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COVIDetection-Net: A Tailored COVID-19 Detection from Chest Radiography Images Using Deep Learning

Ahmed S. Elkorany¹,²,³, Zeinab F. Elsharkawy⁴

¹Dept. of Electronics and Electrical Comm. Eng., Faculty of Electronic Engineering, Menouf 32952, Menoufia University, Egypt
² High Institute of Electronic Engineering, Ministry of Higher Education and Scientific Research, Belbeis, Elsharkia, Egypt
³Dept. of Electronics, information and bioengineering, Politecnico di Milan, Italy
⁴Engineering Department, Nuclear Research center, Atomic Energy Authority, Cairo, Egypt.

Abstract

In this study, a medical system based on Deep Learning (DL) which we called “COVIDetection-Net” is proposed for automatic detection of new corona virus disease 2019 (COVID-19) infection from chest radiography images (CRIs). The proposed system is based on ShuffleNet and SqueezeNet architecture to extract deep learned features and Multiclass Support Vector Machines (MSVM) for detection and classification. Our dataset contains 1200 CRIs that collected from two different publicly available databases. Extensive experiments were carried out using the proposed model. The highest detection accuracy of 100% for COVID/NonCOVID, 99.72% for COVID/Normal/pneumonia and 94.44% for COVID/Normal/Bacterial pneumonia/Viral pneumonia have been obtained. The proposed system superior all published methods in recall, specificity, precision, F1-Score and accuracy. Confusion Matrix (CM) and Receiver Operation Characteristics (ROC) analysis are also used to depict the performance of the proposed model. Hence the proposed COVIDetection-Net can serve as an efficient system in the current state of COVID-19 pandemic and can be used in everywhere that are facing shortage of test kits.

Keywords: Coronavirus Disease 2019, Pneumonia viral, Pneumonia bacterial, Convolutional Neural Network, Deep Learning, Features extraction.

1. Introduction

The COVID-19 that originated in Wuhan, China in December 2019 spread out across the world. It infected until now around 27.76 million people and around 902315 deaths all over the world
As we all see the number of cases increasing rapidly, all countries are facing the shortage of resources to detect COVID-19. Here comes the need to available, cheap, automatic COVID-19 detection method. Applying deep Learning models on Chest radiography images (e.g., X-ray or computed tomography (CT) imaging) can help in detecting COVID-19. Currently, real-time reverse transcription poly-merase chain reaction (rRT-PCR) is the main screening method used for COVID-19 detection [2]. The radiography imaging sensitivity outperforms the usual PCR technique [3-7]. Also the X-ray systems are cheaper and more available in hospitals than CT scan systems [8, 9].

The CRIs based detection system have many advantages over usual blood [10] and PCR [2] exams. These techniques are fast and cheap compared to other techniques. Also, many cases can be tested in the same time. Moreover, the availability of radiology imaging systems in hospitals, makes radiography-based detection systems a suitable variant for COVID-19 testing kit shortage. In August 2020, large number of X-rays chest images for healthy and patients suffering from Covid-19 are publicly available, which enable us to examine and identify the possible patterns that may produce automatic diagnosis of COVID-19.

Deep Learning (DL), which is a part of machine learning systems, is focused mainly on images’ features extraction and classification on automated manner [11-21]. In recent years, machine and deep learning have become basic disciplines in artificial intelligence. Hence, DL has become a basic part of automated clinical decision making.

In the paper, a new COVIDetection-Net system is proposed which is an automatic detection of COVID-19 infection from CRIs. The system depends on ShuffleNet and SqueezeNet architectures for feature extraction and MSVM for disease detection and classification. The utilized dataset contains 1200 CRIs. It contains chest images for healthy (i.e., Normal), and non-healthy (patients infected with COVID, Bacterial pneumonia, or Viral pneumonia). Taking into account the experimental results the proposed COVIDetection-Net can serve as an efficient system in COVID-19 detection.

