A Deep Learning-based System for Detecting COVID-19 Patients

Nidal Nasser[1], Qazi Emad-ul-Haq[2], Muhammad Imran[3], Asmaa Ali[4], Abdulaziz Al-Helali[5]
[1,5]College of Enigneering, Alfaisal University, KSA,{nnasser, aalhelai}@alfaisal.edu
[2,3] College of Computer and Information Sciences, King Saud University, KSA, qulhaq@ksu.edu.sa, dr.m.imran@ieee.org
[4] School of Computing, Queen's University, Canada, ali@cs.queensu.ca

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Abstract— **COVID-19 (Coronavirus) is a very contagious infection that has drawn the world public's attention. Modeling such diseases can be extremely valuable in predicting their effects. Although classic statistical modeling may provide adequate models, it may also fail to understand the data's intricacy. An automatic COVID-19 detection system based on computed tomography (CT) scan or X-ray images is effective, but a robust system's design is a challenging problem. In this paper, motivated by the outstanding performance of deep learning (DL) in many solutions, we used DL based approach for computer-aided design (CAD) of the COVID-19 detection system. For this purpose, we used a state-of-the-art classification algorithm based on DL, i.e., ResNet50, to detect and classify whether the patients are normal or infected by COVID-19. We validate the proposed system's robustness and effectiveness by using two benchmark publicly available datasets (Covid-Chestxray-Dataset and Chex-Pert Dataset). The proposed system was trained on the collection of images from 80% of the datasets and tested with 20% of the data. Cross-validation is performed using a 10-fold cross-validation technique for performance evaluation. The results indicate that the proposed system gives an accuracy of 98.6%, a sensitivity of 97.3%, a specificity of 98.2%, and an F1-score of 97.87%. Results clearly show that the accuracy, specificity, sensitivity, and F1-score of our proposed system are high, and it performs better than the existing state-of-the-art systems. The proposed system based on DL will be helpful in medical diagnosis research and health care systems.**

Keywords — **Coronavirus (COVID-19), detection, machine learning (ML), deep learning (DL).**

I. Introduction

A novel coronavirus (SARS-CoV-2) has spread from Wuhan to China and several other countries since December 2019. Over two million confirmed cases were registered by April 18, and there were more than 1.07 million worldwide deaths [1]. Since preventive vaccines or treatment for COVID-19 disease is not available, early diagnosis is of great value in providing the patient with the potential for effective isolation and decreases the risk of infection to a healthy population. As main COVID-19 screening methods, reverse-transcription polymerase chain reaction (RT-PCR) or gene sequencing for respiratory or blood specimens was implemented [2]. However, the overall RT-PCR positive rate for samples of throat swabs is estimated to be between 30 and 60 percent, resulting in undiagnosed patients that infect large populations of healthy individuals [3]. Chest X-ray imaging is a simple method for quick diagnosis of disease as it is also used for pneumonia diagnosis. Also, chest CT scanning has higher COVID-19 diagnostic sensitivity [4], whereas chest X-ray images provide visual indexes related to COVID-19 [5]. Multilobar involvement and peripheral airspace opacity were seen in reporting chest imaging. The most widely recorded opacity is ground glass (57%) and mixed attenuation (29%) [6]. During the early phase of COVID-19, ground glass patterns are found in areas on the edge of the pulmonary vessels difficult to visually recognize [7]. The diffuse airspace opaces or asymmetric patchy are also noted for COVID-19 [8]. Only specialist radiologists may perceive such subtle anomalies. With the enormous rate of suspicious persons and

