# COVID AFFECTED LUNG SEGMENTATION AND CLASSIFICATION USING CT SCAN IMAGES

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# PROBLEM STATEMENT

- **This project is focused on developing a model that will segment the lung and infection from the CT scan images of chest and further defining a model that can classify the images as covid positive or negative.**

# MOTIVATION

## Problems faced by patients

- The laboratory tests sometime needs transportation from the hospital to lab after collecting samples, which consumes a significant amount of time.

- Accurate and early detection of covid may lead to successful treatment and prevention of mortality among patients.

## Solutions to above problems

- In order to aid the radiologist in reading CT scan images, a computer aided tool is being proposed in this study so that, the developed model can then be used in classifying and segmenting the lung and infection successfully.
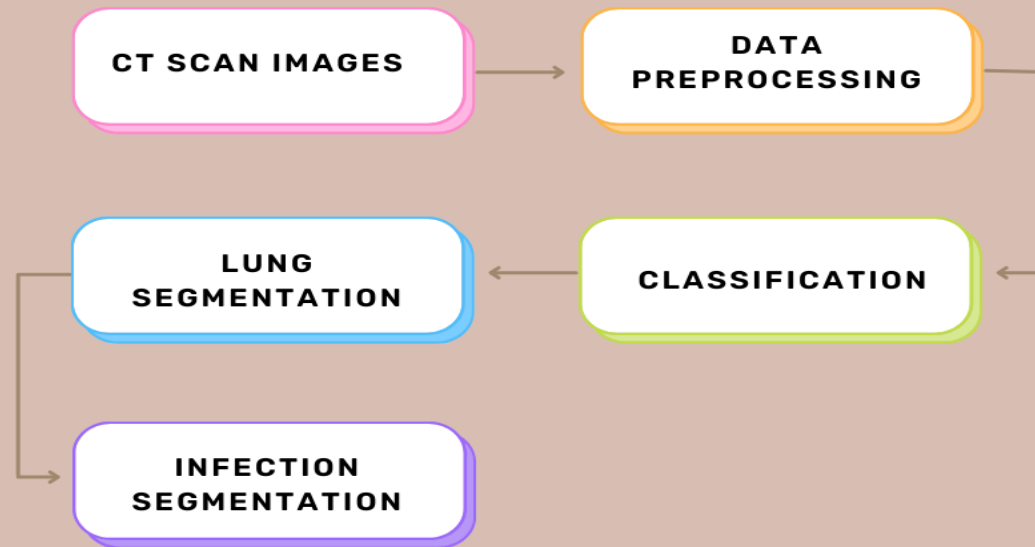
# METHODOLOGY



Figure 1: Workflow diagram

# DATA SET

## Kaggle Dataset – Chest CT Scan Images

- The dataset [9] contains 20 CT scans of patients diagnosed with COVID-19 as well as segmentations of lungs and infections made by experts.
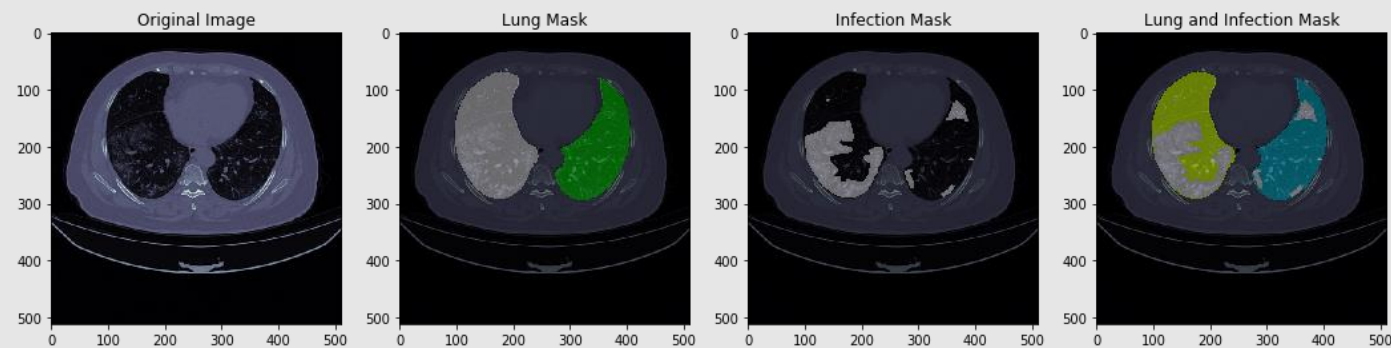


Figure 2: Dataset Collection

# DATA PREPROCESSING

The data pre-processing step includes :

❑ Contrast enhancement

    i.    Using CLAHE (Contrast Limited Adaptive Histogram Equalization) algorithm.