The rest of the paper is organized as follows. Section 2 outlines the related work. Section 3 discusses the methods used in the proposed system. Section 4 shows the COVIDetection-Net experimental setup. Sections 5 and 6 present and discuss the COVIDetection-Net results. Finally, section 7 outlines the conclusion.
2. Related Work
Recently, many researchers proposed different techniques for COVID-19 detection from CRIs. Most researches focused on DL techniques to detect the COVID19 from CRI of patients. Some of them interested in COVID detection from non-COVID cases (binary classification) [8, 9, 11, 22-26]. Others concerned with thee-class classification (COVID vs Normal vs pneumonia) [11], [12-19]. But in fact, fewer focused on COVID19 detection using four-class classification (COVID vs Normal vs Bacterial pneumonia vs Viral pneumonia) [20, 21]. Brunese et al [8] introduced a COVID detection approach based on transfer learning of VGG-16 model. This model used to differentiate between healthy and disease X-ray images with accuracy of 96%. Then, it used for COVID detection from disease X-ray chest dataset with accuracy of 98%.

Dipayan Das et. al [9] presented Truncated inception net to detect COVID-19 positive from non-COVID cases using CRIs. Detection accuracy of 99.9% is obtained. Hemdan et al [22] proposed a COVIDX-Net, DL framework, for automatic diagnosing COVID19 in CRIs. Seven-different convolutional neural networks (CNN) model are used in COVIDX-Net. The used DenseNet and VGG-19 provided the same accuracy of 90% for binary classification. Narin et al [23] used 5-fold cross validation pre-trained models for coronavirus detection from CRIs. The highest accuracy of 98% is obtained using ResNet50 model. Panwar et al [24] presented DL based method nCOVnet for fast COVID19 detection from x-ray chest images. This method used the VGG net and transfer learning using five-different layers that achieved 97.2% detection accuracy. Sethy et al [11] extracted the deep features from the CRIs using the fully connected layer of the pre-trained models. Then, features matching has been done using SVM classifier. The authors utilized 13 different pre-trained net and the highest classification accuracy of 98.66% was obtained using ResNet50. Singh et. al [25] proposed a (CNN) to classify the chest CT patient’s images to COVID-infected or not using multi objective differential evolution (MODE). This approach provided 93.5% accuracy. Tuncer et al [26] presented Residual Exemplar Local Binary Pattern (ResExLBP) features extraction method with iterative ReliefF (IRF) features selection for COVID19 detection from CRIs. An accuracy of 99.69% is achieved using SVM classifier.

Apostolopoulos et. al [12] used transfer learning technique for binary and 3-class classification of COVID, normal and pneumonia CRIs. The produced classification accuracies were 97.4% and 92.85% for binary and 3-class classification, respectively when MobileNet v2 is
used. Kumar et. al [13] utilized the DL ResNet-152 for prediction of COVID 19 patients on CRIs. Synthetic Minority Oversampling Technique (SMOT) is used with DL to balance the imbalanced data points. The extracted learned features are fed to Random Forest (RF) and XGBoost (XGB) classifiers for 3-class classification. The proposed model provided 97.7% accuracy for XGB and 97.3 for RF classifiers. Tree-class COVID classification method of CRIs was proposed in [14]. The method based on DL and 9- different CNN architectures. The best accuracy was 95% for two models. Ozturk et al [15] presented 5-cross validation DarkCovidNet for binary and 3-class classification of CRIs. The presented method provided accuracy of 98.08% and 87.02% for binary and 3-class cases, respectively. The concatenation network of Xception and ResNet50V2 is presented in [16] for detection of pneumonia and COVID19 from CRIs. The overall accuracy of 91.4% is obtained for the three classes (normal, COVID and pneumonia).