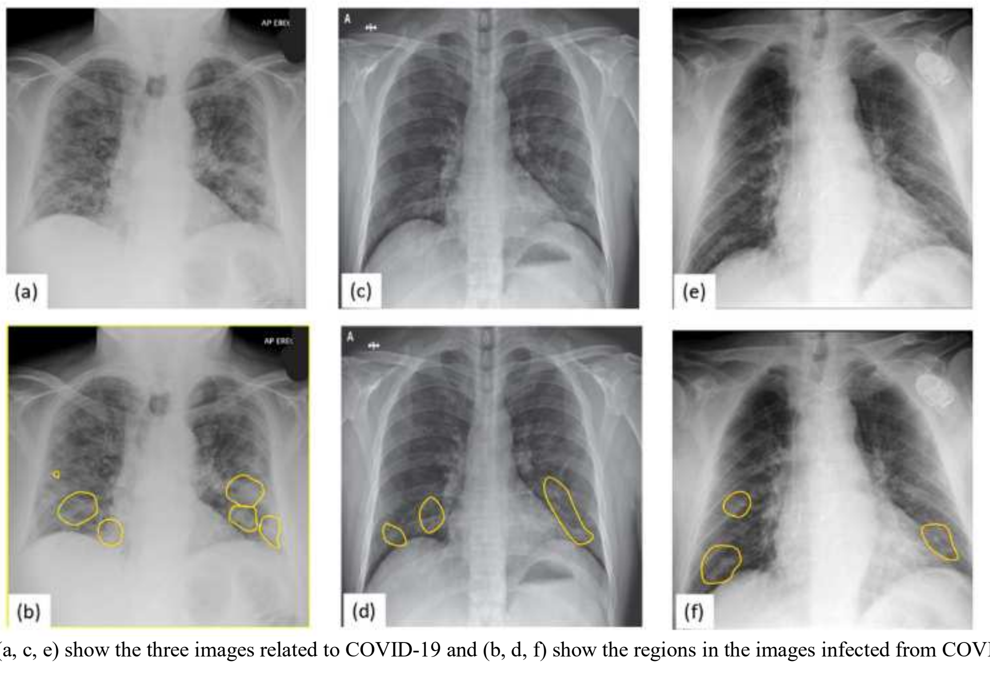

Fig. 1. (a, c, e) show the three images related to COVID-19 and (b, d, f) show the regions in the images infected from COVID-19.

fewer qualified radiologists, efficient and robust automated systems for detecting such diseases will help the diagnosis process and improve early detection rates with high precision. To solve such problems, AI / ML-based automated systems are effective tools.

Various research studies have been carried out to propose automated detection or recognition of COVID-19 cases using chest CT scan or X-ray images but the results achieved are not up to the mark due to the lack of public image databases of COVID-19 patients. There has recently been a small data set containing a COVID-19 X-ray image that enables the training of automated COVID-19 X-ray diagnostics by researchers [9]. These images were taken from research publications that showed the results of the COVID-19 using CT and X-ray images. A board of radiologists analyzed the complete database of images. After analyzing, only a set of those images were retained, which were labeled by the radiologists as a COVID-19 patient. Fig. 1 illustrates the three images with the marked regions. Fig. 1 (a, c, e) shows the images related to COVID-19, and Fig. 1 (b, d, f) shows the regions in the images infected from COVID-19. We then used a subset of ChexPert dataset images as negative COVID-19 samples [10]. We prepared a dataset Covid-Xray of 6000 images from the two available datasets, i.e., Covid-Chestxray-Dataset and Chex-Pert Dataset. Out of 6000 images, 1200 images are used for testing, and 4800 images are used for training.

In this study, a ML-based system is used to detect COVID-19 from Chest X-ray images. Contrary to the hand-engineered feature extraction and classification approach for the medical images, we utilize a deep learning-based end-to-end prediction system that identifies the COVID-19 cases from the input images without any extraction of features. A convolutional neural network (CNN) has achieved much better performance in many applications among the various deep learning models. A CNN is a type of artificial neural network with two main advantages: local connectivity and weight sharing. These advantages make the CNN appropriate for high-dimensional signals such as images. They have been employed in different image enhancement problems, segmentation, feature extraction, and classification [11, 12]. In this study, we trained a state-of-the-art ResNet50 convolutional neural network model for this problem and evaluated its performance for COVID-19 detection. As the number of X-ray images for COVID-19 is limited, so we adopted two strategies in this study:

- Data augmentation technique is used to increase the dataset size by factor 5. For this purpose, we use small rotation, flipping, and adding a small amount of distortion).