# DATA PREPROCESSING
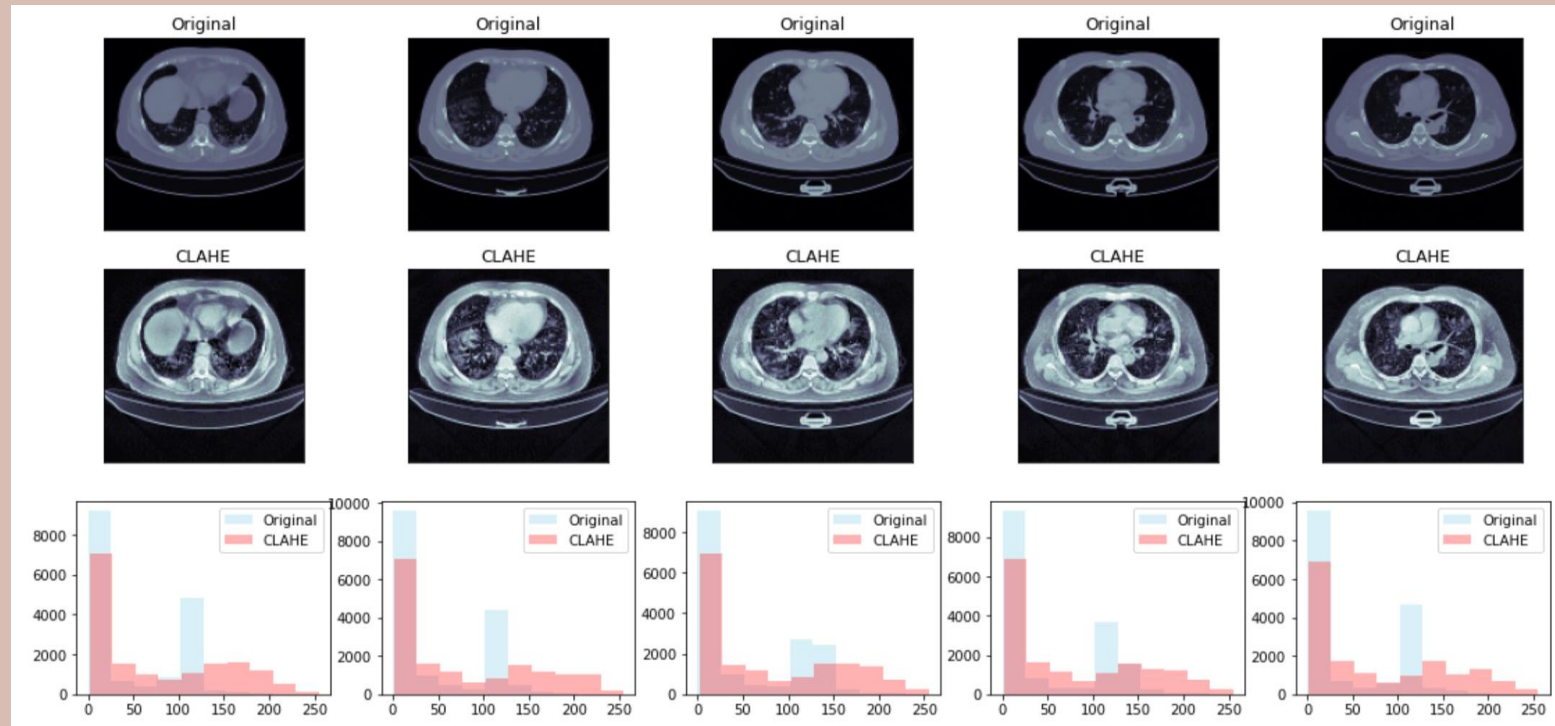


Figure 3: CLAHE Contrast enhancements

# DATA PREPROCESSING

The data pre-processing step includes :

❑ Contrast enhancement

    i.    Using CLAHE (Contrast Limited Adaptive Histogram Equalization) algorithm.

