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COVID-19 PREDICTION USING TRANSFER-LEARNING ON RT-PCR CONFIRMED CXR-IMAGES

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Abstract

Corona-virus is a disease which caused immense destruction to human lives in 21st century. This virus outbreak is considered as an epidemic that spread globally. Crores of people are infected by this virus all over the world. Early detection of the virus is very much important to overcome Covid-19 crisis. This model proposes a convolution neural network model implemented using VGG-19accompanied with Transfer LearningTechnique for the Covid-19 Detection. The Covid-19 dataset considered in this model is a verified report of positive cases confirmed by both RT-PCR and CXR images. Initially, One Hot Encoding Method is used for CXR image data conversion and then pre-processing is done to extract features and then filtered data is forwarded through the VGG-19 and is further processed to Fully Connected Layers. Therefore, the model is later fine-tuned to achieve better classification results. The achieved model accuracy is around 0.94 with a loss is about 0.55.

***Keywords*: COVID-19;Chest X-ray(CXR); Real Time- Polymerase Chain Reaction (RT-PCR); Deep Learning;Convolution Neural Network(CNN); Feature Extraction; Classification;Visual Geometry Group(VGG-19);Receiver Operating Curve(ROC); Accuracy (AUC); Saliency maps; Gradient Activated Class Mapping (Grad-CAM);Heat maps; Confusion Matrix ;Transfer Learning (TL).**

1. Introduction

COVID-19 is the newly emerged contagious disease also known as corona virus which changed the entire world upside down. It is a new strain of Corona virus having a scientific name Orthocoronaviridae or Coronaviridae [Cheng, et al. (2007)]. It is described as Severe Acute Respiratory Syndrome-2 (SARS-CoV-2)[Wang, et al. (2020)]. It is a respiratory disease, which is caused due to a virus genome named SARS-CoV-2.It is primarily identified on December 2019, Wuhan Hubei Province, China[Liu, et al.(2020)].The most common symptoms of this virus are Cough, Fever, difficulty in breathing, Muscle aches, chills, sore throat, runny nose, headache, chest pain, pink eyes and loss of sense of taste and smell. The severity is determined in three stages i.e.,Mild, Moderate and Severe.RT-PCR test is a highly preferred laboratory Covid-19 diagnosis. Other than this test, X-Ray and CT are also prioritized diagnostic tests. Undergoing X-Ray is cost effective, potential and obtains quick response with less radiation dose of o.1mSv [Keles, et al.(2021)].Therefore, the developed model is utilizing both X-Ray and RT-PCR confirmed CXR Covid-19 images to achieve a better and efficient prediction rate. Many prediction models are developed and are explained in the literature survey. In [Abbas, et al.(2021)] a model using CNN is defined using DeTrac which means Decompose, Transfer and Compose. Initially, dataset decomposition is done implementing Transfer Learning for disease detection. In [Sitaula,et al. (2021)] data augmentation is used to enhance the instances in the dataset. Most commonly VGG-16 is used for disease prediction [Sitaula,et al.(2021)] [Shibly,et al.(2020)][Panwar, et al.(2020)] and is compared with various other mechanisms. Some of the alternative techniques practiced are ResNet, ResNetV2, Xception, DenseNet, Google Net, Squeeze Net, Inception Net and VGG-16.All these mechanisms have been used in Covid-19 prediction. The analysis of performance metrics is determined in [Abbas, et al.(2021)][Anand, et al.(2021)][Shibly,et al.(2020)][Panwar, et al.(2020)] explaining the implemented model achieving good prediction results. Transfer Learning technique plays a prominent role in transferring knowledge within the models identified in [Ohata,et al.(2020)][Minaee,et al.(2020)]. Therefore, in this paper we are presenting a model developed using VGG-19 associated with Transfer Learning which helps in better and accurate prediction of the disease. The main objective of this model is to do multiple classification i.e, Normal, Covid-19, Bacterial Pneumonia and Viral Pneumonia detection within the CXR images with or without human intervention.The general work flow of disease prediction is explained with different phases like data pre-processing, feature extraction and classification. Section 2 presents Related Work done on diagnosing Covid-19. Section 3 provides a diagrammatic approach for the developed model.Section 4 covers the experimental evaluation.Section 5 presents the conclusion of the proposed paper.

2. Related Work

Now-a-days, many systems are embedded with Artificial Intelligence techniques reforming normal machines into Computer Assisted Diagnosis Machines for faster and accurate prediction of any disease. These are adopted for early screening of the disease. Some of the developed models are explained above.