- We have optimized the last layer of the ResNet CNN model on ImageNet, rather than learning these models from scratch. So, fewer samples of each class can be used to train the model.

The above two strategies led to creating a network with available images and obtain high performance on 1200 images. Due to the limited number of images for COVID-19, We also compute the confidence interval (CI) of the performance metrics. The main contributions of this paper are as follows:

1) To detect COVID-19 in X-ray images, we prepared a dataset of 6000 images. The COVID-19 images are labeled by an expert radiologist and are only used for research purposes with a clear mark.

2) We used the state-of-the-art ResNet50 convolutional neural network model in this problem to classify COVID-19 patients versus non-COVID normal subjects. We trained the ResNet50 model on 4800 images and tested its performance on 1200 images. An accuracy of 98.6%, a sensitivity of 97.3%, a specificity of 98.2%, and an F1-score of 97.87% have been achieved using the proposed system.

3) We performed an experimental analysis in detail. For this purpose, we use the accuracy, sensitivity, specificity, and F1-score.

4) We use the tSNE plot to visualize the features that clearly discriminate between the two classes.

The rest of the paper is arranged as follows. The description of the dataset is given in Section II. The proposed system is explained in Section III. In Section IV, we present experimental results and discussion. In Section V, we conclude the paper.

II. Images Dataset

In this study, the dataset of 6000 images is prepared using the two datasets. The dataset is divided into two parts, i.e., training and testing. The training and testing sets consist of 4800 and 1200 images, respectively.

One of the datasets used in this study is the Covid-Chestxray dataset, which has been released recently and includes a selection of Joseph Paul Cohen's images in publications on COVID-19 subjects [9, 13]. A chest X-ray and CT scan image combination constitute this data set. From May 3, 2020, there were 250 radiographs of COVID-19 patients in this dataset. Out of 250 images, 184 images are selected for this study that show the perfect identification of COVID-19 patients. This dataset is continuously being updated. This dataset also includes some metadata, such as the age and gender of each patient. From this dataset, all COVID-19 images are selected for our study. In this study, one hundred images are used for testing, and eighty-four images are used for training purposes. All these total 184 images are associated with COVID-19 patients. The data augmentation scheme is also used to increase the training sample size (COVID-19 images) from 84 to 420. We ensure that each patient's images are not overlapped in training and testing sets; either the images of patients are included in the testing set or training set.

To handle the issue of fewer images of non-COVID class in the dataset [13], we have taken more images from the Chex-Pert dataset [10]. The Chex-Pert dataset is a large publicly available dataset consists of 224,316 chest radiographs of 65,240 patients. These images are labeled for 14 different sub-categories (pneumonia, edema, etc.). For our proposed model's training, we used 4380 images from the Chex-Pert dataset, 480 sample images from the no-found class, and 300 sample images from each of the other 13 classes. We used 1100 images from the Chex-Pert dataset, 450 sample images from the no-found class, and 50 sample images from each of the other 13 classes for the testing of our proposed model. Table 1 shows the number of images used for training and testing.

TABLE 1.
NUMBER OF IMAGES USED IN DATASET PREPARATION

Classes	# of Images in Training Data	# of Images in Testing Data

COVID-19	420 (after Data augmentation operations on 84 images)	100
Non-COVID	4380	1100

Fig. 2 presents 16 sample images from the dataset. The first row shows COVID-19 images, the second row shows normal images from the Chex-Pert dataset, and the third and fourth rows show the images affected by one of the 13 diseases in the Chex-Pert dataset.

The resolution of the images in this dataset varies continuously. In the COVID-19 class, we have some high-resolution images (i.e., more than 1900 x 1400) and some low-resolution images (i.e., 400 x 400). This variation is more appropriate for the proposed model because the proposed model can achieve better results after the training regardless of variation in resolution of sample image and image capturing techniques. The data collection in an extremely controlled environment is not viable such as capturing high-resolution images and cleaning the data after preprocessing. As the machine learning field advances in technology, a more focus on sophisticated frameworks and models is developed that can perform work better in the uncontrolled environment, such as variation in sample image resolution, quality, and small-scale labeled data sets. The original dataset collector provides the images of the COVID-19 class from different sources. Therefore, to tackle the resolution problem in the images, we normalized the training images before the training of the model. So the model becomes less sensitive to different resolution as all the images are in the same distribution.

