A deep learning approach for COVID-19 and pneumonia detection from chest X-ray images

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Article Info

ABSTRACT

There has been a surge in biomedical imaging technologies with the recent advancement of deep learning. It is being used for diagnosis from X-ray, computed tomography (CT) scan, electrocardiogram (ECG), and electroencephalography (EEG) images. However, most of them are solely for particular disease detection. In this research, a computer-aided deep learning model named COVID-CXDNetV2 has been presented to detect two separate diseases, coronavirus disease 2019 (COVID-19) and pneumonia, from the X-ray images in real-time. The proposed model is made based on you only look once (YOLOv2) with residual neural network (ResNet) and trained by a vast X-ray images dataset containing 3788 samples of three classes named COVID-19 pneumonia and normal. The model has obtained the maximum overall classification accuracy of 97.9% with a loss of 0.052 for multiclass classification (COVID-19, pneumonia, and normal) and 99.8% accuracy, 99.52% sensitivity, 100% specificity with a loss of 0.001 for binary classification (COVID-19 and normal), which beats some current state-of-the-art results. Authors believe that this method will be applicable in the medical domain for the diagnosis and will significantly contribute to real life.

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1. INTRODUCTION

Coronaviruses (CoVs) are a larger family of harmful viruses that can affect humans and other animals and even can cause death. In the 21st century, two widely zoonotic CoVs, Middle East respiratory syndrome coronavirus (MERS-CoV) and severe acute respiratory syndrome coronavirus (SARS-CoV), spread from animal reservoirs to cause global pandemics with alarming morbidity and mortality [1]. Recently, coronavirus disease 2019 (COVID-19), which is owing to severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2), has been emerged in Wuhan, China, in December 2019 [2]. It has spread out all over the world and affected 307 M people, and results in 5.5 M deaths all over the world till Jan 09, 2022 [3]. COVID-19 epidemic was certified as a global pandemic on March 11, 2020, by the World Health Organization [4].

This virus is contagious and can be transmitted from close contact with affected people or even from sharing ordinary staff [5]. So, isolation is a standard solution to control the spreading of this disease. Even though the reverse transcription-polymerase chain reaction (RT-PCR) is presently the mainstream procedure for detecting COVID-19 disease [6], this method has some limitations like requires special test kits, costly, time-consuming and results are highly false-negative levels and considered in the context of recent exposures to the patient and the existence of clinical signs and symptoms [7]. Moreover, this method has a low sensitivity of 60 to 71% for the COVID-19 identification due to a low viral load present in the test specimen and the laboratory error [8]. Pneumonia is also a lung infection similar syndrome as COVID-19 that causes viruses bacteria, and fungi. From mild to life-threatening, pneumonia can range in seriousness. It is highly hazardous for older people (age >65), kids and young children, and people with health issues or weaker immune systems.

Medical image processing is another feasible technique for COVID-19 or pneumonia detection from chest X-ray (CXR) or computed tomography (CT) images. Thoracic abnormality in CT images shows high sensitivity, so a lot of researchers are focusing on CT images to detect COVID-19 disease [9]. But there are some drawbacks, including the limitation of portability, required deep cleaning of the apparatus used, the high value of radiation, and the higher cost [10]. On the other hand, CXR is very common, cost-effective, portable, available in almost any diagnostic center, and easily accessible [11]. Therefore, CXR based method, which can easily determine lung abnormalities, can be a good alternative tool to diagnose COVID-19 and pneumonia.

In recent times, the deep learning technique has led to medical imaging study. Image classification, segmentation, and pattern finding are the most common task which is handled efficiently by convolutional neural networks (CNNs). In the meantime, this technique has proven successful in detecting bleeding, breast cancer, pneumonia, skin cancer, arrhythmia, diabetic retinopathy, brain disease, and so on. The fast transmission of COVID-19 disease required more radiologists in this field to support the diagnostic centers, which is almost impossible within a short span of time. The proposed deep learning technique of COVID-19 and pneumonia detection can help in this aspect and reduce the cost of the test kit, technologists, and other logistics.

