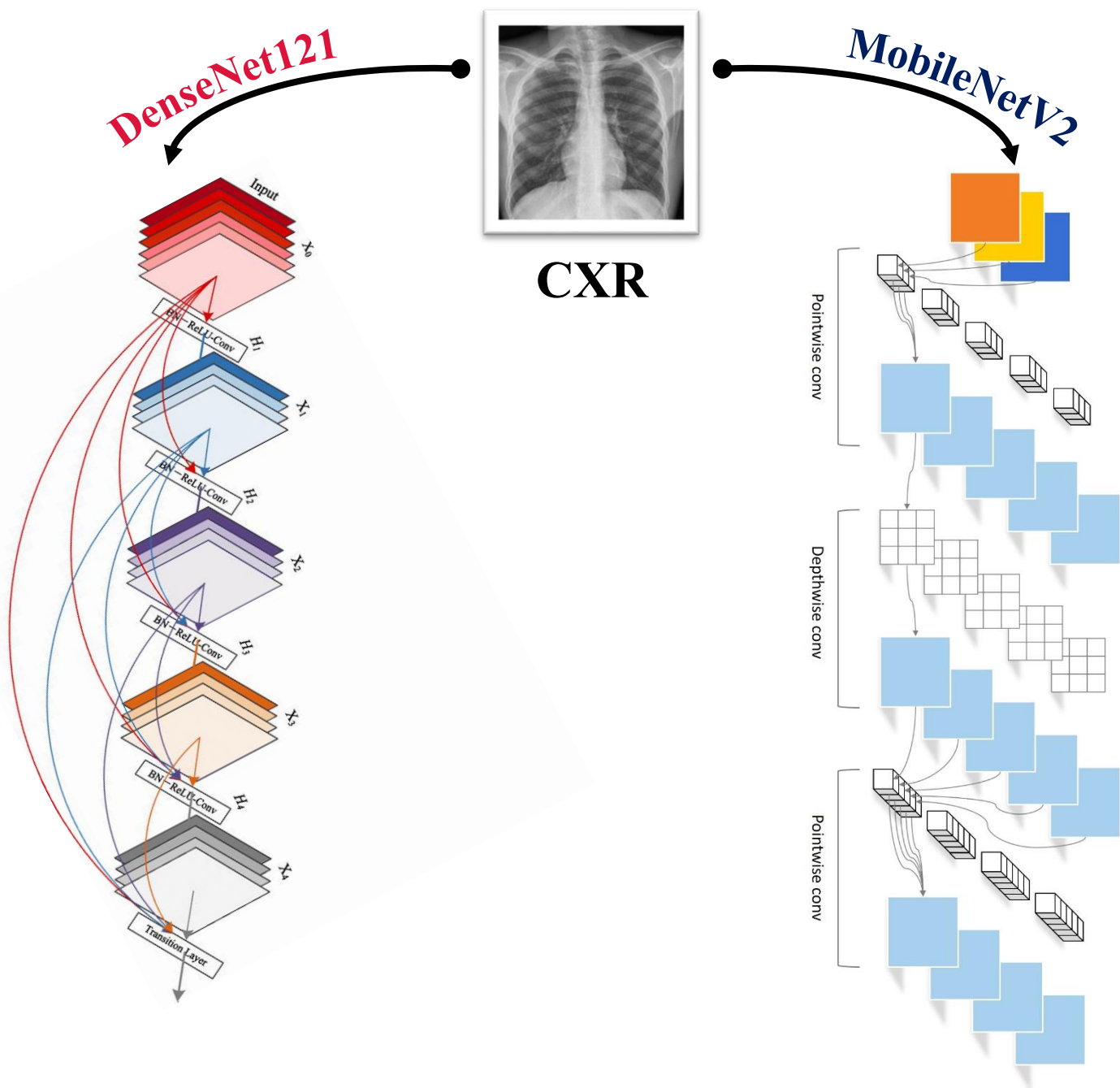


AI481 - AI for Medicine and Healthcare

Assignment 2:

CXR Classification using MobileNetV2 and DenseNet121



| Team Members

- **Hamza Sami Mohammad Alsawaftah**
 - **ID: 161395**
 - **Nidal Khaled Abdel Hameed Shahin**
 - **ID: 162278**
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| Abstract

