Automatic Detection Of COVID-19 And Other Pneumonia from Chest X-ray Images Using Convolutional Neural Networks and Collection of COVID-19 Affected Chest X-ray Images

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Abstract

The most challenging task of the Covid-19 pandemic is the accurate detection of Covid-19 affected people. To fight against this challenge, automatic detection of Covid-19 can help to diagnose patients with more reliability. In this work, we have collected chest X-rays of Covid-19 affected patients and processed the dataset for training purpose. As we have imbalanced datasets as well as data scarcity for Covid-19 class, these might create problems during training of deep neural networks. To overcome that, we have tried to develop a simple CNN model by hyperparameter optimization so that this shallow network can give better results in case of data limitation. Later we compared the performance of our developed model and the existing VGG16 model. Our model has an overall accuracy of 88.12% whereas the VGG16 model has an accuracy of 84.34%.

Keywords
Covid-19, Chest X-Rays (CXRs), Machine Learning, Artificial Intelligence (AI), Convolutional Network.

1. Introduction
Global pandemic novel coronavirus (Covid-19) caused by SARS-CoV-2 (severe acute respiratory syndrome coronavirus-2) has been started since Dec 8, 2019 which was first detected in Wuhan, China. Patients show symptoms like dry cough, sore throats and fever and eventually develop severe pneumonia, acute respiratory distress syndrome (ARDS), acute respiratory failure and other serious complications (Chen et al. 2020). Rapid diagnostic test (RDT) is used to detect Covid-19 virus by taking samples from nose, throat and lungs. Diagnosing Covid-19 affected patients at early stage is now a challenging issue. Reverse transcription-polymerase chain reaction (RT-PCR), a widely accepted diagnostic test, requires extraction of the RNA from patient's samples, which also gives false negative result as accuracy depends on the preparation and manufacturing of RT-PCR test kits and good laboratory practice (Feng et al. 2020). As there is scarcity of this test kit, chest x-ray and CT-scan are other options to detect Covid-19. According to the British Society of Thoracic Imaging (BSTI), patients with oxygen saturations <92% or respiratory rate >20 breaths/min, or patients with marked respiratory symptoms should have chest radiograph as a part of their initial assessment (Cleverley et al. 2020). Pneumonia developed in Covid-19 patients causes the density of the lungs to increase which is seen as ground glass opacity or whiteness in the lungs on radiography. Artificial Intelligence (AI) can help the radiologists to detect Covid-19 affected patients from chest x-ray images accurately in less time.

2. Literature Review
Automatic disease detection and classification with Deep Learning method such as Convolutional Neural Network (CNN), has extensive applications in medical image processing, such as classification of benign and malignant tumors (Han et al. 2020), pneumonia detection (Varshni et al. 2019), segmentation of skin lesion (Iranpoor et al. 2020) and many more. Already, several works of Covid-19 detection have been published where both CT and chest X-ray images were used. Due to high cost and radiation exposure, CT is not suitable for Covid-19 screening though CT gives more accurate detection results in several studies (Sodickson et al. 2009). However, chest X-Ray imaging (CXR) is cost-

effective and commonly used for screening purposes but there is scarcity of Covid-19 X-ray images (Loey et al. 2020). It is extremely difficult to train a very deep network effectively with a small dataset. Hence, transfer-learning can be a viable solution during this situation. Bansal and Sridhar (2020) showed a comparative analysis using six pre-trained models – VGG16, VGG19, ResNet50V2, InceptionV3, Xception and NASNetLarge, where VGG16 and VGG19 achieved highest accuracy with sensitivity and specificity of 100% and 94% respectively. Moutounet-Cartan (2020) trained and tested different deep convolutional neural network architectures on posteroanterior chest X-rays of 327 patients who are healthy (152 patients), diagnosed with Covid-19 (125 patients) and other types of pneumonia. The use of depth wise convolution with variable dilation rates is proposed in a deep convolutional neural network architecture, named as CovXNet, for obtaining a variety of features from chest X-rays in an efficient manner (Mahmud et al. 2020). The proposed CovXNet undergoes training using a considerable amount of chest X-rays that correspond to both normal and (viral/bacterial) pneumonia patients. A small number of Covid-19 affected chest X-rays are used to further train a few more fine-tuning layers after the initial training phase is transferred to them. Abiyev and Ma'aitah (2018) demonstrated the feasibility of chest pathological classification using conventional and deep learning approaches. Back propagation neural networks (BPNNs) with supervised learning and competitive neural networks (CPNNs) with unsupervised learning were constructed on the same dataset for diagnosis chest diseases.