To handle the rapidly growing number of COVID-19 and pneumonia cases, the researchers are usually using CT and X-rays images. In their research [12], presented a deep learning model named the DarkCovidNet on the basis of the darknet object detection method, which can determine corona from X-ray images. This article reported a classification accuracy of 87.02 % for a three-category classification problem, including COVID-19, normal, and pneumonia. Heidari *et al.* [13] have derived a computer-aided diagnosis scheme from CNN to diagnose the COVID-19 infected pneumonia, which has shown overall accuracy of 94.5 % in a three-class disease classification problem. Similarly, researchers have used DenseNet-121 in COVID-CXNet to classify corona from X-ray images [14]. The fusion of two models can be used for increasing the accuracy of the deep learning-based model. For example, Rahimzadeh and Attar [15] have fused the Xception, ResNet50V2, and the neural network, which has achieved 91.4% accuracy. Khan *et al.* [16] have derived a deep CNN model from the Xception model named CoroNet, which has gained 95% accuracy. Also, the transfer learning technique is the best way of medical image classification, especially if the number of samples in the dataset is less [17]. For example, Abbas *et al.* [18] have applied a transfer learning approach and achieved an accuracy of 95.12% to detect COVID-19 using the CXR images.

This research proposes a novel deep learning model named COVID-CXDNetV2 based on the modification of you only look once (YOLOv2) [19] with ResNet [20] for detecting COVID-19 and pneumonia patients as a multiclass classification problem. In addition, a customized CXR images dataset was also formed to train the model by collecting data from four different open-source repositories. The dataset contains 1,102 COVID-19 positive, 1,341 normal, and 1,345 infected viral pneumonia CXR images. The model needs raw CXR images as an input and gives COVID-19, pneumonia, or normal as an output. The main limitation of CXR based COVID-19 and pneumonia detection is that it cannot usually detect accurately in a very early stage of COVID-19 or pneumonia as it does not have high sensitivity in detecting the ground-glass opacities [7].

The paper is organized into three sections: in section 2, the method of this research is presented, which includes dataset, dataset preprocessing, and proposed model architecture. The performance evaluation of the model and comparison of other existing state-of-the-art models in this field are discussed in section 3. Finally, the conclusion and future direction are provided in section 4.

2. METHOD

A novel deep learning model is introduced in this study to automatically identify confirmed COVID-19 patients from viral pneumonia and normal patients using 2D traditional CXR images. An open access customized dataset is also developed to encourage training and evaluation of the proposed model. The

complete operation of the proposed framework is represented in Figure 1. The Figure 1 shows that first collect dataset from different authentic sources and preprocess data to fit the proposed model and apply to the deep learning model to identify diseases from the CXR images.
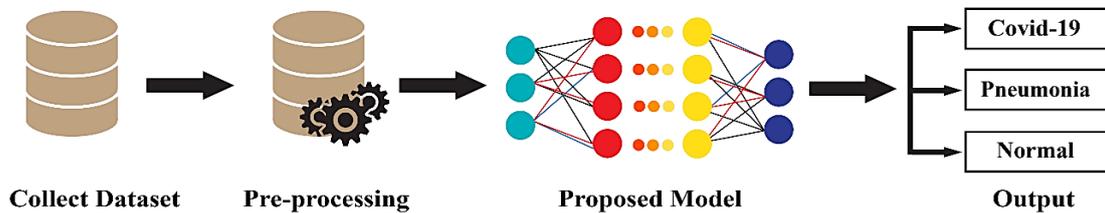
Figure 1. Flow diagram of the proposed method

2.1. Dataset

Small datasets are one of the challenges of medical image processing techniques. In this research, the CXR images were applied to detect COVID-19. However, there are just a few publicly available COVID-19 CXR images because COVID-19 is a recent disease. This analysis uses and assembles a dataset of CXR images taken from four publicly accessible medical repositories which are shown in Table 1.