Ucar et al [17] proposed COVIDiagnosis-Net for COVID19 diagnosis from CRIs. This approach based on deep Bayes-SqueezeNet that produced overall accuracy of 98.26%. Wang et al [18] introduces DCNN model called COVID-Net to detect COVID cases from CRIs. This model was designed for (normal vs pneumonia vs COVID) classification with overall accuracy of 92.4%. Li et. al [19] demonstrated COVID-Xpert based population screening to detect COVID19 cases from X-ray CRIs. The demonstrated method provided 88.9% classification accuracy.

COVID19 detection using 4-class cases from CRIs is presented by Khan et al [20]. The authors presented DCNN model named, CoroNet, based on Xception architecture. The classification accuracy of 89.6% is produced for 4-class cases. Mahmud et al [21] designed CovXNet, CNN based architecture, for COVID19 detection and classification. A stacking algorithm is used for optimization of CovXNet prediction and 90.2% accuracy is obtained for 4-class classification.

Accordingly, it can be concluded that, many researchers studied the COVID detection and introduced different techniques for this problem. However, the most of them did not provide the required high accuracy, especially for 4-class cases. So, the proposed work aims to improve the detection and classification accuracy of COVID 19 using 4-class of CRIs (e.g. COVID vs bacterial pneumonia vs viral pneumonia vs normal cases) using DL model named as COVIDetection-Net. The binary and 3-class versions are also examined by (using) our COVIDetection-Net and compared the results with other methods in Stat-of-art. The
COVIDetection-Net can be used easily to differentiate the COVID19 infection from other pneumonia infection, either bacterial or viral. Hence, the proposed model can be helpful for doctors in the quantification, triage and follow-up of positive cases. It also can be used to minimize the number of cases that need quick testing.

3. Methods
This work focused in developing a detection model named COVIDetection-Net based on DL techniques for COVID 19 detection from CRIs using 4-class cases. The prepared dataset and the proposed COVIDetection-Net are explained in details as follow.

3.1 Dataset
To evaluate the proposed COVIDetection-Net, our dataset is created using two different publically CRIs databases. Firstly, a collection of CRIs from the Github repository was selected [27]. Then, Kaggle repository of normal and pneumonia CRIs was considered [28]. The two repository contains an open database of CRIs (chest X-ray or CT images) and is being updated regularly. A total of 1200 CRIs are selected from the Github and Kaggle repositories, in which 300 images are COVID19, 300 images are bacterial pneumonia, 300 images viral pneumonia and 300 images are normal cases. Table 1 summarized the prepared dataset. The samples of the prepared dataset are shown in Fig.1.

3.2 COVIDetection-Net
Deep networks (CNNs or DL) are useful in machine vision tasks. This made developments in many fields as industry [29], Agriculture and medical disease diagnosis [8, 9, 11, 22-26]. The notability of these CNN networks comes from the useful and robust features that extracted from input images. Hence, the deep networks focus on infection detecting in CRIs and classifying these images into COVID-19, normal, bacterial pneumonia or viral pneumonia. Some of the most usable CNN are ResNet [11, 13, 16, 23], VGG [8, 11, 12, 14], Xception [16, 20], Inception [9, 23], DesNet [11, 22], ShuffleNet [29, 30], and SqueezeNet [17, 31, 32]. These networks pre-trained on ImageNet dataset.
Shufflenet is a CNN also that outperform many networks in speed and accuracy metrics at the same computation condition [30]. In total, it composed of 172 layers including convolution layer, max pooling layer, three stages each contains a stack of ShuffleNet units, one global average pooling, fully connected layer and the output (softmax) layer. The ShuffleNet architecture is shown in Fig. 2.

SqueezeNet is a CNN that comes forward owing to light design of its network. However, it has better performance than AlexNet, it yields fewer 50× than AlexNet in model size [31, 32]. SqueezeNet consists of sixty-eight different layers including two convolution layers (conv1 and
conv10), eight fire modules (fire2- fire9), three max pooling layers, one global average pooling layer and the last one is softmax (output) layer. Figure 3 shows the SqueezeNet graphical representation.