In [Abbas, et al.(2021)], author proposed a deep CNN classification model on Covid -19 using DeTrac,a generic transfer learning model.DeTrac means Decompose, Transfer and Compose applying Class Decomposition Mechanism. Simultaneously, comparison of several pretrained models implementing AlexNet, VGG-19, ResNet, GoogleNet and SqueezeNet is done with/without using Decomposition layer.Among them VGG-19 model has attained highest accuracy. In [Sitaula,et al.(2021)], the author developed a technique using attention module using VGG -16 used to detect spatial relationship among the identified ROI's. Comparison of VGG-16 and VGG-16 using Attention based model and VGG-16 associated with CNN and Attention based module is done. Among them VGG-16 with CNN and Attention based module achieved a better accuracy of 79.58% resolving the problem of overfitting. In [Anand,et al.(2021)], a modified VGGNet architecture is explained, which is used for multiple classification with a very fast training speed, even though it is taking different input size 200x200 and simultaneously attaining an accuracy of 97%. In [Shibly,et al.(2020)], an approach implementing K-Fold Cross-Validation technique collaborated with VGG-16 Network-based Faster Region CNN (Faster R–CNN) is developed for COVID-19 detection performing Binary classification with an accuracy of 97.36%.Various other approaches like DenseNet, ResNet50, InceptionV3, and AlexNet are also validated within this model. Here, the author [Panwar, et al. (2020)], proposes a model nCOVnet used for early prediction of Covid-19 using X-ray images within a time limit of 5 sec applying VGG-16 associated with Transfer Learning. The detected abnormalities within the X-ray images are identified in the form of hazy or patchy shadows with faster detection without any data leakage resulting an accuracy of 97%. In[Apostolopoulos&Mpesiana,(2020)], author proposed a model detecting COVID-19 using transfer learning in combination with CNN. Five types of CNN's like MobileNetv2, VGG-19, Inception, Xception, Inception and ResNetv2 are adapted. It is analyzed that VGG-19 and MobileNetv2 achieved good accuracy results. In [Diaz-Escobar,et al.(2021)], the author described a model which detects COVID-19 infection from lung ultrasound images.VGG 19, Inception V3, Xception and ResNet50 are some of the techniques applied. Additionally, POCOVID-net model is also added comparing all the architectures implementing ANOVA and Friedman tests. Among them Inception V3 achieved the best average accuracy of 89.1% using Post-hoc analysis. Here [Lawton, et al.(2021)],for Covid disease Prediction,transfer learning is implemented within the CT lung scans.Here Histogram Equalization and Contrast Limited Adaptive Histogram Equalization are applied with various deep learning architectures like ResNet-101, VGG-19, DenseNet201, EfficientNet-B4, and MobileNet-V2.Among them VGG-19 correlated with CLAHE attained 95.75%.In[Ohata,et al.(2020)], the author proposed a method using Transfer Learning using CXR images.Various CNN architectures like MobileNet, DenseNet, Inception, NasNet, Xception, ResNet and VGGNet were utilized for feature extraction. All these CNNs are colloborated with numerous algorithms like K- Nearest Neighbor, Naïve Bayes, Random Forest, Multilayer Perceptron (MLP) and Support Vector Machine . Each machine learning algorithm is separately implemented on every single CNN architecture for binary classification. Among them, SVM classifier with MobileNet CNN architecture obtained a test extraction time of 0.443 ms, 21ms attaining an accuracy of around 98%.Here,a deep learning framework [Minaee,et al.(2020)],is developed for detecting Covid -19 in CXR.Four CNN models namely ResNet18, ResNet50, SqueezeNet and DenseNet are pretrained on the training dataset using Transfer learning. These four models are trained to test the model.