In this paper, a simple but efficient CNN model is developed which is trained with a small dataset having four classes of chest X-rays corresponding to normal, viral pneumonia, bacterial pneumonia and Covid-19 patients. In order to optimize the proposed network, hyperparameter tunning is used to find out the best combination of different layers i.e., Conv2d layers, Maxpooling layers, Dropout layers etc. At the same time, optimal number of filters, kernel sizes etc. in those layers are determined by the tunning techniques. Finally, the performance of the newly developed CNN model is compared with that of the well-known VGG16 model (Simonyan and Zisserman 2014) after employing transfer learning method.

3. Dataset Description

3.1 Chest X-ray Online Dataset

Chest X-ray datasets are available in various online sources. In this study, we used normal, viral and bacterial chest X-ray dataset along with Covid-19 chest X-ray dataset. To compare our collected chest X-ray data, we needed open-source X-ray datasets from online (Kermany et al. 2018), (Mooney 2018). We downloaded from multiple sources as there are not much useful x-ray dataset available online. We collected X-ray data of Normal X-rays, Viral pneumonia X-rays, Bacterial Pneumonia X rays and finally Covid 19 X-rays. We found a total of 1584 Bacterial Pneumonia x-rays, 1345 viral X-rays, 1041 Normal X-rays and 789 Covid-19 X-rays. Some images from our dataset are illustrated in Figure 1.

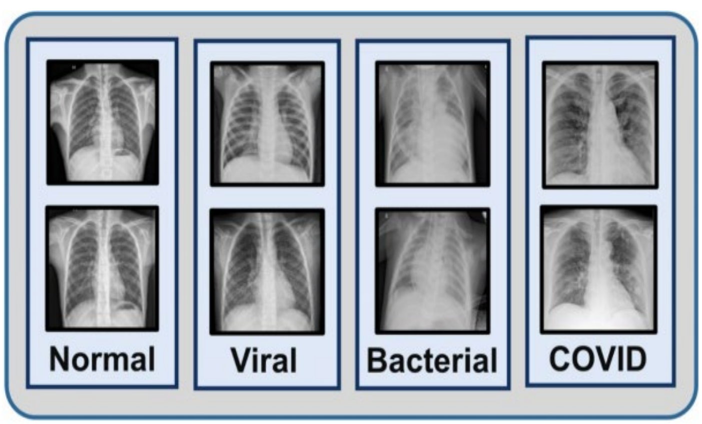

Figure 1. Four Types of Images

3.2 COVID -19 X-ray Data Collection

We have collected 933 chest X-ray images from radiology department of Combined Military Hospital (CMH), Dhaka after taking formal approval of the respected authority. They have also assured us that if we need more X-ray images, they will provide us those maintaining proper protocol. As part of project, we are trying to prepare a data set of Covid-19 X-ray images. Following works are completed for dataset preparation:

1) Data Collection: Till now we have collected 933 raw chest X-ray data of 496 (149 with multiple images and 347 with single image) Covid-19 patients from an authorized source. Among them, 370 X-rays were from male patients and 126 X-rays were collected from female patients. The summary of age diversity of patients is shown in the Figure 1. It can be observed from the figure that the number of patients is highest in the range of 50 to 60 years. By this age range (Figure 2) and gender differentiation (Figure 3), our data can be used in a number of significant ways.

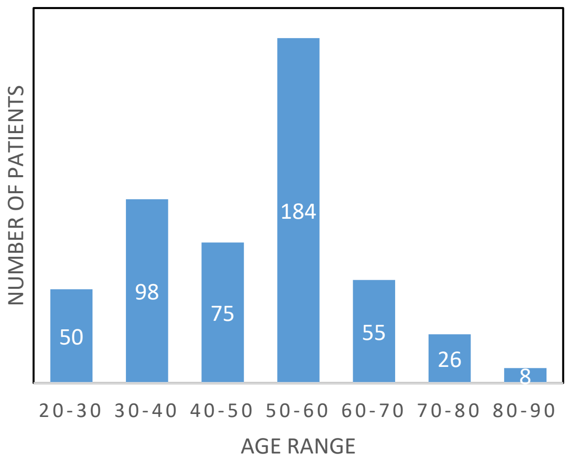

Figure 2. Number of Samples based on age range.

