Overview of deep learning models for identification Covid-19

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ABSTRACT

The well-being and health of global population is continuously and badly affected by COVID-19 pandemic. Thus, to prevent the spread the pandemic between individuals, there is high importance in implementing automatic detection systems as rapid alternative diagnosis. The virus is affecting the person's respiratory system as well as creating white patchy shadows in the X-ray images of the lungs of individuals experiencing COVID-19. Also, deep learning can be defined as a useful and efficient AI technique used for analyzing chest X-ray images for reliable and effective screening of COVID-19; therefore, distinguishing people infected with COVID-19 and normal persons, and after that the infected individuals will be isolated for mitigating the virus spread. This study provides an overview regarding a few of the modern deep learning-based COVID-19, with design steps and types, also it compares the diagnostic method of COVID-19 with other methods of deep learning created with the use of radiology images. After a comparison between the most recent methods used in the previous works, it was found that RestNet50 pretrained and DCNN model gives accuracy of 98%, which is the highest reported so far from among other proposed models were discussed in this paper.

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1. Introduction

Coronavirus disease 2019 (COVID-19) can be defined as one of the infectious diseases resulting from severe acute respiratory syndrome coronavirus-2 (SARS-CoV-2). Initially, COVID-19 has been identified in the year 2019 in Wuhan, China, and from that time, it was spread rapidly and globally, leading to the (2019–2020) coronavirus pandemic [1]. Many industries were affected and a lot of people were quarantined due to the spread of COVID-19, and this resulted in the fact that the life quality of human is devastatingly affected. COVID-19, majorly referred to as novel coronavirus turned into a pandemic disease causing a lot of mortalities. Later, this continuous outbreak was considered as a global public-health emergency by the World Health Organization (WHO) [2]. In many countries, legislatures are forcing flight limitations, fringe limitations, social-distancing and increasing awareness of hygiene. Yet, the spread of the virus is still rapid [3]. Because of the COVID-19′s high-transmissibility, its detection is of high importance in the way for controlling and planning to prevent the disease. At the same time, the limitations in experts and medical equipment and detective tools caused the detection of the disease to be slow. Therefore, it increased the number of casualties and patients. When quickly detecting the disease, there will be a decrease in its number of casualties and its prevalence [4].

The first phase is getting the detection, recognizing the disease symptoms, and using distinctive signs for accurately detecting the disease. Based on the disease type, symptoms might be shortness of breath, cough, acute respiratory problems, and common fever and cold, while for a few days, patients might also have a cough for no clear reason. Dissimilar to SARS, COVID-19 is not just affecting the respiratory system, yet also it affects other organs in the body, like liver and kidneys. Typically, symptoms of a new coronavirus resulting in COVID-19 start some days following an individual becomes infected, while in a few individuals, symptoms might show later [4]. It is assumed that the elderly individuals experiencing basic clinical issues such as diabetes, cardiovascular ailment, hepatic or renal maladies, ceaseless respiratory infection and malignant growth were bound to create genuine disease [3].

One of the major COVID-19 symptoms are the respiratory problems, which might be identified via chest's X-ray imaging. Also, a disease with mild symptoms might be detected via chest CT scans. Typically, the detection can be done by analyzing the signal data

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and images obtained with the techniques of medical imaging like MRI, CT and X-ray by means of deep learning models. Due to such analysis, one can diagnose and detect many diseases like brain tumor, diabetes mellitus, breast and skin cancer, and so on [7]. Therefore, examining such images might accurately detect the disease's existence in suspected individuals and even individuals with no initial symptoms. The use of such data might be also covering other issues, like the limitations of diagnostic kits as well as their production. The major benefit of CT scan is the availability of CT scan devices in the majority of laboratories and hospitals, while doctors are majorly using CT scan images for detecting the infections. Without the typical symptoms, like fever, using the chest CT scans has a fairly excellent capability for detecting the disease [4].

In laboratories, one of the major ways to detect COVID-19 is by human experts. Thus, injuries in chest radiology image and symptoms are examined via the specialist for detecting the existence of COVID-19 from a healthy person experiencing other diseases. However, such process has high costs and, especially, long-term detection. Recently, deep learning and computer vision were applied for detecting various lesions and diseases in the body in automatic way. A few instances are: detecting tumor volume and types in the brain, head, lungs and so on, considering that X-ray images and chest CT scans are the major approaches to diagnose COVID-19. In addition, the chest X-rays are showing multiple white patchy shadows in the lungs of a person affected with COVID-19. Using deep learning and computer vision might be of high importance in diagnosing COVID-19. Since the spread of the disease, a lot of studies utilized deep learning and machine vision techniques and they reported excellent results [4].

