PNEUMONIA CLASSIFICATION

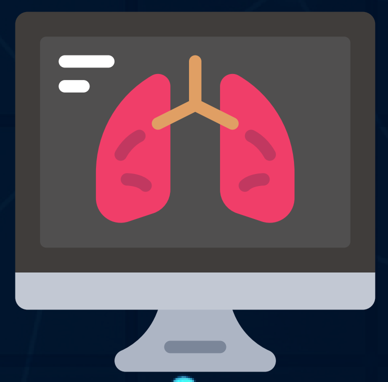
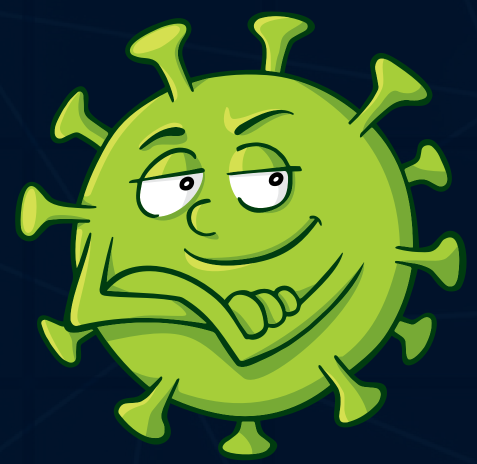


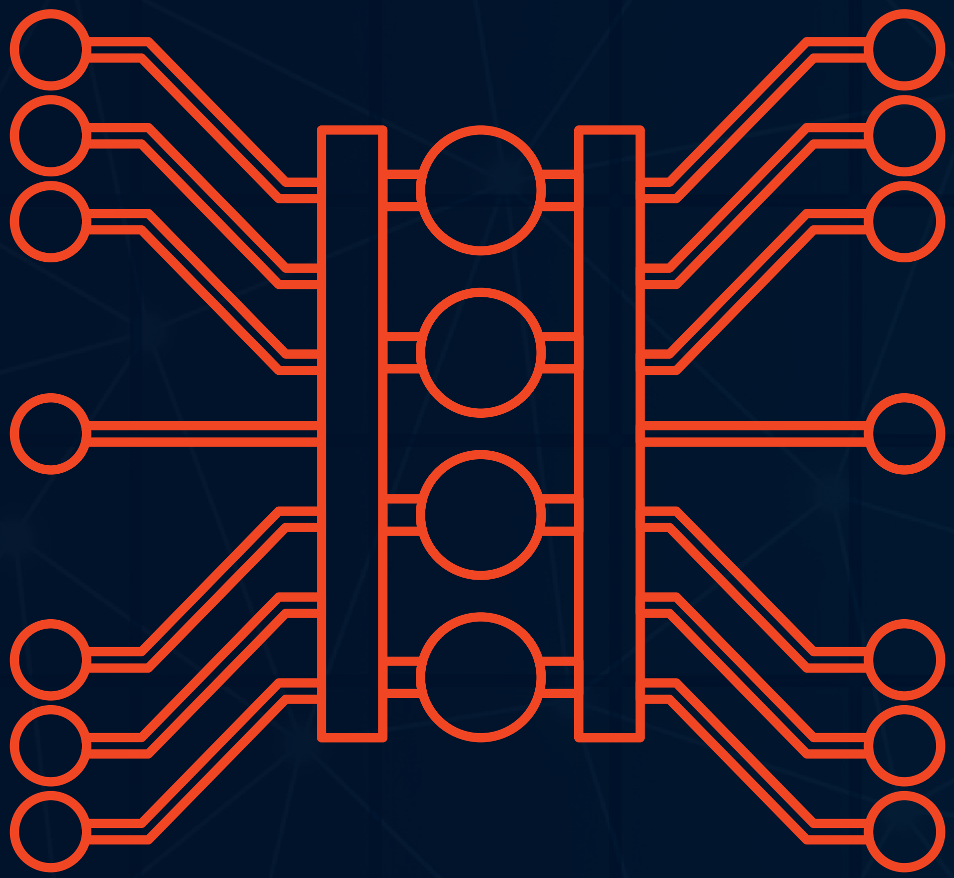
TABLE OF CONTENT

01 PNEUMONIA PROBLEM

Pneumonia is a life-threatening lung infection that requires prompt diagnosis and treatment. It's is a prevalent respiratory disease and a respiratory infection that primarily affects the lungs, causing inflammation in the air sacs. It can be caused by bacteria, viruses, or fungi and is characterized by symptoms such as cough, fever, difficulty breathing, and chest pain. Pneumonia can range from mild to severe, with complications more likely in the elderly and individuals with weakened immune systems. Diagnosis often involves chest X-rays and laboratory tests.



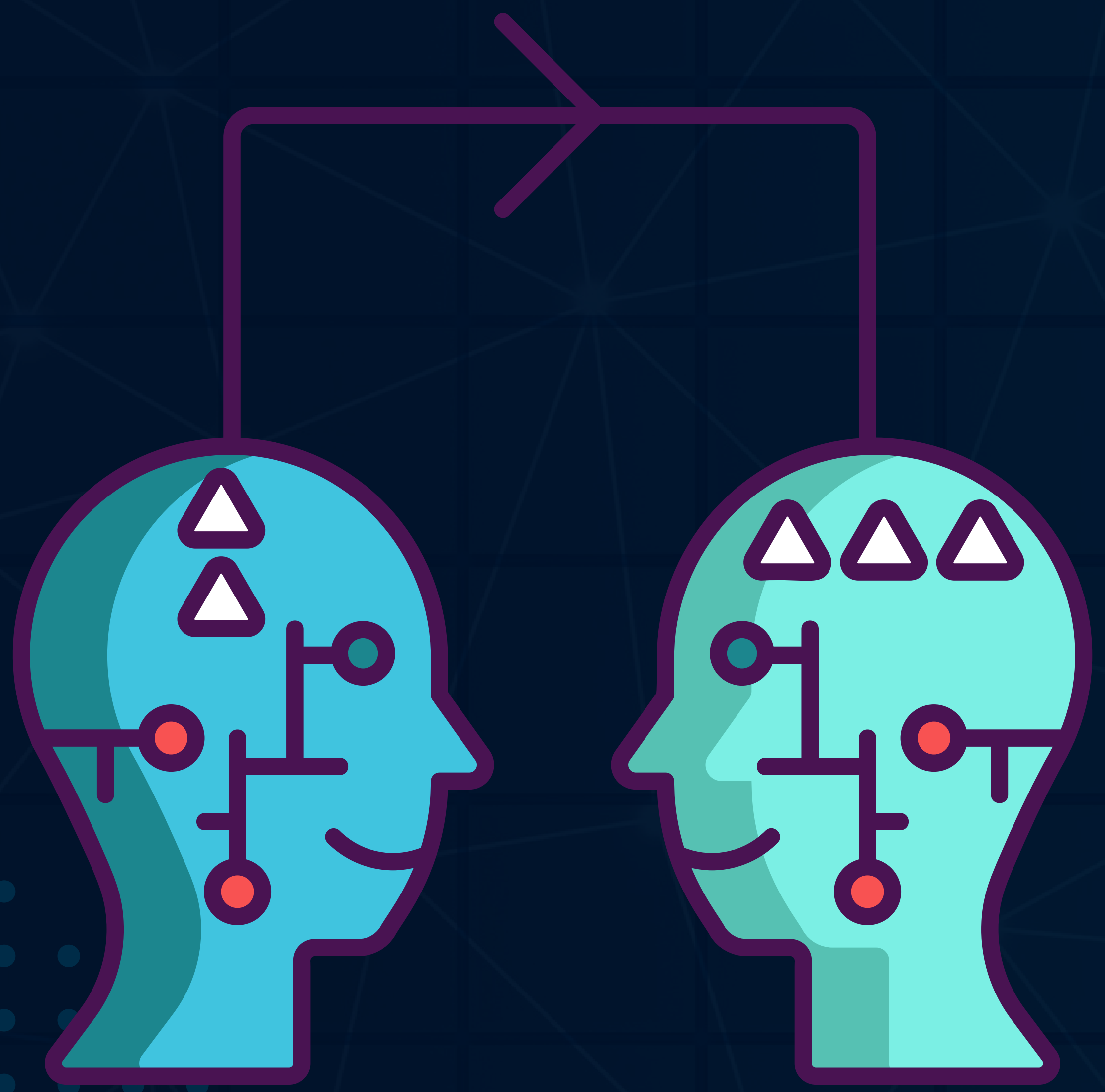
02 ABSTRACT



The use of deep learning techniques, particularly convolutional neural networks (CNNs), has emerged as a promising approach for pneumonia classification using medical imaging data.

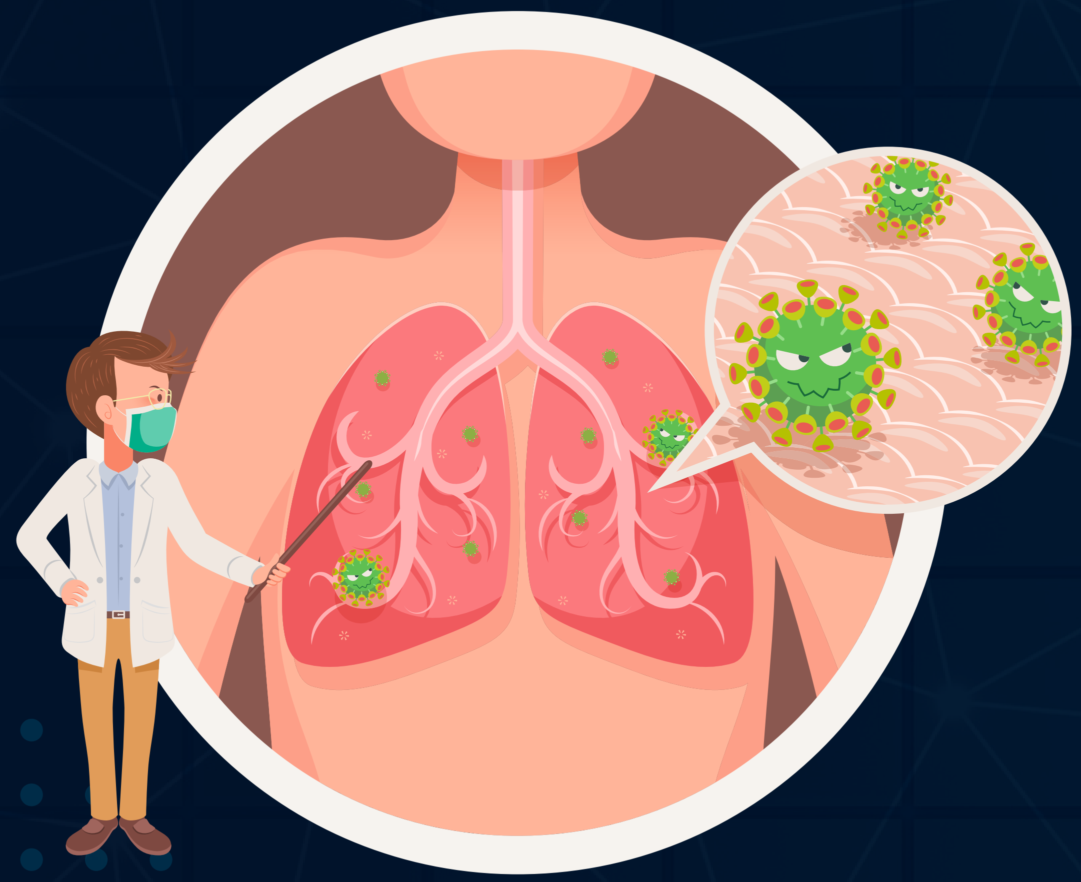
These models demonstrate the potential to enhance diagnostic accuracy, assist healthcare professionals in making informed decisions, and improve the overall management of pneumonia cases. By analyzing radiological images, these models can accurately differentiate between pneumonia and healthy lungs, aiding in the early detection and treatment of the disease.