III. Proposed System

Our objective is to develop a system for COVID-19 detection using deep learning. Deep learning has shown outstanding performance, and it outperforms traditional techniques based on hand-engineered features [14, 15]. As such, we will use deep learning to design the proposed system. In this section, we present the details of the proposed system.

A. Transfer Learning

In this study, we used the state-of-the-art ResNet50 convolutional neural network model to classify COVID-19 patients versus non-COVID normal subjects. For this purpose, we used the transfer learning approach to fine-tune the ResNet50 CNN model on the training dataset. In this approach, a trained model for one particular task can be adapted to another similar task. To apply the task-specific learning on a smaller dataset, we can use the ImageNet model to train the model for the classification of images. The ImageNet is a well-known model that consists of millions of labeled images. Transfer training is especially useful for tasks in which appropriate samples in large numbers for training a model are not available, such as medical images associated with various diseases [22-24]. This approach can be used for those models that have high complexity and require a large number of parameters for training the model [25]. By using transfer learning, models begin with good initial values, requiring minor adjustments to tackle the new problem better.

The pre-trained model is used for a particular role in two main ways. In the first method, the pre-trained model is used for the extraction of features, and the classifier is trained on it

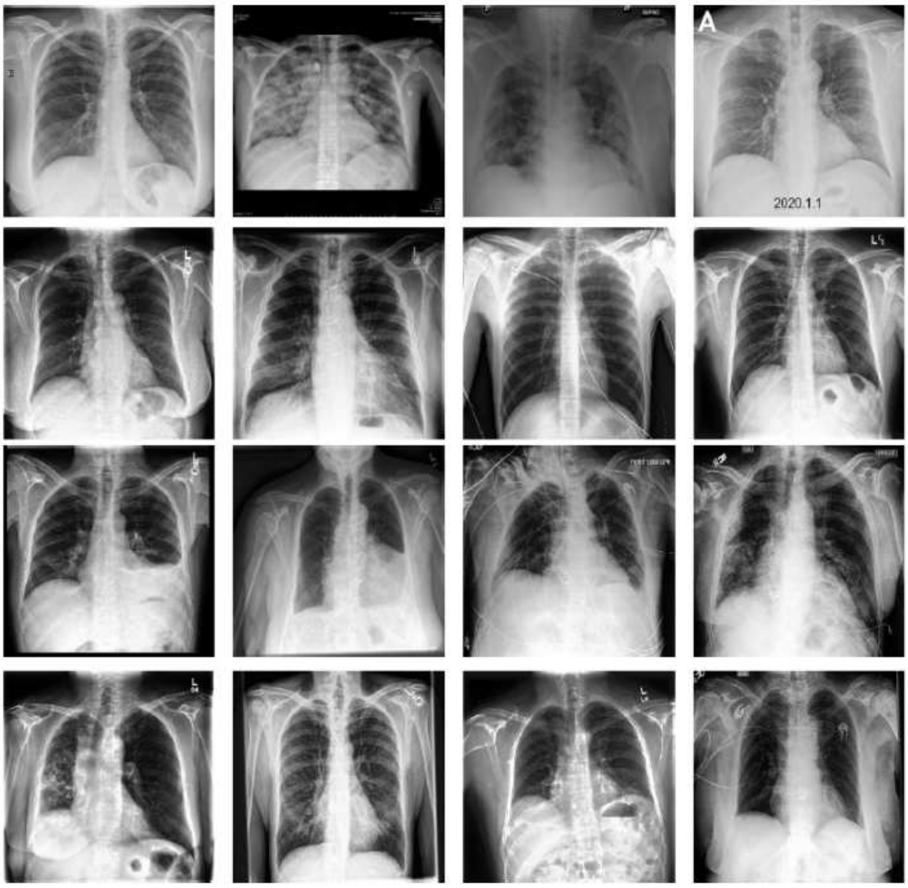

Fig. 2. 16 sample images from the dataset. First row shows Covid-19 images, second row shows normal images from Chex-Pert dataset, and third and fourth rows show the images effected from one of the 13 diseases in in Chex-Pert dataset.

to classify the data. In the second approach, based on the new task, the part of the model network or the entire network is fine-tuned. The pre-trained model weights will be used as the initial values, and they will be updated during the training procedure.