The proposed COVIDetection-Net based on SqueezeNet and ShuffleNet CNN models for deep learned features extraction. Then, multiclass SVM classifier is used for classification task. Figure 4 illustrates the architecture of the proposed COVIDetection-Net. In the beginning, the input images of the prepared dataset are resized into 300 × 300 pixels. SqueezeNet produces 1000 features on its global average pooling (pool 10) layer from the input image, and ShuffleNet generates 544 features on its global average pooling (node_200) layer. The total 1544 valuable extracted features of ShuffleNet and SqueezeNet are used for training and testing the multiclass SVM classifier with 70% and 30% of CRI dataset, respectively. The proposed model classifies the CRIs into COVID-19, normal, bacterial pneumonia or viral pneumonia with high accuracy compared to other published methods.
4. Experimental setup

4.1 Implementation

Three scenarios are implemented for detection of COVID-19 from CRIs. In each scenario, three models are implemented: the proposed COVIDetection-Net, the pre-trained ShuffleNet and SqueezeNet CNN that trained end-to-end on the prepared CRI dataset using architectures shown in Figs. 2, 3 and 4. The first one is the main 4-class scenario, in which the three models (i.e. COVIDetection-Net, ShuffleNet and SqueezeNet) are trained to classify the CRIs to four categories: COVID19, Pneumonia-viral, Pneumonia-bacterial or Normal. The second is the 3-class scenario that used to classify CRIs to COVID19, Pneumonia or Normal. In this case, viral pneumonia and bacterial pneumonia are combined in a single class called Pneumonia class. The other scenario is the binary 2-class (COVID19, Non-COVID), in which the Normal and Pneumonia classes are combined in a Non-COVID class. All models are trained with 70% of the CRI dataset and tested with the rest 30% of the CRI dataset.
4.2 Evaluation metrics

The performance of the proposed model is depicted in the form of Receiver Operation Characteristics (ROC) Curve and Confusion matrix (CM). Recall, specificity, Precision, F1-Score and Accuracy metrics are also used to evaluate the networks performance, which are given as follows.

\[
\text{Recall} = \frac{\text{Sum of all True Positives (TP)}}{\text{Sum of all True Positives (TP)} + \text{All False Negatives (FN)}}
\]

\[
\text{Specificity} = \frac{\text{Sum of all True Negatives (TN)}}{\text{Sum of all True Negatives (TN)} + \text{All False Positives (FP)}}
\]

\[
\text{Precision} = \frac{\text{Sum of all True Positives (TP)}}{\text{Sum of all True Positives (TP)} + \text{All False Positives (FP)}}
\]

\[
F1 - \text{score} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}
\]

\[
\text{Accuracy} = \frac{\text{No. of images correctly classified}}{\text{Total no. of images}}
\]

5. The Proposed System Results

The results of the main 4-class scenario are presented in Table 2. The table compares between the performance of the proposed COVIDetection-Net and the two other models: ShuffleNet and SqueezeNet. The above-mentioned evaluating metrics are the top metrics used to evaluate the performance of classification models. The proposed COVIDetection achieved the highest recall, specificity, precision, F1-score and accuracy of 100% for COVID class. While higher performance is obtained of other classes comparatively to SqueezeNet and shuffleNet models as presented in Table 2. It is indicated that the performance of the two pneumonia classes (bacterial and viral) are lower than other classes, subsequently lower overall accuracy. This accuracy is significantly increased when combining the two pneumonia classes into one pneumonia class. This can be cleared in 3-class scenario of the proposed, SqueezeNet and shuffleNet models as shown in Table 3. It is clear from the table that the COVID detection is still achieved with the highest performance comparatively to other two models. The accuracies of the pneumonia class after combining of its two infections (bacterial and viral) are increased from 88.9% to 99.4% for COVIDetection-Net, from 84.45% to 98.3% for ShuffleNet and from 81.65% to 96.7% for SqueezeNet. Finally, the performance results of the binary classification of the three models for COVID19 detection are depicted in Table 4. The proposed COVIDetection-
Net provides the highest detection accuracy of 100% of the COVID19 in the three scenarios (i.e. 4-class, 3-class and binary). Additionally, the average recall, specificity, precision, F1-score and accuracy of the proposed 4-class, 3-class and binary COVIDetection-Net are summarized in Table 5.