AI is used effectively in various tasks and fields [5]. Deep learning can be defined as one of the AI functions used for imitating the way that human brain works in data processing and generating patterns to be used in decision-making. Also, deep learning is one of the machine learning fields, while machine learning is a type of AI [6]. Deep learning is often referred to as deep neural network or deep neural learning. Recently, the models of deep learning were effectively utilized in many fields and resulted in excellent performances on many problems, like segmentation, classification, visual recognition, speech recognition, NLP and in medical image processing. The models of deep learning were effectively utilized in different areas like segmentation, classification and lesion detection of medical data [7–9].

The presented study provides an overview of the modern related works regarding the use of deep learning for detecting COVID-19 and other diseases, while also it provides a comparison between them. Besides, this study involves the deep learning image classifiers, and it discusses the major phases for diagnosing the disease. The remaining parts of this study are presented in the following way: the related works are provided in section (2), deep learning image classifiers are presented in section (3), deep learning steps are presented in section 4, lastly, the conclusions are presented in section 5.

2. Related works

1. In 2016, Srdjan Sladojevic and Marko Arsenovic [10], provided a novel method to use deep learning for automatically classifying and detecting plant diseases from leaf images. In addition, the created model has the ability for detecting leaf existence and distinguishing between healthy leaves and 13 different diseases, which might be diagnosed visually. New plant disease image database has been formed, which consists of at least 3000 original images obtained from available internet sources and extended to no less than 30,000 with the use of adequate transformations. Furthermore, the experimental results reached a precision between (91–98) %, for separate class tests. The final overall accuracy related to the trained model has been 96.3%. Fine tuning didn't show considerable alterations in the overall accuracy, yet the process of augmentation showed more impact for achieving good results.

2. In 2017, U. Rajendra Acharya and Hamido Fujita and et al [11], suggested a CNN method for detecting (automatically) the various segments of ECG. The signals of ECG have been acquired from a publicly-available arrhythmia database. Also, the study acquired V-Fib (Ventricular Fibrillation) ECG signals from Creighton University ventricular tachyarrhythmia, AFL (Atrial Flutter) and A-Fib (Atrial Fibrillation) ECG signals from MIT-BIH atrial fibrillation, and AFL (Atrial Flutter), A-Fib (Atrial Fibrillation) and NSR (Normal Sinus Rhythm) ECG signals from MIT-BIH arrhythmia database. The signals of ECG were utilized for 2 s and 5 s durations with no QRS detection. Also, the study achieved accuracy, specificity and sensitivity of 92.50%, 93.13% and 98.09%, for 2 s of ECG segments. They obtained sensitivity of 99.13%, accuracy of 94.90% and specificity of 81.44% for 5 s ECG duration. Furthermore, the algorithm is serving as one of the adjunct tools for assisting clinicians in verifying their diagnosis. The drawbacks of the suggested algorithm is that it requires a lot of data (big data) for training and takes more time for training the data.

3. In 2018, Fang Liu, PhD and Zhaoye Zhou, PhD and et al [12], created a fully-automated deep learning-based cartilage lesion detection system by means of classification and segmentation CNNs. In addition, the fat suppressed T2-weighted fast spin-echo MRI datasets regarding the knees of 175 patients experiencing knee pain have been analyzed (retrospectively) via the use of deep learning. Besides, Receiver Operating Curve (ROC) analysis as well as k statistic have been utilized for assessing the diagnostic performance and intra observer agreements to detect cartilage lesions for 2 individual evaluations done via the cartilage lesion detection system. Furthermore, the results of specificity and sensitivity associated with the cartilage lesion detection system at optimal threshold based on Youden index have been 85.2% and 84.1%, for evaluation 1 and 87.9% and 80.5%, for evaluation 2. Areas within the ROC curve have been 0.914 and 0.917 for evaluations 2 and 1, specifying high overall diagnostic accuracy to detect cartilage lesions.

