ISSN: 1803-3814 (Printed), 2571-3701 (Online)
https://doi.org/10.13164/mendel.2022.1.001

MENDEL Soft Computing Journal

The Use of an Incremental Learning Algorithm for Diagnosing COVID-19 from Chest X-ray Images

Rimah Amami[1,✉], Suleiman Ali Al Saif[1], Rim Amami[2], Hassan Ahmed Eleraky[1],Fatma Mellouli[1],Mariem Baazaoui[2]

[1]Computer Science Department, Deanship of Preparatory Year and Supporting Studies, Imam AbdulRahman bin Faisal University, Dammam, KSA

[2]Basic Science Department, Deanship of Preparatory Year and Supporting Studies, Imam AbdulRahman bin Faisal University, Dammam, KSA

raamami@iau.edu.sa✉,saalsaif@iau.edu.sa,rabamami@iau.edu.sa,haeleraky@iau.edu.sa,mjbaazaoui@iau.edu.sa,fmmallouli@iau.edu.sa

Abstract

The new Coronavirus or simply Covid-19 causes an acute deadly disease. It has spread rapidly across the world, which has caused serious consequences for health professionals and researchers. This is due to many reasons including the lack of vaccine, shortage of testing kits and resources. Therefore, the main purpose of this study is to present an inexpensive alternative diagnostic tool for the detection of Covid-19 infection by using chest radiographs and Deep Convolutional Neural Network (DCNN) technique. In this paper, we have proposed a reliable and economical solution to detect COVID-19. This will be achieved by using X-rays of patients and an Incremental-DCNN (I-DCNN) based on ResNet-101 architecture. The datasets used in this study were collected from publicly available chest radiographs on medical repositories. The proposed I-DCNN method will help in diagnosing the positive Covid-19 patient by utilising three chest X-ray imagery groups, these will be: Covid-19, viral pneumonia, and healthy cases. Furthermore, the main contribution of this paper resides on the use of incremental learning in order to accommodate the detection system. This has high computational energy requirements, time consuming challenges, while working with large-scale and regularly evolving images. The incremental learning process will allow the recognition system to learn new datasets, while keeping the convolutional layers learned previously. The overall Covid-19 detection rate obtained using the proposed I-DCNN was of 98.70% which undeniably can contribute effectively to the detection of COVID-19 infection.

Received: 07 November 2021
Accepted: 28 March 2022
Online: 03 April 2022
Published: 30 June 2022

Keywords: *Incremental training, DCNN, Covid-19, ResNet-101.*

1 Introduction

The new waves of Covid-19 and its mutating variant has had crippling global consequences, impacting all aspects of life across the globe. This has caused extreme concerns to the health community. Even though the vaccinations have been found, scientists are unclear of the long term implications. Recently, machine learning has been widely used for the acceleration of biomedical research by building up a decision-support tool, such as an image detection system. Several studies have been conducted based on the deep learning methods for detection of disease using a chest X-ray image datasets [18]. The present paper investigates the efficiency and the robustness of the deep learning approach to detect the Covid-19 on chest radiographs. This was achieved by incremental learning process and DCCN in order to detect the positive Covid-19 patients from amongst healthy normal cases and pneumonia patients. We proposed an efficient training approach by incrementally growing DCNN to learn new chest X-ray images, while sharing the initial part of the base network. Hence, an updated network is formed which included a new set of images in the learning process, while using previously learned convolutional layers. It is important to clarify that the incremental learning model is not a replacement for the batch learning model, which uses all datasets for all classes that are available from the beginning of the training process. On the contrary, in the incremental learning model, new images samples or new classes are already available even after the training of the base network is started. In the Covid-19 context, the incremental learning will provide a perfect solution to the problem of continuously adding new chest X-ray images. It will update the network without the need to access the training data for previously learned tasks.

In order to detect the cases with Covid-19, in this study we used radiographs of COVID-19 patients, pneumonia patients and of healthy volunteers. The incremental learning was used to update the network and including new samples without forgetting old tasks. In this work, the main focus of DCNN was to classify the X-ray images into COVID-19, normal or pneumonia. We compared two of the most powerful and commonly used deep convolutional networks, which are VGG (VGG16) and ResNet (ResNet101, ResNet50).