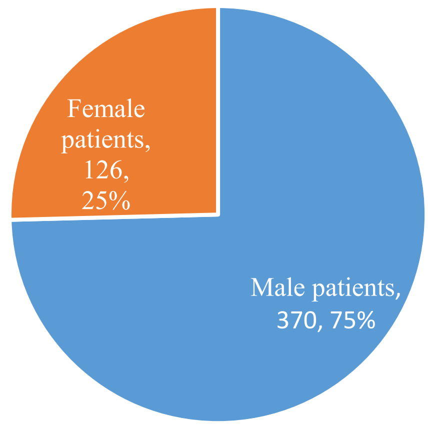

Figure 3. Number of Samples based on gender

2) Image Extraction: Extraction software Dicom Image Viewer was used to extract X-ray images from raw data us. This is a professional tool to view and measure the cases and causes form an X-ray. The images were in (.dicom) format and we extracted / exported them into (.jpg) format. We deleted a few pictures because of bad quality and bad results. The extracted X-ray images contained single PA view X-ray of 346 persons and multiple X-rays of 150 persons.
999

3) Image Preparation:

a. Extracted Images were renamed with a unique identical name to remove the original identity of the patients and institution from the file names. To crop these images, we used Photo editor tool which is default to the windows operating system named ‘photos’.
b. All the Images were cropped to remove the identity of the patients and institutions as well as unnecessary parts of the body like the stomach area.
c. Images were resized to 1024x1024 pixels to use these as a dataset of Machine Learning tools. The process of image extraction and preprocessing is shown in Figure 4

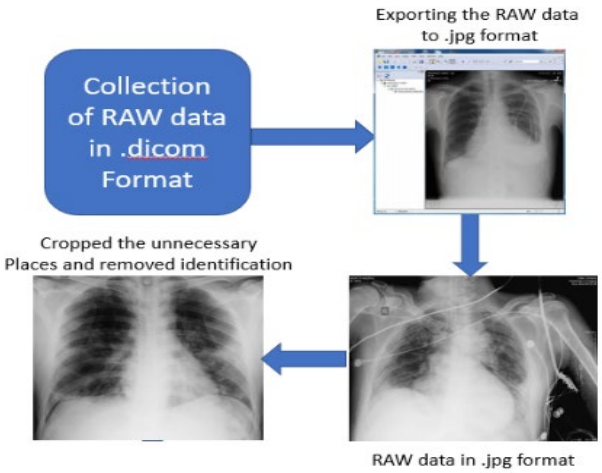

Figure 4. X-ray Data Processing form raw.

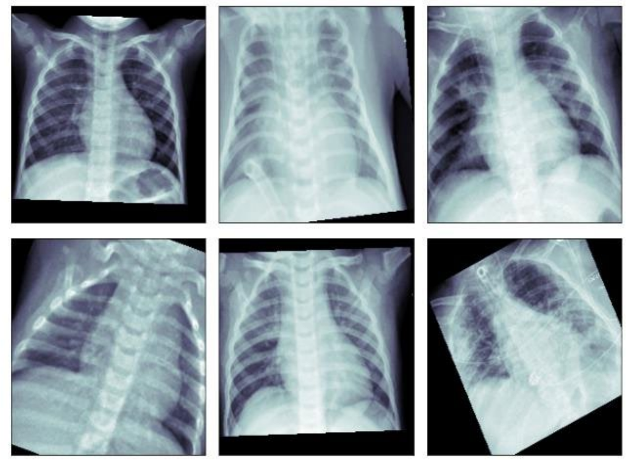

Figure 5. Preprocessing of the images to boost the database.

