



# **CHEST X-RAY CLASSIFICATION USING CONVOLUTIONAL NEURAL NETWORKS**

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# INTRODUCTION

- Chest X-ray imaging plays a crucial role in the diagnosis of respiratory diseases such as COVID-19 and Pneumonia. However, visual similarities between different pulmonary conditions often make manual diagnosis challenging.
- This project focuses on designing a **custom Convolutional Neural Network (CNN)** to automatically classify chest X-ray images into **COVID-19, Normal, and Pneumonia** categories.
- The emphasis of this work is not only on achieving high accuracy, but also on maintaining **balanced class-wise performance** and **good generalization**, which are essential for medical imaging applications.

# APPROACH

## Dataset preparation and augmentation:

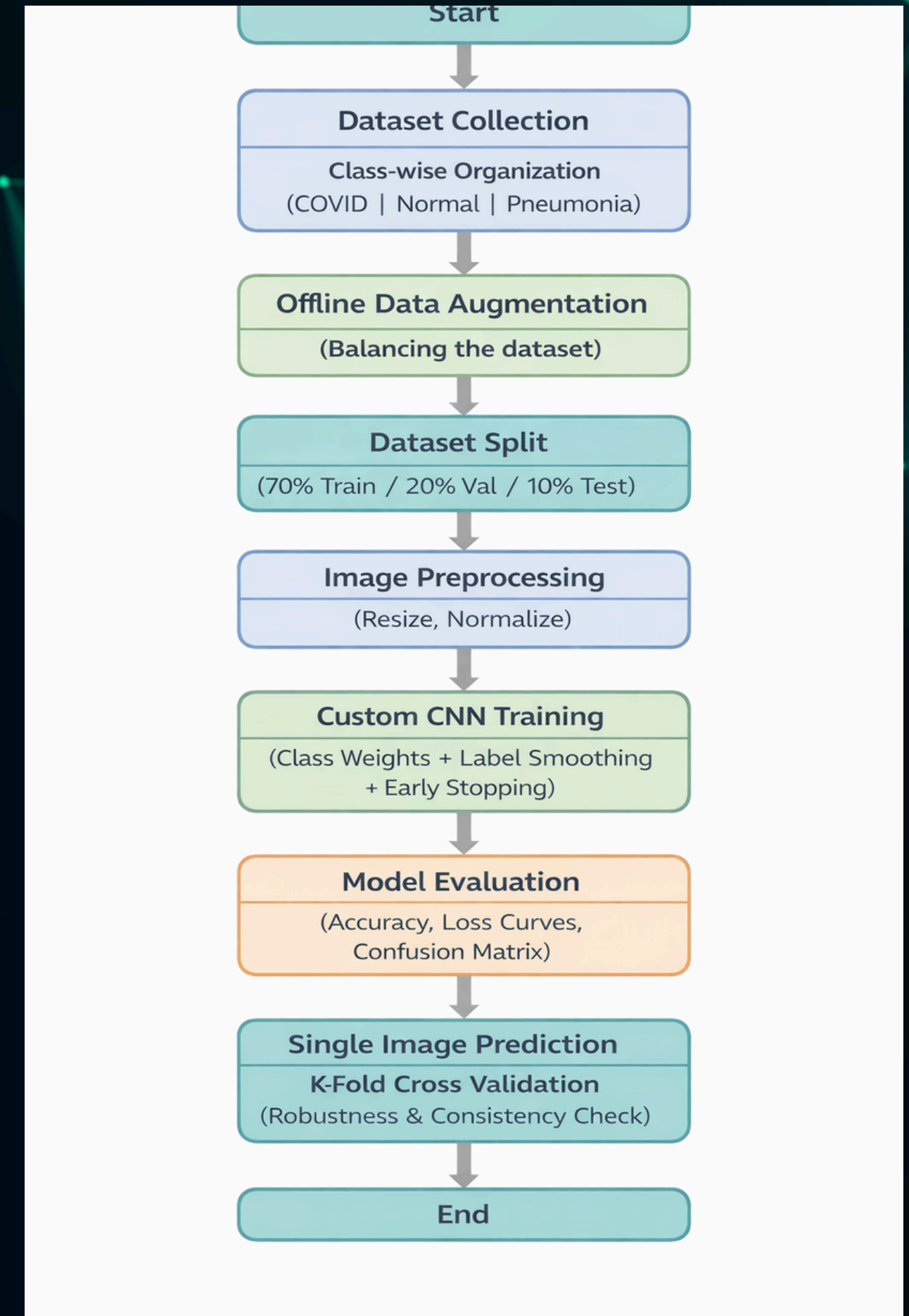
The chest X-ray dataset was organized into class-wise directories and split into training, validation, and test sets (70:20:10). Offline data augmentation was applied once to balance the dataset.