In this assignment, we explore the application of **CNN-based** architectures, specifically: **MobileNetV2** and **DenseNet121**, to classify chest X-ray (CXR) images into three categories: **Normal**, **COVID-19**, and **Pneumonia**. Models were trained from scratch without pre-trained weights, identical training configurations and settings applied were adapted from the proposed reference of AlexNet implementation.

| Introduction

In respiratory diseases diagnosis, **CXR imaging** is **vital**. Machine and Deep Learning models, **Convolutional Neural Networks** (CNNs) in particular, were the core of automating these diagnoses. In this study, famous architectures like **MobileNetV2** and **DenseNet121** were used to classify chest X-ray images, following guidelines established in the provided GitHub AlexNet notebook [\[1\]](#).

| Method

- **Dataset:** Used **COVID-QU-Ex** dataset [2], balanced distribution and richer in images, compared to the proposed alternatives.
 - **Models:** **MobileNetV2** and **DenseNet121**, initialized with “**weights=None**”, fine-tuned their final layers for three output classes.
 - **Preprocessing:**
 - Images were **converted** from **grayscale** to **RGB**.
 - **Resized** to **(224x224)** to match the models’ architectures.
 - **Normalized** images using dataset-specific computed **mean** and **standard deviation** (std).
 - **Training Settings:**
 - **Optimizer:** Adam
 - **Learning rate:** 0.0001
 - **Batch size:** 32
 - **Epochs:** 10
 - **Loss function:** Cross Entropy Loss
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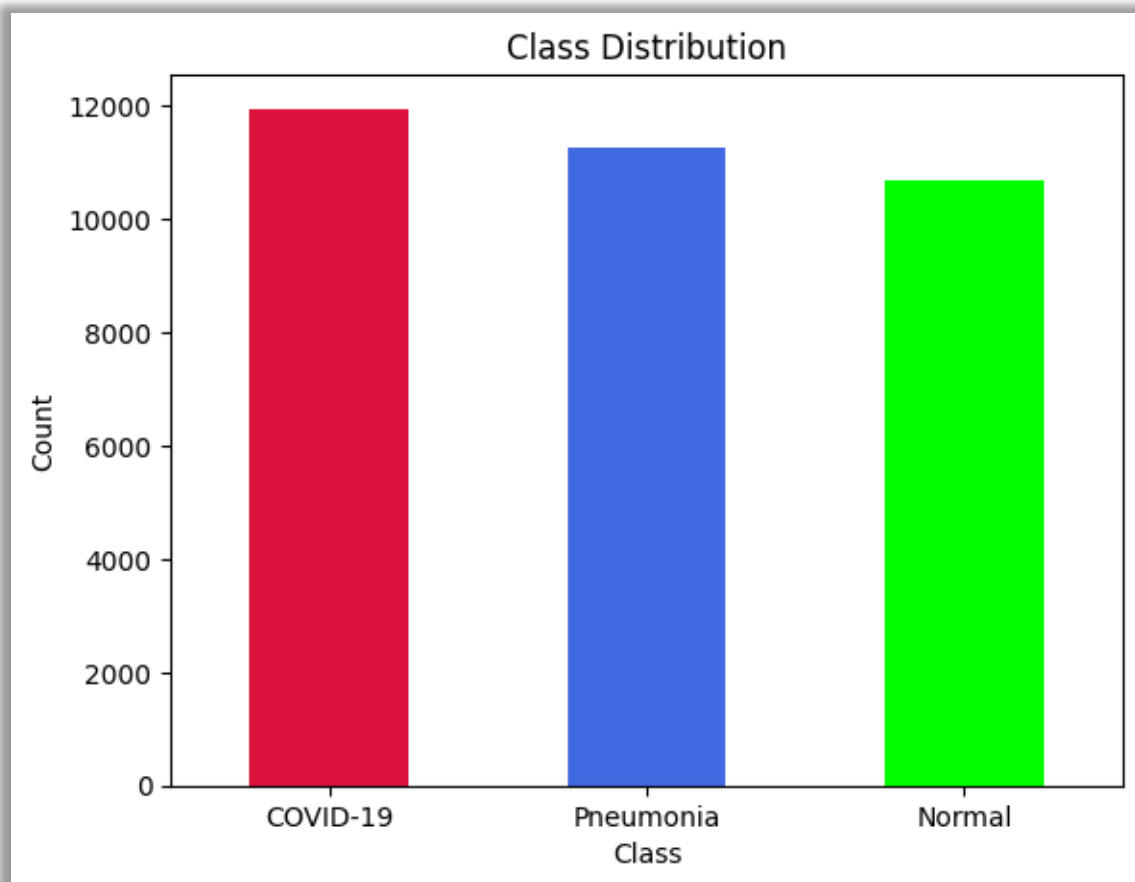
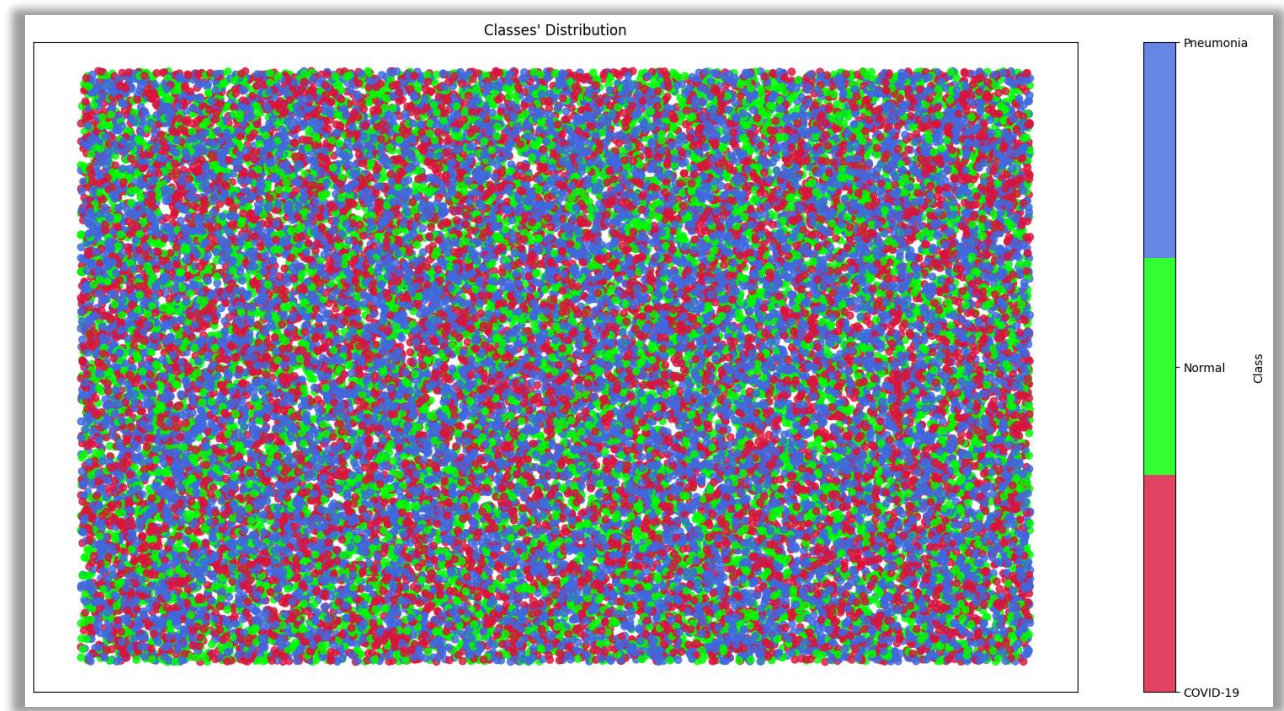
| Experiment

Trained both models **from scratch** using the configuration described above. After each epoch in training, **Validation** was performed to monitor the F1-Score and **save** the model with the best performance.