The customized dataset is generated by filtering four datasets with a posteroanterior (PA) view of X-ray images and avoiding data leakage. After assembled, 3788 2D CXR images are considered for affected COVID-19 detection; among them, 1102 images are positive COVID-19, 1,345 images are infected viral pneumonia, and 1,345 images are normal cases. The customized dataset is publicly available on Kaggle [21].

Table 1. Summary of dataset collection

Name	Pneumonia	COVID-19	Normal
Dataset_1[22]	0	59	0
Dataset_2[23]	0	53	0
Dataset_3[21]	1345	219	1341
Dataset_4[14]	0	818	0

2.2. Dataset preprocessing

The dataset is collected from four different sources, so the CXR size of the images varies from 205×243 to 3804×3487 pixels. During training, all images are resized to 256×256 pixels. Images are also normalized to prevent more computation time and reduce random access memory (RAM) usage. In the case of deep learning algorithms, data augmentation is a strategy to enhance the dataset size for real-time practical application. Due to the small number of data sets, data augmentation is a useful medical imaging technique. Data augmentation is a technique to generate copies of one image into multiple possibilities of geometric transformations, blur, luminance, flipping, noise injection, color modification, cropping, and rotation variances of the image, for effective and generalized training. In this experiment, the values of parameters i.e., p_lighting: 0.75, p_affine: 0.75, maximum zoom: 1.1, maximum warp: 0.2, maximum lighting: 0.2 are used for the CXR image transformation. But, due to the location of the heart, lungs, and other organs, the flipping of the CXR image is ignored. The technique also helps reduce overfitting when training the model. After data augmentation, the dataset is sliced into two parts, 80% is used for training, and 20% is utilized for validation tests, and 80% for the training of a total number of CXR images.

2.3. Model architecture

In this study, the proposed model was developed using a deep learning approach. This approach is a subfield of artificial intelligence (AI) that trains to learn models using artificial neural networks (ANNs). There are several kinds of deep learning algorithms, but CNN are the most broadly used. YOLO is one of the well-known deep learning models that utilize CNN architecture for real-time object detection tasks. This technique utilizes only one neural network to the entire image. Then splits it into sections and identifies the bounding boxes and probabilities of each part. The estimated probabilities are used to weigh these boxes. The proposed COVID-CXDNetV2 model architecture was designed by modifying YOLOv2 inspired by Ozturk *et al.* [12] and residual neural network (ResNet) to detect COVID-19 patients from pneumonia and normal CXR images. Residual network connections are shortcut or skip connection that takes activations from one layer and feed it to another layer. According to the connection, the weight layer sequence output is the sum of the

present weight and past activation (the main input) and then crosses over a non-linear activation function. There are residual blocks in ResNet that help in training deeper networks. The advantage of training a residual network is that the training error does not rise when training a deeper network. The residual network connections are shown in Figure 2.
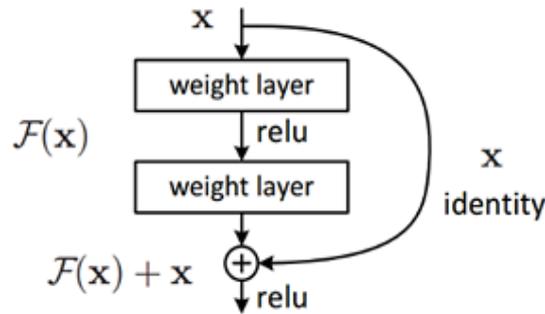
Figure 2. Residual connection

The proposed COVID-CXDNetV2 architecture is presented in Figure 3 and marked in several colors to make it easier to understand. The proposed model consists of 14 convolution blocks, five max-pooling layers, four residual connections, one convolution layer, one flatten layer, and one linear layer with various filter numbers, sizes, and stride sizes. The dimension of the input color image is 256×256×3, which indicates the CXR image with 256 height and 256 widths with three channels (green, red, and blue). The first convolutional block takes the image that has eight kernels of size 3×3 with padding one and stride one. The convolution block has a single convolution layer with batch normalization and the leaky rectified linear unit (LReLU) activation function. The convolution layer is a significant aspect of the CNN model framework that utilizes the convolution operation (*) rather than regular matrix multiplication. It involves a set of learnable filters for detecting features in the input image. If I is the input image, kernel K, m×n is the kernel size, and S is the output, the 2D convolution process is given by (1).