4. In 2019, Ali Narin and Ceren Kaya and et al [13–17], provided 3 CNN-based models (InceptionV3, ResNet50 and InceptionResNetV2) to detect coronavirus pneumonia infected patients by means of CXR radiographs. Also, the experiments depend on the generated dataset with CXR images of 50 COVID-19 and 50 normal patients. Taken into account the obtained performance results, it has been identified that the pre-trained ResNet50 model offers maximum classification performance with accuracy of 98% among other 2 suggested models (accuracy of 97% regarding InceptionV3 and accuracy of 87% regarding Inception-ResNetV2). The major issue is the extremely few COVID-19 X-ray images utilized to train the deep learning models [38–42].

5. In 2020, Kishore Medhia and Md. Jamilb and et al [2], utilized a deep CNN approach for dependable and rapid COVID-19 identification from patient's CXR images. This approach used 2 datasets: one for CXR identification, while the other for statistical analysis of symptoms. The first dataset consists of information for at least 14,000 patients with 44 distinctive attributes such as gender, age, onset data, con-

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firmation date, symptoms, travel history, chronic diseases, and so on. On the other hand, the second dataset consists of CXR images in addition to clinical symptoms for at least 150 patients diagnosed with COVID-19. The common workflow regarding such suggested system majorly contains 5 main phases: 1) data acquisition, 2) pre-processing, 3) segmentation, 4) feature extraction, and 5) classification model. In the suggested method, the performance evaluation provided better results in comparison to other approaches with accuracy of approximately 93%. The suggested system couldn't be tested in extensive environment since till now, there are extremely few available COVID19 X-ray images. Although CT scan images could have yielded further accuracy, these experiments couldn't be carried out as COVID-19 CT scan image dataset isn't yet publicly available.

6. In 2020, Sabbir Ahmed, Moi Hoon Yap and et al [14] suggested a new architecture of CNN, ReCoNet (residual image based COVID-19 detection network), to detect COVID-19. This might be done from Chest X-ray (CXR) images shed light on the pre-processing task being significant to enhance COVID-19 fingerprints. In addition, the suggested modular architecture contains a CNN-based multilevel pre-processing filter block in cascade with multilayer CNN based feature extractor as well as a classification block. Also, a technique of data augmentation is utilized to boost the performance of the network. Then, the entire network is trained and tested with COVIDx dataset of 15,134 original CXR images yielding an overall benchmark accuracy, specificity and sensitivity of 97.48%, 97.53% and 96.39%. Due to the absence of large scale COVID-19 CXRs for fully validating ReCoNet, they seek more support and resources from clinical partners for the dataset to be expanded.

7. In 2020, E. Hemdan, M. A. Shouman, et al [15]. They have proposed an innovative deep learning model; which has been referred to as the COVIDX-Net for assisting the radiologists in the automatic diagnosis of coronavirus in the images of X-rays. This study has been validated on a total of 50 X-ray images of the with 25 confirmed positive cases of COVID-19. COVIDX-Net comprises 7 separate deep CNN models, like the VGG-19, DenseNet-201, Inception-V3, ResNet-V2, InceptionResNet-V2, MobileNet-V2 and Xception. VGG-19 and DenseNet architectures have shown a sufficient and similar performance of the automated classification of COVID-19 with the f1-scores of 0.91 and 0.89 for COVID-19 and normal, respectively. The least sufficient performance of the classification has been obtained by implementing Inception V3 model with 0.67 f1-scores for the normal cases and 0 for the cases of COVID-19. The limitations of their suggested algorithm the lack in the public data-sets of COVID-19.

8. In 2020, Ioannis D. Apostolopoulos, Tzani Bessiana [16]. They evaluated the efficiency of the state-of-art CNN models for the classifications of the medical images. In particular, the the process that has been referred to as the transfer learning has been implemented. With the transfer learning, detecting a variety of the anomalies in the small medical image data-sets has been considered as one of the achievable targets, which usually yields outstanding results. The data-set that has been used in the present work represents a set of 1427 X-Ray images, 700 of the images have been with confirmed common pneumonia, 224 of them with confirmed Covid-19, and 504 of them with normal conditions have been included. A general 97.82% accuracy has been accomplished in detecting Covid-19.