❑ Cropping the CT-scan images such that they focus only on the lung part.

    i.    Firstly we have binarized the image and then performed bio-medical imaging techniques such as erosion and dilation.

    i.    Then we have used K-means to find the clusters and drew bound box around it and then cropped the image.
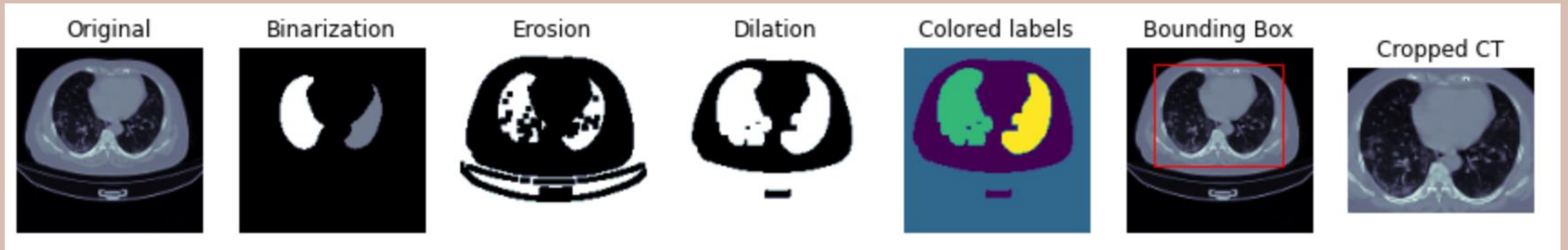
# DATA PREPROCESSING



Figure 4: Dataset cropping process
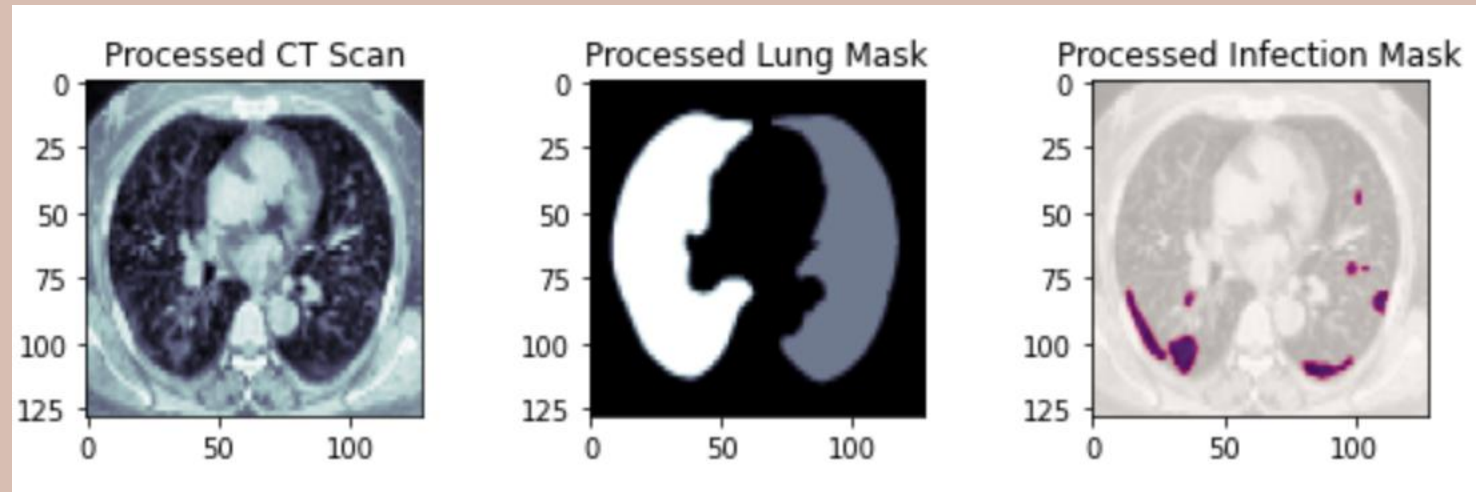
# DATA PREPROCESSING



Figure 5: Final preprocessed dataset

# CLASSIFICATION

❑ The pre-processed 2D CT-scans are labeled as Covid-19 positive or negative based on their infection masks.

❑ The labeled dataset is then used to train a CNN model which gives a value between 0 and 1. Threshold is decided using ROC curve and the prediction is converted to binary values.

# CLASSIFICATION

We have defined a 2D convolutional neural network (CNN) model using the Keras API.

