## **Detection of Covid Positive Cases using Image Processing**

## **Data Source**

## Loading Required Libraries

```
import warnings
warnings.simplefilter(action='ignore', category=FutureWarning)
# Data Reading
from glob import glob
from PIL import Image
# Data Processing
import numpy as np
import pandas as pd
import cv2
import random
import albumentations as A
# Data Analysis
import plotly.express as px
import matplotlib.pyplot as plt
import seaborn as sns
# Data Modeling & Model Evaluation
from sklearn.model_selection import train_test_split
from keras.preprocessing import image
from tensorflow.keras import layers, models
import tensorflow as tf
os.environ['TF_CPP_MIN_LOG_LEVEL'] = '3'
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay, classification_report, recall_score, accuracy_score, processes a confusion c
# Grad-CAM
import keras
import matplotlib.cm as cm
```

## Reading The Data

```
levels = ['Normal', 'COVID']
path = "../input/covid19-radiography-database/COVID-19_Radiography_Dataset"
data_dir = os.path.join(path)

data = []
for id, level in enumerate(levels):
    for file in os.listdir(os.path.join(data_dir, level)):
        data.append(['{}/{}'.format(level, file), level])

data = pd.DataFrame(data, columns = ['image_file', 'corona_result'])

data['path'] = path + '/' + data['image_file']
data['corona_result'] = data['corona_result'].map({'Normal': 'Negative', 'COVID': 'Positive'})
samples = 13808

data.head()
```

₹		image_file	corona_result	path
	0	Normal/Normal-859.png	Negative	/input/covid19-radiography-database/COVID-19
	1	Normal/Normal-158.png	Negative	/input/covid19-radiography-database/COVID-19
	2	Normal/Normal-10121.png	Negative	/input/covid19-radiography-database/COVID-19
	3	Normal/Normal-1811.png	Negative	/input/covid19-radiography-database/COVID-19
	4	Normal/Normal-97.png	Negative	/input/covid19-radiography-database/COVID-19
		'		ata.duplicated().sum())) snull().value_counts()))
₹		nber of Duplicated Samp nber of Total Samples:		

# Exploratory Data Analysis

#### ✓ 1. Count Plot

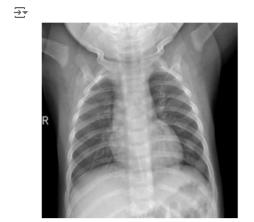
## 2. Image Samples

```
data['image'] = data['path'].map(lambda x: np.asarray(Image.open(x).resize((75,75))))
data.head()
```

₹		image_file	corona_result	path	image
	0	Normal/Normal-859.png	Negative	/input/covid19-radiography-database/COVID-19	[[5, 5, 6, 6, 5, 6, 6, 6, 6, 6, 6, 5, 6, 5, 5,
	1	Normal/Normal-158.png	Negative	/input/covid 19-radio graphy-database/COVID-19	[[64, 85, 96, 97, 115, 138, 130, 133, 141, 112
	2	Normal/Normal-10121.png	Negative	/input/covid 19-radio graphy-database/COVID-19	$\hbox{\tt [[0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,}}$
	3	Normal/Normal-1811.png	Negative	/input/covid 19-radio graphy-database/COVID-19	[[0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 5, 9, 15, 2
	4	Normal/Normal-97.png	Negative	/input/covid19-radiography-database/COVID-19	[[96, 111, 136, 152, 170, 163, 160, 176, 175,
n_sar	nple	es = 3			

```
fig, m_axs = plt.subplots(2, n_samples, figsize = (6*n_samples, 3*4))
```

```
for n_axs, (type_name, type_rows) in zip(m_axs, data.sort_values(['corona_result']).groupby('corona_result')):
   n_axs[1].set_title(type_name, fontsize = 15)
   for c_ax, (_, c_row) in zip(n_axs, type_rows.sample(n_samples, random_state = 1234).iterrows()):
       picture = c_row['path']
        image = cv2.imread(picture)
        c_ax.imshow(image)
```



c\_ax.axis('off')











## → 3. Random Image Analysis

```
plt.figure()
\verb|image = cv2.imread(".../input/covid19-radiography-database/COVID-19_Radiography_Dataset/COVID/COVID-1002.png"|)|
plt.imshow(image)
plt.axis('off')
plt.show()
```





We observe that the image has 3 channels, hence it in in RGB scale even if these are X-ray images.