The remainder of this study is structured as follows: In Section 2, we presented previous studies conducted for the Covid-19 detection from X-ray image samples, using the deep learning approaches. The proposed Incremental-DCNN (I-DCNN) method is detailed in section 3, where we also give an overview of the structure of datasets. Experimental analysis and the discussion are mentioned in section 4. The conclusion is presented in section 5.

2 Related Work

Recently, the deep learning approaches has been widely used to expedite Covid-19 detection and to improve accuracy in biomedical research [19]. Deep learning demonstrated a robust performance in many applications such as, medical image detection [2], data classification, image segmentation and speech recognition [8], etc. Chest radiographs are used to diagnose patients with Covid-19 infections, as the virus primarily affects the lungs. As a result, there are several deep learning methods that have investigated the detection of covid 19 infection using publicly available chest radiographs datasets [7].

Panwar et al. [20] established an application for disease detection using deep learning neural network-based method nCOVnet. The proposed method achieved 97.62% positive patients in 5 seconds. In another study, Zulfaezal et al. [11] used a deep learning model based on the ResNet-101 convolutional neural network architecture to investigate the Covid-19 positive cases from chest X-ray images. The accuracy of the proposed system was 71.9%, respectively. An automatic COVID-19 detection system was presented in [6] by Alqudah et al. The authors applied a different method in their study which included Support Vector Machine (SVM), random forest, K-Nearest Neighbor (KNN) with the CNN using soft-max. They achieved an accuracy rate of 98%. The proposed method to detect the virus by Jain et al. [17] has shown a high detection accuracy of 97.77%. Their method consisted of using the deep residual learning networks to differentiate the COVID-19 from viral pneumonia X-ray images. On the other hand, Togaçar et al. [25] presented a system of covid-19 detection based on deep learning models (MobileNetV2, SqueezeNet) and the Social Mimic optimization method. This proposed method obtained a detection rate of 99.27%.
The overall classification of Covid-19 rate obtained in the study [9] proposed by Apostolopoulos et al. was of 96.78%. They demonstrated that the accuracy of VGG19 and the MobileNet v2 architectures outperforms the CNNs for the diagnosis of the Covid-19 from X-ray images. Singh et al. [23] carried out a study to detect positive COVID-19 patients from chest images by tuning the initial parameters of CNN using multi-objective differential evolution based on convolutional neural networks. The proposed method outperforms several COVID-19 classification models by 1.9789%. Sakshi Ahuja et al. [5] proposed a model to diagnosis the positive Covid-19 patients by using deep transfer learning from CT scan images segmented to three-level using stationary wavelet. The classification rate obtained by the authors using the ResNet18 architecture was 99.4%. The authors in [4] investigates the behavior of automatically detect the Covid-19 by using X-ray images. They used a High-Resolution Network (HRNet) for feature extraction embedding with the UNet for segmentation purposes. Moreover, several deep learning architectures were evaluated. The accuracy achieved by the proposed approach was 99.26%. In this paper[3], the authors proposed to investigate the approach of a deep convolutional neural network-based architecture for the COVID-19 detection using X-ray images. The proposed detection system achieved 95.20% in accuracy. In the work of Das and al[13]. the convolutional neural network is applied to automatically detect the Covid-19 from X-ray images. The main idea of the contribution was to combine the models using a new method of weighted average ensembling technique, to detect if the patient was Covid-19 positive. A classification accuracy of 91.62% was achieved with this proposed approach.

3 Proposed Method

3.1 Incremental Learning vs Batch Learning

Presently, COVID-19 is spreading widely across the world and presenting different challenges even with the presence of any various vaccines. Scientists continue to deal with large, regularly evolving and complex datasets for Covid-19 detection within a small amount of time. This many variables create challenges and pressure on existing traditional learning methods which restarted from scratch when new datasets and classes are available. The proposed method in this study investigates the impact of an incremental training when new datasets of X-ray images are available. Hence, the network will be adapted to the new datasets, rather than train the entire process from the very beginning.