02 ABSTRACT



Nonetheless, the process of training deep learning models from scratch demands abundant labeled data and significant computational resources, which may not be easily accessible. To overcome this challenge, transfer learning comes into play, enabling us to harness the power of pre-trained CNN models that have already undergone extensive training on vast image datasets. By adapting these pre-trained models to new tasks using smaller datasets, transfer learning empowers us to make efficient use of existing knowledge and achieve desirable outcomes.

03 INTRODUCTION

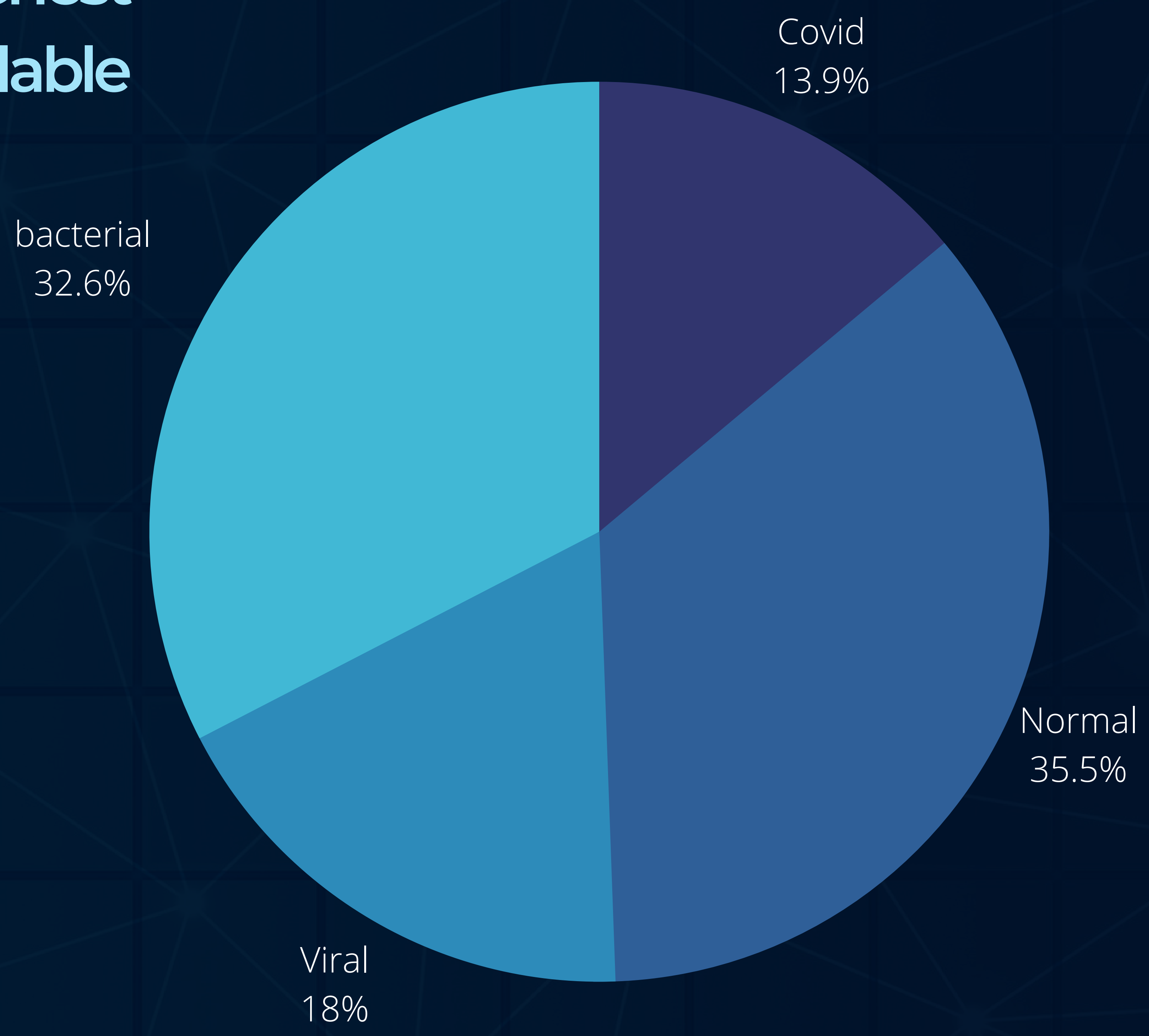


In the field of Pneumonia classification, our objective is to develop a robust deep learning model capable of accurately categorizing chest X-ray images as either pneumonia-infected or non-infected using state-of-the-art techniques like convolutional neural networks (CNNs) and transfer learning models. By employing architectures such as densenet121, mobilenetv2, xception, and vgg16, we aim to achieve high accuracy in the classification of pneumonia cases based on the analysis of medical images. This Project aims to contribute to the early and accurate diagnosis of pneumonia, enabling timely intervention and improved patient outcomes.

04 OUR DATASET

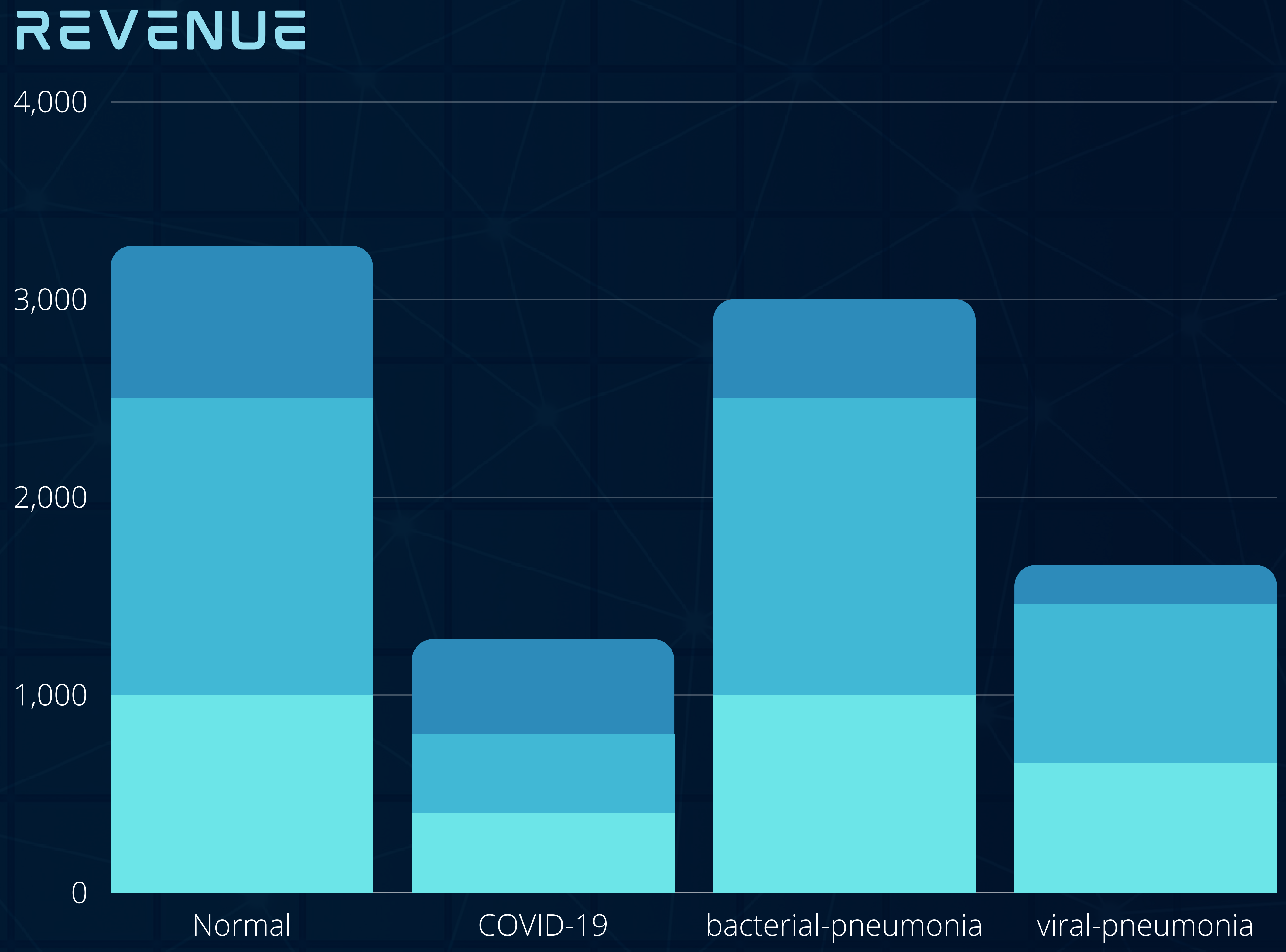
This is a combined curated dataset of COVID-19 Chest X-ray images obtained by collating 15 public available datasets .

- Curated X-Ray Dataset
  - Normal
  - Pneumonia-Bacterial
  - Pneumonia-Viral
  - COVID-19



04 OUR DATASET

- The present dataset contains :
  - 1281 COVID-19 X-Rays
  - 3270 Normal X-Rays
  - 1656 viral-pneumonia X-Rays
  - 3001 bacterial-pneumonia X-Rays.



04 OUR DATASET

TEST PERSENTAGE

15%

TRAIN PERSENTAGE

85%

DIVEDING DATA TO TRAIN AND TEST

05 PREPROCESSING

A

Checking the size of images in different categories :

- COVID,
- Normal,
- Bacterial
- Viral.

B

reading JPG images from each category's directory, retrieves their shapes, and generates a frequency count of the unique image shapes using Pandas. The resulting count provides information on the distribution of image sizes within each category.

C

- preparing training data for a model by resizing the images to a consistent size (150x150) and storing them with their respective class labels.
- Separate labels and inputs
- divede data to train and test

CNN and TL Models

CNN

densenet121

mobilenetv2

xception

vgg16

EfficientNetV2B1

ResNet50V2

06 CNN MODEL

(CNN) model implemented using the Keras framework.

The model architecture consists of multiple layers:

1. Conv2D layer with 180 filters, a kernel size of (3,3), and ReLU activation function.
2. Conv2D layer with 150 filters, a kernel size of (3,3), and ReLU activation function.
3. MaxPool2D layer with a pooling size of (4,4) for downsampling.
4. Conv2D layer with 120 filters, a kernel size of (3,3), and ReLU activation function.
5. Conv2D layer with 80 filters, a kernel size of (3,3), and ReLU activation function.
6. MaxPool2D layer with a pooling size of (4,4) for downsampling.
7. Flatten layer to convert the 2D feature maps into a 1D feature vector.
8. Dense layer with 256 units and ReLU activation function.
9. Dropout layer with a dropout rate of 0.3 to prevent overfitting.
10. Dense layer with 128 units and ReLU activation function.
11. Dropout layer with a dropout rate of 0.4.
12. Dense layer with 4 units and softmax activation function for multi-class classification.

The model is compiled with the Adam optimizer, sparse categorical cross-entropy loss function, and accuracy as the evaluation metric. This model is suitable for our image classification tasks with four output classes.