## ✓ 4. B-Channel

```
plt.title('B channel', fontsize = 14)
plt.imshow(image[:,:,0])
plt.axis('off');
plt.show()
```



### ∨ 5. Ben Graham's Method

First, we convert the images to greyscale and then apply Gaussian blur to them.

```
all_covid = []
all_normal = []
all_normal.extend(glob(os.path.join(path, "Normal/*.png")))
all_covid.extend(glob(os.path.join(path, "COVID/*.png")))
random.shuffle(all_normal)
random.shuffle(all_covid)

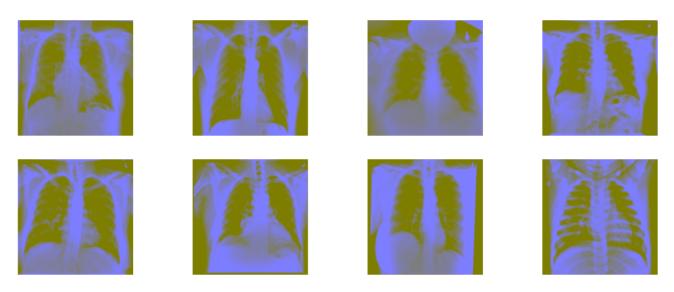
images = all_normal[:50] + all_covid[:50]

fig = plt.figure(figsize = (18, 7))
fig.suptitle("Ben Grahamns Method of Analysis", fontsize = 15)
columns = 4; rows = 2
```

```
for i in range(1, columns*rows +1):
    img = cv2.imread(images[i])
    img = cv2.resize(img, (512, 512))
    img = cv2.cvtColor(img, cv2.COLOR_BGR2HSV)
    img = cv2.addWeighted (img, 4, cv2.GaussianBlur(img, (0,0), 512/10), -4, 128)
    fig.add_subplot(rows, columns, i)
    plt.imshow(img)
    plt.axis(False)
```



#### Ben Grahamns Method of Analysis

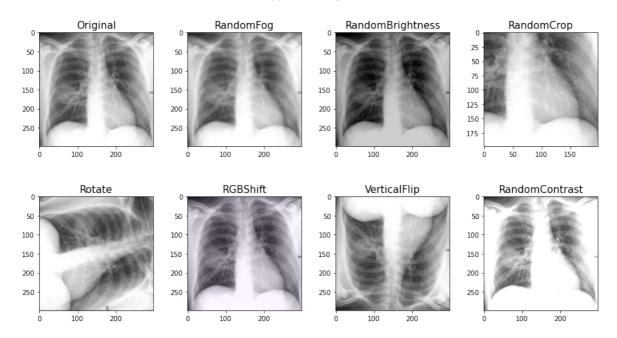


#### 6. Albumentations Visualization

```
def plot_multiple_img(img_matrix_list, title_list, ncols, main_title = ""):
    fig, myaxes = plt.subplots(figsize = (15, 8), nrows = 2, ncols = ncols, squeeze = False)
    fig.suptitle(main_title, fontsize = 18)
    fig.subplots_adjust(wspace = 0.3)
    fig.subplots_adjust(hspace = 0.3)
    for i, (img, title) in enumerate(zip(img_matrix_list, title_list)):
        myaxes[i // ncols][i % ncols].imshow(img)
       myaxes[i // ncols][i % ncols].set_title(title, fontsize = 15)
   plt.show()
chosen_image = cv2.imread("../input/covid19-radiography-database/COVID-19_Radiography_Dataset/COVID/COVID-1002.png")
albumentation_list = [A.RandomFog(p = 1), A.RandomBrightness(p = 1),
                      A.RandomCrop(p = 1,height = 199, width = 199), A.Rotate(p = 1, limit = 90),
                      A.RGBShift(p = 1), A.VerticalFlip(p = 1), A.RandomContrast(limit = 0.5, p = 1)]
img_matrix_list = []
bboxes_list = []
for aug_type in albumentation_list:
    img = aug_type(image = chosen_image)['image']
    img_matrix_list.append(img)
img_matrix_list.insert(0,chosen_image)
titles_list = ["Original", "RandomFog", "RandomBrightness", "RandomCrop", "Rotate", "RGBShift", "VerticalFlip", "RandomContr
plot_multiple_img(img_matrix_list, titles_list, ncols = 4, main_title = "Different Types of Augmentations")
```