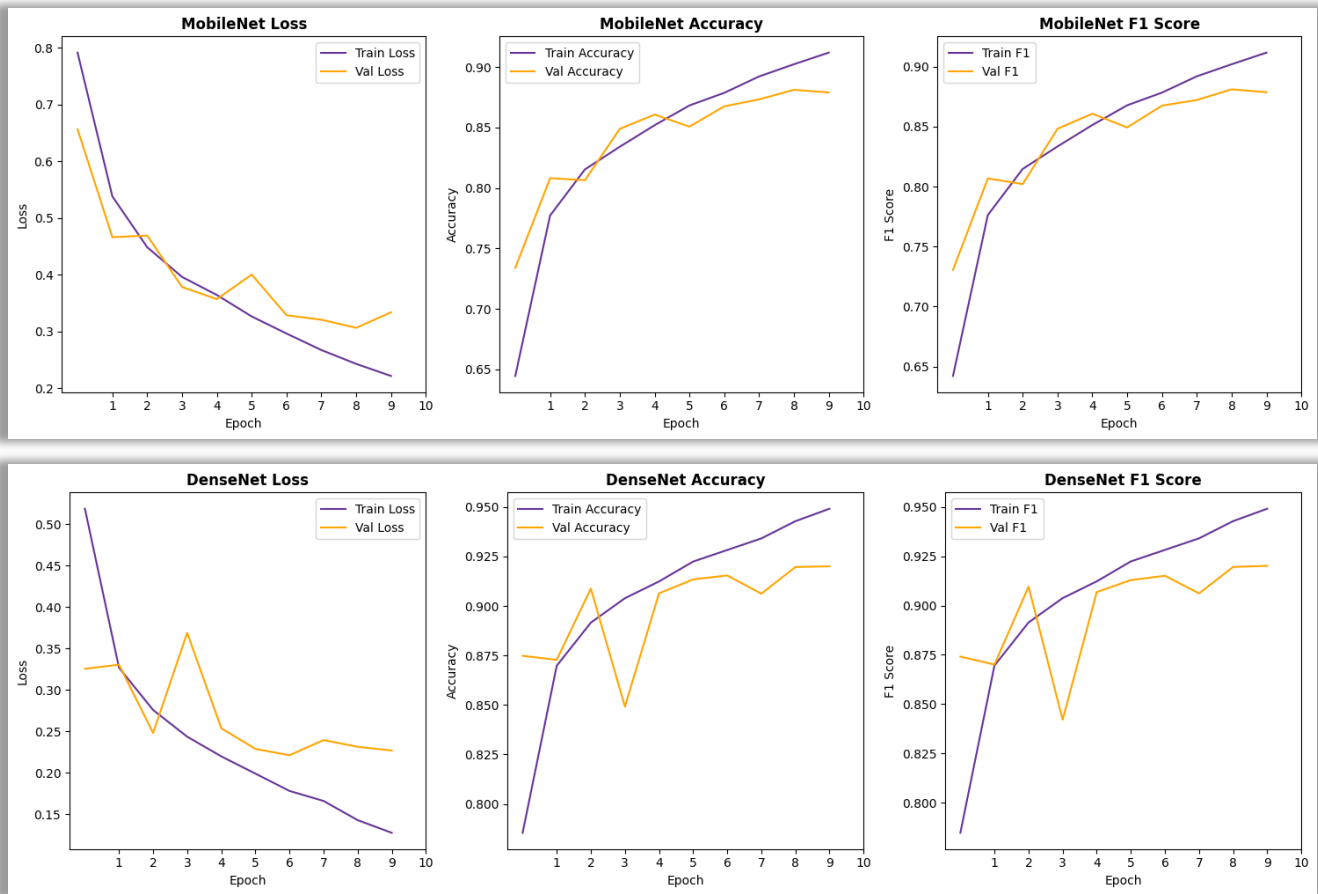
Evaluation (Testing) was done on a separate specialized **test set**, reporting both **macro** and **per-class** precision, recall, F1-Score, and accuracy for each model. Generated **plots** to compare training & validation loss, accuracy, and F1-Score trends. Confusion matrices and classification reports were also visualized.