The idea is to develop a training method that divides the original network N into T sub-networks N_k where $T = 1 \ldots, n$ which are then gradually incorporated in the running network during the training stage. It must be pointed out, that a sub-network can be consisted of one or several layers.
Fig. 1 below, illustrates the proposed incremental learning process, that starts with the sub-network T_1. It is included to the classifier partition of datasets. This process is repeated until all the T sub-networks are inserted in the actual architecture by initializing the weights of each sub-network.

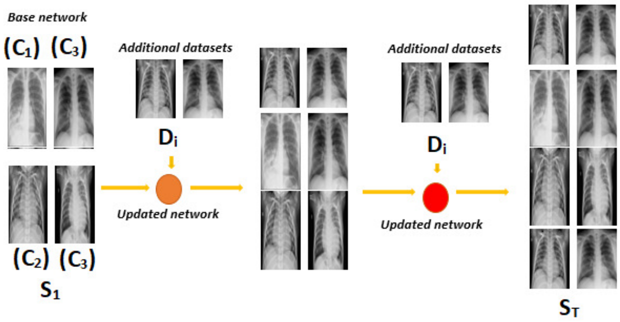

Figure 1: The incremental learning process.

As shown in Fig. 1, the three classes considered in this study are: Covid-19, viral pneumonia and healthy cases noted as $C_i = 1, 2, 3$. The dataset given to train the detection system is represented as $D_i = d1, d2, \ldots..dk$ where each subset d_i included the training X-ray images. In our proposed incremental model, the training process is accomplished in T steps and each time the network is adjusted.

3.2 I-DCNN

The detection system proposed in this work uses the DCNN based on Resnet-101 architecture. Residual Network or shortly ResNet is a specific type of neural network that was developed by He et al. [15]. ResNets are constructed from residual blocks as shown in Fig. 2:

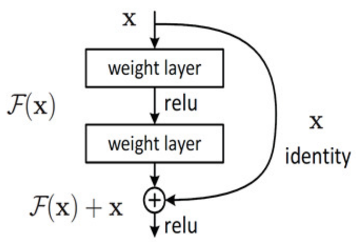

Figure 2: Residual learning: Building block.

Let's consider that x is representing the inputs of the first layers and $H(x)$ is an underlying mapping that will be explicitly fitted by few stacked layers using the residual function:

$$H(x) = F(x) + x \tag{1}$$

Furthermore, the operation $F + x$ can be executed by feed-forward neural networks with shortcut connections [10], [15]. This shortcut connections is defined by:

$$y = F(x, W_i) + x \tag{2}$$

where the dimension of the input x and the output $F(x)$ must be equal. y is the output function. The function $F(x, W_i)$ denotes the residual block and can represent, also, several convolutional layers. The DCNN architecture based on Resnet-101 network introduced, in this paper, is inspired by the architecture proposed by He et al. [15] and involves, five major parts, i.e., conv1, conv2, conv3, conv4 and conv5 (See Fig. 3).