### Different Types of Augmentations

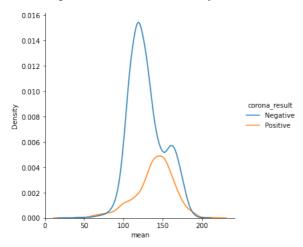


## → 7. Image Value Distribution

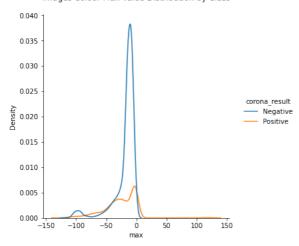
```
mean_val = []
std_dev_val = []
max_val = []
min_val = []
for i in range(0, samples):
   mean_val.append(data['image'][i].mean())
   std_dev_val.append(np.std(data['image'][i]))
   max_val.append(data['image'][i].max())
   min_val.append(data['image'][i].min())
imageEDA = data.loc[:,['image','corona_result','path']]
imageEDA['mean'] = mean\_val
imageEDA['stedev'] = std_dev_val
imageEDA['max'] = max_val
imageEDA['min'] = min_val
imageEDA['subt_mean'] = imageEDA['mean'].mean() - imageEDA['mean']
ax1 = sns.displot(data = imageEDA, x = 'mean', kind="kde", hue = 'corona_result');
plt.title('Images Colour Mean Value Distribution by Class\n', fontsize = 12);
ax2 = sns.displot(data = imageEDA, x = 'max', kind="kde", hue = 'corona_result');
plt.title('\nImages Colour Max Value Distribution by Class\n', fontsize = 12);
ax3 = sns.displot(data = imageEDA, x = 'min', kind="kde", hue = 'corona_result');
plt.title('\nImages Colour Min Value Distribution by Class\n', fontsize = 12);
```



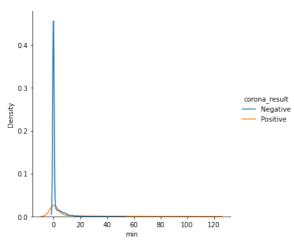




Images Colour Max Value Distribution by Class



Images Colour Min Value Distribution by Class



The Mean vs Density plot insights for pixels:

- $1. \ The \ max \ pixel \ value \ for \ Covid \ Negative \ cases \ is \ greater \ than \ 0.014 \ and \ less \ than \ 0.016.$
- 2. The max pixel value for Covid Positive cases is greater than 0.004 & less than 0.006.

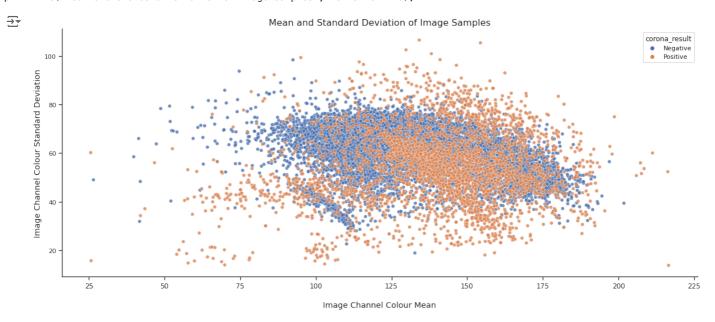
The Max vs Density plot insights for pixels:

- 1. The max pixel value for Covid Negative cases is greater than 0.035 and less than 0.040.
- 2. The max pixel value for Covid Positive cases is 0.005.

The Min vs Density plot insights for pixels:

- 1. The max pixel value for Covid Negative cases is greater than 0.4.
- 2. The max pixel value for Covid Positive cases is greater than 0.0 and less than 0.1.