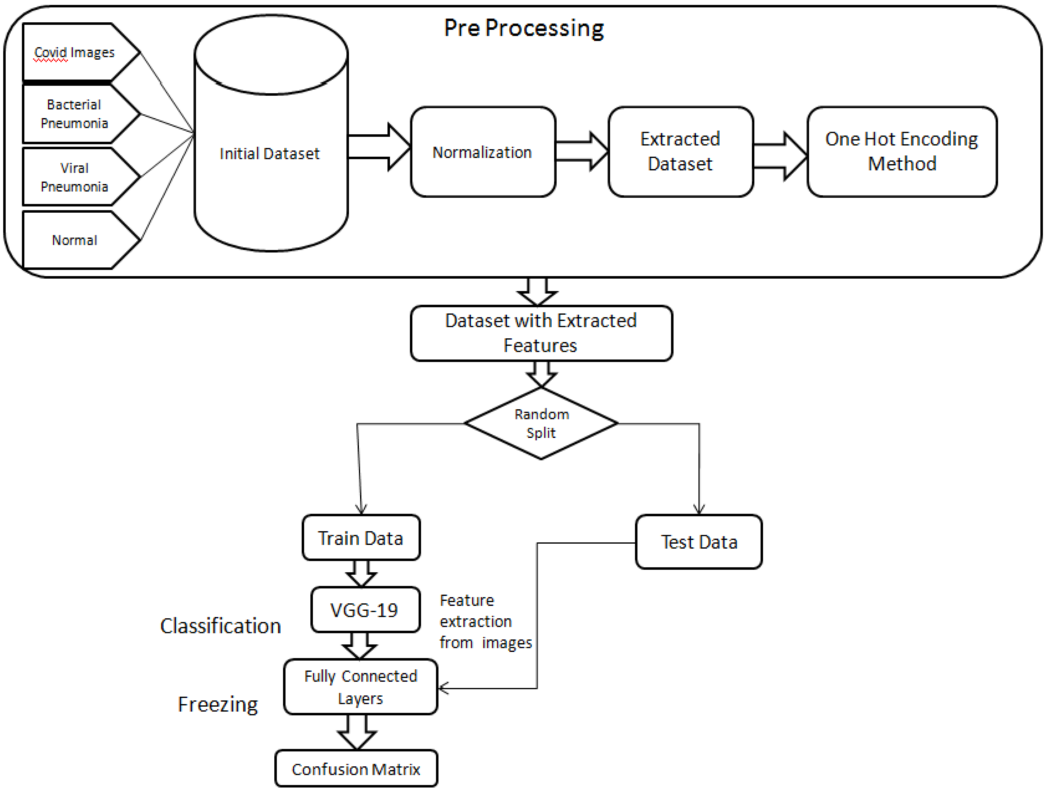

Fig. 1. Work Flow of Covid-19 Prediction Model

3. Proposed Methodology

The initial dataset consists of images along with its metadata files. All the considered X-Ray images are of Posterior Anterior View. This image dataset consists of various X-ray images which are categorized as Normal, Covid-19, Viral-Pneumonia and Bacterial-Pneumonia. The Covid-19 CXR image dataset used in this model is a confirmation report determined using RT-PCR test. The considered dataset is displayed in Table 1.

Category	Train	Test
Normal	1349	234
Bacteria	2540	246
Viral	1355	149
COVID-19	66	10

Table 1. Dataset with multiple categories

Therefore, all these distributed X-ray images are further processed to numpy files. These numpy files are converted and normalized with respect to ratio of the images. The designed workflow is determined in Fig 1.
One Hot Encoding is one of the mostly used pre-processing techniques used to encrypt data with minimal processing from one form to another i.e., categorical data to vector form. Every component of vectors are represented by either 0 or 1. Every category will be 'zero' other than the element denoting the respective category. Therefore, mapping of X-ray images done with their concerned labels. These transformed labels are converted to one hot vectors, and is fed as input to the neural network for classification purposes. Among many encoding techniques identifying the best technique which suits our model will have a great impact on model's performance. If the number of vector values are more we use sparse vectors and matrix, where data is accumulated in a compressed format. Later dataset is splitted into Train data and Test data with a ratio of 80:20.
VGG-19 is a type of pretrained Convolution Neural Network which is of 19 layers deep. It is a combination of 16 convolution layers and 3 fully connected layers. It transforms input X-ray image, extracts the features and then processes it into an efficient model as an output. In our model VGG-19 is implemented to exhibit good performance with best accuracy.