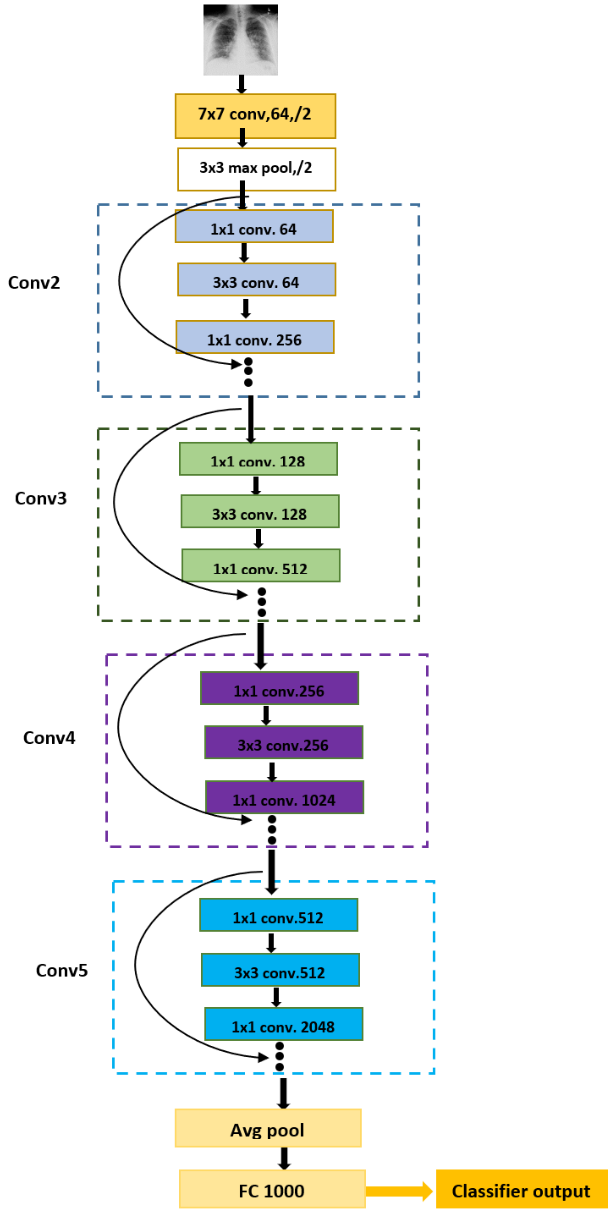

Figure 3: The architecture of ResNet-101.

The Fig. 4 summarizes the sizes of outputs at every layer and the dimension of the convolutional kernels at every stage in the architecture.

Based on this baseline network, the first step on RestNet is a block named conv1 which involves 3 operations which are: (1) convolution using a kernel size of 7 and feature map size of 64, (2) batch normalization and (3x3) max pooling with stride 2 operation [24]. The max pooling is achieved by applying a max filter and aims to reduce the dimensions of a feature map by eliminating non-maximal components. From all the activations in a rectangular region, the maximum value

Layer Name	Output size	101-layer
conv1	112x112	7x7, 64, stride 2 3x3 max pool. Stride2
conv2	56x56	[1x1, 64; 3x3, 64; 1x1, 256] x3
Conv3	28x28	[1x1, 128; 3x3, 128; 1x1, 512] x4
Conv4	14x14	[1x1, 256; 3x3, 256; 1x1, 1024] x23
Conv5	7x7	[1x1, 512; 3x3, 512; 1x1, 2048] x3
	1x1	Average pool, 1000-d fc, softmax

Figure 4: Size of outputs and convolutional kernels for ResNet-101.

will be selected. The formula for max-pooling is as follow:

$$f_{max}(x) = max_i(x_i) \tag{3}$$

At the end of ResNet 101, an average pooling and a Softmax classifier close the network. The average pooling is calculated as follow:

$$f_{avg}(x) = \frac{1}{N}\sum_{i=1}^{N} x_i \tag{4}$$

Where x is a vector that contains the activation values from a rectangular region. The softmax function is used to normalize the output class probability and its expressed as follows:

$$f_j(z) = \frac{exp^{z_j}}{\sum_n exp^z_n} \tag{5}$$

Where $f(z)$ is the softmax , z_j is the score of the correct class and z_n are the score values of each n class.

The Fig. 5 presents a comparison in term of the cost of computational complexity between several deep learning architectures such as: AlexNet, GoogleLeNet, VGG-16, VGG-19, ResNet-34, ResNet-50 and ResNet-101.

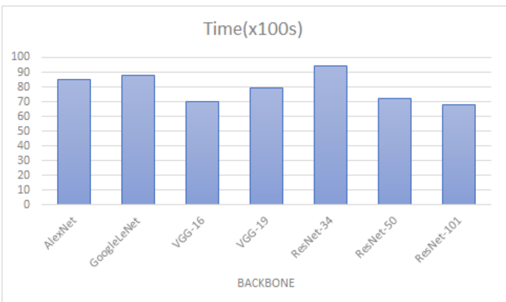

Figure 5: Comparing computational complexity of several networks: AlexNet, GoogleLeNet, VGG-16, VGG-19, ResNet-34, ResNet-50 and ResNet-101.