9. In 2020, Sohaib Asif, Yi Wenhui, and et al [3]. they used deep convolutional neural networks (DCNN) for the automatic detection of the patients with COVID-19 pneumonia with the use of the digital x- ray images of the chest. The data-set includes 1345 viral pneumonia images, 864 COVID-19, and 1341 of the x-ray images of normal chest. The DCNN based model InceptionV3 with the transfer learning were suggested for detecting patients that have been infected by coronavirus pneumonia, with the use of the X-ray radiographs of the chest and gives an over 98% classification accuracy.

10. In 2020, L. Wang, Z. Q. Lin and et al [17]. They introduced COVID-Net, a DCNN design has been modeled for detecting the cases of COVID-19 from chest X-ray (CXR) images. They introduced as well COVID-x, which is a data-set that comprises 13,975 chest X-ray images over 13,870 patient cases. They have researched the way that COVID-Net makes predictions by using a method of explain ability as an attempt for not merely gaining more knowledge about the critical factors that are related to the cases of COVID-19 that may be helpful for the clinicians for improving the screening, however, also auditing COVID-Net as a transparent and responsible way for the validation of the fact that it makes the decisions according to the relevant information that has been obtained from chest X-ray images. In final the COV-IDNet has been capable of achieving high accuracy that reached up to 93.3% test accuracy.

11. In 2021, Ghulam Gilanie, and et al [18] They proposed an automatic approach of detecting Covid-19 with the use of the CNNs. There have been 3 data-sets obtained from the Radiology Department (i.e. Diagnostics). The utilized data-set included CT as well as X-Ray images (7021 images of both pneumonia and normal, whereas there have been 1066 images with Covid-19 infection). The suggested approach has been capable of achieving an average specificity (95.65%), accuracy (96.68%), and sensitivity (96.24%).

12. In 2021, Fudan Zheng, Liang Li and et al [19]. They have developed a computed tomography system of image diagnosis through the deep learning for the rapid diagnosis of COVID-19 through the integration of the Res-Net with the SE blocks. This architecture was successful in the identification of COVID-19 CT from the healthy individuals' CT, typical viral pneumonia patient CT, and bacterial pneumonia patient CT separately. They have obtained CT images of 262, 219, 100, and 78 individuals for COVID19, typical viral pneumonia [35–37], bacterial pneumonia, and healthy individuals, respectively. The model has been capable of achieving a general recall of 0.94, precision of 0.95, and accuracy of 0.94.

Table1, lists a comparison between the works that have been explained, by the utilized image types, number of the utilized cases, utilized methods, limitations and accuracy. It had discovered that the X-ray and the CT images are the only one may be utilized. The accuracy of the suggested system is dependent upon booth number of used images, and Deep CNN architecture. Finally, the limitations regarded to the number of the used images. Comparison of the results obtained from state-of-art approaches was presented in Table1. In [13] Covid19 and non-Covid19 images were classified with a general achieved 98% accuracy (with the use of the RestNet-50 pretrained model). Similarly, the [3] had classified Covid19 and non-Covid19 and Viral Pneumonia images that consist of small data-set, in other words, normal (1341), viral pneumonia (1345), and Covid-19 (864) with general achieved also 98% accuracy [42], which has been defined as the highest reported yet.

Table 1

Comparison of the COVID-19 diagnostic method with other deep learning methods developed.

Study	Type of Image	Number of Cases	Method Used	Accuracy (%)	limitation
Ali Narin et ai [13]	CXR	50 normal 50 COVID-19 (+)	Deep Convolutional Neural Network)CNN (ResNet50	98	Limited amount of the COVID-19 X-ray images that have been utilized to train the models of the deep learning.
Kishore		Medhi et al [2]	CXR	150 COVID-19 (+)and 14,000 patients	information
Deep		Convolutional Neural Network	93%	The	suggested system couldn't be tested in the extensive environments as quite limited amount of the X-ray images of COVID-19 are available until now.
Sabbir		Ahmed et al [14]	chest X-ray	7966 normal 5451	Pneumonia 207 COVID-19 (+)
(CNN)		model, ReCo-Net (residual image-based network of COVID19 detection)	97.48%	Lack in the large-scale COVID19 CXR numbers for the full	validation of the ReCo-Net,
Ezz El-Din et al [15]	chest X-ray	25 COVID-19(+) 25 Normal	COVID-X-Net that has been based upon 7 separate DCNN architectures; which are: DenseNet-201, VGG-19, Inception-V3, ResNet-V2, InceptionResNet-V2, Xception, and MobileNet-V2	90%	lack of public COVID-19 datasets
Tzani		Bessiana et al [16]	chest X-ray	224 COVID-19(+) 504 Normal 700	pneumonia
CNN	97.82%	imbalance of the dataset. size of samples of Covid-19 has been small.			
Sohaib Asif et al [3]	chest X-ray	864 COVID19 (+) 1345 Viral Pneumonia 1341 Normal	deep convolutional neural networks (DCNN)	98%	limited number of available datasets
Linda Wang et al [17]	Chest X-Ray	13,870 patient cases	COVID-Net	93%	Small size of the cases of COVID19 infection and the related chest x-ray images.
Ghulam		Gilanie et al [18]	CT and X-Ray	1066 Covid-19 (+) 7021 Normal	CNN
96.68%					
Fudan Zheng et al [19]	CT images	262 Covid19(+) 100 bacterial pneumonias, 78 healthy controls, 219 typical viral pneumonias.	deep learning	94%	limited of public COVID-19 datasets