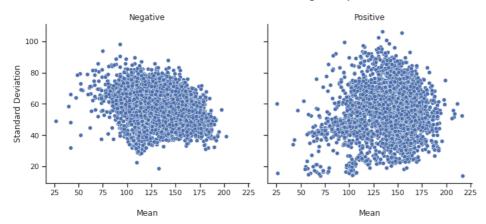
```
plt.figure(figsize = (20, 8))
sns.set(style = "ticks", font_scale = 1)
ax = sns.scatterplot(data = imageEDA, x = "mean", y = imageEDA['stedev'], hue = 'corona_result', alpha = 0.8);
sns.despine(top = True, right = True, left = False, bottom = False)
plt.xticks(rotation = 0, fontsize = 12)
ax.set_xlabel('\nImage Channel Colour Mean', fontsize = 14)
ax.set_ylabel('Image Channel Colour Standard Deviation', fontsize = 14)
plt.title('Mean and Standard Deviation of Image Samples', fontsize = 16);
```



We observe that there are 2 clusters formed, one for Covid Positive, one for Covid Negative and both have several overlappings. Overlapping Color Mean range: (100 - 175)

We observe that for pixels having Std Deviation below 30 are all Covid Positive Images (Orange Colored).

Mean and Standard Deviation of Image Samples



Comparing both Scatter plots, we observe that Postivie Samples have outliers (pixel points).

### 8. Self Insights

## Data Modeling

```
Train Test Split
```

```
all_data = []
# Storing images and their labels into a list for further Train Test split
for i in range(len(data)):
    image = cv2.imread(data['path'][i])
    image = cv2.resize(image, (70, 70)) / 255.0
    label = 1 if data['corona_result'][i] == "Positive" else 0
    all_data.append([image, label])
x = []
y = []
for image, label in all_data:
    x.append(image)
    y.append(label)
# Converting to Numpy Array
x = np.array(x)
y = np.array(y)
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size = 0.2, random_state = 42)
x\_train, \ x\_val, \ y\_train, \ y\_train, \ y\_train, \ test\_split(x\_train, \ y\_train, \ test\_size = 0.1, \ random\_state = 42)
print(x_train.shape, x_test.shape, x_val.shape, y_train.shape, y_test.shape, y_val.shape)
→ (9941, 70, 70, 3) (2762, 70, 70, 3) (1105, 70, 70, 3) (9941,) (2762,) (1105,)

    CNN Model

cnn_model = models.Sequential()
cnn_model.add(layers.Conv2D(filters = 128, kernel_size = (3, 3), activation = 'relu', input_shape = (70, 70, 3)))
cnn_model.add(layers.MaxPooling2D((2, 2)))
cnn_model.add(layers.Dropout(0.3))
cnn_model.add(layers.Conv2D(filters = 64, kernel_size = (3, 3), activation = 'relu'))
cnn_model.add(layers.MaxPooling2D((2, 2)))
cnn_model.add(layers.Dropout(0.5))
cnn_model.add(layers.Conv2D(filters = 64, kernel_size = (3, 3), activation = 'relu'))
cnn_model.add(layers.Flatten())
cnn_model.add(layers.Dense(units = 16, activation = 'relu'))
cnn_model.add(layers.Dropout(0.2))
cnn_model.add(layers.Dense(units = 2))
cnn_model.compile(optimizer = 'adam',
           loss = tf.keras.losses.SparseCategoricalCrossentropy(from_logits = True),
           metrics = ['accuracy'])
cnn_model.summary()
→ Model: "sequential"
```

Layer (type)	Output	Shape		Param #
conv2d (Conv2D)	(None,	68, 68,	128)	3584
max_pooling2d (MaxPooling2D)	(None,	34, 34,	128)	0
dropout (Dropout)	(None,	34, 34,	128)	0
conv2d_1 (Conv2D)	(None,	32, 32,	64)	73792
max_pooling2d_1 (MaxPooling2	(None,	16, 16,	64)	0

```
0
dropout_1 (Dropout)
                               (None. 16, 16, 64)
conv2d_2 (Conv2D)
                               (None. 14. 14. 64)
                                                           36928
flatten (Flatten)
                               (None, 12544)
                                                           0
dense (Dense)
                               (None, 16)
                                                           200720
dropout_2 (Dropout)
                               (None, 16)
                                                           0
dense 1 (Dense)
                                                           34
                               (None, 2)
Total params: 315,058
```