07 MODELS ACCURACY

CNN

TRAINING ACCURACY

95.6%

TRAINING LOSS

11.73%

EVALUATE ACCURACY

88.06%

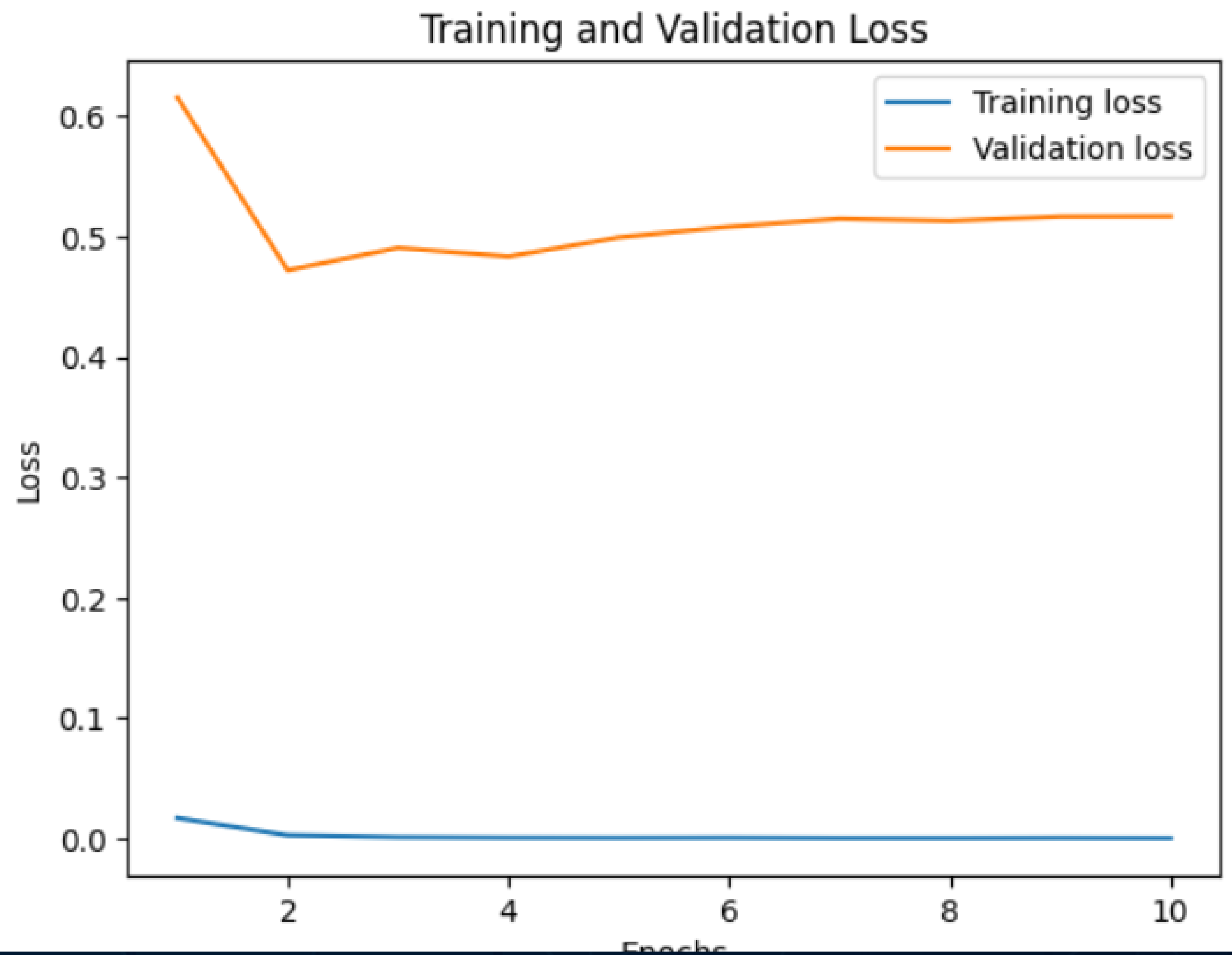
EVALUATE LOSS

44.54%

07 MODELS ACCURACY DENSENET121

GAP BETWEEN TRAINING ACCURACY AND VALIDATION ACCURACY

GAP BETWEEN TRAINING LOSS AND VALIDATION LOSS



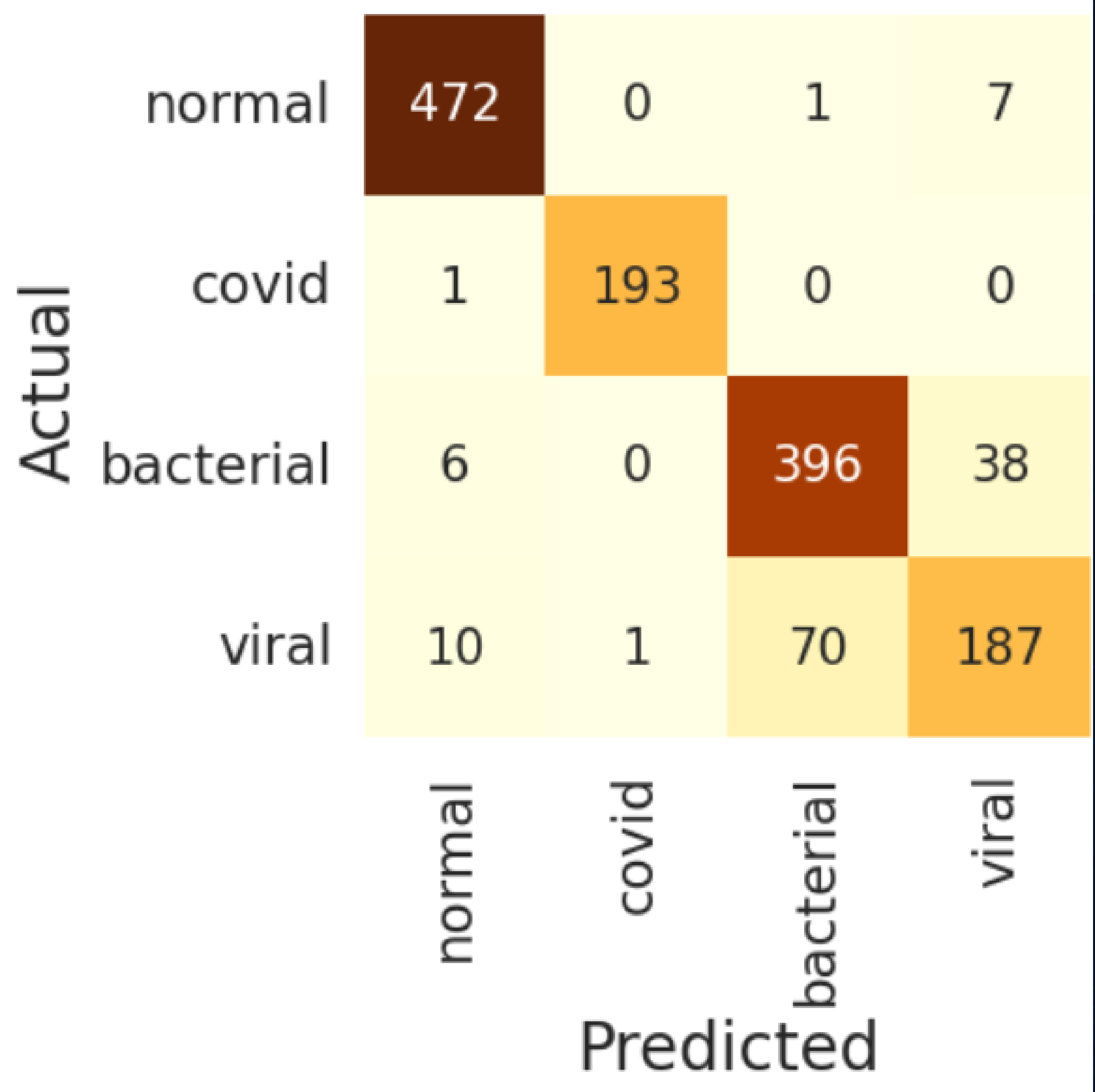
From epoch 11

07 MODELS ACCURACY DENSENET121

CLASSIFICATION REPORT

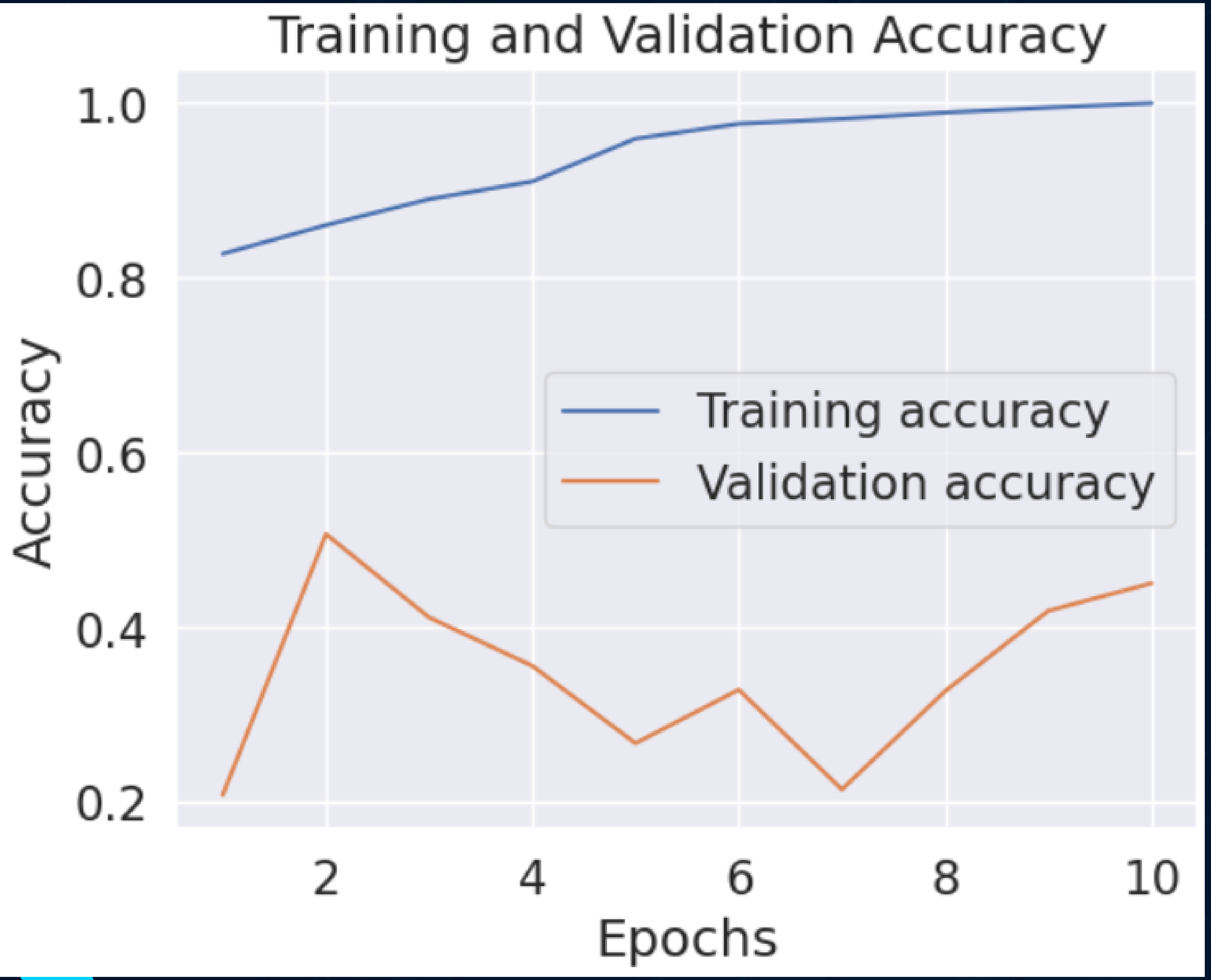
	precision	recall	f1-score	support
normal	0.9652	0.9833	0.9742	480
covid	0.9948	0.9948	0.9948	194
bacterial	0.8480	0.9000	0.8732	440
viral	0.8060	0.6978	0.7480	268
accuracy			0.9030	1382
macro avg	0.9035	0.8940	0.8976	1382
weighted avg	0.9012	0.9030	0.9011	1382