3. Deep learning image classifiers

In the following some of available state-of-art deep learning classifiers of the images [15].

1. VGG-19: which stands for Visual Geometry Group Network has been developed according to the CNN model that has been presented by Oxford Robotics Institute's A. Zisserman and K. Simonyan [20]. VGG-Net's performance has been quite beneficial on Image-Net dataset. For the purpose of improving the functionality of the image extraction, VGG-Net utilized smaller 3x3 filters, in comparison with the Alex-Net 11x11 filter. There are 2 versions of this network; which are: VGG-16 and VGG-19 have various layers and depths.

2. Inception-V3: Inception network or GoogLe-Net has been a 22-layer network and won the 2014 Image net challenge with 93.30% top-5 accuracy. The InceptionV3 network includes a number of the symmetrical and asymmetrical building blocks, in which every one of the blocks had a number of the branches of the convolution, Pooling Layers also, could be called subsampling layers, is reduce the spatial size of the feature maps. concatenated, dropouts, this layer is used to prevent overfittings

[21], and fully-connected layers This is a traditional Multi-Layer Perceptron (MLP) in the fully connected layer all the neurons in the layer are connected to all the neurons in the next layer, this layer is used for classification task [22,23].

3. DenseNet-121: this network has numerous compelling advantages: they lightened vanishing-gradient issues, encouraged feature reuse, reinforced feature propagation, and reduced the number of the parameters considerably. DenseNet-121 is a Dense Net model generated by 121 layers, the model has been loaded by pretrained weight values from the Image-Net database.

4. ResNet-V2: He and associates have developed this model through the use of the skip connections for jumping over a few network layers for achieving strong behaviors of convergence. The enhanced ResNet version has been referred to as the ResNetV2. Even though ResNet is similar to VGG-Net, it's nearly 8 times deeper [24].

5. Xception: its architecture represents a linear stack of depth wise separable convolution layers that have residual connections to the easy definition and modification of DNN architecture. The Xception is an improvement of Inception architecture replacing regular modules or inception with the distinct depth convolutions.

6. Inception-ResNetV2: A CNN is 164 layers deep, as it combines Inception model with the residual connections. Inception-ResNetV2 is an InceptionV3 variation.

7. MobileNet-V2: Sandler *et al.* Have suggested MobileNet-V2 model as a CNN architecture for the machines with the limited computing powers, such as the smart-phones. Mobile-Nets achieved this key benefit through the reduction of the number of the parameters of learning, and presenting inverted-residuals-with-linear bottleneck-blocks for the great reduction of the consumption of memory.

Can benefit from transfer learning by using one of this a pre-trained model in the CNN layer because the transfer learning approach is a very effective method to build a model with high accuracy, especially when there is limited small data [25].

4. Deep learning steps

There are three main steps of deep learning to conduct the diagnostic procedure of disease (Fig. 1), as [15]:

Step1: Pre-processing

All the X-ray images were obtained in 1 data-set and loaded for the scaling at a fixed 224×224 pixel size for being proper for the additional processing within deep learning pipe-line. One-hot encoding [26] has been applied afterwards on image data labels for indicating the case for every one of the images in the data-set.