## Efficient data loading:

Image data generators were used to resize, normalize, and load images efficiently during model training and evaluation.

## Model training and evaluation:

A lightweight CNN was trained using class-weighted loss, label smoothing, and early stopping. Model performance was evaluated using accuracy, loss curves, confusion matrices, single-image inference, and 5-Fold cross validation to assess robustness.





# MODEL ARCHITECTURE

- Defined a Sequential CNN architecture.
- Added a first convolutional layer with 16 filters ( $3 \times 3$ ), ReLU activation, and same padding.
- Applied a MaxPooling layer ( $2 \times 2$ ) to reduce spatial dimensions.
- Added a second convolutional layer with 32 filters ( $3 \times 3$ ), ReLU activation, and same padding.
- Applied another MaxPooling layer ( $2 \times 2$ ).
- Flattened the extracted feature maps using a Flatten layer.
- Added a fully connected Dense layer with 128 neurons and ReLU activation.
- Applied Dropout (0.2) to reduce overfitting.
- Added an output Dense layer with Softmax activation for three-class classification.
- Compiled the model using the Adam optimizer, categorical cross-entropy loss with label smoothing, and accuracy as the evaluation metric.

# AUGMENTATION

**Train Validation Test ratio split:**

70:20:10

**Size of augmented dataset:**

```
Augmented dataset already exists. Skipping augmentation.  
Dataset split complete (70 / 20 / 10)  
Found 4346 images belonging to 3 classes.  
Found 1241 images belonging to 3 classes.  
Found 623 images belonging to 3 classes.
```

**Operation used to perform the augmentation:**

- Slight zooming in and out
- Minor brightness adjustments
- Heavy transformations such as large rotations or flips were avoided to preserve medical relevance.

# CODE

**Contains the code for training and testing the model:**

[https://github.com/smrutichan/Chest\\_XRay\\_CNN\\_Classification/blob/main/train\\_model.py](https://github.com/smrutichan/Chest_XRay_CNN_Classification/blob/main/train_model.py)

**Contains the code for creating a seperate directory to create and save augmented images:**

[https://github.com/smrutichan/Chest\\_XRay\\_CNN\\_Classification/blob/main/augmentor.py](https://github.com/smrutichan/Chest_XRay_CNN_Classification/blob/main/augmentor.py)

**Contains the code for K-Fold cross validation:**

[https://github.com/smrutichan/Chest\\_XRay\\_CNN\\_Classification/blob/main/kfold\\_cross\\_validation.py](https://github.com/smrutichan/Chest_XRay_CNN_Classification/blob/main/kfold_cross_validation.py)

# OUTPUT

## Number of parameters:

Model: "sequential"

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 48, 48, 16)	448
max_pooling2d (MaxPooling2D)	(None, 24, 24, 16)	0
conv2d_1 (Conv2D)	(None, 24, 24, 32)	4,640
max_pooling2d_1 (MaxPooling2D)	(None, 12, 12, 32)	0
flatten (Flatten)	(None, 4608)	0
dense (Dense)	(None, 128)	589,952
dense_1 (Dense)	(None, 3)	387

Total params: 595,427 (2.27 MB)  
Trainable params: 595,427 (2.27 MB)  
Non-trainable params: 0 (0.00 B)