$$S(i,j) = (I * k)(i,j) = \sum m \sum n \, I(m,n)k(i-m, j-n) \tag{1}$$
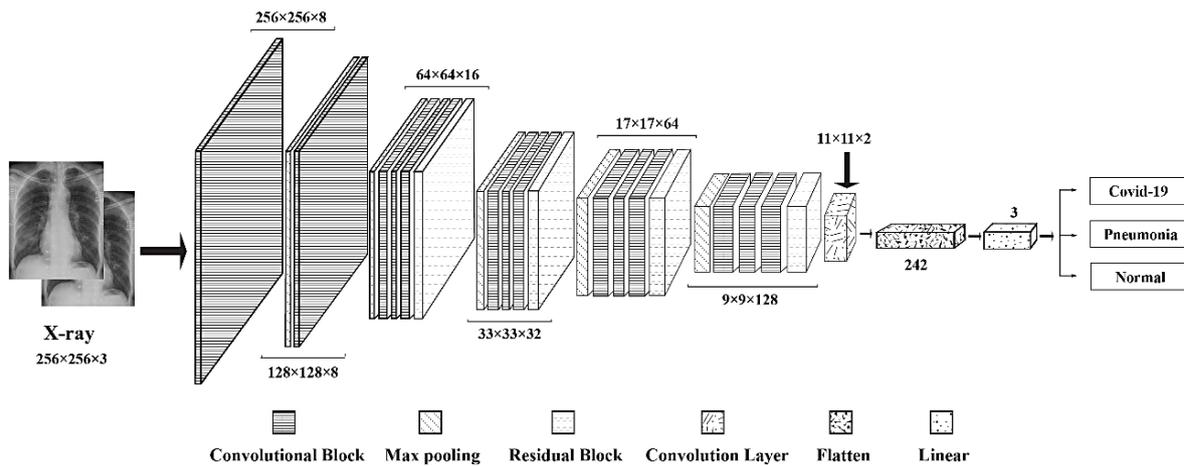
Figure 3. Architecture of COVID-CXDNetV2

Batch normalization is used to normalize the input image, minimize training time, and improve model robustness. An LReLU non-linear activation function is used in that the value is a small fraction in the negative section of their derivatives. Then a max-pooling layer with a stride of 2 and a 2×2 filter is used. After the process, the output shape of image 128×128×8 is utilized in the second convolution block, which

contains 16 filters. In Figure 3, the third block has one max pooling layer with a stride of 2, and a 2×2 filter is utilized after the second convolution block, and the output shape of the image downsizes to 64×64×16. The block also includes three convolutional blocks with kernels 32, 16 and 32 of size 3×3, 1×1, and 3×3, respectively, as well as one residual block. This process continues for four, five, and six blocks in the figure. After that, a single convolution layer with two kernels of size 3×3/1, a flatten layer, and a linear layer was used. The linear layer has 3 or 1 neurons to classify COVID-19 or pneumonia or normal CXR images (3 neurons for pneumonia, normal and COVID-19; 1 neuron for COVID-19 or normal). All layers and their parameters and output shape of the proposed architecture are shown in Table 2.