CONFUSION MATRIX

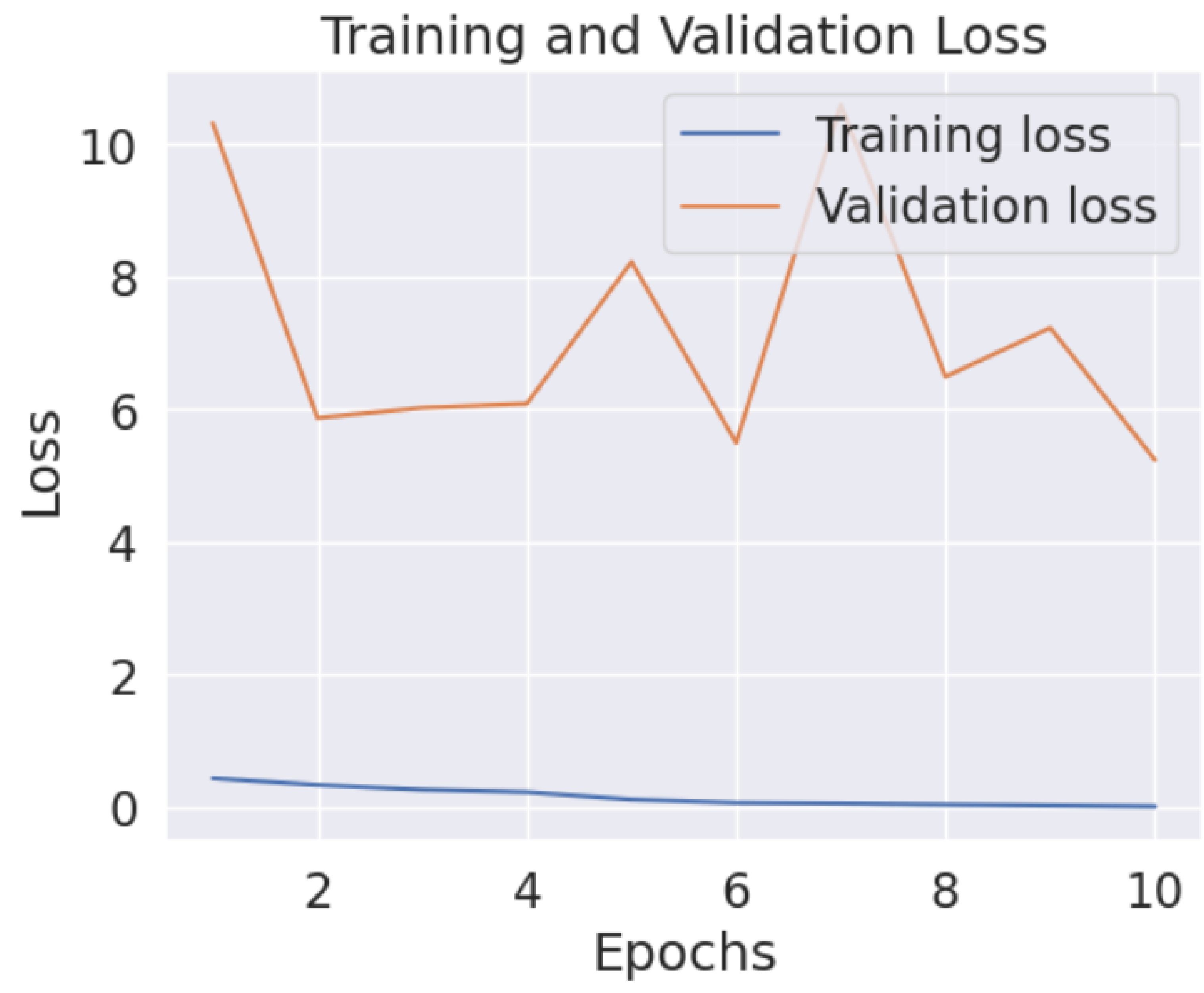


07 MODELS ACCURACY MOBILENET

GAP BETWEEN TRAINING ACCURACY AND VALIDATION ACCURACY



GAP BETWEEN TRAINING LOSS AND VALIDATION LOSS

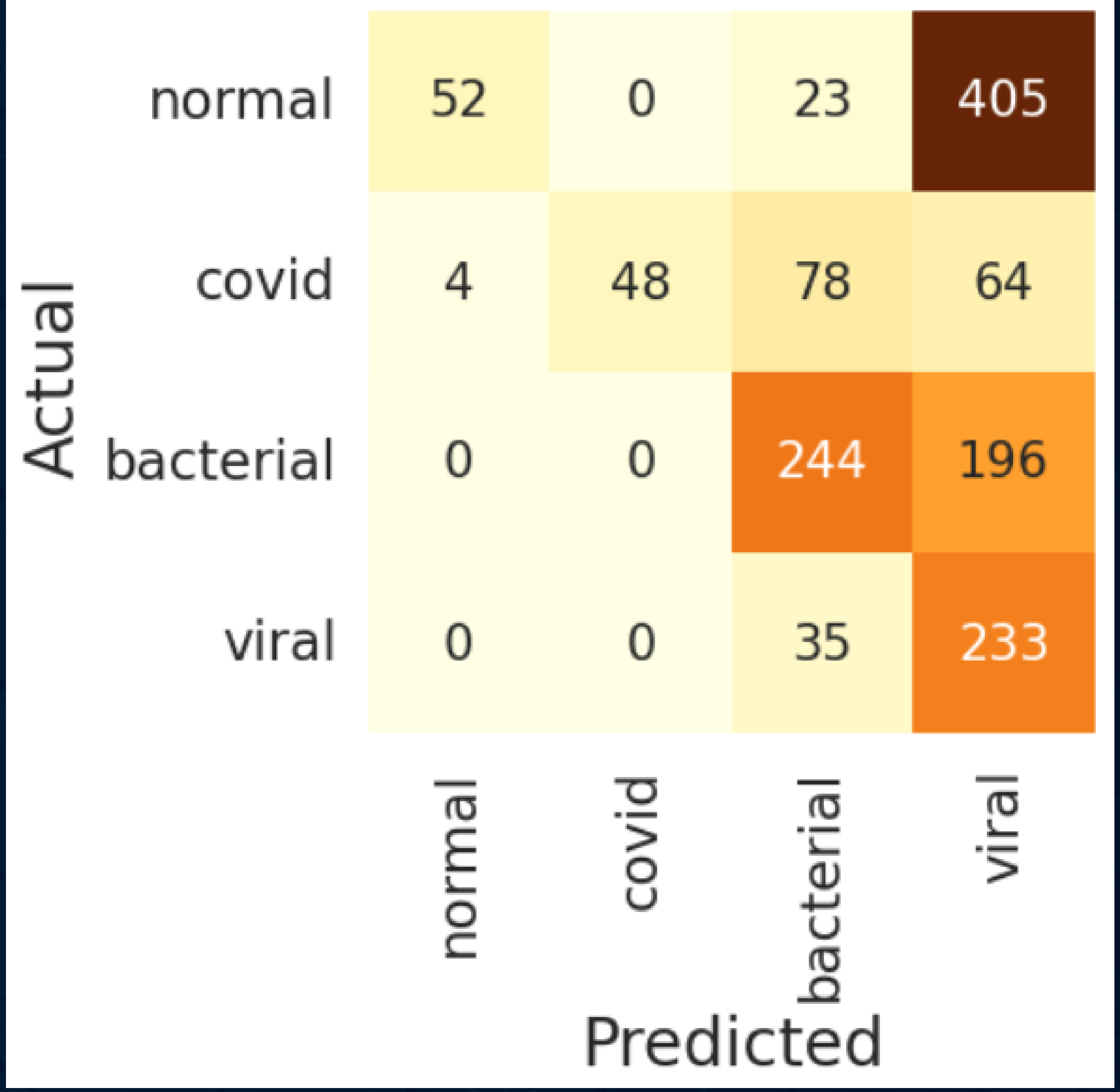


07 MODELS ACCURACY MOBILENET

CLASSIFICATION REPORT

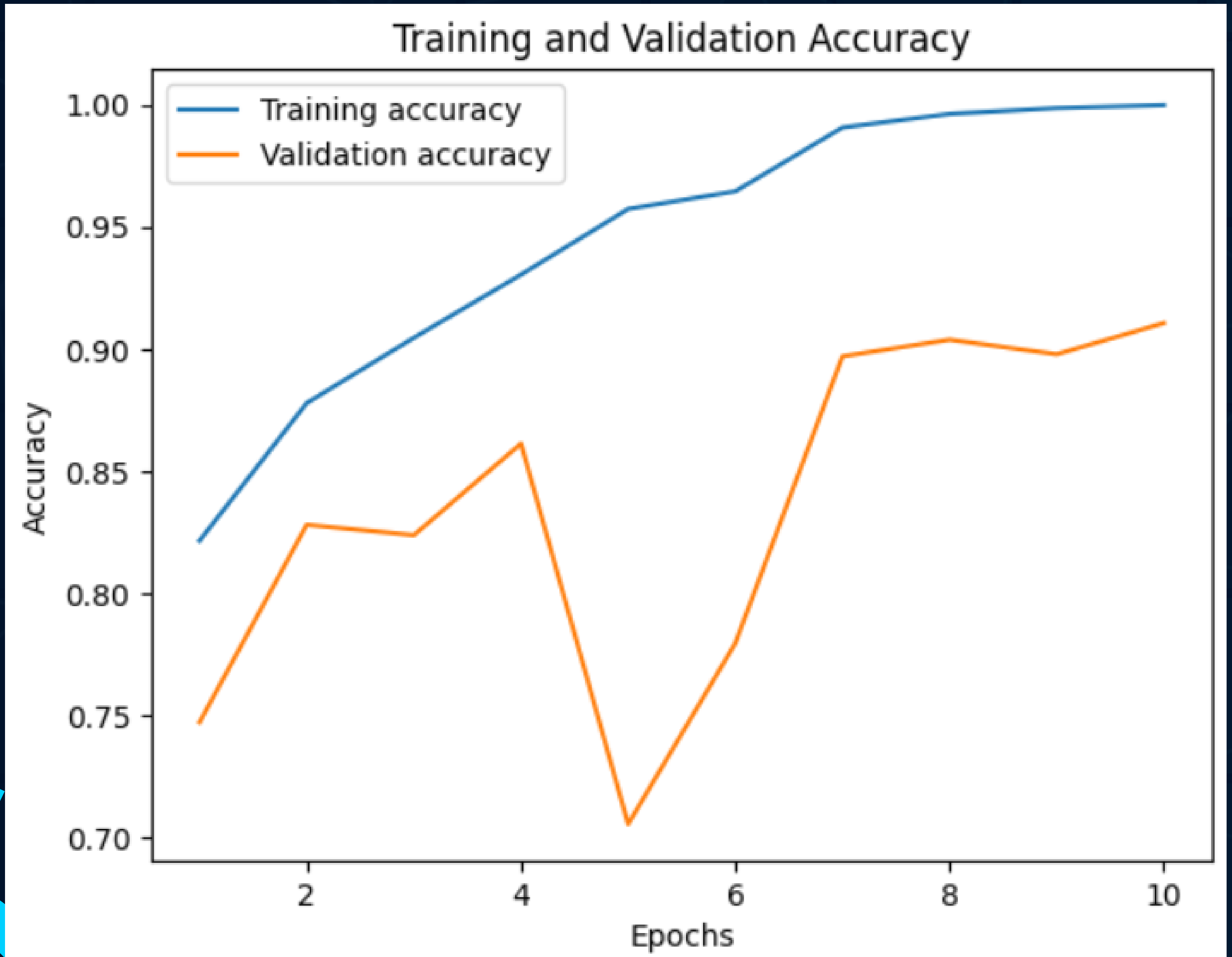
	precision	recall	f1-score	support
normal	0.9286	0.1083	0.1940	480
covid	1.0000	0.2474	0.3967	194
bacterial	0.6421	0.5545	0.5951	440
viral	0.2595	0.8694	0.3997	268
accuracy			0.4175	1382
macro avg	0.7075	0.4449	0.3964	1382
weighted avg	0.7176	0.4175	0.3901	1382