Trainable params: 315,058

```
Non-trainable params: 0
es = tf.keras.callbacks.EarlyStopping(monitor = 'val_loss', mode = 'min', verbose = 1, patience = 4)
#tf.random.set_seed(42)
history = cnn_model.fit(x_train, y_train,
                        epochs = 50, batch_size = 256,
                        validation_data = (x_val, y_val),
                        callbacks = [es])
    Epoch 1/50
\overline{2}
                                   ======] - 10s 75ms/step - loss: 0.5983 - accuracy: 0.7305 - val_loss: 0.5330 - val_accura
    39/39 [===
    Epoch 2/50
    39/39 [====
                        ==========] - 2s 53ms/step - loss: 0.5099 - accuracy: 0.7330 - val_loss: 0.4462 - val_accurac
    Epoch 3/50
                                =======] - 2s 54ms/step - loss: 0.4548 - accuracy: 0.7336 - val_loss: 0.3705 - val_accurac
    39/39 [====
    Epoch 4/50
    39/39 [====
                               ========] - 2s 53ms/step - loss: 0.4100 - accuracy: 0.8087 - val_loss: 0.3403 - val_accurac
    Epoch 5/50
    39/39
          [====
                               ========] - 2s 57ms/step - loss: 0.3683 - accuracy: 0.8456 - val_loss: 0.3147 - val_accurac
    Epoch 6/50
    39/39 [====
                                      ====] - 2s 52ms/step - loss: 0.3441 - accuracy: 0.8642 - val_loss: 0.2937 - val_accurac
    Epoch 7/50
    39/39
          [====
                        ============= ] - 2s 53ms/step - loss: 0.3256 - accuracy: 0.8743 - val_loss: 0.2735 - val_accurac
    Epoch 8/50
    39/39
                                           - 2s 53ms/step - loss: 0.3040 - accuracy: 0.8917 - val_loss: 0.2549 - val_accurac
    Epoch 9/50
    39/39
                           =========] - 2s 54ms/step - loss: 0.2909 - accuracy: 0.8971 - val_loss: 0.2394 - val_accurac
    Epoch 10/50
    39/39
                               ========] - 2s 53ms/step - loss: 0.2799 - accuracy: 0.9016 - val_loss: 0.2399 - val_accurac
    Epoch 11/50
                       ========= ] - 2s 53ms/step - loss: 0.2667 - accuracy: 0.9097 - val_loss: 0.2278 - val_accurac
    39/39 [======
    Epoch 12/50
    39/39 [======
                      :=============== ] - 2s 53ms/step - loss: 0.2605 - accuracy: 0.9100 - val_loss: 0.2207 - val_accurac
    Epoch 13/50
    39/39 [=
                                           - 2s 53ms/step - loss: 0.2459 - accuracy: 0.9159 - val_loss: 0.2047 - val_accurac
    Epoch
          14/50
    39/39 [====
                                             2s 56ms/step - loss: 0.2281 - accuracy: 0.9273 - val_loss: 0.1909 - val_accurac
          15/50
    Epoch
    39/39
          [==
                                           - 2s 52ms/step - loss: 0.2213 - accuracy: 0.9296 - val_loss: 0.1822 - val_accurac
    Epoch 16/50
    39/39 [=====
                           :========] - 2s 52ms/step - loss: 0.2065 - accuracy: 0.9347 - val_loss: 0.1775 - val_accurac
    Epoch 17/50
    39/39
                                           - 2s 52ms/step - loss: 0.2123 - accuracy: 0.9301 - val_loss: 0.1719 - val_accurac
    Epoch 18/50
    39/39
          [====
                                   ======1
                                           - 2s 52ms/step - loss: 0.1914 - accuracy: 0.9394 - val_loss: 0.1706 - val_accurac
    Epoch 19/50
    39/39
                                              2s 55ms/step - loss: 0.1817 - accuracy: 0.9442 - val_loss: 0.1740 - val_accurac
    Epoch 20/50
    39/39
                                             2s 55ms/step - loss: 0.1781 - accuracy: 0.9453 - val_loss: 0.1612 - val_accurac
    Epoch 21/50
    39/39 [====
                                           - 2s 53ms/step - loss: 0.1694 - accuracy: 0.9478 - val_loss: 0.1627 - val_accurac
    Epoch 22/50
                                        ==] - 2s 53ms/step - loss: 0.1712 - accuracy: 0.9449 - val_loss: 0.1564 - val_accurac
    39/39 [=
    Epoch 23/50
    39/39 [=====
                                   ======] - 2s 53ms/step - loss: 0.1583 - accuracy: 0.9515 - val_loss: 0.1621 - val_accurac
    Epoch 24/50
    39/39 [=
                                           - 2s 54ms/step - loss: 0.1594 - accuracy: 0.9484 - val_loss: 0.1610 - val_accurac
          25/50
    Epoch
    39/39 [====
                                           - 2s 54ms/step - loss: 0.1490 - accuracy: 0.9539 - val_loss: 0.1552 - val_accurac
    Epoch 26/50
    39/39 [====
                                       ===] - 2s 53ms/step - loss: 0.1460 - accuracy: 0.9563 - val_loss: 0.1402 - val_accurac
    Epoch 27/50
    39/39 [=
                                         =] - 2s 52ms/step - loss: 0.1328 - accuracy: 0.9611 - val_loss: 0.1499 - val_accurac
    Fnoch 28/50
    39/39 [====
                                           - 2s 53ms/step - loss: 0.1256 - accuracy: 0.9624 - val_loss: 0.1265 - val_accurac
    Epoch 29/50
    39/39
          [====
                                        :==] - 2s 54ms/step - loss: 0.1215 - accuracy: 0.9664 - val_loss: 0.1281 - val_accurac
yp_train = cnn_model.predict(x_train)
yp_train = np.argmax(yp_train, axis = 1)
yp_val = cnn_model.predict(x_val)
```

```
yp_val = np.argmax(yp_val, axis = 1)
yp_test = cnn_model.predict(x_test)
yp_test = np.argmax(yp_test, axis = 1)
```