Table 2. The architectural summary of the proposed model

Type	Filters	Size/Stride	Output
Convolutional	8	3×3/1	256×256
Maxpool	8	2×2/2	128×128
Convolutional	16	3×3/1	128×128
Maxpool	16	2×2/2	64×64
Convolutional	32	3×3/1	64×64
Convolutional	16	1×1/1	66×66
Convolutional	32	3×3/1	66×66
Residual			66×66
Maxpool	32	2×2/2	33×33
Convolutional	64	3×3/1	33×33
Convolutional	32	1×1/1	35×35
Convolutional	64	3×3/1	35×35
Residual			35×35
Maxpool	64	2×2/2	17×17
Convolutional	128	3×3/1	17×17
Convolutional	64	1×1/1	19×19
Convolutional	128	3×3/1	19×19
Residual			19×19
Maxpool	128	2×2/2	9×9
Convolutional	256	3×3/1	9×9
Convolutional	128	1×1/1	11×11
Convolutional	256	3×3/1	11×11
Residual			11×11
Convolutional	2	3x3/1	11×11
Flatten	242		
Linear	3 or 1		

The proposed model is implemented using PyTorch 1.4 open-source machine learning framework. The network architecture is trained by utilizing the Adam optimizer with 3e-3 learning rate, 32 batch sizes, and the maximum number of epochs 100. Adam optimizer converts the learning rate and attributes weight to decrease the loss of the learning network architecture. The 'cross-entropy' loss function is used to evaluate the performance of a classification model since it is utilized to solve the classification problem. All the computational and analysis are done on the Google Colaboratory platform with a Tesla T4 GPU.

3. EVALUATION AND DISCUSSION

The performance of the COVID-CXDNetV2 model is evaluated using six different metrics: accuracy, sensitivity, specificity, precision, and F1 score [24]–[26]. They are defined as (2) to (6).

$$\text{Accuracy} = \frac{\sum TP + \sum TN}{\sum TP + \sum TN + \sum FN + \sum FP} \tag{2}$$

$$\text{Sensitivity} = \frac{\sum TP}{\sum TP + \sum FN} \tag{3}$$

$$\text{Specificity} = \frac{\sum TN}{\sum FP + \sum TN} \tag{4}$$

$$\text{Precision} = \frac{\sum TP}{\sum TP + \sum FP} \tag{5}$$

$$\text{F1 score} = \frac{2\sum TP}{2\sum TP + FP + FN} \tag{6}$$

In this study, two experiments (one for the multiclass classification and another for the binary classification) are performed to judge the efficiency and performance of the proposed COVID-CXDNetV2 model to classify COVID-19 or pneumonia from CXR images. The confusion matrix for multiclass and binary classification of the model are included in Figure 4.

According to (2)-(6), the COVID-CXDNetV2 model obtained an overall classification accuracy of 97.33% for multiclass disease classification. For COVID-19 detection the model achieved 99.13% sensitivity, 99.81% specificity, 99.56% precision and 99.34% F1 score. Similarly, the performance for detecting only pneumonia diseases is shown in Table 3. The model also obtained 99.79% classification accuracy, 99.52% sensitivity, 100% specificity, 100% precision, and 99.76% F1 score for binary classification (normal and COVID-19).
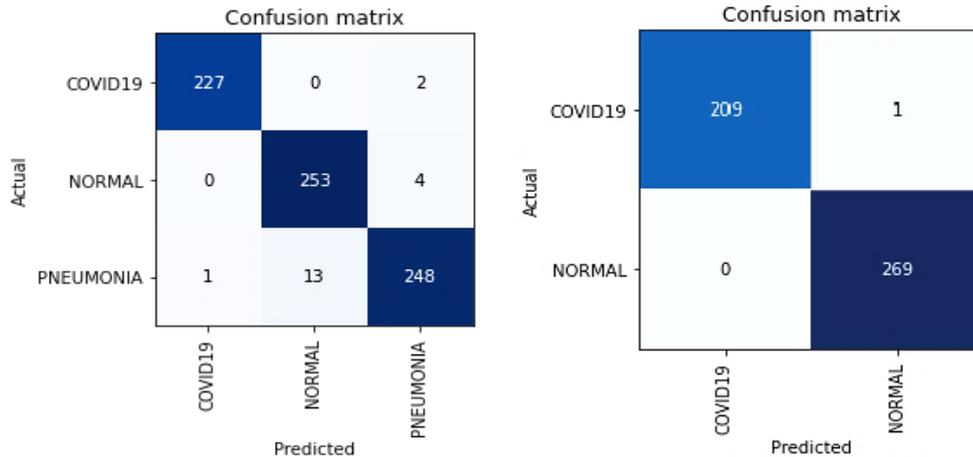
Figure 4. Confusion matrix for multiclass classification and binary classification respectively