The primary layer on the model is the input layer which accepts the RGB image with 224 x 224 x 3 pixels. The remaining layers are a sequence of Convolution, Max Pooling, Fully Connected, Softmax layers. Convolution layers are used to extract the features from the image without any distraction within the pixels. Feature map is retrieved from convolution layer forwarded to pooling layer merging the identical features, decreasing the feature map size. Various kernels and spatial padding is applied on the image to adjust the resolution. ReLu function is continued for better learning and classification of the X-ray image. The output is forwarded to fully connected layer preceded with Softmax function for adjusting the probability ranges within 0 and 1. A deep learning algorithm which takes an image as input and also assigns weights and biases to the objects in the images so that they are differentiated from one another. Such algorithm is said to be Convolution Neural Network Algorithm. A CNN captures Spatial and Temporal dependencies in an image by applying relevant filters without losing any features. It is used to filter a complex image into a simpler image adopting various patterns. VGG19 is used as a base model to extract features within the input. Additionally, after base model pooling layer, dropout layer, dense and flatten layer are added to the model.

Transfer Learning Technique used to train the model which helps in identifying several attributes like weights and features. It makes use of the knowledge which is acquired by previously utilized CNN, and thus the respective knowledge is further reused to solve similar problems. This transferred knowledge will be represented in the form of a new dataset with some extracted features and those features are processed for further classification. One of the important aspect of transfer learning is to freeze all layers except the last three layers ,i.e., fully connected, SoftMax and classification layers.These layers are trained later to recognize new categories/features.Accurate results are to be fetched from the defined pre-trained models. Transfer learning enforces to have independent and identical training data along with its test data.Thus transfer learning helps in reducing the training time in executing the model resulting in improving the performance of the model.Therefore, the hierarchical network structure provides high-level feature maps, reduced computation complexity and improved generalization ability. Simultaneously, visualization is done to predict the images generating confusion matrix. Based on this ROC Curve is generated displaying accuracy and error percent.

Algorithm: Implementation of VGG-19 technique:

Input: X-rays images of PA View
Output: Prediction of image (Covid, Normal, Viral Pneumonia and Bacterial Pneumonia)

Step 1: Loading image dataset along with its meta dataset.

Step 2: Categorizing images into Covid and Non -Covid.

Step 2.1: The dataset of Covid-19 images used in this model are obtained by diagnosing the disease using two types of tests i.e., X-ray and RT-PCR.

Step 2.2: The dataset of Non-Covid images consists of Normal, Bacterial Pneumonia and Viral Pneumonia.

Step 3: Images and their labels are converted to NumPy files and are separated to four categories i.e., Normal, Bacterial Pneumonia, Viral Pneumonia and Covid-19.

Step 4: The entire dataset is separated into two parts where 80 percent data used to train the model and the remaining 20 percent used to test the model.

Step 5: Pre-processing the data applying various techniques.

Step 5.1: Normalizing the dataset.

Step 5.2: Mapping of images.
Step 5.3: Applying One Hot Encoding Technique to perform vectorization.

Step 6: Obtaining the extracted dataset.

Step 7: Considering VGG-19 as the base model with some parameters like learning rate, epochs, batch size.

Step 8: Features are extracted from the VGG19 CNN and are forwarded to FC Layer.

Step 9: Transfer learning technique is applied Connecting base model with Fully Connected Layers.

Step 10: Later Freezing of layers is done for an initial level of execution.

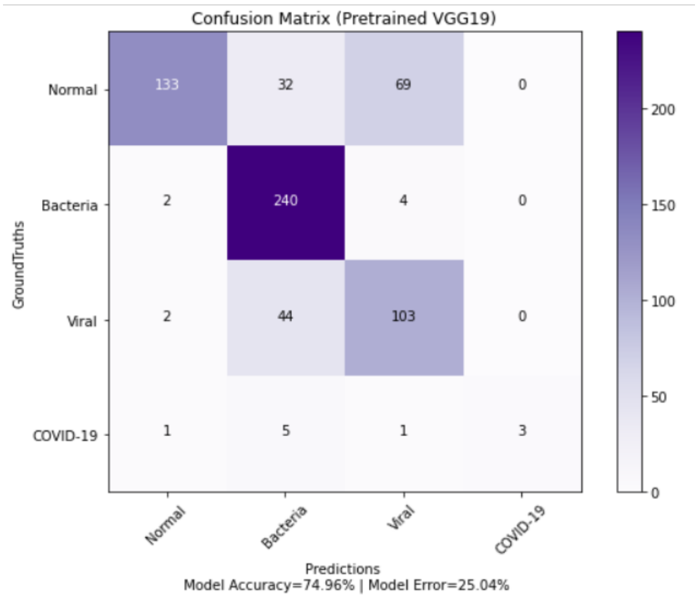

Fig.2. Confusion matrix for the model

Step 11: Model compatibility tested on trained dataset and later on test dataset.