![Accuracy Comparison Graph](image)

Fig. 5 the accuracy comparison between SqueezeNet, ShuffleNet and COVIDetection-Net.

The proposed COVIDetection achieved higher overall accuracy of 94.44%, 99.72% and 100 for 4-class, 3-class and binary classification task, respectively. Figure 5 shows the accuracy comparison between the proposed model and the two other models (SqueezeNet and shuffleNet). It is clear from the figure that the COVIDetection-Net outperform these models. The performance of the main 4-class COVIDetection-Net is displayed in the form of CM in Fig 6(a) and ROC curve in Fig 7. Ninety CRIs from each class are tested and all COVID images are detected successfully. The AUC values of 1, 1, 0.95 and 97 are obtained for COVID, Normal, Pneumonia-bacterial, Pneumonia-viral, respectively. The CM of the proposed 3-class and binary COVIDetection-Net are shown in Fig. 6(b) and (c). In the 3-class cases, 180 Pneumonia images are tested against 90 images of each Normal and COVID classes. However, the binary classification problem comprising 90 CRIs of COVID against 270 CRIs of Non-COVID cases.
Figure 6 indicates that the best detection of COVID cases in all classification scenarios and it is the main aim of these study.

Fig. 6 Confusion matrices of the COVIDetection-Net (a) the main 4-class, (b) 3-class and (c) the binary classification
6. Discussion

To evaluate the performance of the proposed COVIDetection-Net, a comparison study between the proposed model and other models are performed as mentioned before in Tables 2, 3, 4 and Fig. 5. The results prove the superiority (notability) of the proposed COVIDetection-Net. Moreover, our proposed COVIDetection-Net superior other existing state-of-the-art studies that used CRIs in COVID19 detection as given in Table 6. The performance values of each study are listed in the table for binary, 3-class and 4-class cases in the term of classification accuracy.

Table 7 gives performance comparison study of the proposed COVIDetection-Net with CoroNet and CovXNet on 4-class classification case. The CRIs datasets of the proposed model and the two other compared models are selected from the same databases [27, 28]. The CoroNet model [20] is based on Xpection model with a dropout layer and two fully-connected layers added at the end. This model used for COVID19 detection on dataset contains 284 COVID, 310 Normal, 330 Pneumonia-bacterial and 327 Pneumonia-viral. While the CovXNet [21] used depthwise convolution with varying dilation rates for efficient features extraction, then optimization of its prediction can be obtained using stacking algorithm. The CovXNet model
used to diagnose the COVID 19 infection on a dataset consisting of 305 CRIs from each class (i.e. COVID, Normal, Pneumonia-bacterial and Pneumonia-viral). The average classification accuracies of 89.6%, 90.2% and 94.44% are obtained using CoroNet, CovXNet and our proposed model, respectively. The proposed COVIDetection-Net outperforms the CoroNet and CovXNet models in accuracy, recall, Specificity, Precision, F1-score and AUC.

All results ensure that our proposed COVIDetection-Net surpasses other studies that used CRIs in COVID19 detection on 4-class, 3-class and binary classification tasks. Hence the proposed COVIDetection-Net can serve as an efficient model in the current state of COVID-19 pandemic.

7. Conclusion
A deep learning COVIDetection-Net model is proposed to detect and classify COVID-19 and other types of pneumonia infection from chest radiography images. This system is based on efficient deep features that are extracted using ShuffleNet and SqueezeNet and MSVM are used for features matching. The proposed system is able to implement 4-classes, 3-classes and binary classification tasks with overall accuracies of 94.44%, 99.72% and 100%, respectively. It also provides the highest detection accuracy of 100% of the COVID class on binary and multi-class classification. The highest performance of COVID detection is achieved using the proposed COVIDetection-Net system when compared with ShuffleNet, SqueezeNet and other studies in literatures. Hence, the proposed system can be used as an efficient model in different countries affected by COVID-19 to overcome a shortage of detection resources.