Table 3. The performance of the model for each disease

Class	Precision	Sensitivity	Specificity	F1 score
COVID-19	99.56%	99.13%	99.81%	99.34%
Normal	95.11%	98.44%	96.68%	96.75%
Pneumonia	97.64%	94.66%	98.77%	96.13%

The accuracy, validation loss and training loss of the COVID-CXDNetV2 has been evaluated through a different number of epochs (20, 40, 60, 80, 100), which is shown in Table 4. The model may overfit if the number of epochs is very high, and the training accuracy will reach 100%. If validation loss > training loss, the model is overfitting. In opposite, the model is underfitting. For a good fit of the model, the difference between validation loss and training loss should be minimum. The best results were obtained using that approach at epoch 80 for multiclass classification and 100 for binary classification, where the validation and training loss is minimum. In both multiclass and binary classification, the training and validation loss decreases as the number of epochs increases which are shown in Figure 5. The initial position of the loss graph is highly distorted between training and validation losses. After a few epochs, the training and validation losses are approximately equal. In the last position of the graph, the validation loss increases gradually. So, the model obtained maximum overall classification accuracy of 97.9% at 80 epochs for multiclass and 99.8% at 100 epochs for binary classification where the losses and difference between training and validation loss are minimum.

Table 4. Performance evaluation of multiclass and binary classification for different epochs

	Multiclass classification			Binary class classification		
Epoch	Accuracy (%)	Training loss	Validation loss	Accuracy (%)	Training loss	Validation loss
20	92.5	0.212981	0.202916	97.9	0.067623	0.067721
40	94.9	0.141943	0.153560	99.5	0.033901	0.023971
60	96.9	0.083831	0.088530	99.8	0.018865	0.013667
80	**97.9**	**0.052176**	**0.070637**	99.8	0.007013	0.015052
100	97.3	0.034904	0.085641	**99.8**	**0.001320**	**0.014740**

A lot of researchers are conducting research for COVID-19 or pneumonia diseases detection from CXR images. Ozturk *et al.* [12] presented DarkCovidNet to identify COVID-19 cases from CXR images and have obtained an accuracy of 87.02% for multiclass classification and 98.08% accuracy for binary classification. Another deep learning model [15] is developed based on Xception + ResNet50V2 obtained an accuracy of 91.4% for three classes. Apostolopoulos and Mpesiana [27] achieved a classification accuracy of 93.48% and 93.5% for using the VGG19 and MobileNetV2 model, respectively, for three-class classification cases. A deep learning network, CoroNet is used [16] to detect corona from CXR images and achieved 95% accuracy for multiclass classification. However, the result of the proposed COVID-CXDNetV2 model is superior compared to other existing researches, which is shown in Table 5. The table only included the research that analyzed the performance of COVID-19 detection from CXR images.