In this study, we can only fine-tune the final layer of CNN since the number of images in the COVID-19 class is very small and uses the pre-trained model to extract the discriminative features. Then the output of the ResNet50 model [16] is evaluated. We also discuss the architecture of the ResNet50 model in the next section and explains its utilization in this problem. Fig. 3 displays the ResNet50 CNN model architecture.

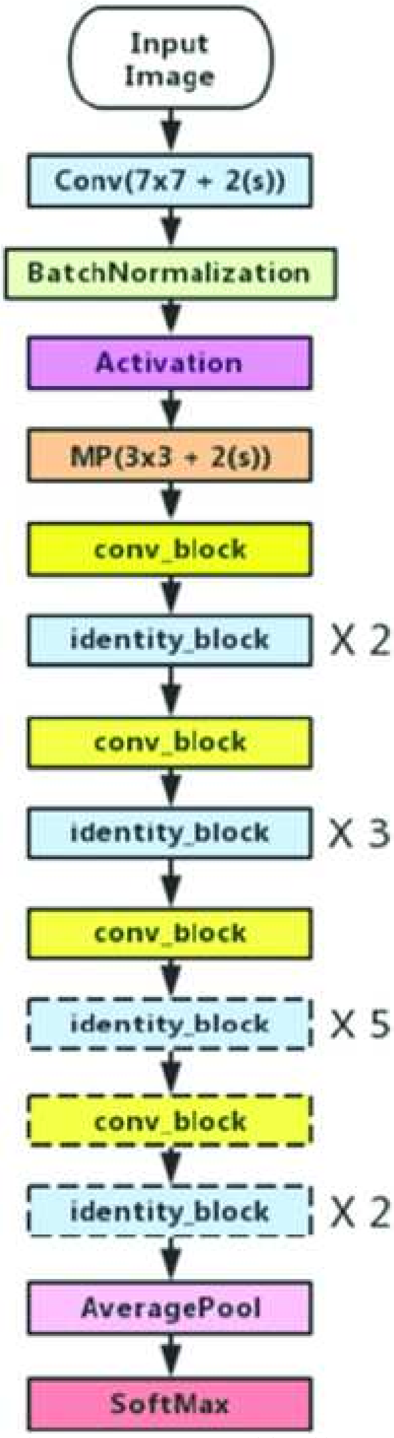

Fig. 3. REsNet50 CNN Model Architecture

B. ResNet50 CNN Model for COVID-19 Detection

In this study, we used the pre-trained ResNet50 CNN model. This model is trained on a well-known dataset called ImageNet. ResNet50 model is one of the most popular CNN architectures for more robust training, which was also the winner of the ImageNet competition 2015. ResNet50 architecture uses the identity shortcut connection that helps to skip the layers and allows the fast learning process. This architecture allows the initial layers to have a direct connection in the network. Therefore, it will make it simple for the initial layers to update the gradients.

C. Model Training

In this study, the proposed ResNet50 model is used with a cross-entropy loss function. This loss function is used to minimize the difference between the target and actual probability values. It is defined using the following equation:

$$L_{CE} = \sum_{i=1}^{N} Pp_i \log q_i \quad (1)$$

where p_i and q_i represent the actual and predicted probability values for every sample image, respectively. Then, we use the stochastic gradient descent algorithm in order to reduce the loss function.

IV. Experimental Results and Discussion

A. Model Hyper-Parameters

During the experiment, the ResNet50 model is fine-tuned after 120 epochs. The batch size is set to 30. Adam optimizer is used to optimize the cross-entropy loss function. Adam optimizer parameters were set to 0.0001 for learning rate, 0.9 for beta-1, and 0.999 for beta-2. The image resolution was set to 224 x 224 for all the images before giving the input to the network.