CONFUSION MATRIX

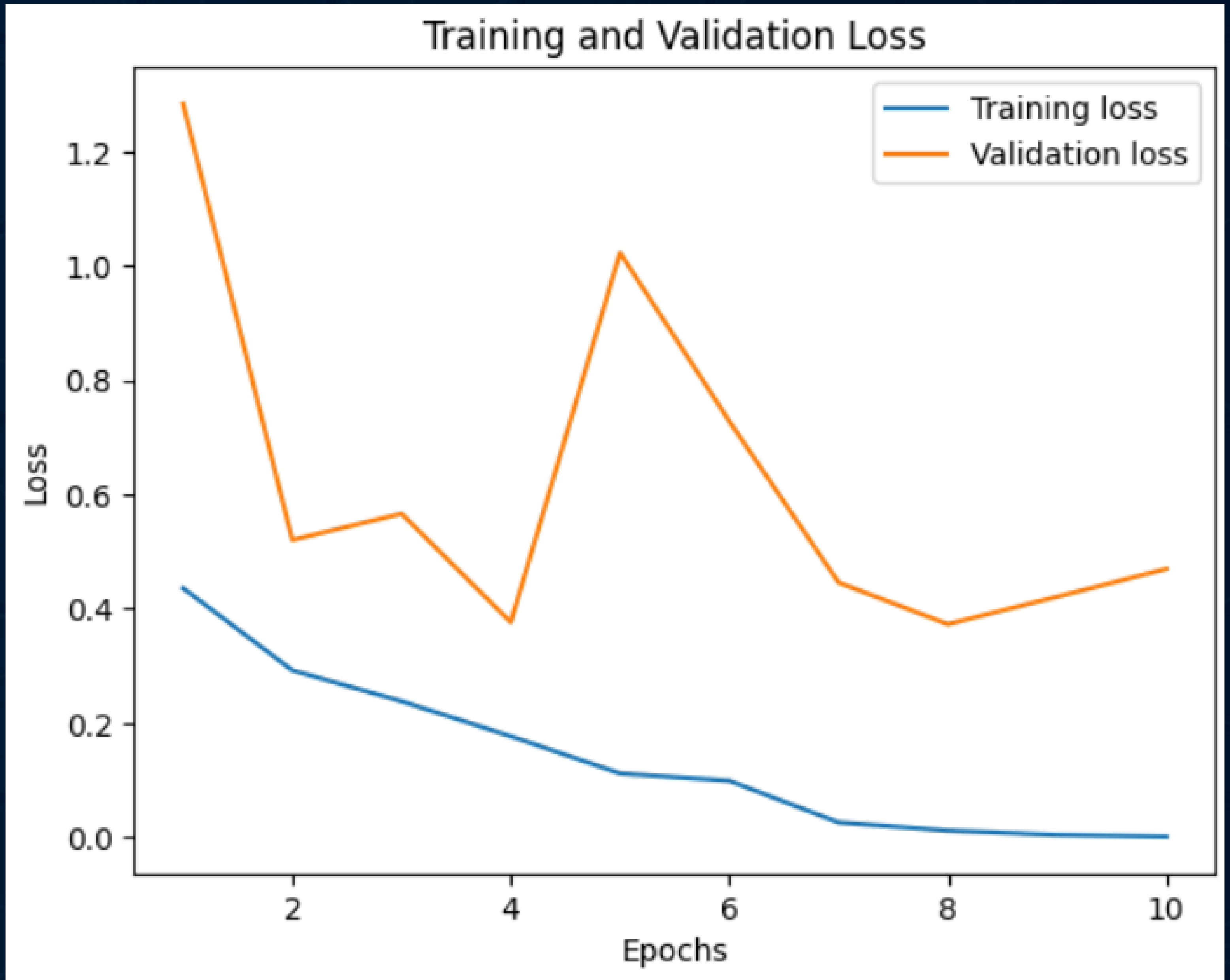


07 MODELS ACCURACY XCEPTION

GAP BETWEEN TRAINING ACCURACY AND VALIDATION ACCURACY



GAP BETWEEN TRAINING LOSS AND VALIDATION LOSS

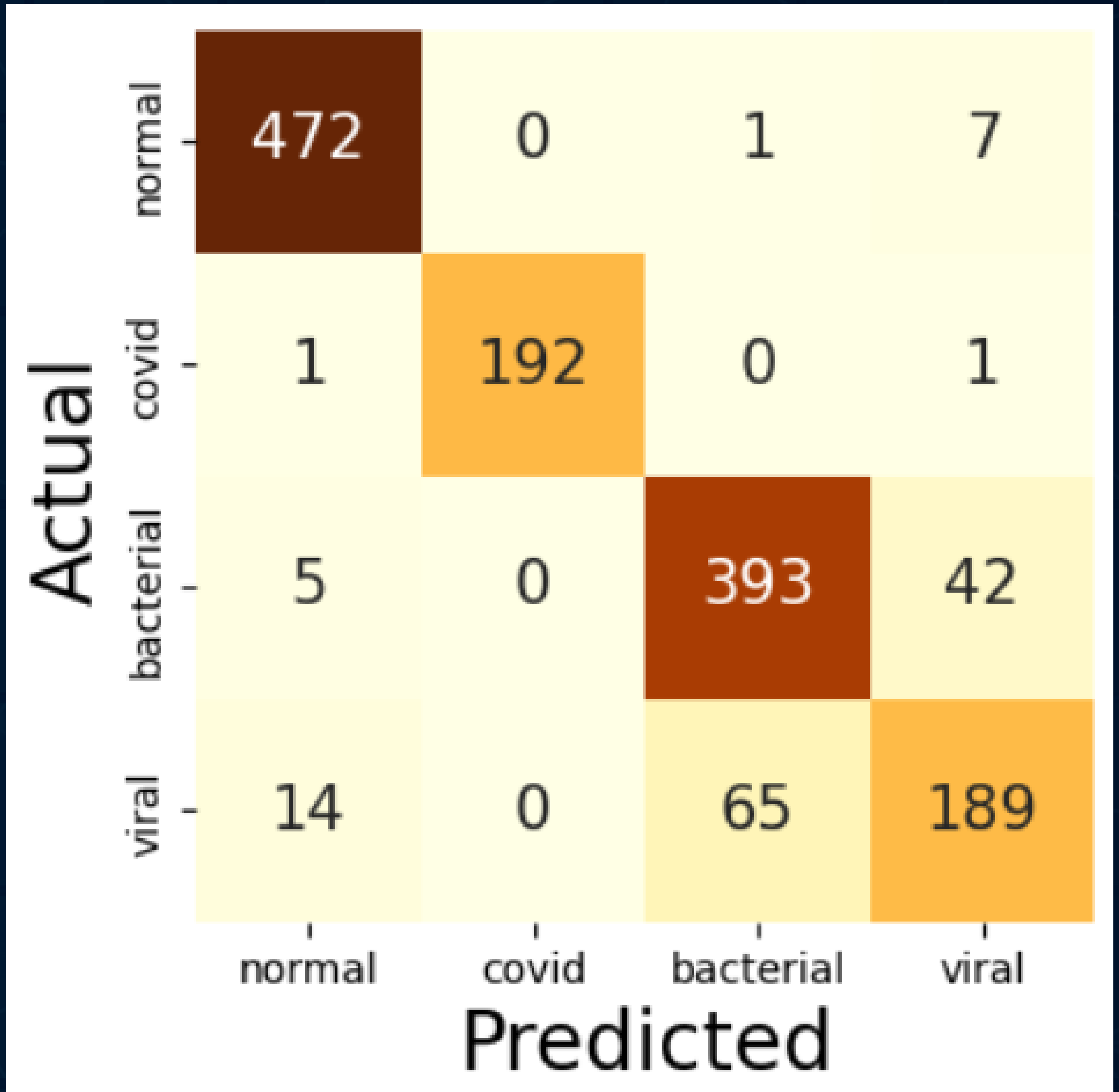


07 MODELS ACCURACY XCEPTION

CLASSIFICATION REPORT

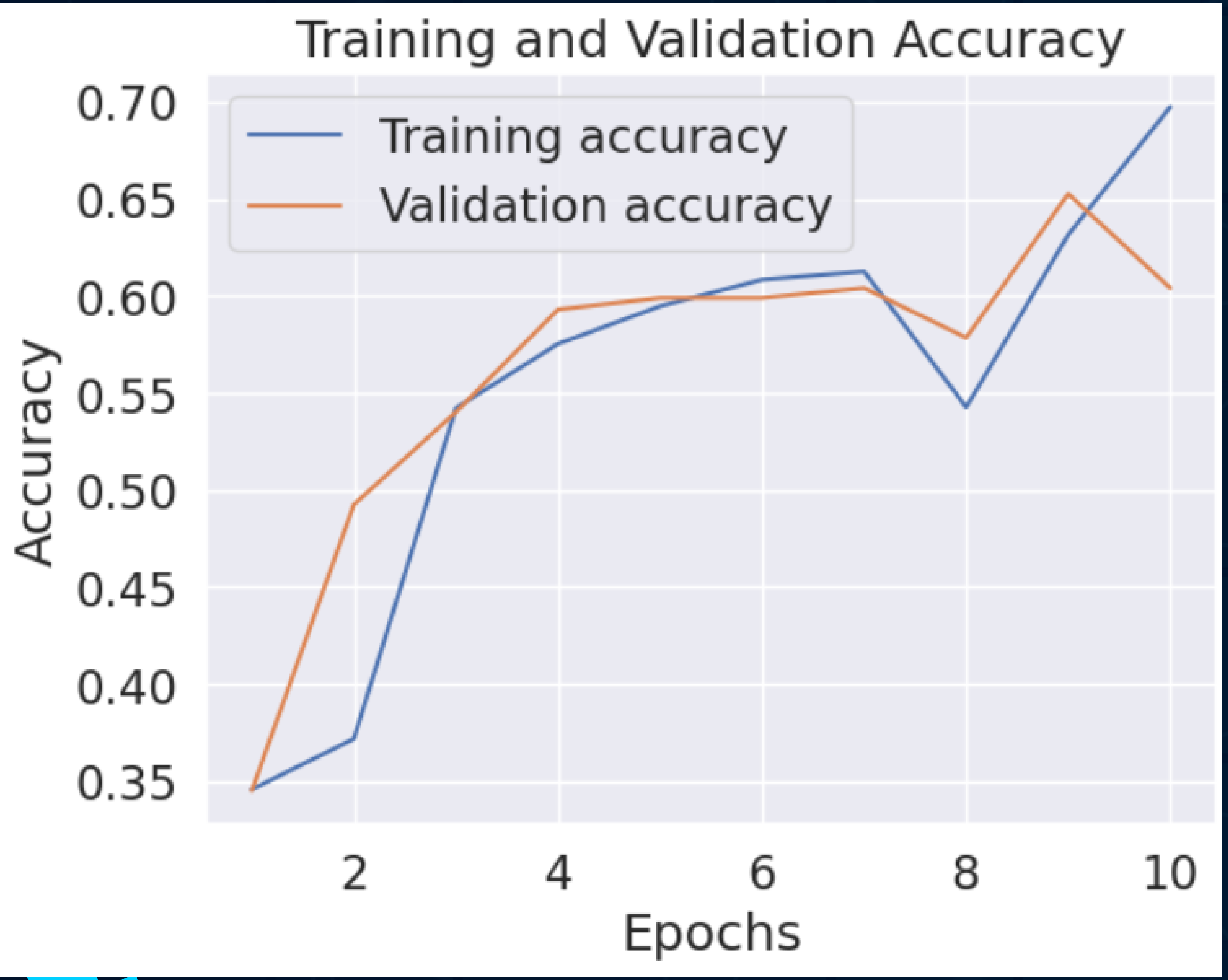
	precision	recall	f1-score	support
normal	0.9593	0.9833	0.9712	480
covid	1.0000	0.9897	0.9948	194
bacterial	0.8562	0.8932	0.8743	440
viral	0.7908	0.7052	0.7456	268
accuracy			0.9016	1382
macro avg	0.9016	0.8929	0.8965	1382
weighted avg	0.8995	0.9016	0.8999	1382

