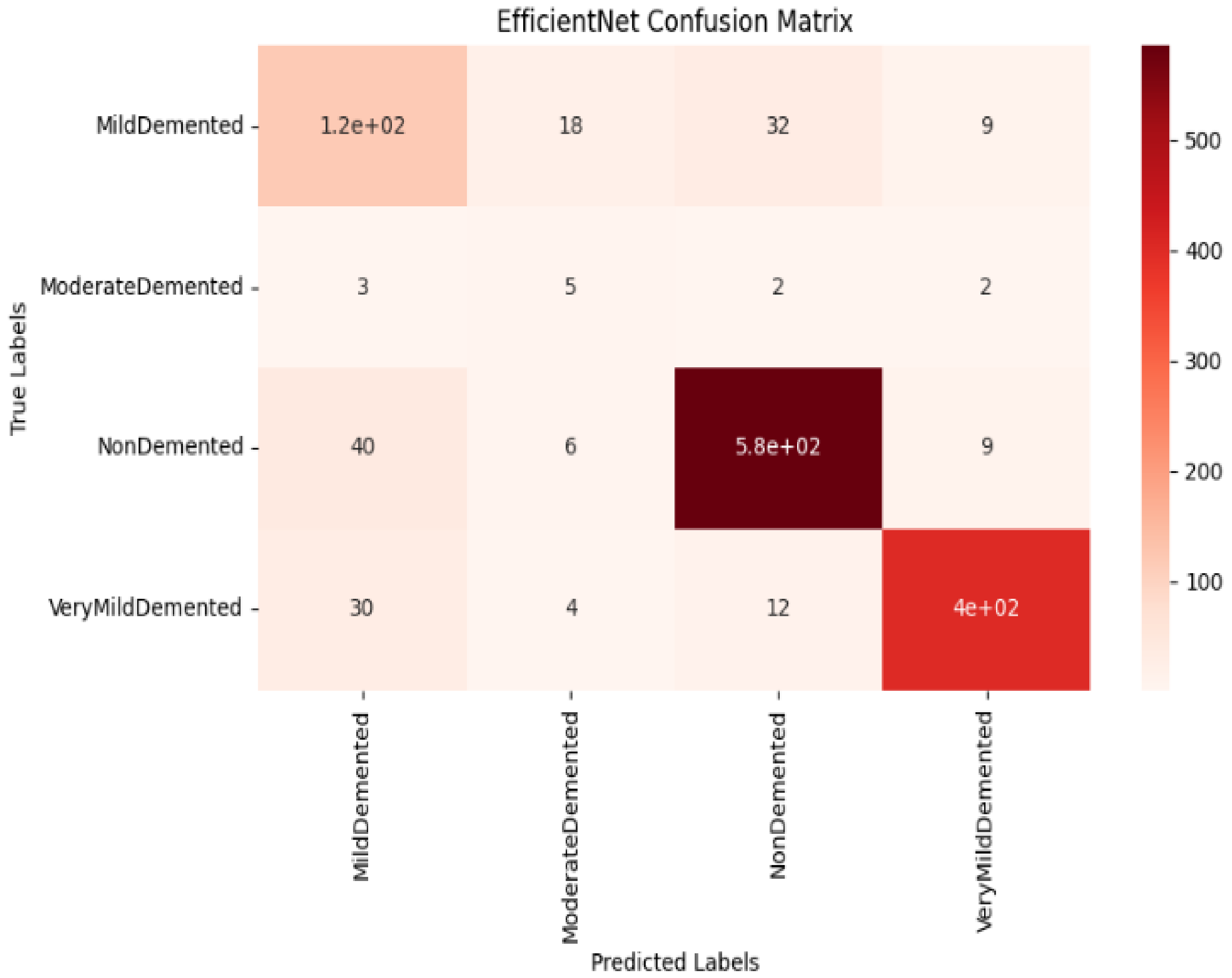
Resnet-50 Results



VGG-16 Classification Report

	precision	recall	f1-score	support
0	0.65	0.61	0.63	179
1	0.33	0.33	0.33	12
2	0.90	0.90	0.90	640
3	0.93	0.88	0.90	448
accuracy			0.76	1279
macro avg	0.70	0.68	0.69	1279
weighted avg	0.83	0.76	0.79	1279