As shown in Fig. 5, the network ResNet-101 provides the best performance in term of computational complexity followed by ResNet-50, while AlexNet network performs poorly compared to all tested networks.

3.3 Datasets

The chest X-ray images used in this study consisted of the available samples on public medical repositories including mainly three classes; Covid-19, viral pneumonia and healthy cases. All datasets used were converted to JPG format and enabled accessibility from several research publications on Covid-19. We combined subset extracted from the GitHub website [12] and from ChexPert datasets [16] that consisted of 224,316 chest radiographs of 65,240 patients labeled with the help of board-certified radiologists. The first confirmed Covid-19 subset extracted from [12] consisted of 165 images. The second Covid-19 datasets are accessible on the Kaggle website with 219 X-ray images [21]. The third subset were extracted from the study of El-Shafai et al. [14] which consisted of 4044 COVID images, however, only 1000 X-ray images were used. The total number of datasets extracted in this paper wad 1384 for Covid-19, 1345 for viral pneumonia and 1340 for healthy cases. Table 1 summarizes the distribution of datasets presented in this study.

Table 1: Datasets distribution.

Dataset	patients	Size
Covid-19	1384	non-standard size
Viral Pneumonia	1345	non-standard size
Healthy Cases	1340	non-standard size

The result of combined datasets had around 4069 chest X-ray images. The study used 2439 samples for the training stage and 1630 were used as testing samples. The detection system consisted of the incremental learning phase and the testing phase. In the training phase, 60% of total radiographs will be used while the testing phase 40% from the original datasets will be used. Samples of datasets used in this study are shown in 6:

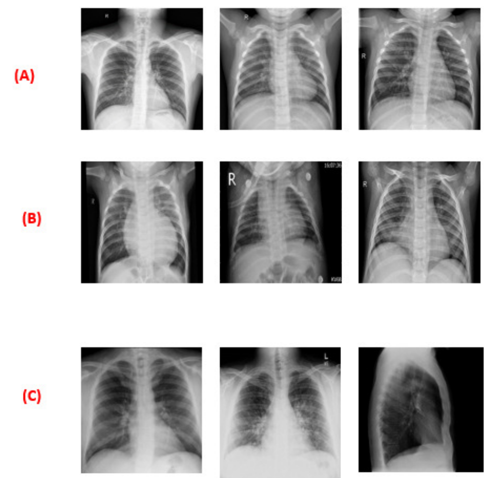

Figure 6: Samples of datasets: (A) healthy cases, (B) viral pneumonia cases and (C) Covid-19 cases.

Regarding image size, the datasets used have no standard size (the dimensions of the largest image are 512 height*512 width while the smallest image in the radiographs are 120*154). In the pre-processing stage of the detection system, the chest radiographs were resized to dimension 512*512 width and normalized in order to increase the detection accuracy. The age range of patients were between 36 and 58 for healthy volunteers dataset, 32 and 65 for the COVID-19 radiographs, 25 and 52 for the viral pneumonia dataset.

An incremental-DCNN was used to train three most known convolutional neural networks, including ResNet101, ResNet50, VGG16 to detect COVID-19 virus from the chest X-ray images.

4 Experimental Results

Our experimental results on healthy, viral pneumonia, and Covid-19 X-ray images showed that the proposed I-DCNN using ResNet101 architecture outperformed the Batch learning-DCNN. This was evident when it dealt with large datasets and ,also, several well-established network architectures. The proposed method in this study lead to stable and robust identification of Covid-19 cases based on the X-ray images. We evaluated the Incremental-DCNN based on ResNet101 accuracy and compare it with the standard DCNN with different architectures. We also compared the performance of our proposed Incremental-DCNN versus different methods in the literature that detects positive Covid-19 patients based on chest images.

The detection results of Normal cases, viral pneumonia and Covid-19 are shown in table 2 using Incremental learning process and DCNN.