❑ **Input layer:** Takes input images with shape (128, 128, 1) where 1 represents a single grayscale channel.

❑ **Convolutional layers:** The model has four convolutional layers, each followed by a max pooling layer and batch normalization layer. The convolutional layers have 64, 64, 128, and 256 filters, respectively, and use a 3x3 kernel. The activation function used for each convolutional layer is Rectified Linear Unit (ReLU).

❑ **Global Average Pooling layer:** This layer takes the output of the last convolutional layer and calculates the average value for each feature map.

# CLASSIFICATION

❑ **Dense layers:** The output of the global average pooling layer is connected to a dense layer with 512 units and the activation function is ReLU. A dropout layer with a dropout rate of 0.3 is then applied to help prevent overfitting.

❑ **Output layer:** The final dense layer has a single output unit with a sigmoid activation function. This is because the model is designed to perform binary classification, where the output represents the probability that an image belongs to a certain class.
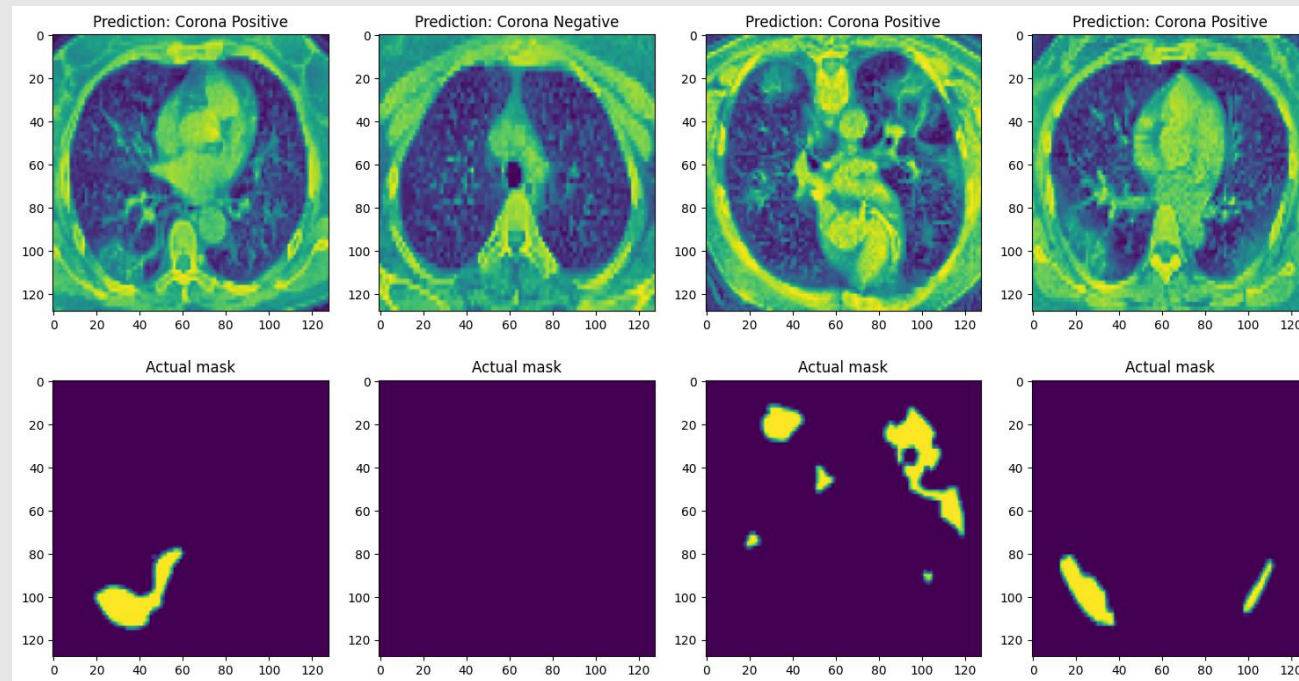
# CLASSIFICATION



Figure 7: Covid Infected Classification Result

# LUNG SEGMENTATION

❑ The pre-processed 2D CT-scans and the lung masks are used to train a CNN model which marks the lung area in the ct-scans. A **U-net architecture** is implemented for this task.

❑ The first layer is the input layer, which takes in the 128x128 grayscale image. The input is then passed through four convolutional layers. Each convolutional layer applies a set of filters to the input image and applies an activation function (ReLU) to the output. The first convolutional layer has 16 filters, the second has 32, the third has 128, and the fourth has 256.