Compliance with Ethical Standards

Conflict of interest The authors declare that they have no conflict of interest.

Ethical approval This article does not contain any studies with human participants performed by any of the authors.
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Table 1: The summary of the prepared dataset.

| The classes               | Number of images |
|---------------------------|------------------|
| Covid                     | 300              |
| Normal                    | 300              |
| Bacterial Pneumonia       | 300              |
| Viral Pneumonia           | 300              |

Table 2: Performance comparison of 4-class COVIDetection-Net, ShuffleNet and SqueezeNet.

| Method            | class         | Recall | specificity | Precision | F1-Score | Accuracy |
|-------------------|---------------|--------|-------------|-----------|---------|----------|
| SqueezeNet        | Covid         | 98.89  | 98.89       | 96.74     | 97.80   | 98.9     |
|                   | Normal        | 95.56  | 98.52       | 95.56     | 95.56   | 95.6     |
|                   | Bacterial Pneumonia | 78.89  | 95.56       | 85.54     | 82.08   | 78.9     |
|                   | Viral Pneumonia | 84.44  | 92.96       | 80        | 82.16   | 84.4     |
| ShuffleNet        | Covid         | 100    | 99.63       | 98.90     | 99.45   | 100      |
|                   | Normal        | 98.89  | 99.63       | 98.89     | 98.89   | 98.9     |
|                   | Bacterial Pneumonia | 82.22  | 95.19       | 85.06     | 83.62   | 82.2     |
|                   | Viral Pneumonia | 86.67  | 94.81       | 84.78     | 85.71   | 86.7     |
| COVIDetection Net | Covid         | 100    | 100         | 100       | 100     | 100      |
|                   | Normal        | 100    | 98.89       | 96.77     | 98.36   | 100      |
|                   | Bacterial Pneumonia | 85.56  | 97.41       | 91.67     | 88.51   | 85.6     |
|                   | Viral Pneumonia | 92.22  | 96.30       | 89.25     | 90.71   | 92.2     |

Table 3: Performance comparison of 3-class COVIDetection-Net, ShuffleNet and SqueezeNet.

| Method            | class         | Recall | specificity | Precision | F1-Score | Accuracy |
|-------------------|---------------|--------|-------------|-----------|---------|----------|
| SqueezeNet        | Covid         | 98.89  | 99.63       | 98.89     | 98.89   | 98.9     |
|                   | Normal        | 98.89  | 98.15       | 94.68     | 96.74   | 98.8     |
|                   | Pneumonia     | 96.67  | 98.89       | 98.86     | 97.75   | 96.7     |
| ShuffleNet        | Covid         | 100    | 99.63       | 98.9      | 99.45   | 100      |
|                   | Normal        | 96.67  | 99.26       | 97.75     | 97.21   | 96.7     |
|                   | Pneumonia     | 98.33  | 98.33       | 98.33     | 98.33   | 98.3     |
| COVIDetection Net | Covid         | 100    | 100         | 100       | 100     | 100      |
|                   | Normal        | 100    | 99.63       | 98.9      | 99.45   | 100      |
|                   | Pneumonia     | 99.44  | 100         | 100       | 99.72   | 99.4     |
Table 4 Performance comparison of binary COVIDetection-Net, ShuffleNet and SqueezeNet.

| Method   | class     | Recall | specificity | Precision | F1 Score | Accuracy |
|----------|-----------|--------|-------------|-----------|----------|----------|
| SqueezeNet | Covid    | 100    | 98.52       | 95.74     | 97.83    | 100      |
|          | Non-covid | 98.52  | 100         | 100       | 99.25    | 98.5     |
| ShuffleNet | Covid    | 96.67  | 100         | 100       | 98.31    | 96.7     |
|          | Non-covid | 100    | 96.67       | 98.90     | 99.45    | 100      |
| COVIDetection Net | Covid | 100    | 100         | 100       | 100      | 100      |
|          | Non-covid | 100    | 100         | 100       | 100      | 100      |