B. Evaluation Metrics

The ten-fold cross-validation was used to evaluate the proposed system, where the dataset is divided into 10 folds. Each time, nine folds (80% of the data) are used for training, and one fold is used for testing. For generalization, this process is repeated for each fold. Therefore, all folds are used for training and testing. The training set was further divided into 10% for validation and 90% for training the model. The performance of the proposed system is evaluated using the following metrics:

$$Accuracy\ (Acc) = \frac{TP + TN}{Total\ Samples} \quad (2)$$

$$Specificity\ (Spec) = \frac{TN}{TN + FP} \quad (3)$$

$$Sensitivity\ (Sens) = \frac{TP}{FN + TP} \quad (4)$$

$$F1 - Score = \frac{2 * TP}{(2*TP+FP+FN)} \quad (5)$$

We used Matlab (2020b) to implement the proposed system. We used the server system with Intel (R) Xeon (R) CPU-F8-2920 @ 3.5 GHz (30 CPUs), having 64GB RAM, 11GB Nvidia Graphics Card.

C. Results and Discussion

The probability score generated by the ResNet50 model decides that the test image belongs to the COVID-19 class or non-COVID class. These scores can then be compared to a threshold value to determine whether the input image is associated with COVID-19 or not. The projected labels are used to determine each model's sensitivity and specificity. In this study, we used four different threshold values, i.e., 0.15, 0.20, 0.25 and 3.0. Out of these four threshold values, we observe that the ResNet50 model achieved better results with a 0.15 threshold value. The average performance results are given in Table 2.

TABLE 2.
PERFORMANCE OF RESNET50 CNN MODEL

	Performance Measures	$ResNet50$ CNN $Model$
COVID-19 Vs non-COVID	Acc	0.986±0.0038
	$Sens$	0.9736±0.0053
	$Spec$	0.982±0.0041
	$F1-Score$	0.97.87±0.0029

It is also noted that there are only one hundred images for testing in the COVID-19 class; therefore, the specificity and sensitivity of the proposed system are not highly reliable as the total of sample images in the COVID-19 class are not too much. To achieve a more accurate estimate of sensitivity and specificity rates, there is a need for more test images labeled with COVID-19. However, on the other side, we can also compute 95% CI (confidence interval) of the obtained specificity and sensitivity values. The purpose of estimating CI is to check the range of specificity and sensitivity values for each class's test instances. The CI can be defined as:

$$r = z\sqrt{\frac{accuracy\ (1-accuracy)}{N}} \qquad (6)$$

Whereas z represents the significance level of the CI and N represents the total number of instances for the particular class. Our study used the CI of 95%, so the corresponding z value is equal to 1.96%. It is very important to have a good performance model for the detection of COVID-19. For this purpose, a cut-off threshold value is selected to 97.3% sensitivity of ResNet50 model.

As for the diagnosis of COVID-19, it is essential to have a sensitive model, we choose the threshold value for the ResNet50 CNN model as 97.3% sensitivity, and we compare the specificity rates of the model. From Table 3, we can observe that CI is 2.4% for sensitivity and 1.3% for specificity. As we have 1100 sample test images in the non-COVID class, the CI for sensitivity is higher than the specificity.

TABLE 3.
SPECIFICITY AND SENSITIVITY VALUES OF RESNET50 CNN MODEL

Model	Specificity	Sensitivity
ResNet50	98.2 ± 1.3	97.3 ± 2.4

Table 4 shows the confusion matrix on the testing data that has three mistakes by classifying three COVID-19 images as a non-COVID and has nine mistakes by classifying thirteen non-COVID images as a COVID-19. The results of the confusion matrix in Table 4 show that the proposed system is classifying the test data with a high accuracy rate.

TABLE 4.
CONFUSION MATRIX WITH RESNET50 MODEL

		Predicted Class	
		COVID-19	**Non-COVID**
Actual Class	COVID-19	97 (97.0%)	3 (4.0 %)
	Non-COVID	13 (1.18%)	1087 (98.82%)

Fig. 4 visualizes the tSNE plot of the features. In Fig. 4, we observe two separate clusters representing the Covid and non-COVID classes. This plot shows the clear discrimination of features belonging to the two classes. Only a few of the images of both classes are misclassified. The tSNE plot authenticates the dominance of the proposed system. In our future work, we will increase the dataset size in order to train the model on more images. This will increase the generalization power of the model as well as also help to reduce the false-positive cases of the current study.