4) Preprocessing: These images are pre-processed in the coding part to resize them to 224x224 pixels, to be fed to the network. The dataset includes both training and testing images. 25% of the data are used for tests. For the training part we used re-scale, sheer, zoom, flip, and shift to the images (Figure 5) to improve our training parameters and we got a significant amount of testing accuracy. Figure 6 illustrates our total dataset.

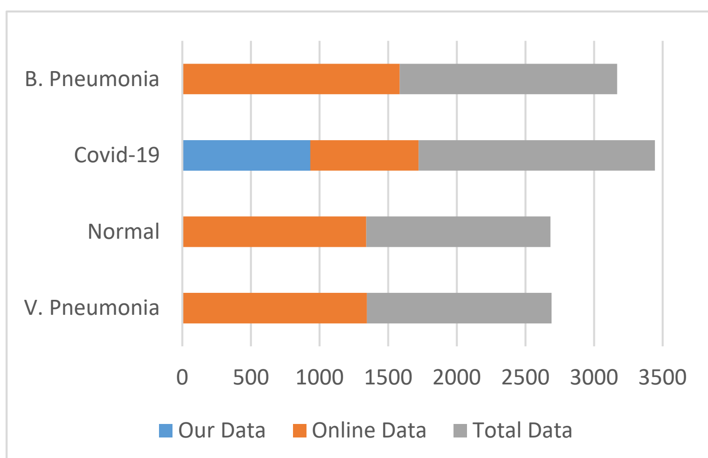

Figure 6. Complete Dataset

4. Automatic Disease Detection

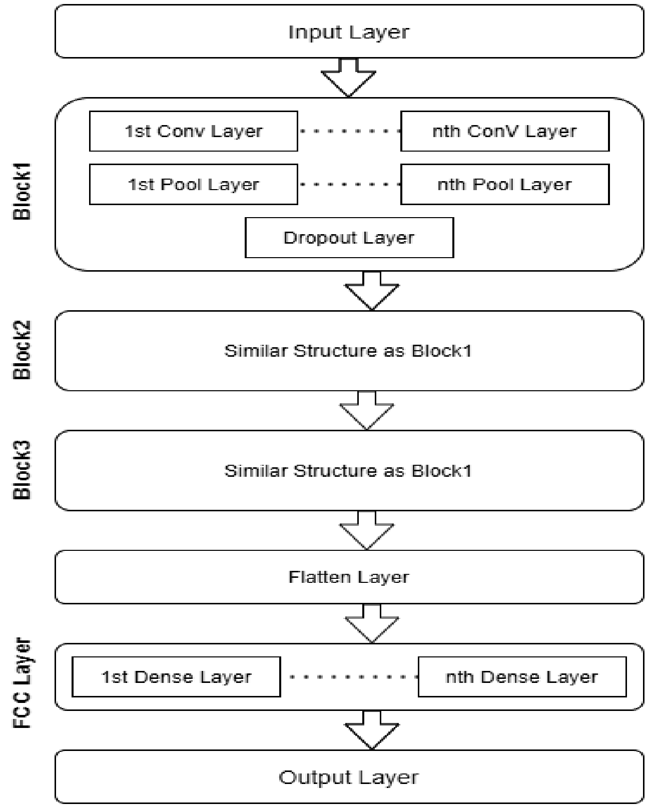

Figure 7. Basic Structure of The CNN Model.

4.1 Developing A New CNN Model:

The diagram shown in Figure 7 represents the basic structure of the proposed CNN model. It consists of one input layer, three block of feature extraction layers, one flattening layer, several fully connected layers and the final output layer. Each block of feature extraction layers consists of several Conv2d layers, Maxpooling layers and Dropout layers. Again, fully connected layers consist of several Dense layers.

1) Hyperparameter Tuning by Varying No of Layers: First, we want to explore the best combination of Conv., Pool, and Dense layers which will provide the highest accuracy. In order to find that, we keep the number of filters and kernel size fixed and vary the number of Conv2d and Pooling Layers in each block of the feature extraction network. Additionally, we also vary a number of dense layers in FCC layers. Instead of setting up a grid of hyperparameter values and searching best combination by training a model and scoring on the testing data which is very expensive and time-consuming, we use a random search algorithm. Here Random Search Algorithm (Bergstra and Bengio 2012) sets up a grid of hyperparameter values and selects random combinations to train the model and score on test data. In this way it finds better combination of parameter in the shortest possible time.