CONFUSION MATRIX

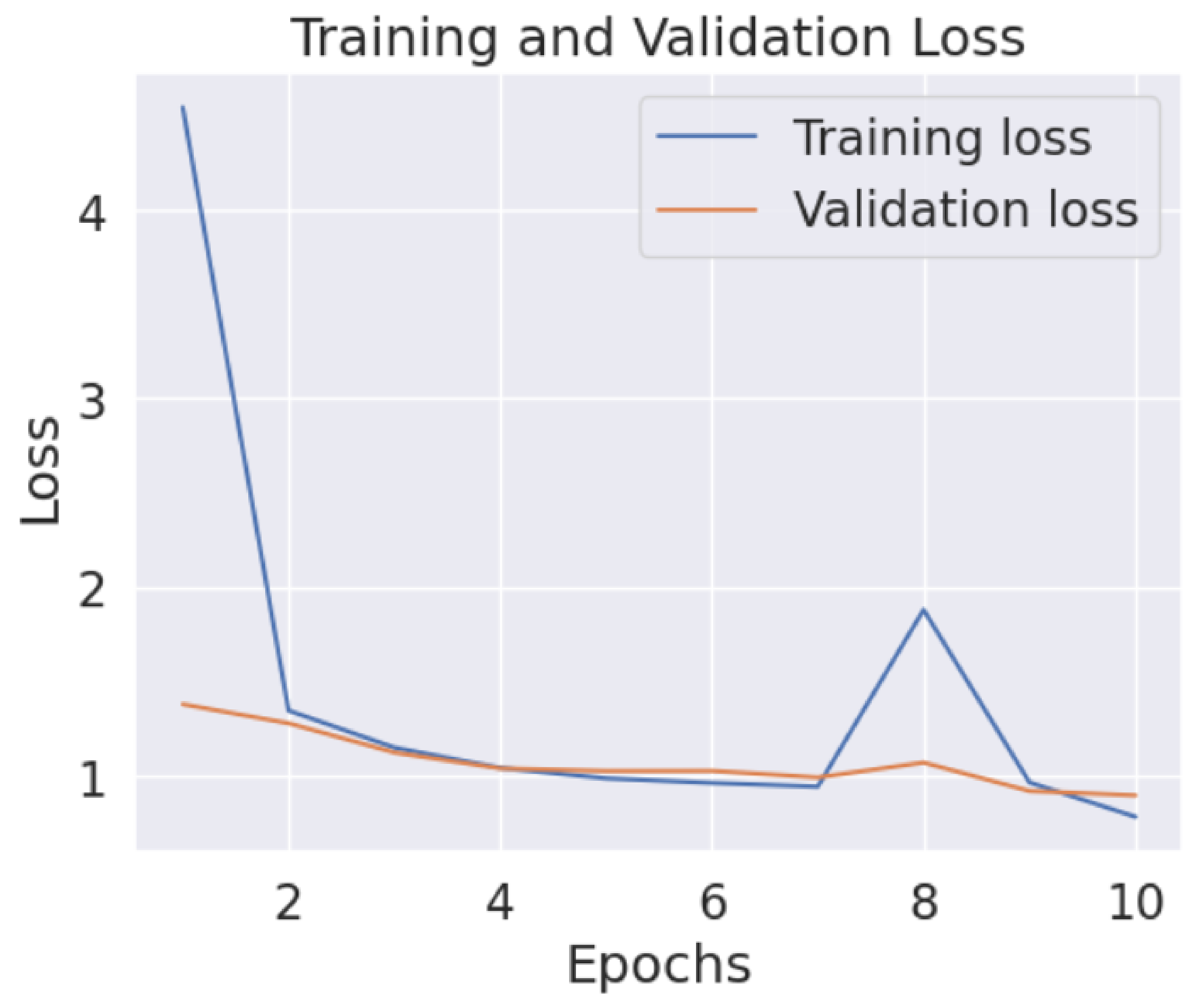


07 MODELS ACCURACY VGG16

GAP BETWEEN TRAINING ACCURACY AND VALIDATION ACCURACY



GAP BETWEEN TRAINING LOSS AND VALIDATION LOSS

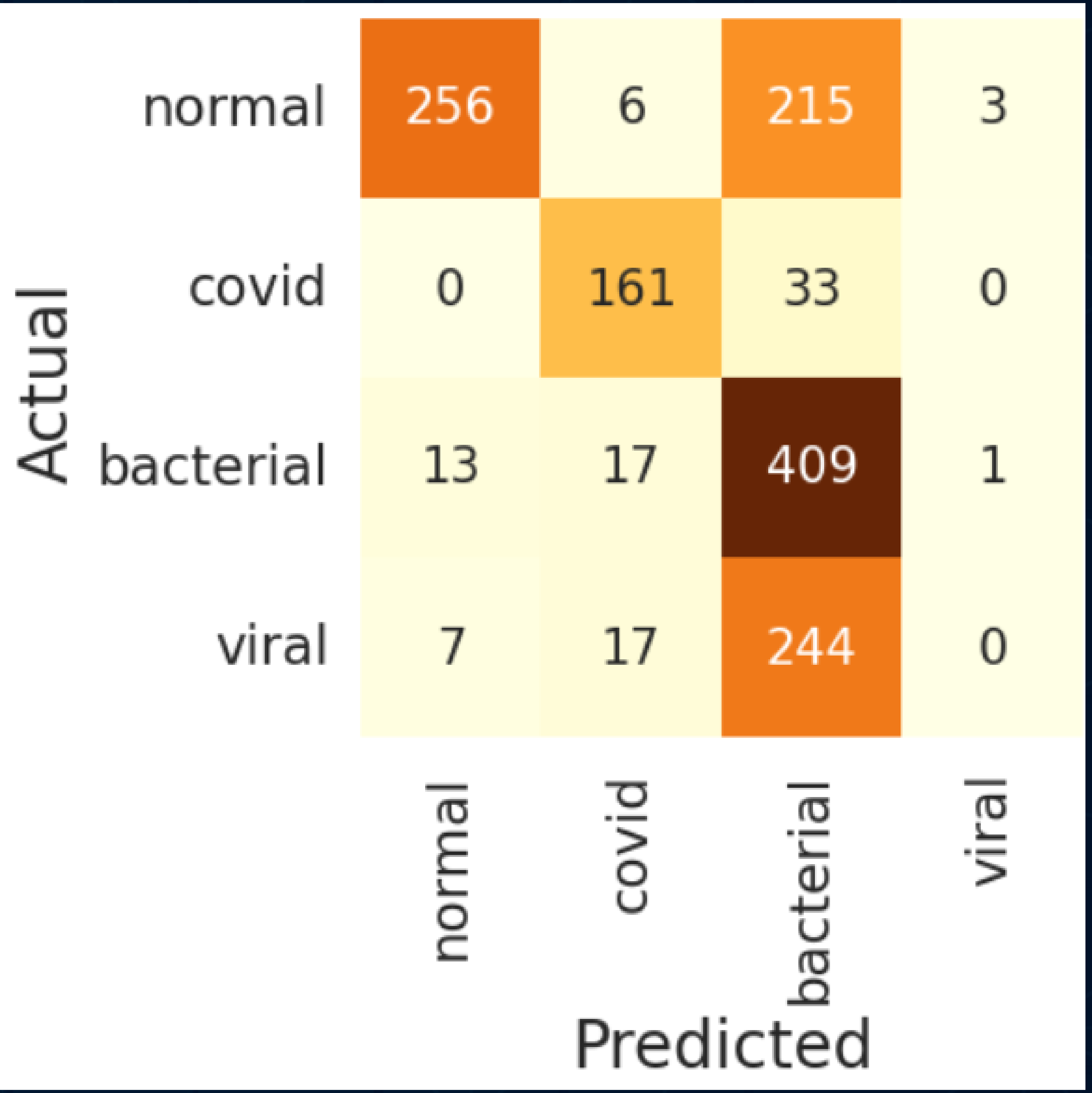


07 MODELS ACCURACY VGG16

CLASSIFICATION REPORT

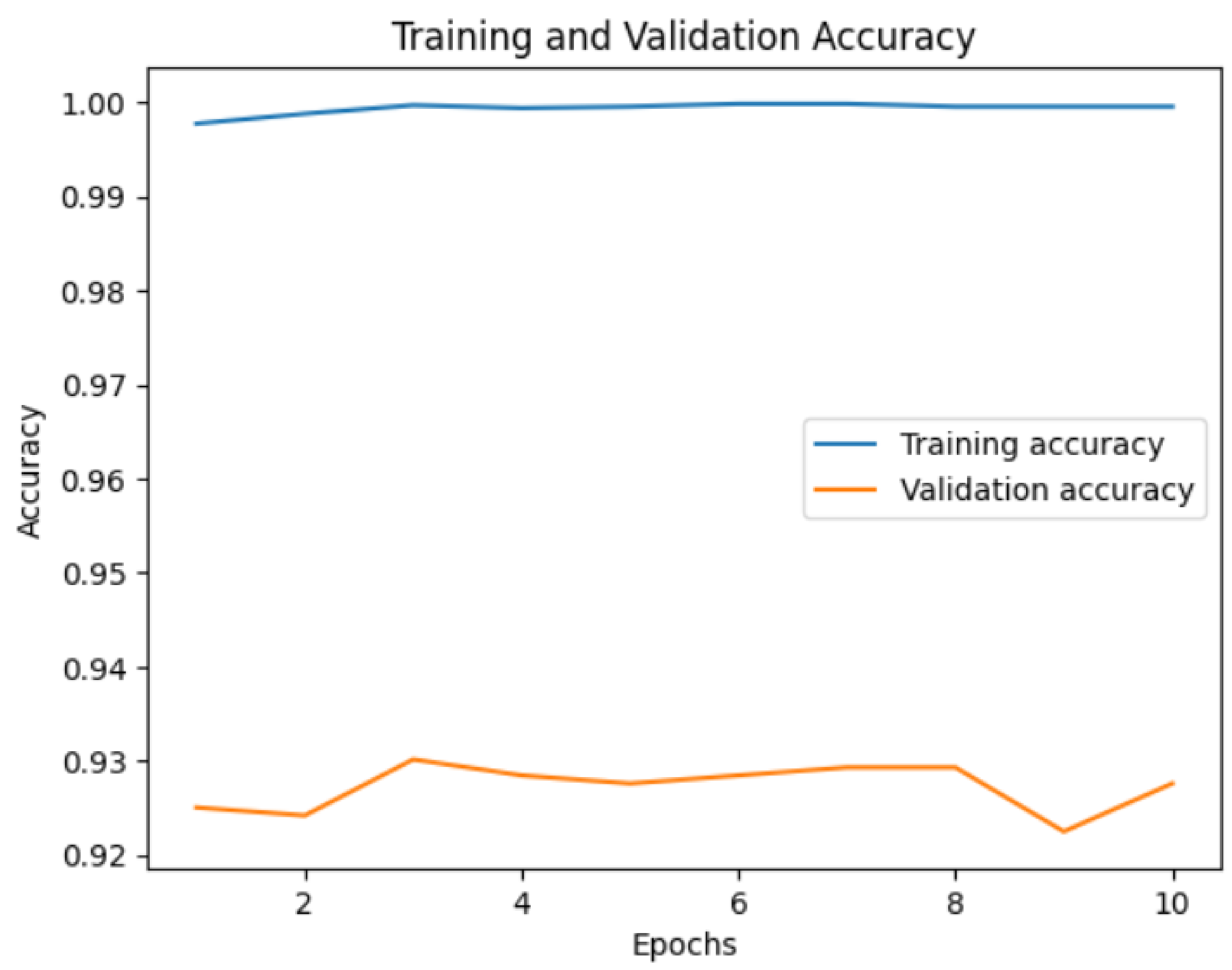
	precision	recall	f1-score	support
normal	0.9275	0.5333	0.6772	480
covid	0.8010	0.8299	0.8152	194
bacterial	0.4539	0.9295	0.6100	440
viral	0.0000	0.0000	0.0000	268
accuracy			0.5977	1382
macro avg	0.5456	0.5732	0.5256	1382
weighted avg	0.5791	0.5977	0.5439	1382