D. Comparison

The comparison results are shown in Table 5. We have taken the results, which are reported in the original papers to avoid any bias due to parameter tuning. It is noted that the proposed system outperforms the other state-of-the-art systems. From this comparison, we conclude that the proposed end-to-end model based on a ResNet50 convolutional neural network outperforms the recent works on COVID-19 versus non-COVID classification by achieving an accuracy of

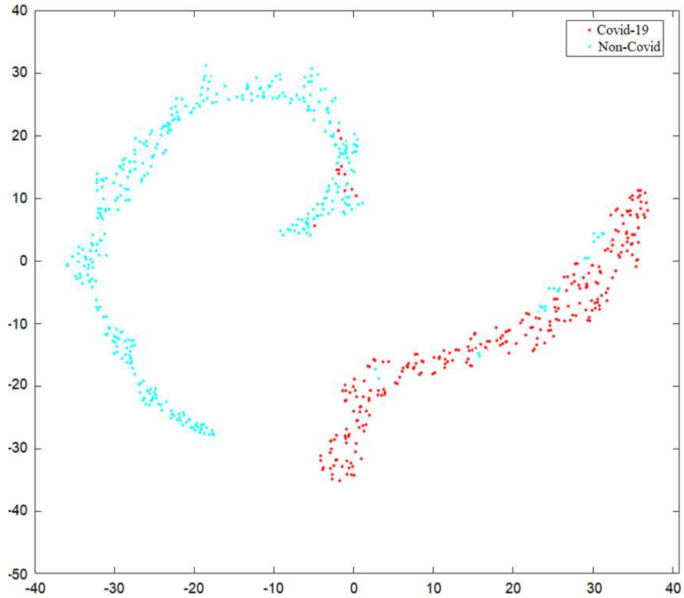

Fig. 4. tSNE plot for two-class problem for features visualization

98.6%, the sensitivity of 97.3%, a specificity of 98.2%, and F1-score of 97.87%.

TABLE 5.
COMPARISON OF OTHER METHODS WITH THE PROPOSED SYSTEM

Research Studies	Method	Class	Acc (%)
Ozturk et al. [17] 2020	DarkNet	2	98.08
Maghdid et al. [18] 2020	AlexNet, Modified CNN	2	94
Hemdan et al. [19] 2020	VGG19, DenseNet201, ResNetV2, InceptionV3, InceptionResNetV2, Xception, MobileNetV2	2	90
Panwar et al. [20] 2020	nCOVnet	2	88.10
Stephanie et al. [21] 2020	Deep learning	2	90.8
Proposed System	ResNet50 CNN Model	2	98.6

V. CONCLUSION

In this study, we have proposed an intelligent and robust system for detecting coronavirus disease (COVID-19) using a state-of-the-art deep learning approach. We used Chest X-ray images as a dataset and fine-tuned the ResNet50 CNN model on our training dataset. We validate the proposed system's robustness and effectiveness by using two benchmark publicly available datasets (Covid-Chestxray-Dataset and Chex-Pert Dataset). At first, a dataset of 6000 images is prepared from Covid-Chestxray and Chex-Pert Datasets. The proposed system was trained on the collection of images from 80% of the datasets and tested with 20% of the data. Results clearly show that the performance metrics of our proposed system are high. Cross-validation is done using a 10-fold cross-validation technique. In this study, a detailed experimental analysis is performed to evaluate the performance of the proposed system. The results indicate that the proposed system gives an accuracy of 98.6%, sensitivity of 97.3%, specificity of 98.2%, and F1-score of 97.87%. The comparison shows that the proposed system performs better than the existing systems. The proposed technique based on DL will be helpful in medical diagnosis research and health care systems. It will also support the medical experts for COVID-19 screening and lead to a precious second opinion.

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