The obtained results in this study to detect Covid-19 are encouraging and promising.

Fig. 7 presents the confusion matrix for I-DCNN approach based on ResNet-101 architecture for three-class problems X-ray images (Healthy, Covid-19 and Viral Pneumonia).

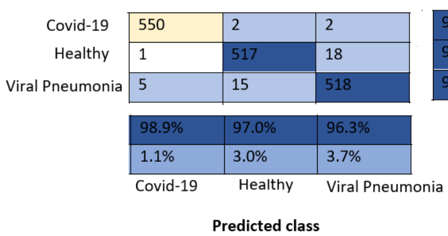

Figure 7: Confusion matrix for classification of healthy, Covid-19 and Viral Pneumonia using Incremental-DCNN.

As shown in Fig. 7, only two Covid-19 X-ray images were misclassified to viral pneumonia out of 554 (false negative) and four images out of 538 from viral pneumonia were misclassified Covid-19 (false positive). Furthermore, only two Covid-19 X-ray image were wrongly detected as healthy cases images and only one of healthy X-ray images out of 536 were detected as COVID-19 image. Based on this confusion matrix, we may conclude that the proposed Incremental-Deep learning approach is extremely robust in detecting Covid-19 X-ray images from viral pneumonia X-ray images especially that the X-ray images used in this study are incrementally trained when they become available. On the other hand, five pneumonia X-ray images were wrongly identified as COVID-19 while 15 X-ray images were misclassified to healthy cases. It is observed that the proposed approach is more confused in distinguishing images from healthy cases class and viral pneumonia class while still performing a robust classification of Covid-19 images. For a medical decision-support tools, it is crucial to not detect any Covid-19 cases as healthy cases (false negative) or vice versa (false positive). In the proposed I-DCNN model, the deep layer of images holds the features to distinguish between Covid-19, healthy and viral X-ray images. The reason why this approach failed to correctly detect the Covid-19 images lies in the fact that, in the deep layer, some features of the available images from Covid-19 group are like healthy cases images. Hence, those confusing cases have to be confirmed using another detection tool. This similarity can be explained by the little symptoms of Covid-19 (or simply absence of symptoms) in the X-ray images.

It can be summed up that the proposed approach has the ability to detect most of the Covid-19 X-ray images with a robust performance.

In this table 2, we investigated the impact of incremental training on the robustness of our detection system of Covid-19. We noticed that the incremental DCNN based on ResNet101 outperforms the detection systems based on ResNet 50 and VGG16 with an ERR by 02.30%, 08.41%, 09.24% respectively.

Table presents the overall Covid-19 detection rate and the precision archived by the proposed Incremental-DCNN based on different architectures such as VGG16, ResNet50 and ResNET101. The performance of our detection system is evaluated using the most common statistical measures like accuracy and precision.

The experimental results shown in table3 demonstrates the effectiveness of ResNet101 and incremental learning for the detection of cases infected by Covid-19. The accuracy of the I-DCNN based on ResNet101 outperforms the detections systems based on VGG16 and RestNet 50 by 6% and 3.5% respectively.

Table 4 presents a comparison of the proposed Incremental-DCNN method with other recent methods from the state-of-art for the Covid-19 detection problem using X-ray chest images.

Table 2: Comparison of EER(%), Efficiency (DCF(%)), Sensitivity(%) and Specificity(%) for the different Covid-19 detection systems using a incremental learning different architectures VGG16, ResNet50 and ResNet101.

System	Case	EER	DCF	Sensitivity	Specificity
	Normal	08.74±02.17	89.63±02.10	87.05	89.66
	viral pneumonia	09.08±01.39	85.77±01.87	88.01	86.41
VGG16	Covid-19	09.24±01.67	90.53±01.09	89.30	86.72
	Normal	09.81±01.28	89.16±01.37	86.12	87.06
	viral pneumonia	09.15±01.77	89.45±00.58	87.05	86.60
ResNet50	Covid-19	08.41±01.72	90.19±00.84	87.07	88.14
	Normal	04.14±00.92	94.37±01.52	94.32	94.67
	viral pneumonia	05.17±01.68	91.27±01.16	90.22	91.29
ResNet101	Covid-19	02.30±01.57	94.48±01.37	96.25	94.85

Table 3: Comparison of overall Accuracy(%) and Precision(%) for the different Covid-19 detection systems using an Incremental learning and different architectures (VGG16, ResNet50, ResNet101).