❑ After each convolutional layer, a max pooling layer is applied, which reduces the dimensionality of the feature maps output by the convolutional layer.

❑ After the fourth convolutional layer, a dense layer with 256 neurons and a ReLU activation function is applied to further process the output.

# LUNG SEGMENTATION

❑ The output is then passed through three up-sampling layers, each followed by a convolutional layer. The up-sampling layers increase the size of the feature maps and the convolutional layers apply a sigmoid activation function to generate the lung segmentation output. The final convolutional layer has a single filter to identify the lungs in the input image.
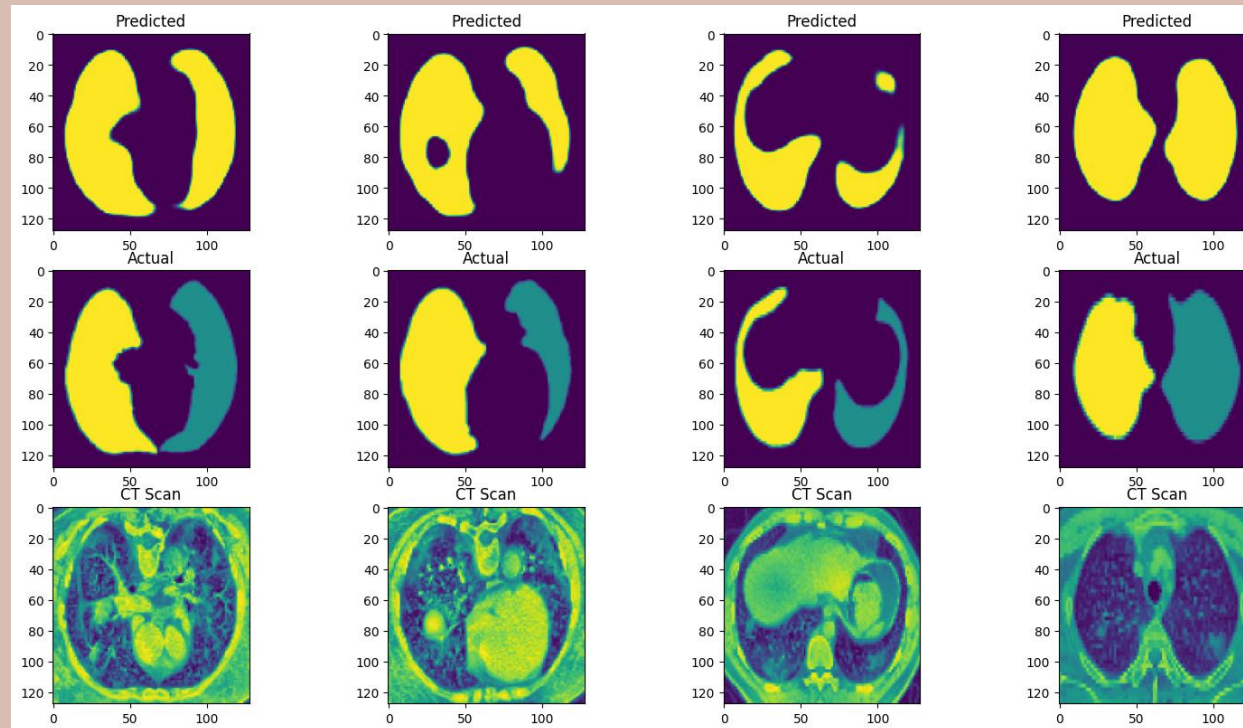
# LUNG SEGMENTATION



Figure 9: Lung Segmentation

# INFECTION SEGMENTATION

❑ The infection segmentation function defines a UNet model for lung infection segmentation using CT scan images.

❑ The model consists of four encoding blocks and four decoding blocks. Each encoding block has two convolutional layers followed by batch normalization, ReLU activation, max pooling, and dropout layers.

❑ The output of each encoding block is concatenated with the output of the corresponding decoding block before passing it to the next decoding block. Each decoding block has a transposed convolutional layer, followed by two convolutional layers with batch normalization and ReLU activation.