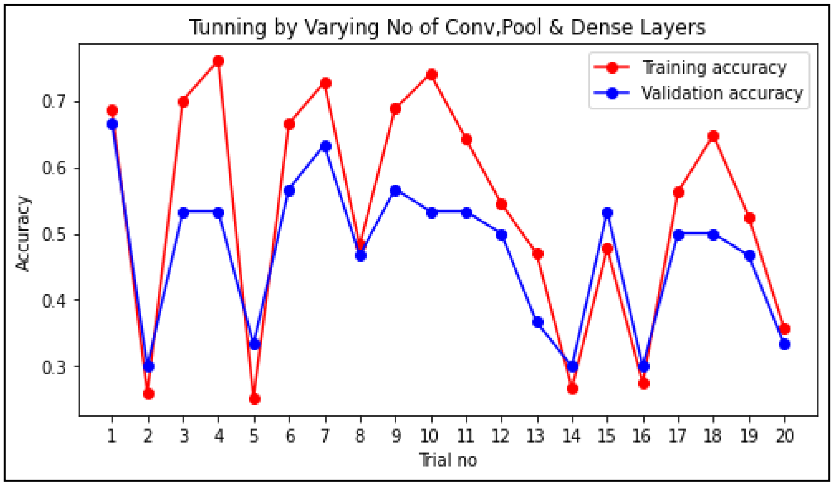

Figure 8. Tuning Proposed CNN Network by Varying No of Layers.

When optimizing the number of layers, we use 32 no of filters having kernel size (2,2) for input Conv. layers, 64 no filters having kernel size (2,2) for Conv. layers of block1 and 2, 128 no filters having kernel size (2,2) for Conv. layers of block3. In addition to that, we use Maxpool layers having pool size (3,3) for block 1,2&3 and 123 no neurons for dense layers of FCC. We use 400 images of 4 different classes for training purpose and 40 images to test purpose. After completing 20 trials with 5 epochs for each trial (Figure 8), we get 66.67% accuracy having following combination-

'No of Conv Layers in block1': 2, 'No of pool layers in block1': 1,
'No of Conv layers in block2': 0, 'No of pool layers in block2': 1,
'No of Conv layers in block3': 2, 'No of pool layers in block3': 2,
'No of Dense layers in FCC': 1
Total Params: 2,637,700, Trainable Params: 2,637,700
Non-trainable Params: 0

2) Hyper Parameter Tuning by Varying No of Filters and Kernel Size: After tuning the of layers, we are trying to optimize the filters and kernel for Conv. layers size by hyperparameter tuning. Here we fixed the number of conv., pool, and dense layers (which we found previously) and varied the number of filters and kernel for all Conv. layers used in previously tuned networks. Here we also use 400 images of 4 different classes for training purposes and 40 images to test purposes. After completing 40 trials with 5 epochs for each trial (Figure 9), we get 73.33% accuracy.