#### Model Evaluation

```
def evaluation_parametrics(name, y_train, yp_train, y_val, yp_val, y_test, yp_test):
    print("\n-----\n".format(name))
    cm_train = confusion_matrix(y_train, yp_train)
    t1 = ConfusionMatrixDisplay(cm_train)
    s1 = round((cm_train[0,0]/(cm_train[0,0] + cm_train[0,1])),4)
    print("Classification Report for Train Data\n")
    print(classification_report(y_train, yp_train))
    print("-
    print("Recall on Train Data: ", round(recall_score(y_train, yp_train),4))
    print("Specificity on Train Data: ", s1)
    print("Accuracy on Train Data: ", round(accuracy_score(y_train, yp_train),4))
print("Precision on Train Data: ", round(precision_score(y_train, yp_train),4))
print("F1 Score on Train Data: ", round(f1_score(y_train, yp_train),4))
    print("--
    cm_val = confusion_matrix(y_val, yp_val)
    t2 = ConfusionMatrixDisplay(cm_val)
    s2 = round((cm_val[0,0]/(cm_val[0,0] + cm_val[0,1])),4)
    print("\nClassification Report for Validation Data\n")
    print(classification_report(y_val, yp_val))
    print("-
    print("Recall on Val Data: ", round(recall_score(y_val, yp_val),4))
    print("Specificity on Val Data: ", s2)
    print("Accuracy on Val Data: ", round(accuracy_score(y_val, yp_val),4))
print("Precision on Val Data: ", round(precision_score(y_val, yp_val),4))
print("F1 Score on Val Data: ", round(f1_score(y_val, yp_val),4))
    print("--
    cm_test = confusion_matrix(y_test, yp_test)
    t3 = ConfusionMatrixDisplay(cm_test)
    s3 = round((cm_test[0,0]/(cm_test[0,0] + cm_test[0,1])),4)
    print("\nClassification Report for Test Data\n")
    print(classification_report(y_test, yp_test))
    print("--
    print("Recall on Test Data: ", round(recall_score(y_test, yp_test), 4))
    print("Specificity on Test Data: ", s3)
    print("Accuracy on Test Data: ", round(accuracy_score(y_test, yp_test), 4))
print("Precision on Test Data: ", round(precision_score(y_test, yp_test), 4))
    print("F1 Score Test Data: ", round(f1_score(y_test, yp_test), 4))
    print("--
    t1.plot()
    t2.plot()
    t3.plot()
```