❑ The final layer is a 1x1 convolutional layer with sigmoid activation, which outputs the segmentation mask.
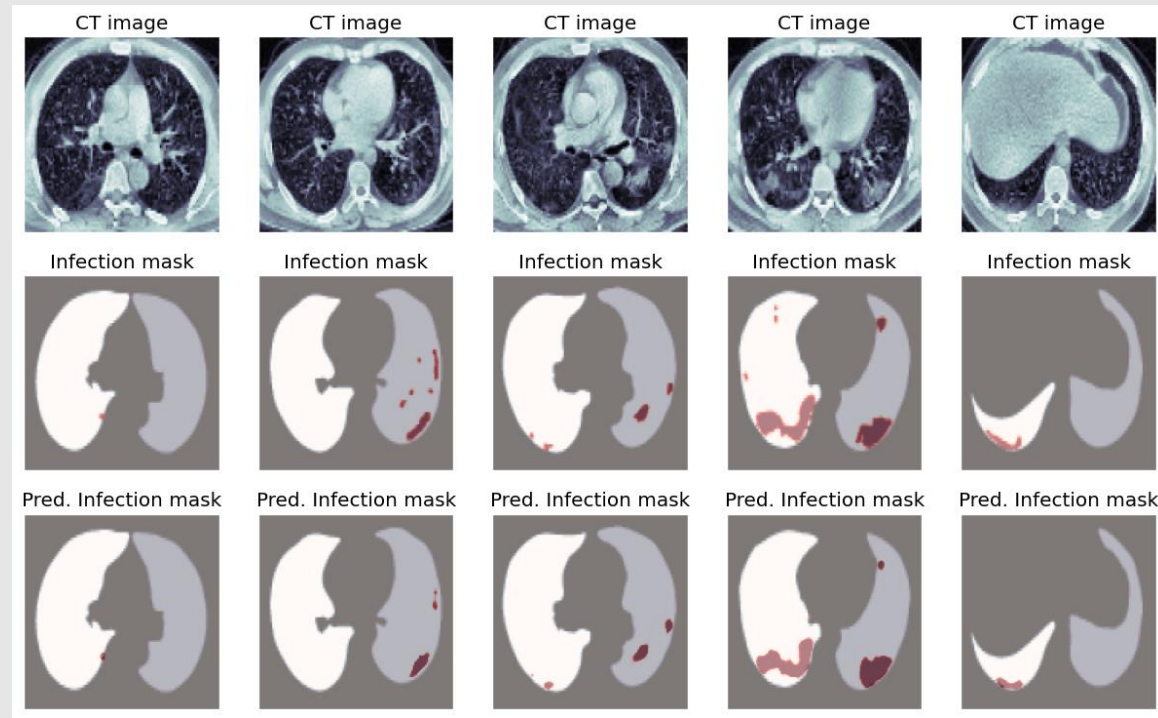
# INFECTION SEGMENTATION



Figure 11: Infection Segmentation output

# RESULT & DISCUSSION

❑ After preprocessing we have classified the data into covid positive and covid negative based on the 2D CNN model.
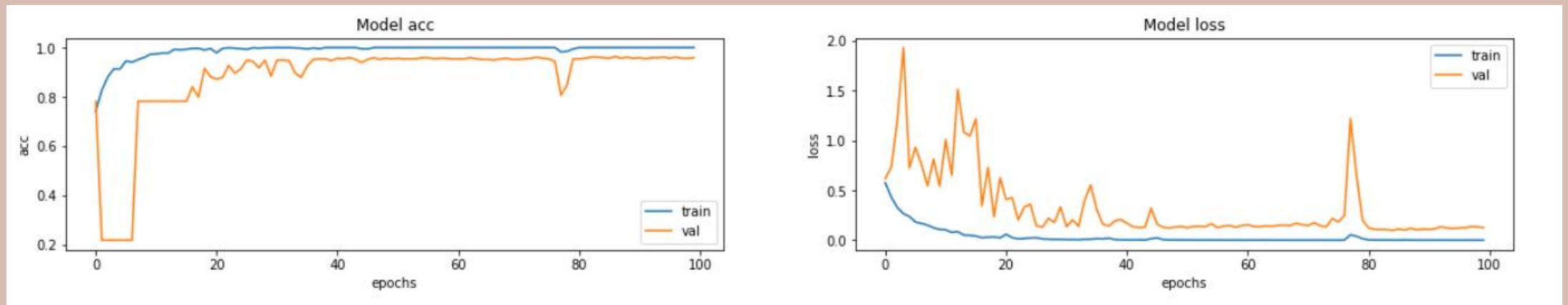