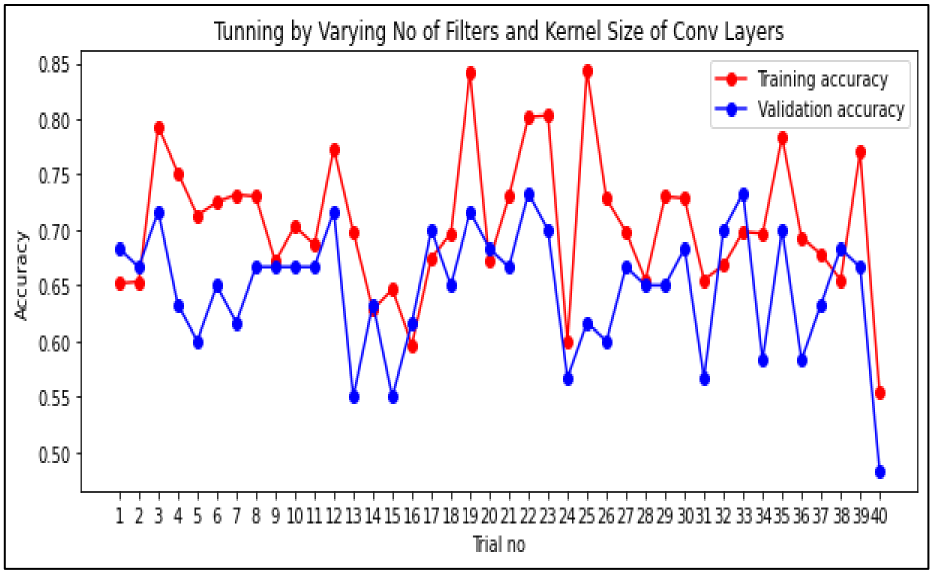

Figure 9. Tuning CNN Network by varying No of Filters and Kernel Size.

4.2 Performance Evaluation:

After optimizing our proposed CNN network by hyper parameter tuning, we train the model on whole dataset. We use almost equal numbers of chest X-ray images of each class (Normal, Covid-19, Bacterial & Viral) to train the model. After applying data augmentation, we boost up the data volume. For testing purpose, we use 40 images for each class. Figure 10 shows an overall accuracy of 98.06% and validation accuracy of 88.75% after completing 50 trials.

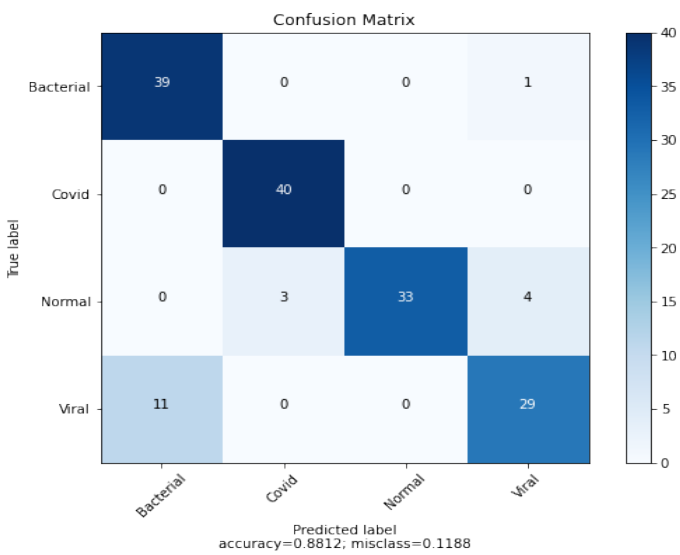

Figure 10. Recognition rates of the CNN on validation data.

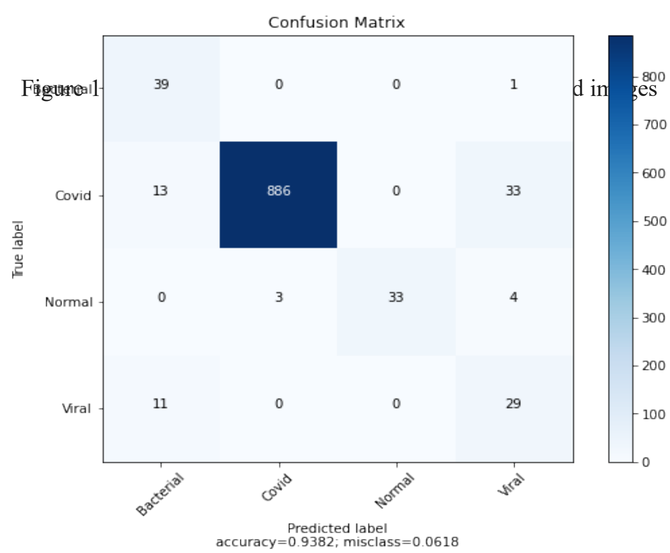

Figure 11. CNN model predicted 886 X-ray images

4.3 Prediction on Newly Collected COVID-19 Data:

After successful Training and Testing on the dataset (collected from different online sources), we apply our developed CNN model to predict our newly collected COVID-19-affected chest X-ray images. It can be found from Figure 11 that the new CNN model can successfully predict 886 X-ray images (out of 932) as Covid affected. It falsely predicts 13 as Bacterial pneumonia affected and 33 images as Viral pneumonia affected. The accuracy of predicting our newly collected Covid dataset is 95.06%.