## For training and testing accuracies:

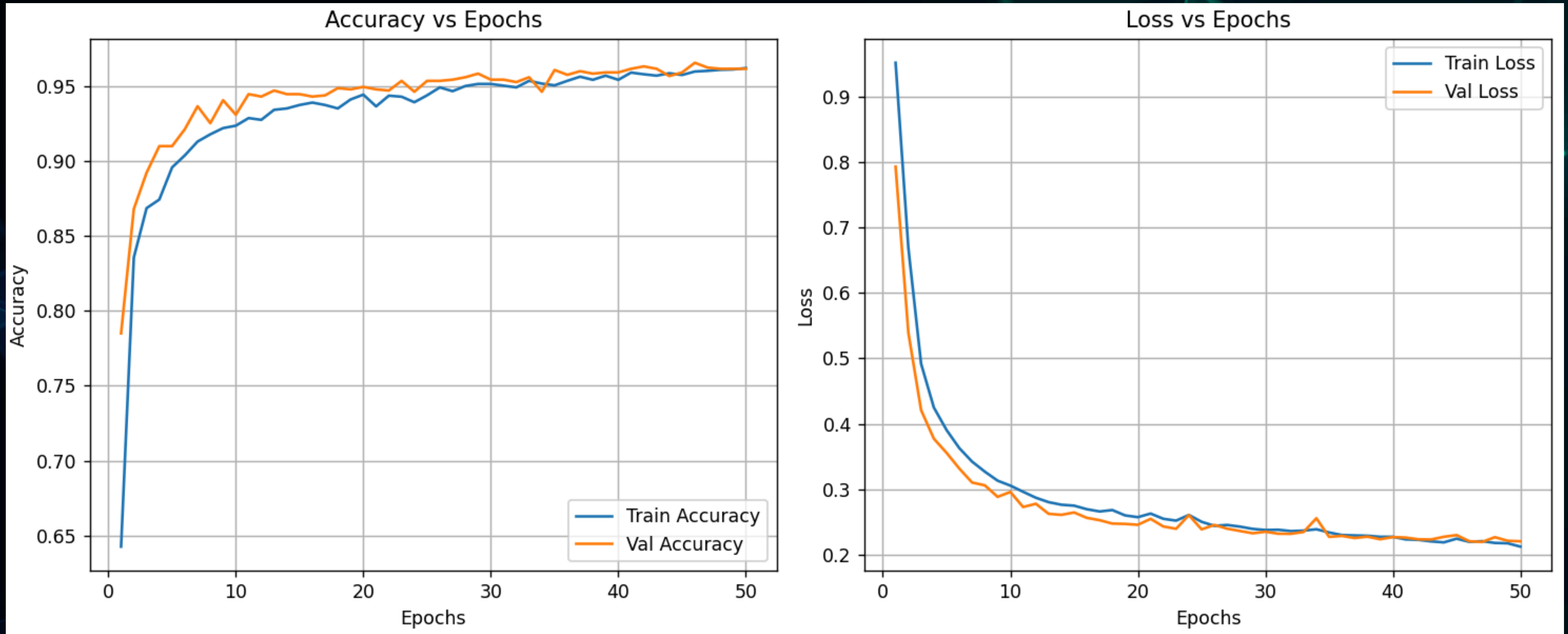
```
===== TRAINING SUMMARY =====  
Total Training Time      : 350.36 seconds  
Final Training Accuracy  : 0.9613  
Final Validation Accuracy: 0.9662  
Test Accuracy            : 0.9551  
=====
```

Model saved successfully.