| Results & Visuals

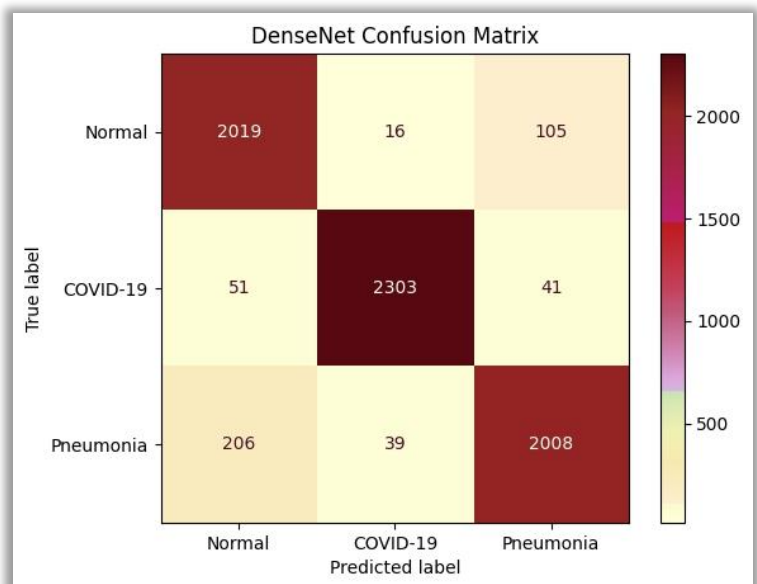
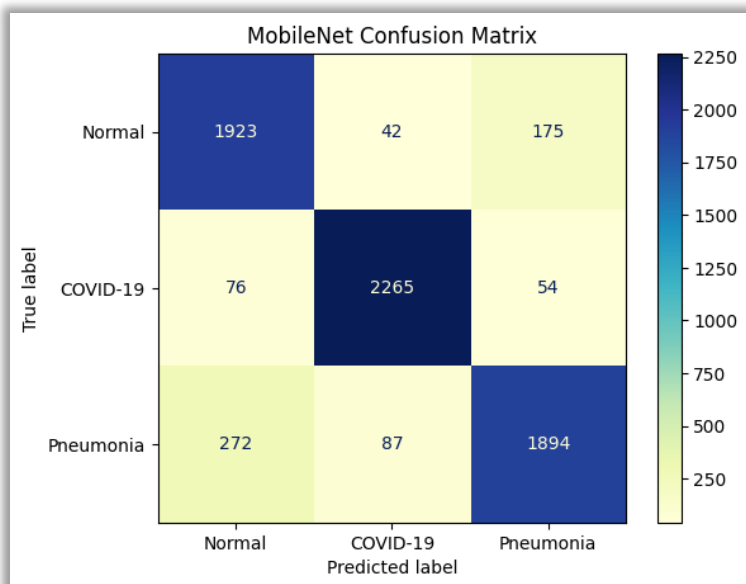
1st | Data distribution (class-wise) [3]