4.4 Performance Comparison with Existing Model (VGG16):

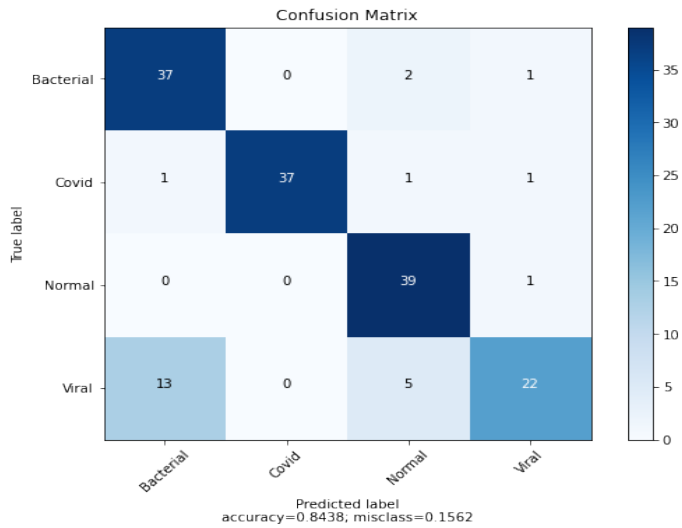

Figure 12. Recognition rates of VGG16 on validation data.

Likewise other related works (Zhu et al. 2020 and Tammina 2019), a transfer learning method employing an established deep learning architecture was also explored here to compare the performance of the proposed CNN model. Sample weights trained on the ImageNet dataset were loaded into a VGG16 model (Zhu et al. 2020). The dataset was normalized and resized into 224x224 pixel images to make it compatible with VGG16. 80% of the images were split into training and 20% were for testing. To avoid overfitting, only the top layers were trained, and all convolutional layers were frozen. The standard VGG16 architecture was used, except for the fully connected layers. After exiting the convoluted layers, the model output was flattened and then processed through three Dense layers, one of which is a regression Dense layer. As opposed to the 110 needed for the traditional training method, The model was able to achieve high predictive ability by only training it for 10 epochs. Because the use of more epochs results in overfitting and an increase in computational time. Adam optimizer and 0.001 learning rate were employed in this model. The performance of the VGG16 model is shown by a confusion matrix in Figure 12.

Table 1. Results comparison with the earlier model

	New CNN Model	**VGG16**
Normal	82.50%	97.50%
Covid-19	100.00%	92.50%
Bacterial	97.50%	92.50%
Viral	72.50%	55.00%
Overall Accuracy	**88.12%**	**84.38%**

From Table 1, we can see that our newly developed CNN model can detect Bacterial and Covid-19 images with a high accuracy of 97.5% and 100% respectively while VGG16 yields 92.5% accuracy for both types of images. Although in case of normal images, the validation accuracy of the proposed CNN model degrades comparatively, the detection performance of that model does not go below 70% for any of the four cases. Hence, the proposed scheme can serve as an efficient tool for detecting COVID-19 affected X-ray images with a very high accuracy.

5. Conclusion

To reduce the spreading of corona virus, early detection and the isolation of the Covid-19 positive people is the first priority. Automatic Covid-19 detection will reduce the detection time and help the doctors to identify Covid-19 affected people more accurately. In this work, we developed a model with three blocks of feature extraction layers. Best combination of the layers was found out by varying the number of Conv2d and Pooling Layers in each block keeping the filters and kernel size fixed. Later best result found out by varying the filters and kernel size. The developed model has overall accuracy of 98.06% and validation accuracy of 88.75% whereas the VGG16 model gives 84.38% accuracy. Our developed model on our collected data has shown accuracy of 95.06%. So, we can hope that our model can help the doctors to detect the Covid-19 patients more accurately and preciously. One of the achievements from this study is the collection and preparation of dataset of Covid-19 chest X-ray and making it publicly available for further use and study. All the images are publicly available at: https://shorturl.at/guzHT.

6. Acknowledgement

The paper was produced as a result of a project work that was conducted in BUET and the authors acknowledge the BUET authority's cooperation and help. The authors also like to thank the Director of Combined Military Hospital, Dhaka for the permission to collect sample data from the Covid-19 specialized laboratory of the hospital.

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