System	Case	accuracy (%)	Precision
	Normal	93.50	91.70
I-DCNN	viral pneumonia	92.85	90.66
VGG16	Covid-19	92.78	92.40
	Normal	96.30	97.20
I-DCNN	viral pneumonia	94.71	96.10
ResNet50	Covid-19	95.33	94.90
	Normal	99.80	97.89
I-DCNN	viral pneumonia	98.02	99.24
ResNet101	Covid-19	98.68	99.77

Table 4: Comparison of the performance of our proposed Incremental DCNN and different methods in the state-of-art.

System	Accuracy(%)
[1]	93.10%
[22]	97.36%
[17]	97.77%
[20]	97.72%
Proposed method	**98.68%**

5 Conclusion

This paper illustrates a promising deep learning system that is able to efficiently detect COVID-19 from chest X-ray images. This is achieved by implementing an incremental learning. The detection process is carried out by DCNN to differentiate the Covid-19 cases from pneumonia or healthy normal cases. Furthermore, we investigated, in this study, the effectiveness of the incremental learning and the RestNet101 architecture in order to detect the Covid-19 patients. The 98.70% success was achieved in the detection of COVID-19 cases, which is considered as a great progress in biomedical studies. This detection system can be utilized as an alternative low cost diagnostic tool which provides accurate and quick results. This study could be helpful to the medical staff in order to effectively manage the COVID-19 infected cases after getting its fast detection. In future studies, we could consider including the new variants of Covid-19 and utilize the X-ray images datasets of other organs affected by the Covid-19. We aim to develop, also, a covid-19 detection system based on new features in order to enhance the quality of the images datasets and improve the detection rates.

6 Data Availability

The datasets generated during and/or analysed during the current study are available in the GitHub (https://github.com/ieee8023/covid-chestxray-dataset/tree/master/images) and Kaggle (https://www.kaggle.com/tawsifurrahman/covid19-radiography-database) repository.

References

[1] Abbas, A., Abdelsamea, M. M., and Gaber, M. M. Classification of covid-19 in chest x-ray images using detrac deep convolutional neural network. *Applied Intelligence 51*, 2 (2021), 854–864.

[2] Abdulla, S. H., Sagheer, A. M., and Veisi, H. Improving breast cancer classification using (smote) technique and pectoral muscle removal in mammographic images. *Mendel 27*, 2 (2021), 36–43.

[3] Agrawal, T., and Choudhary, P. Focuscovid: Automated covid-19 detection using deep learning with chest x-ray images. *Evolving Systems* (2021), 1–15.

[4] Ahmed, S., Hossain, T., Hoque, O. B., Sarker, S., Rahman, S., and Shah, F. M. Automated covid-19 detection from chest x-ray images: a high-resolution network (hrnet) approach. *SN computer science 2*, 4 (2021), 1–17.

[5] Ahuja, S., Panigrahi, B. K., Dey, N., Rajinikanth, V., and Gandhi, T. K. Deep transfer learning-based automated detection of covid-19 from lung ct scan slices. *Applied Intelligence 51*, 1 (2021), 571–585.

[6] Alqudah, A. M., Qazan, S., and Alqudah, A. Automated systems for detection of covid-19 using chest x-ray images and lightweight convolutional neural networks. *Research Square* (2020), 10.21203/rs.3.rs–24305/v1.

[7] Alquran, H., Alsleti, M., Alsharif, R., Qasmieh, I. A., Alqudah, A. M., and Harun, N. H. B. Employing texture features of chest x-ray images and machine learning in covid-19 detection and classification. *Mendel 27*, 1 (2021), 9–17.

[8] Amer, R., and Al Tmeme, A. Hybrid deep learning model for singing voice separation. *Mendel 27*, 2 (2021), 44–50.