Figure 12: Classification Model accuracy and loss curve

# RESULT & DISCUSSION

❑ In the next step we have segmented the lung image using the UNet architecture with dice-coefficient of 0.8370 and validation-dice-coefficient of 0.8297.
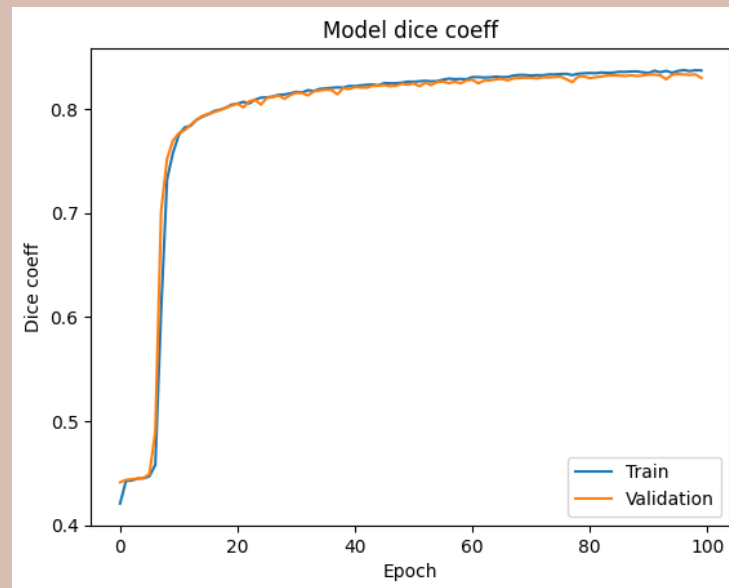


Figure 13: Lung Segmentation Model Dice coefficient

# RESULT & DISCUSSION

❑ In the last step we have segmented the infection using UNet architecture achieving a dice-coefficient of 0.8238 and validation-dice-coefficient 0.7622.
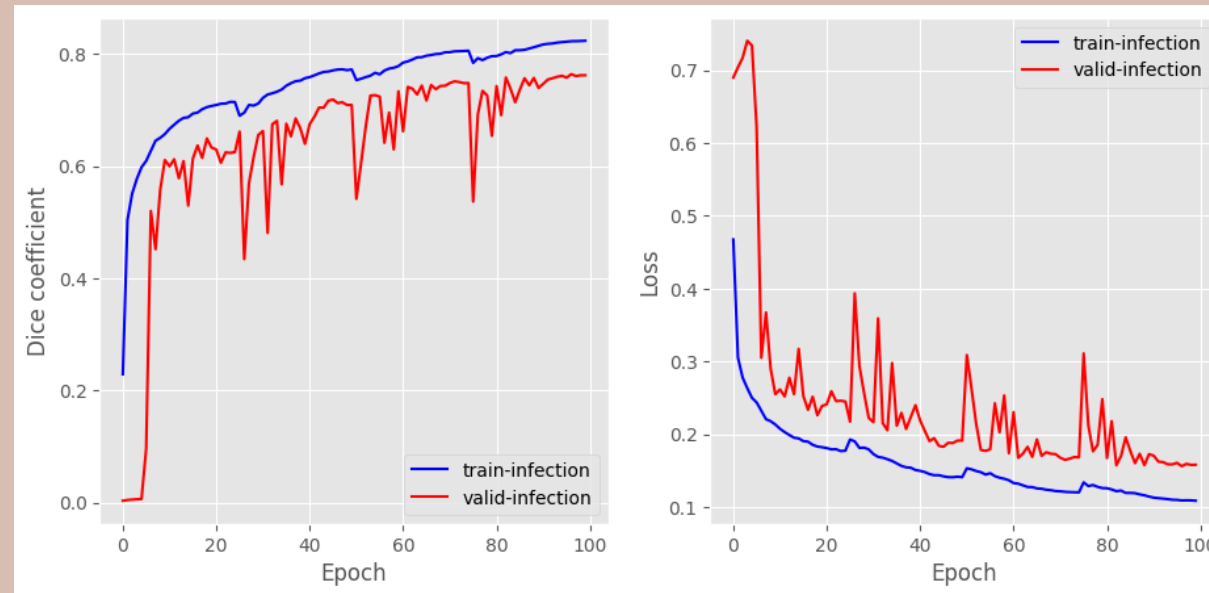


Figure 14: Infection Segmentation Model Dice Coefficient and Loss

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# THANK YOU