VGG-16 Results

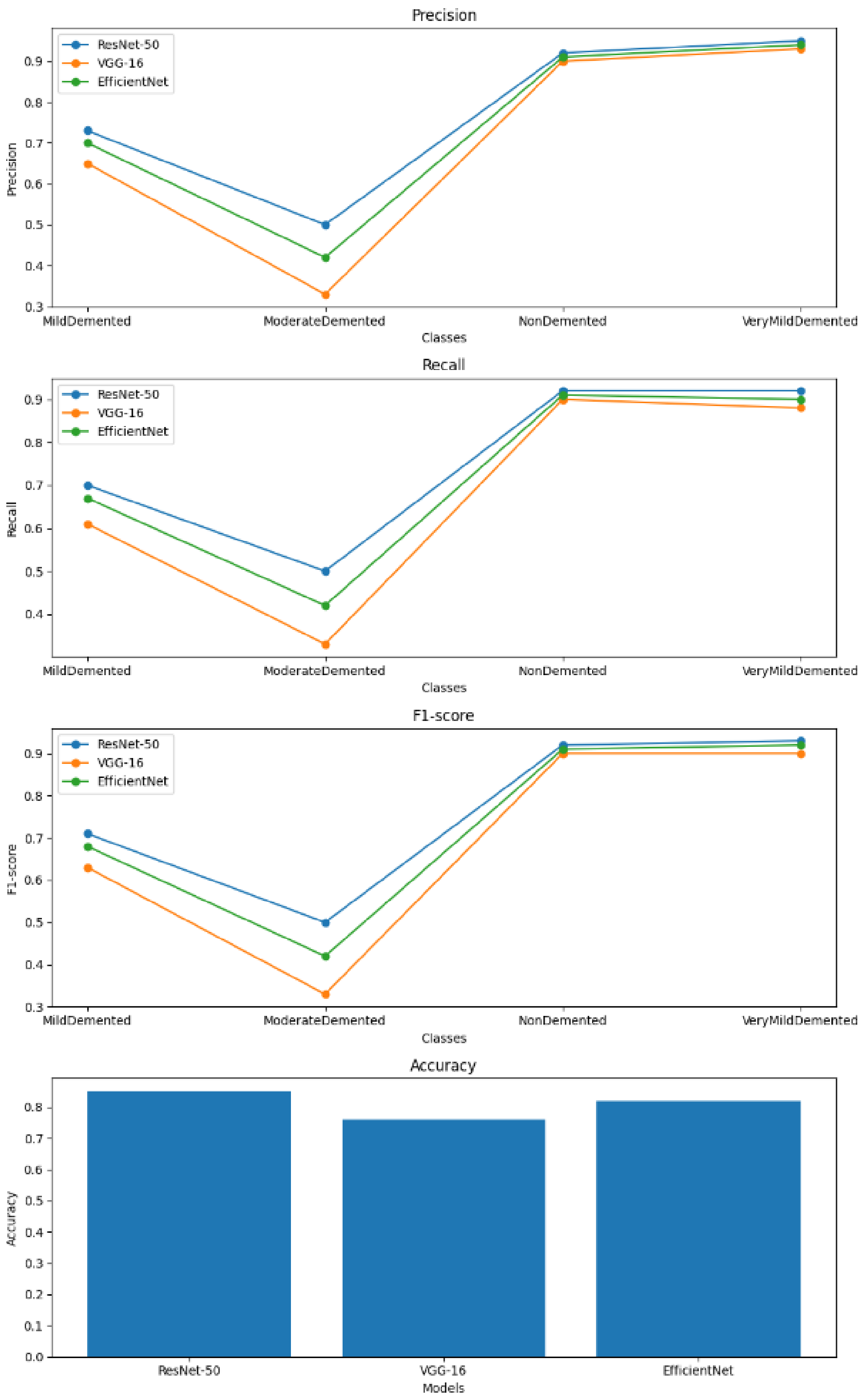


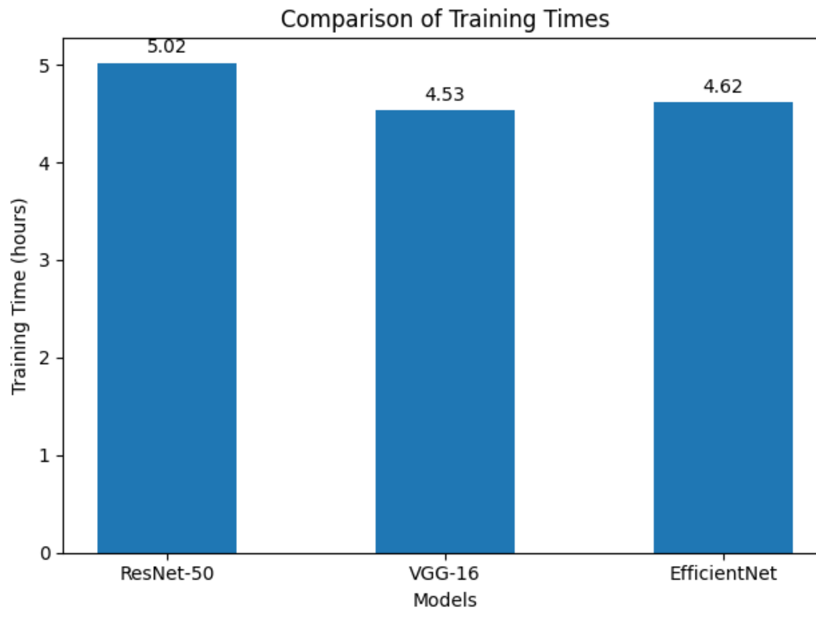
EfficientNet Classification Report

	precision	recall	f1-score	support
0	0.70	0.67	0.68	179
1	0.42	0.42	0.42	12
2	0.91	0.91	0.91	640
3	0.94	0.90	0.92	448
accuracy			0.82	1279
macro avg	0.74	0.73	0.73	1279
weighted avg	0.86	0.82	0.84	1279

EfficientNet Results

Comparison of the models





Application in Clinical Settings

Integrating pretrained models into clinical settings can revolutionize early Alzheimer's prediction. The use of *ResNet50*, *DenseNet*, and *EfficientNet* can enable healthcare professionals to make **timely** and accurate diagnoses, leading to improved patient care.