Step 12: Confusion matrix is generated when analyzing True Positive, True Negative, False Positive and False Negative.

Step 13: Accuracy and loss percentage is plotted as per the results obtained from the designed model.

4. Experimental Evaluation

4.1 Confusion matrix

It illustrates the validation of developed classification model in tabular form when tested on trained dataset. It is measured depending on Precision, Recall and F-measure. The attributes utilized for the confusion matrix are True Positive, True Negative, False Positive and False Negative. In this proposed methodology we do multiple classification with four types of categorizations. Hence, confusion matrix is generated with 16 values. Based on these values the performance assessment is done for the designed model. The model accuracy achieved by our model is 74.96% where as the error rate is 25.04%.

The TP values for the Normal X-ray images is 133, detected Bacterial images is of 240, Viral Pneumonia images are of 103 and Covid-19 with 3 images as showed in Fig 2. The accuracy is generated using the values of TN/TP/FP/FN.

4.2 Receiver Operating Characteristics (ROC)

ROC Curve is a graph plotted to measure the performance metrics analyzing the input data. It is based on True Positive Rate (TPR) and False Positive Rate (FPR) where TPR determines the accurate prediction, FPR displays the inaccurate prediction. It has a marginal line called an optimal cut point differentiating both accurate and inaccurate categories. After calculating both true, false positives, then slope and y-intercept will be calculated based on linear regression. The measurement of ROC plot is done by Area Under Curve (AUC) using Trapezoidal method. In Fig 3, TPR is elevated on y-axis and FPR explained on x-axis. The obtained AUC is displayed showing multiple classification which has achieved a certain threshold value. Normal images, displayed in cyan color with an area of 0.95 representing Class 0, Bacterial Pneumonia is presented in Blue with an area of 0.95 denoting Class 1, Viral Pneumonia presented in Green color with 0.87 denoting Class2 and finally Covid-19 is denoted with class 3 with an area of 0.97.

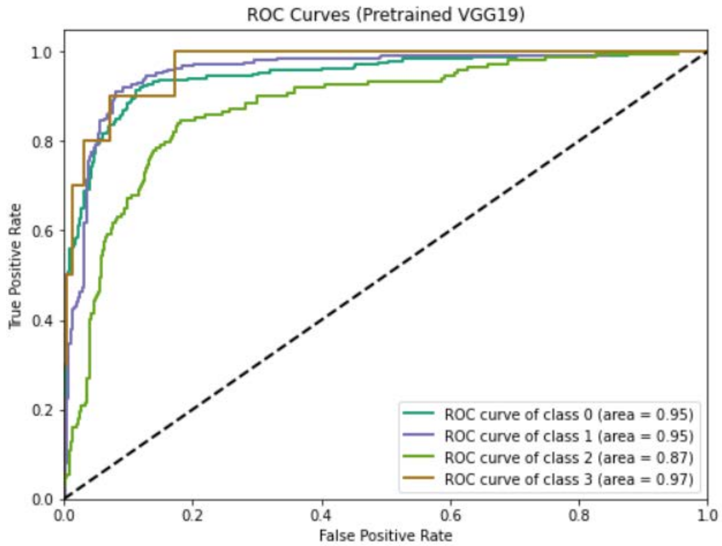

Fig.3. ROC Curve of VGG19 model

4.3 Prediction

Accuracy and Loss percent are used for validating the performance of the algorithm validating both test and train data identifying the fitness of the model by taking data as input and analyzing output in the form of graphs. The layers in the model have a great impact on the model performance. Therefore, training of data is done in epochs to identify hyper parameters. This model is validated using 20 epochs plotting the graph for Test/Train Accuracy and Train/Test Loss. In Fig 4(a),the Number of Epochs is taken on X-axis and Accuracy is taken on Y axis. Accuracy of the pretrained VGG-19 model is determined for both trained data and test data. The Number of Epochs range from 0 to 20.As the trained data is validated, gradual increase of accuracy is observed and after some epochs there is a constant increase in the accuracy of the model. Similarly, while viewing the test data, fluctuations are noticed in the accuracy levels and finally a raise is observed while reaching on 20 epochs. Therefore, for 20 epochs the accuracy is around 0.94.