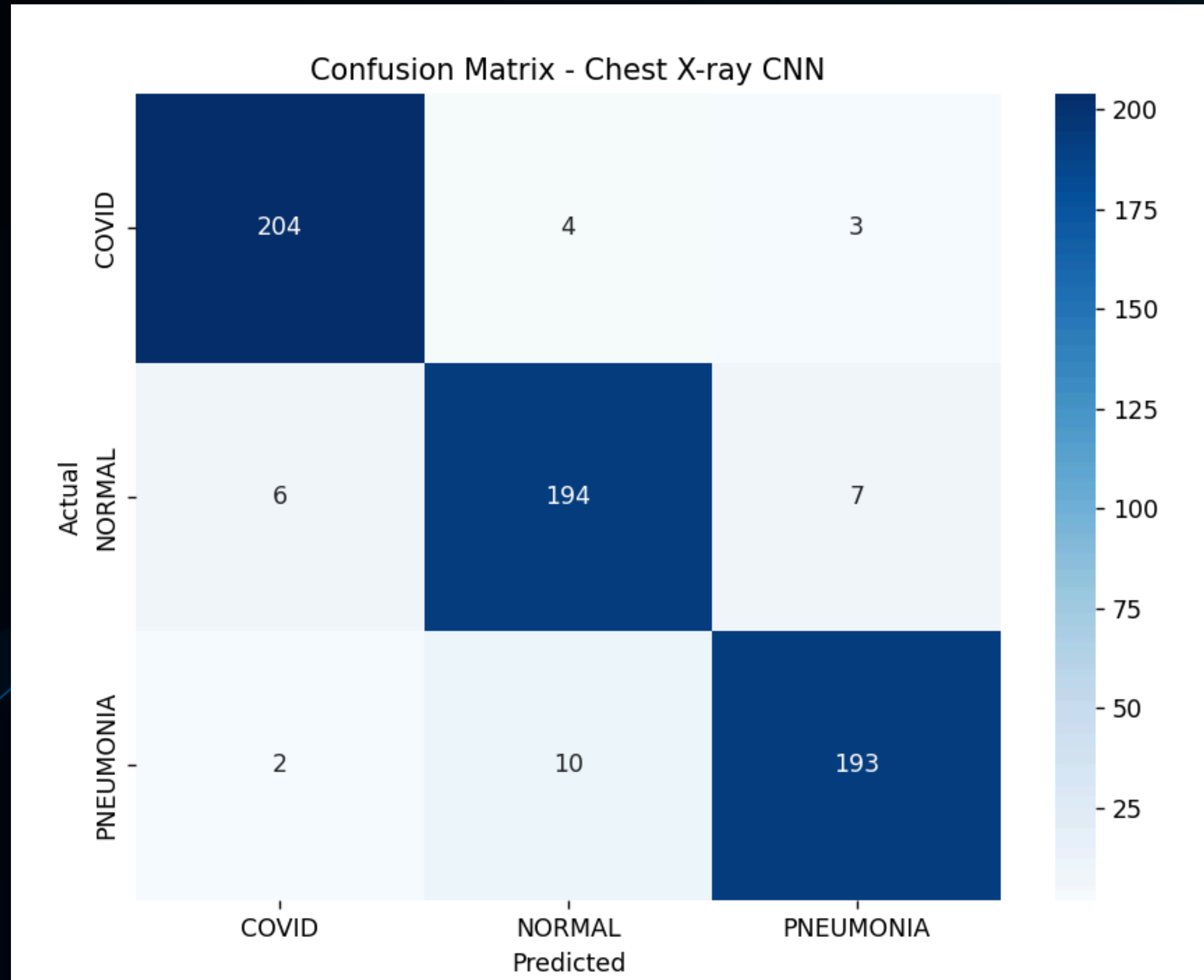
# OUTPUT

Accuracy vs Loss graph:





# CONFUSION MATRIX



# OUTPUT:

## K-Fold Cross Validation accuracy:

===== K-FOLD RESULTS =====

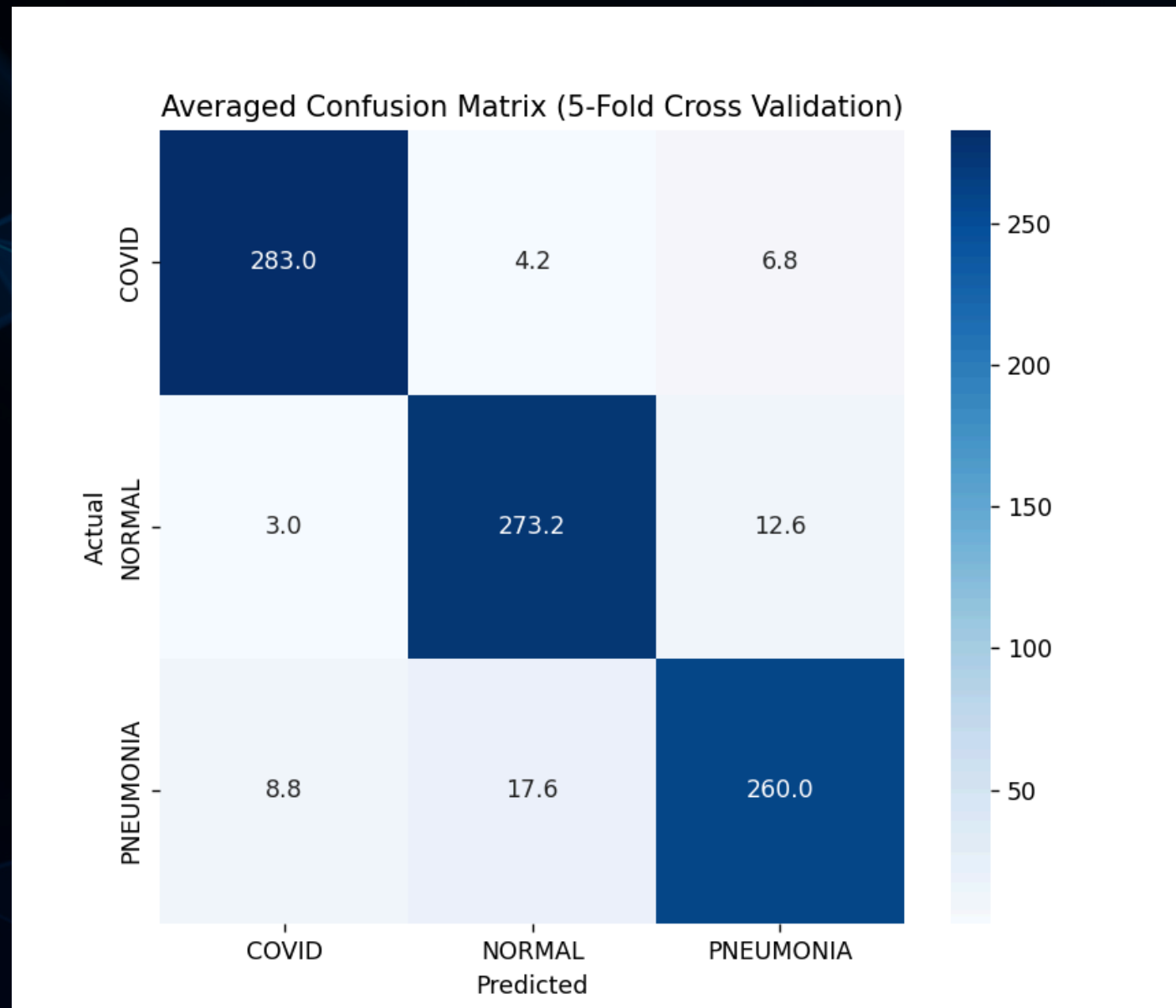
Fold Accuracies: [0.9471264481544495, 0.9436133503913879, 0.9459148645401001, 0.9367088675498962, 0.9298043847084045]

Mean Accuracy : 0.9406

Standard Deviation : 0.0065

=====

## Confusion Matrix for K-fold cross validation:



# INFERENCE:

- Offline data augmentation improved class balance and reduced overfitting.
- Label smoothing improved generalization and test accuracy.
- Class-weighted loss prevented class dominance.
- K-Fold cross validation confirmed the robustness of the model.
- Some confusion between Normal and Pneumonia remains due to intrinsic visual similarities.
- Low-resolution images limited further accuracy improvements without using pretrained models.

# CONCLUSION:

- A custom CNN can effectively classify chest X-ray images into COVID-19, Normal, and Pneumonia categories.
- Balanced data handling and loss function tuning significantly improved model robustness.
- Label smoothing and class-weighted loss enhanced generalization without increasing training time.
- The final model demonstrated strong performance on unseen test data.



The background features a dark navy blue field with abstract, glowing wireframe structures. On the left, a complex, multi-faceted teal wireframe shape is prominent. On the right, a more elongated, angular blue wireframe structure is visible. The overall aesthetic is modern and technological.

**THANK YOU**