CONFUSION MATRIX

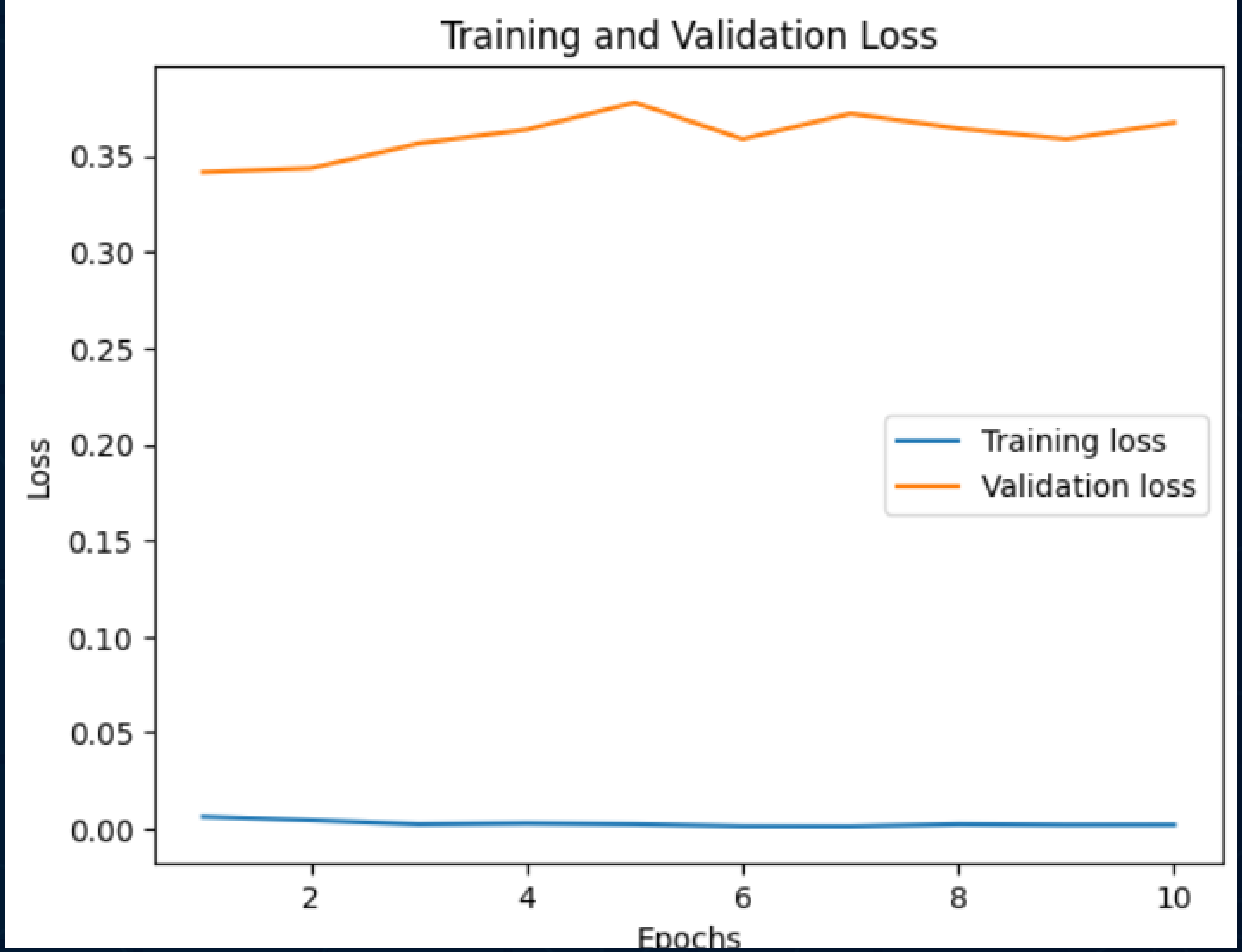


07 MODELS ACCURACY EFFICIENTNETV2B1

GAP BETWEEN TRAINING ACCURACY AND VALIDATION ACCURACY



GAP BETWEEN TRAINING LOSS AND VALIDATION LOSS

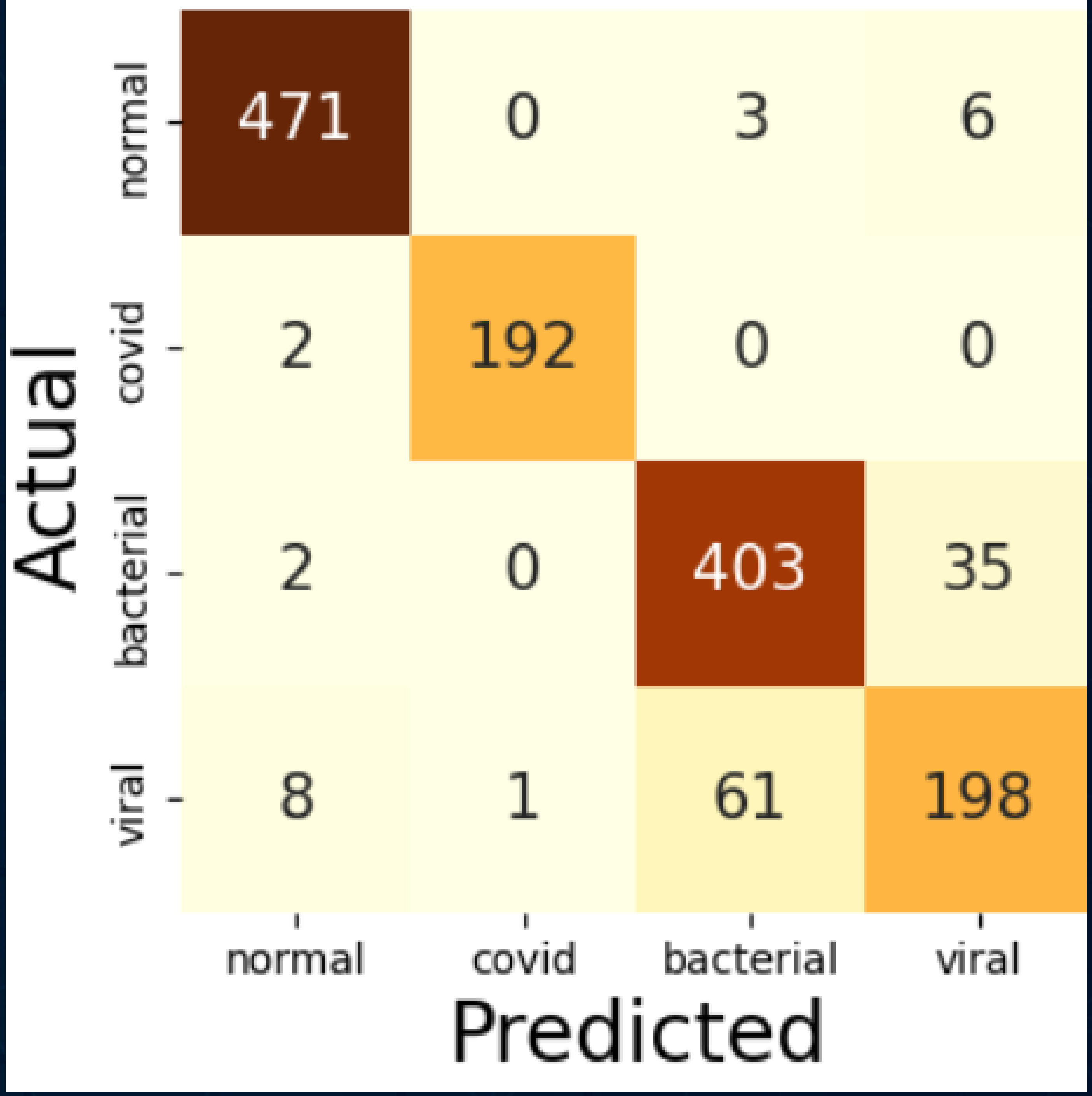


07 MODELS ACCURACY
EFFICIENTNETV2B1

CLASSIFICATION REPORT

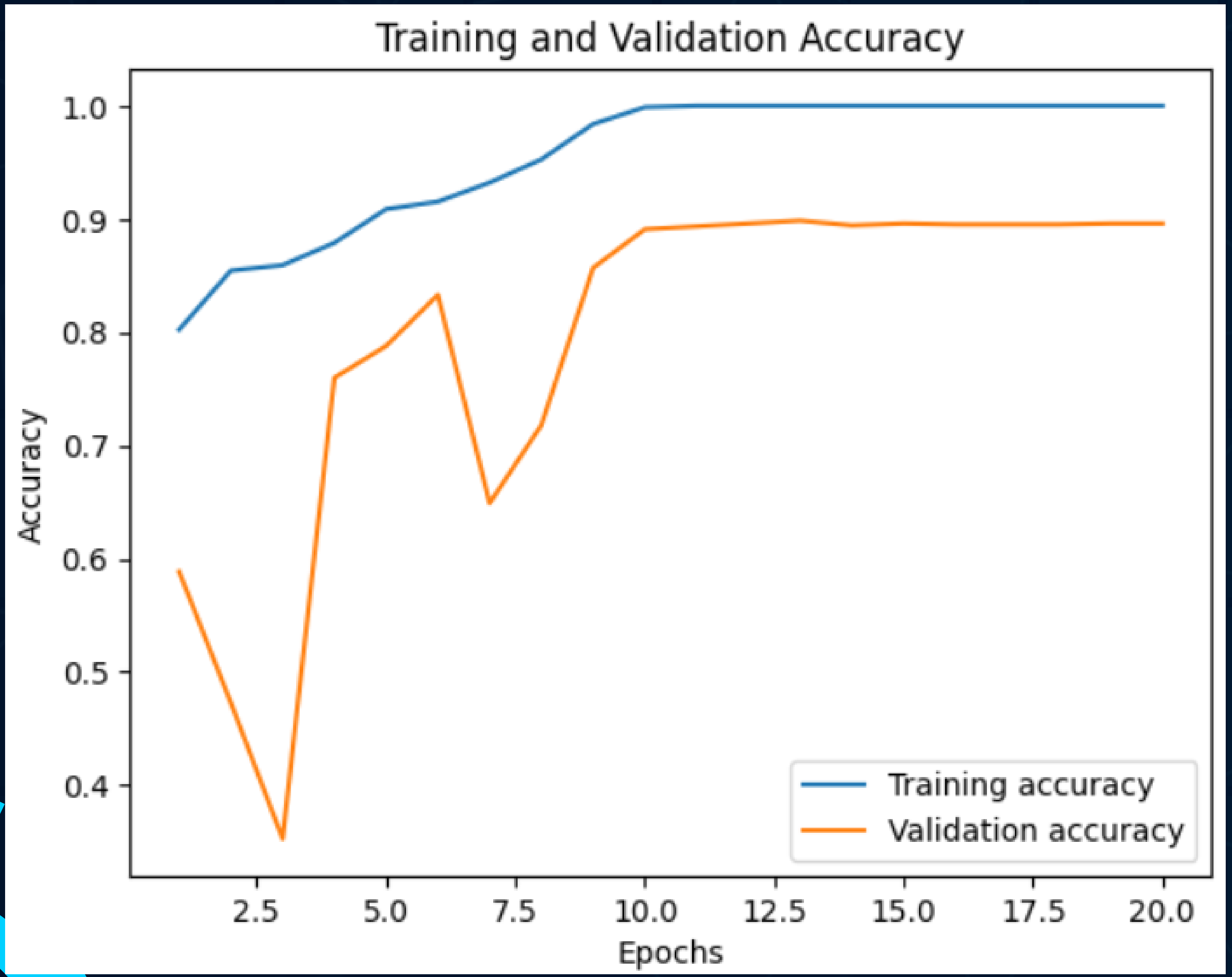
	precision	recall	f1-score	support
normal	0.9752	0.9812	0.9782	480
covid	0.9948	0.9897	0.9922	194
bacterial	0.8630	0.9159	0.8886	440
viral	0.8285	0.7388	0.7811	268
accuracy			0.9146	1382
macro avg	0.9153	0.9064	0.9100	1382
weighted avg	0.9137	0.9146	0.9134	1382