evaluation\_parametrics("Convolution Neural Network", y\_train, yp\_train, y\_val, yp\_val, y\_test, yp\_test)



## ----Convolution Neural Network---

### Classification Report for Train Data

	precision	recall	f1-score	support
0 1	0.99 0.95	0.98 0.98	0.99 0.97	7287 2654
accuracy macro avg weighted avg	0.97 0.98	0.98 0.98	0.98 0.98 0.98	9941 9941 9941

Recall on Train Data: 0.983 Specificity on Train Data: 0.9815 Accuracy on Train Data: 0.9819 Precision on Train Data: 0.9508 F1 Score on Train Data: 0.9667

### Classification Report for Validation Data

precision	recall	f1-score	support
0.97	0.96	0.97	844
0.89	0.91	0.90	261
		0.95	1105
0.93 0.95	0.94 0.95	0.93 0.95	1105 1105
	0.97 0.89	0.97 0.96 0.89 0.91 0.93 0.94	0.97 0.96 0.97 0.89 0.91 0.90 0.93 0.94 0.93

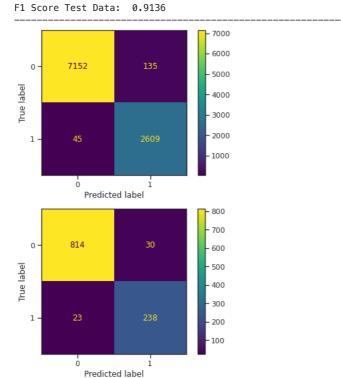
Recall on Val Data: 0.9119

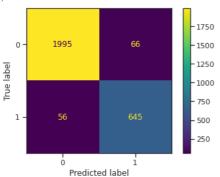
Specificity on Val Data: 0.9645 Accuracy on Val Data: 0.952 Precision on Val Data: 0.8881 F1 Score on Val Data: 0.8998

#### Classification Report for Test Data

support	f1-score	recall	precision	
2061 701	0.97 0.91	0.97 0.92	0.97 0.91	0 1
2762 2762 2762	0.96 0.94 0.96	0.94 0.96	0.94 0.96	accuracy macro avg weighted avg

Recall on Test Data: 0.9201 Specificity on Test Data: 0.968 Accuracy on Test Data: 0.9558 Precision on Test Data: 0.9072





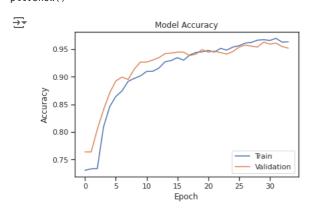
#### # list all data in history

print(history.history.keys())

dict\_keys(['loss', 'accuracy', 'val\_loss', 'val\_accuracy'])

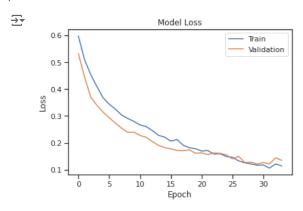
## # Summarize History for Accuracy

```
plt.plot(history.history['accuracy'])
plt.plot(history.history['val_accuracy'])
plt.title('Model Accuracy')
plt.ylabel('Accuracy')
plt.xlabel('Epoch')
plt.legend(['Train', 'Validation'], loc = 'lower right')
plt.show()
```