CXR images are recommended because they are easily accessible for disease identification. During the pandemic situation, they are frequently utilized in health clinics throughout the world. As the performances of the proposed COVID-CXDNetV2 are comparatively more efficient than the other existing work, it can be used for diagnosing COVID-19 in an easy manner.
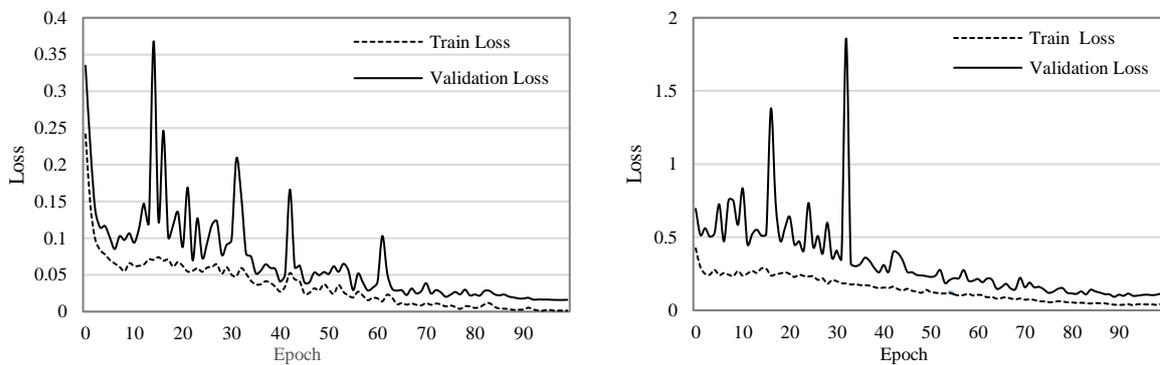
Figure 5. Loss graph for multiclass classification (left) and binary classification (right)

Table 5. Performance comparison of the COVID-CXDNetV2 model with other existing models

Approach	Method	Multiclass classification			Binary class classification		
		Accuracy (%)	Sensitivity (%)	Specificity (%)	Accuracy (%)	Sensitivity (%)	Specificity (%)
Sethy *et al.* [28]	Resnet50+ SVM	-	-	-	95.38	-	-
Hemdan *et al.* [29]	COVIDX-Net	-	-	-	90.0	-	-
Gunraj *et al.* [30]	COVID-Net	93.3	-	91.0	96.6	-	91.0
Apostolopoulos and Mpesiana [27]	MobileNetV2	93.5	98.6	-	96.7	98.6	-
Narin *et al.* [31]	ResNet50	-	-	-	98.0	96.0	-
Ozturk *et al.* [12]	DarkCovidNet	87.02	-	-	98.08	-	-
Rahimzadeh and Attar [15]	Xception + ResNet50V2	91.4	-	80.53	-	-	-
Heidari *et al.* [13]	VGG16	94.5	98.4	-	98.1	98.4	-
Apostolopoulos and Mpesiana [27]	VGG19	93.48	92.85	98.75	98.75	92.85	98.75
Khan *et al.* [16]	CoroNet	95	-	95.0	98.8	-	95.0
Rahimzadeh and Attar [15]	Xception + ResNet50V2	-	-	-	99.5	-	80.53
Abbas *et al.* [18]	DeTraC Deep CNN	95.12	97.91	91.87	-	-	-
Proposed Model	**COVID-CXDNetV2**	**97.9**	**99.13**	**99.81**	**99.79**	**99.52**	**100**

4. CONCLUSION AND FUTURE WORK

COVID-19 has become a life-threatening disease worldwide, and a lot of researchers are conducting research to detect this disease. Computer vision-based recognition is one of the most prominent ways to detect COVID-19 disease from X-ray images. Pneumonia is a lung disease with very similar symptoms and can also be detected from X-ray images. This research proposed a deep learning-based COVID-19 and pneumonia diseases detection model that recognizes the disease as a multiclass and binary classification problem from X-ray images. The proposed model builds by modifying YOLOv2 with ResNet. A vast customized X-ray dataset of 3788 2D posteroanterior (PA) X-ray images has been used for training the model. Among those X-rays, 1,102 images are labeled as COVID-19 positive, 1,345 images are labeled

pneumonia positive, and 1,345 are labeled normal, meaning those are both COVID-19 and pneumonia negative. Eventually, the model has been compared with other existing computer vision-based COVID-19 diseases detection and the pneumonia detection results, and this model achieved height accuracy, sensitivity, and specificity. In addition, the training loss recorded was 0.052 for multiclass classification cases and 0.001 for binary classification cases during the training process. The accuracy of this model has beat the performance of the state of art results of this research area. The accuracy of this model largely depends on the dataset. Increasing the number of samples by collecting more images or by image synthesis and augmentation may help increase the proposed model's accuracy.

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