CONFUSION MATRIX

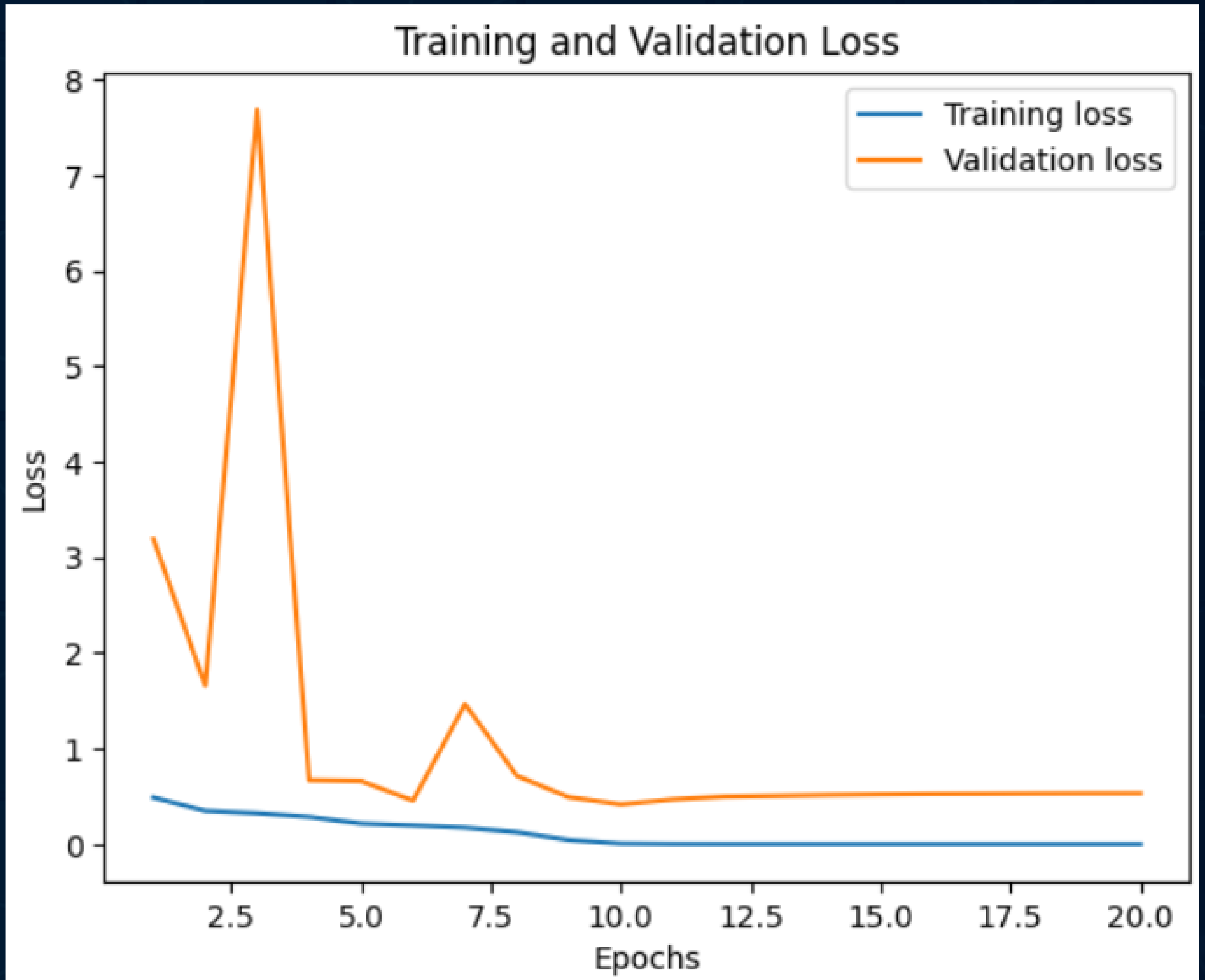


07 MODELS ACCURACY RESNET50V2

GAP BETWEEN TRAINING ACCURACY AND VALIDATION ACCURACY



GAP BETWEEN TRAINING LOSS AND VALIDATION LOSS

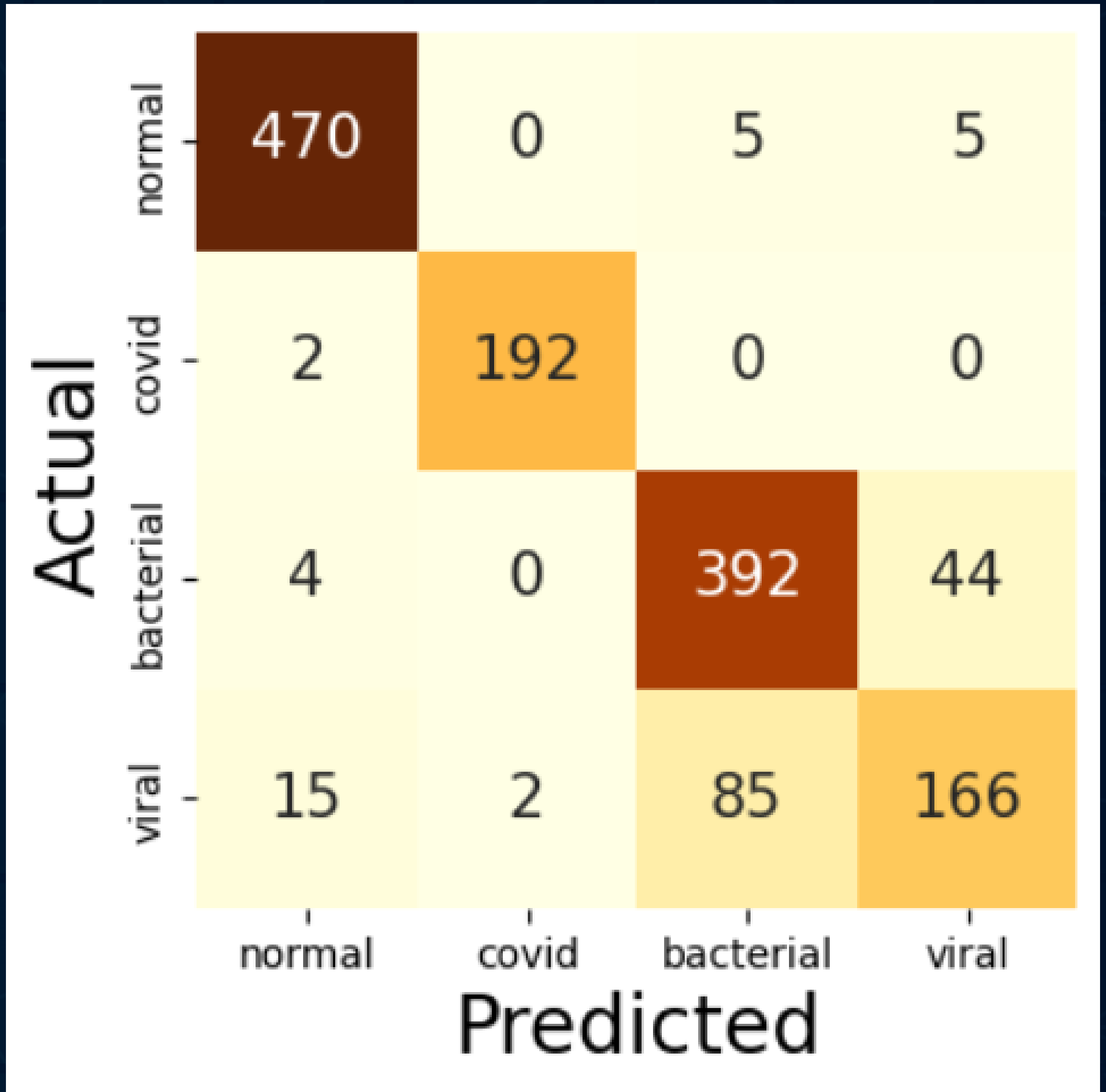


07 MODELS ACCURACY
RESNET50V2

CLASSIFICATION REPORT

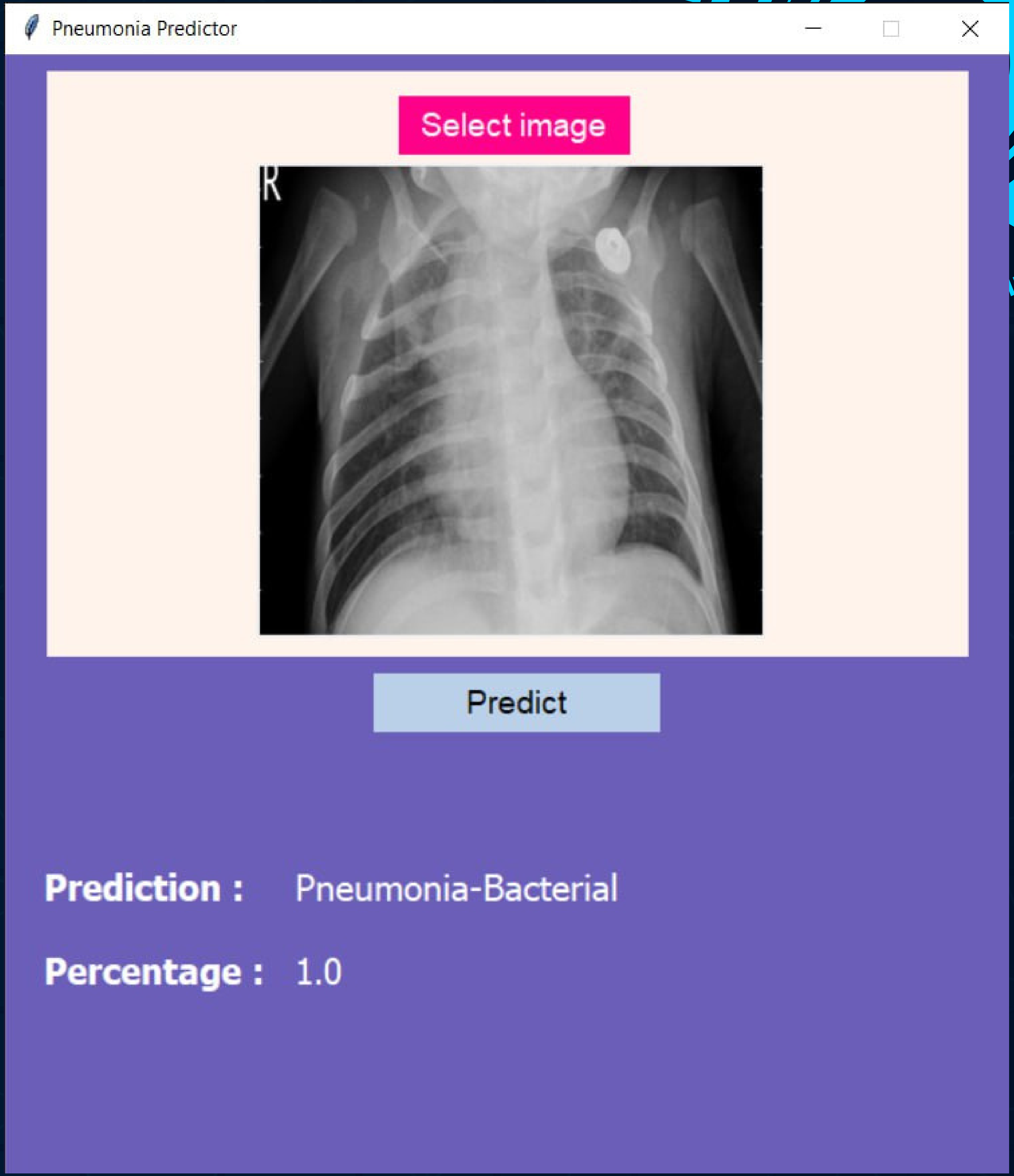
	precision	recall	f1-score	support
normal	0.9572	0.9792	0.9681	480
covid	0.9897	0.9897	0.9897	194
bacterial	0.8133	0.8909	0.8503	440
viral	0.7721	0.6194	0.6874	268
accuracy			0.8828	1382
macro avg	0.8831	0.8698	0.8739	1382
weighted avg	0.8801	0.8828	0.8792	1382

CONFUSION MATRIX



08

DEPLOYMENT



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THANKS!

Do you have questions?
Google it 😇