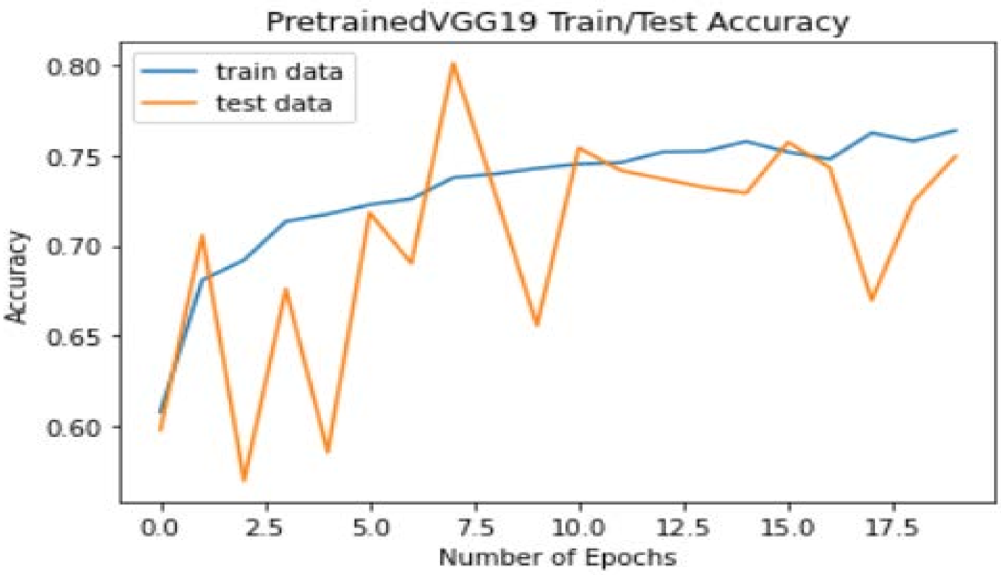

Fig.4(a). VGG19 Train and Test Accuracy

Simultaneously in Fig 4(b), Number of Epochs is taken on X-axis and Loss is represented on Y axis. When the training data is considered there is a sudden fall in the loss and it further decreases when it reaches the final epoch. As per the testing data there is no constant loss instead there is a continuous rise and fall in the loss for each and every epoch. Therefore for 20 epochs the loss is about 0.55. Similarly, when tested with 30 epochs the model accuracy is around 0.94 and model loss is identified as 0.53. Therefore, when testing with 20 and 30 epochs the accuracy has been constant i.e., 0.94 achieving good model performance when implemented using a limited dataset. Hence, this model has achieved better prediction rate as it is trained using both CXR and RT-PCR diagnostic tests.

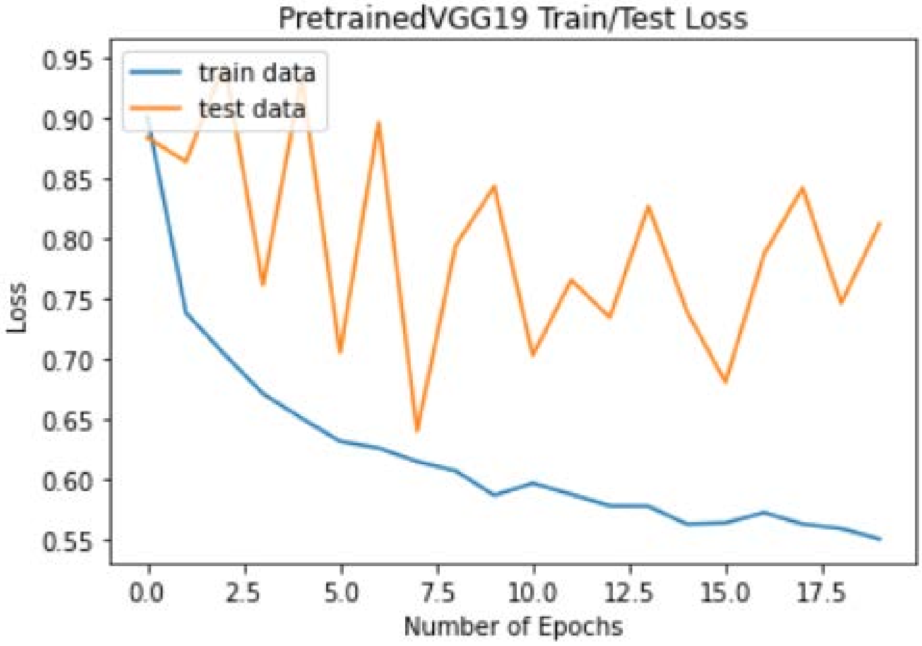

Fig.4(b).VGG19 Train and Test Loss

Classification of images is done applying some visualization techniques. Image filtration is done using Saliency Maps and Gradient-Weighted Class Activation Mapping (Grad-CAM). Saliency maps will visually process the image highlighting the abnormal pixels used for classifying the image. Concurrently, Grad-CAM technique is implemented displaying the abnormal regions within the image generating a heat map which is further used in detailed decision making for image classification. Thus, both Saliency maps and heat maps are used in classifying the given image into it's respective category as displayed in Fig 5.