Table 5 Performance of the proposed 4-class, 3-class and binary COVIDetection-Net

| Model    | Recall | specificity | Precision | F1 Score | Overall accuracy |
|----------|--------|-------------|-----------|----------|------------------|
| 4-classes | 94.45  | 98.15       | 94.42     | 94.4     | 94.44            |
| 3-classes| 99.81  | 99.88       | 99.63     | 99.72    | 99.72            |
| Binary   | 100    | 100         | 100       | 100      | 100              |
Table 6 Comparison of the classification accuracy (%) of the proposed COVIDetection with other existing approaches.

| Study                  | Architecture                  | Binary | 3 class | 4 class |
|------------------------|-------------------------------|--------|---------|---------|
| Brunese et al [8]      | VGG 16 (transfer learning)    | 97     | -       | -       |
| Panwar et al [24]      | nCOVnet                       | 88.1   | -       | -       |
| Hemdan et al [22]      | COVIDXNet (DenseNet201)       | 90     |         |         |
| Narin et al [23]       | ResNet50                      | 98     |         |         |
| Singh et. al [25]      | CNN+ MODE                     | 93.5   | -       | -       |
| Dipayan Das [9]        | Truncated inception Net       | 99.9   | -       | -       |
| Tuncer et al [26]      | ResExLBP + IRF+SVM            | 99.69  | -       | -       |
| Sethy et al [11]       | ResNet50/svm                  | 95.38  | 95.33   |         |
|                        | AlexNet                       | 93.32  | 94.86   |         |
|                        | GoogleNet                     | 91.44  | 91.73   |         |
|                        | DenseNet201                   | 93.88  | 93.86   |         |
| Wang et al [18]        | COVID-Net                     | -      | 92.4    |         |
| Makris [14]            | VGG16                         | -      | 95.88   | -       |
| Kumar et. al [13]      | ResNet152/ XGB                | -      | 97.7    | -       |
|                        | ResNet152/ RF                 | -      | 97.3    | -       |
| Li et. al [19]         | DenseNet-121                  |        | 88.9    | -       |
| Ucar et al [17]        | COVIDiagnoses (squeezenet)    |        | 98.3    |         |
| Rahimizadeh et. al [16]| Concatenation (Xception+ ResNet50V2) | | 91.4 | |
| Ozturk et al [15]      | DarkNet                       | 98.08  | 87.02   |         |
| Apostolopoulos et. al [12]| VGG 19 MobileNet v2             | 98.75  | 93.48   | 92.85   | -   |
| Khan et al [20]        | Coronet (Xception)            | 99     | 95      | 89.6    |
| Mahmud et al [21]      | CovXNet                       | 97.4   | 89.6    | 90.2    |
| **The Proposed**       | **COVIDetection Net**         | **100** | **99.72** | **94.44** |
Table 7: The performance comparison of 4-class CoroNet, CovXNet and Proposed COVIDetection-Net.

| Method     | Recall % | Specificity % | Precision % | F1-score % | AUC   | Amount of CRIs                  |
|------------|----------|---------------|-------------|------------|-------|---------------------------------|
| CoroNet [20] | 89.92    | 96.4          | 90          | 89.8       | -     | 284 COVID + 310 Normal + 330 Pneumonia-bac + 327 Pneumonia-vir |
| CovXNet [21] | 89.9     | 89.1          | 90.8        | 90.4       | 0.911 | 305 COVID + 305 Normal + 305 Pneumonia-bac + 305 Pneumonia-vir |
| Proposed   | 94.45    | 98.15         | 94.42       | 94.4       | 0.98  | 300 COVID + 300 Normal + 300 Pneumonia-bac + 300 Pneumonia-vir |