### # Summarize History for Loss

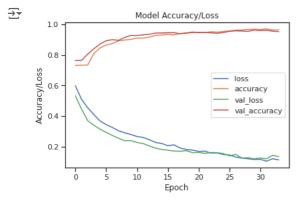
```
plt.plot(history.history['loss'])
plt.plot(history.history['val_loss'])
plt.title('Model Loss')
plt.ylabel('Loss')
plt.xlabel('Epoch')
plt.legend(['Train', 'Validation'], loc = 'upper right')
plt.show()
```



## # Accuracy Loss Graph

```
pd.DataFrame(history.history).plot()
plt.title('Model Accuracy/Loss')
plt.ylabel('Accuracy/Loss')
```

```
plt.xlabel('Epoch')
plt.show()
```



We observe that Train & Validation Accuracy's Curve slightly overlap and same with Loss Curve.

Hence, Overfitting is avoided, this is possible because of Dropout Regularization & Early Stopping Metrics.

## Image Analysis using Grad-CAM

### ∨ Config- Parameters

### 

```
# To Get Image into numpy array
def get_img_array(img_path, size):
    img = keras.preprocessing.image.load_img(img_path, target_size = size)
   array = keras.preprocessing.image.img_to_array(img)
   array = np.expand_dims(array, axis = 0)
    return array
# Top create heatmaps for the samples
def make_gradcam_heatmap(img_array, model, last_conv_layer_name, pred_index = None):
    grad_model = tf.keras.models.Model([model.inputs], [model.get_layer(last_conv_layer_name).output, model.output])
   with tf.GradientTape() as tape:
        last_conv_layer_output, preds = grad_model(img_array)
        if pred_index is None:
            pred_index = tf.argmax(preds[0])
        class_channel = preds[:, pred_index]
    grads = tape.gradient(class_channel, last_conv_layer_output)
   pooled_grads = tf.reduce_mean(grads, axis=(0, 1, 2))
    last_conv_layer_output = last_conv_layer_output[0]
   heatmap = last_conv_layer_output @ pooled_grads[..., tf.newaxis]
   heatmap = tf.squeeze(heatmap)
   heatmap = tf.maximum(heatmap, 0) / tf.math.reduce_max(heatmap)
    return heatmap.numpy()
```

#### Heatmap

```
# Storing Heatmap values into list

covid_noncovid_heatmap = []

for i in img_path:
    img_array = preprocess_input(get_img_array(i, size = img_size))
    model = model_builder(weights = "imagenet")
    model.layers[-1].activation = None
    preds = model.predict(img_array)
    heatmap = make_gradcam_heatmap(img_array, model, last_conv_layer_name)
    covid_noncovid_heatmap.append(heatmap)
```

### Creating a Superimposed Viz

```
# To Display GradCAM output for the samples
def save_and_display_gradcam(img_path, heatmap, cam_path = "cam.jpg", alpha = 0.4):
    img = keras.preprocessing.image.load_img(img_path)
    img = keras.preprocessing.image.img_to_array(img)
    heatmap = np.uint8(255 * heatmap)
    jet = cm.get_cmap("jet")
    jet_colors = jet(np.arange(256))[:, :3]
    jet_heatmap = jet_colors[heatmap]
    jet_heatmap = keras.preprocessing.image.array_to_img(jet_heatmap)
    jet_heatmap = jet_heatmap.resize((img.shape[1], img.shape[0]))
    jet_heatmap = keras.preprocessing.image.img_to_array(jet_heatmap)
    superimposed_img = jet_heatmap * alpha + img
    superimposed_img = keras.preprocessing.image.array_to_img(superimposed_img)
    superimposed_img.save(cam_path)
    imag.append(cv2.imread(img_path))
    imag.append(cv2.imread("./cam.jpg"))
for i in range(len(img_path)):
    save\_and\_display\_gradcam(img\_path[i], covid\_noncovid\_heatmap[i])
titles_list = ["Positive-1", 'Positive-1 Grad', 'Positive-2', 'Positive-2 Grad', 'Negative-1', 'Negative-1 Grad', 'Negative-2', 'Ne
plot_multiple_img(imag, titles_list, ncols = 4, main_title = "GRAD-CAM COVID-19 Image Analysis")
```

## 

## GRAD-CAM COVID-19 Image Analysis