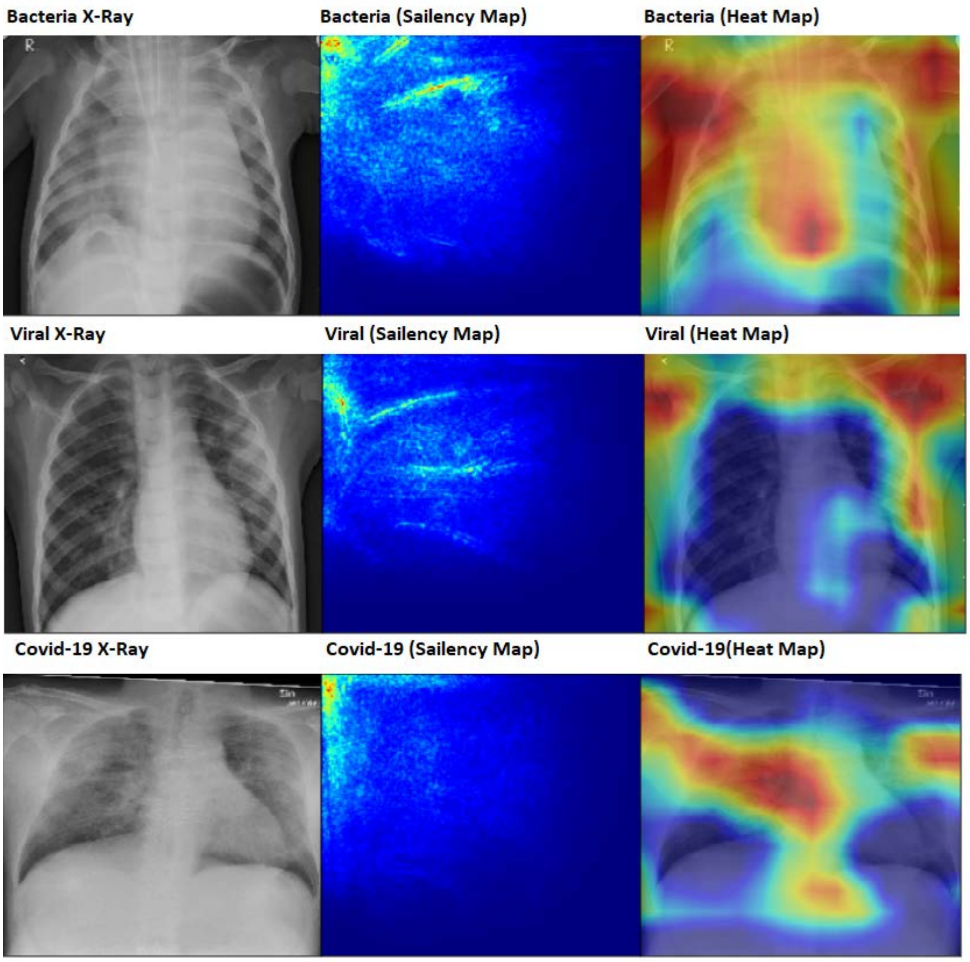

Fig 5. Abnormalities highlighted in Saliency map/Heat map

5. Conclusion

In this model, prediction of multiple classification is done i.e., Normal, Bacterial Pneumonia, Viral Pneumonia and Covid-19.All the images are used to train and test the model. The considered Covid-19 image dataset is very important as it is fetched based on the Corona positive report obtained by both RT-PCR test and CXR. Therefore, the abnormal features identified within the images are extracted using VGG-19 and is later forwarded through Fully Connected Layers achieving good prediction rate. The accuracy of about 0.94 is determined based on the performance metrics. Better accuracy may be achieved when tested on more data. Along with CXR there are some more tests like Antibody test and CT Scans. Therefore, if this model is implemented with some other diagnostic test like CT scan or Antibody report we can get better result.

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