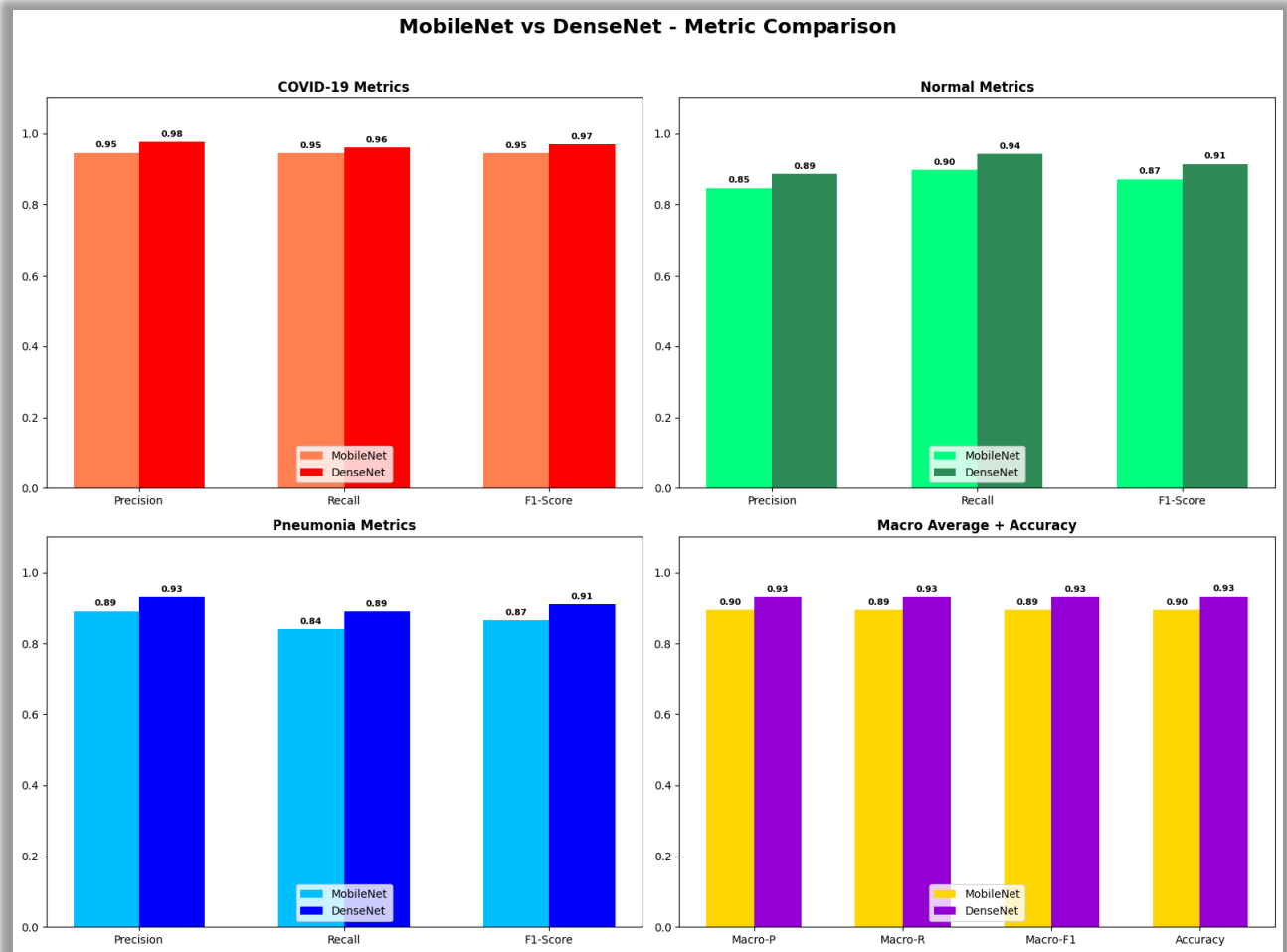
2nd| Training and Validation Trends [3]



3rd| Evaluation Confusion Matrices [3]



4th Evaluation Metrics Visual [3]



5th Evaluation Metrics as a Table

Model	Class	Precision	Recall	F1	Accuracy
MobileNetV2	Macro Avg	0.90	0.89	0.89	0.90
	Normal	0.85	0.90	0.87	-
	COVID-19	0.95	0.95	0.95	-
	Pneumonia	0.89	0.84	0.87	-
DenseNet121	Macro Avg	0.93	0.93	0.93	0.93
	Normal	0.89	0.94	0.91	-
	COVID-19	0.98	0.96	0.97	-
	Pneumonia	0.93	0.89	0.91	-

| Discussion

MobileNetV2 and **DenseNet121** both were effective for CXR classification under this constrained setup [1]. **DenseNet's** with its **deeper** architecture captured finer & more complex details, thus had **better F1-scores**, especially for **COVID-19** cases. **MobileNetV2**, being **lightweight**, had **3x faster** training time **but** slightly **lower** predictive performance.

Batch size (32) and epochs (10) ensured a feasible computation without sacrificing the models' abilities.

| Conclusion

Even when trained from **scratch**, both **MobileNetV2** and **DenseNet121** showed **promising results** for the detection of respiratory disease under the given configuration. **DenseNet121** was the **superior** model in terms of overall **classification performance**, **MobileNetV2** also demonstrated strong potential for supporting medical decisions.

| References

[1] Roshan Sadath, "Medical-Image-Diagnosis-using-Convolutional-Neural-Networks" ([GitHub Link](#))

[2] COVID-QU-Ex ([dataset source link](#))

[3] Notebook ([Google Collaboratory](#)), Run-Ready with all requirements ([Kaggle Environment](#))