[9] Apostolopoulos, I. D., and Mpesiana, T. A. Covid-19: automatic detection from x-ray images utilizing transfer learning with convolutional neural networks. *Physical and engineering sciences in medicine 43*, 2 (2020), 635–640.

[10] Bishop, C. M., et al. *Neural networks for pattern recognition.* Oxford university press, 1995.

[11] Che Azemin, M. Z., Hassan, R., Mohd Tamrin, M. I., and Md Ali, M. A. Covid-19 deep learning prediction model using publicly available radiologist-adjudicated chest x-ray images as training data: preliminary findings. *International Journal of Biomedical Imaging 2020* (2020).

[12] Cohen, J. P., Morrison, P., and Dao, L. Covid-19 image data collection. *arXiv preprint arXiv:2003.11597* (2020).

[13] Das, A. K., Ghosh, S., Thunder, S., Dutta, R., Agarwal, S., and Chakrabarti, A. Automatic covid-19 detection from x-ray images using ensemble learning with convolutional neural network. *Pattern Analysis and Applications 24*, 3 (2021), 1111–1124.

[14] El-Shafai, W., and Abd El-Samie, F. Extensive covid-19 x-ray and ct chest images dataset. *Mendeley Data 3*, 10 (2020).

[15] He, K., Zhang, X., Ren, S., and Sun, J. Deep residual learning for image recognition. In *Proceedings of the IEEE conference on computer vision and pattern recognition* (2016), pp. 770–778.

[16] Irvin, J., Rajpurkar, P., Ko, M., Yu, Y., Ciurea-Ilcus, S., Chute, C., Marklund, H., Haghgoo, B., Ball, R., Shpanskaya, K., et al. Chexpert: A large chest radiograph dataset with uncertainty labels and expert comparison. In *Proceedings of the AAAI conference on artificial intelligence* (2019), vol. 33, pp. 590–597.

[17] Jain, G., Mittal, D., Thakur, D., and Mittal, M. K. A deep learning approach to detect covid-19 coronavirus with x-ray images. *Biocybernetics and biomedical engineering 40*, 4 (2020), 1391–1405.

[18] Jaiswal, A. K., Tiwari, P., Kumar, S., Gupta, D., Khanna, A., and Rodrigues, J. J. Identifying pneumonia in chest x-rays: a deep learning approach. *Measurement 145* (2019), 511–518.

[19] Jasthy, S., Vangipuram, R., and Dutta, S. R. A systematic review and analysis on deep learning techniques used in diagnosis of various categories of lung diseases. *Mendel 27*, 2 (2021), 80–89.

[20] Panwar, H., Gupta, P., Siddiqui, M. K., Morales-Menendez, R., and Singh, V. Application of deep learning for fast detection of covid-19 in x-rays using ncovnet. *Chaos, Solitons & Fractals 138* (2020), 109944.

[21] Rahman, T., Chowdhury, M., and Khandakar, A. Covid-19 radiography database. Kaggle, 2020. https://www.kaggle.com/tawsifurrahman/covid19-radiograph y-database/data.

[22] Shibly, K. H., Dey, S. K., Islam, M. T.-U., and Rahman, M. M. Covid faster r–cnn: A novel framework to diagnose novel coronavirus disease (covid-19) in x-ray images. *Informatics in Medicine Unlocked 20* (2020), 100405.

[23] Singh, D., Kumar, V., Kaur, M., et al. Classification of covid-19 patients from chest ct images using multi-objective differential evolution–based convolutional neural networks. *European Journal of Clinical Microbiology & Infectious Diseases 39*, 7 (2020), 1379–1389.

[24] Souli, S., Amami, R., and Yahia, S. B. A robust pathological voices recognition system based on dcnn and scattering transform. *Applied Acoustics 177* (2021), 107854.

[25] Toğaçar, M., Ergen, B., and Cömert, Z. Covid-19 detection using deep learning models to exploit social mimic optimization and structured chest x-ray images using fuzzy color and stacking approaches. *Computers in biology and medicine 121* (2020), 103805.