Step2: Training Model and Validation

For the purpose of starting the one deep learning model's training phase, the pre-processed data-set has been divided 80–20 based on Pareto principle. Which indicates 20% of the image data is utilized in the phase of the testing. Once more, the splitting of 80% data is utilized to construct equal sets of training and validations. Sub-sample arbitrary training image data selections for DL classifier, and apply after that metrics of evaluation for showing the performance that has been recorded on the set of the validation and Achieving high accuracy of the system comes from the high performance of the system with few errors [27].

Step3: Classification

In the last framework's step, the data of testing is provided to tuned deep learning classifier for the categorization of all of image patches. Every classifier's accuracy has been viewed as a key parameter to evaluate the efficiency of every one of the classifiers [28]. At workflow's end, the general efficiency analyses for every one of the deep learning classifiers will be assessed according to the metrics that have been described in Table2. [29,30].

TP, TN, FP, and FN that have been given in Eq. (1) – (5) are the number of the True Positive, True Negative, False Positive, and False Negative, respectively. Given a test data-set and model [31]. Where [32,33]:

- True positive (TP): which specifies the number of the positive samples that were correctly classified.
- False Negative (FN): which specifies the number of positive samples that were incorrectly classified.
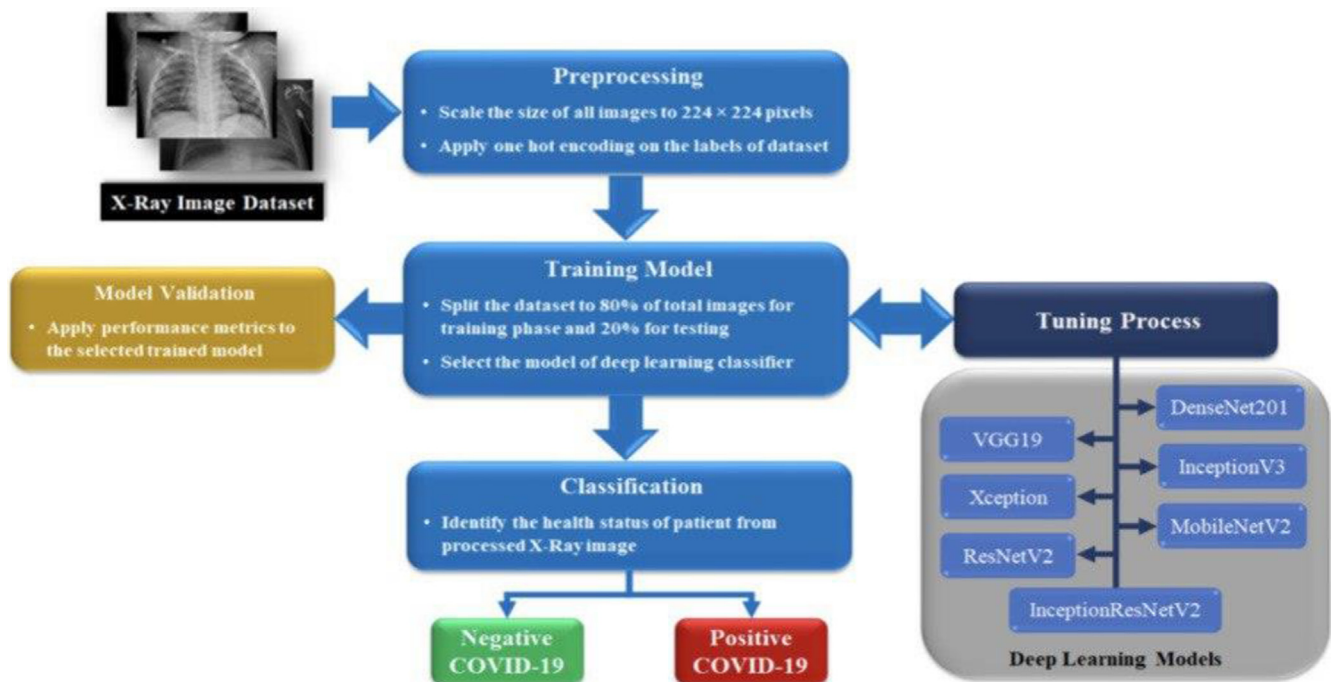

Fig. 1. Framework for the classification of COVID19 status in the CXR images.

Table 2
The metrics questions.

Equation Number	Equation Name	Equation
1	Accuracy	$(TN + TP)/(TN + TP + FN + FP)$
2	Recall	$TP/(TP + FN)$
3	Specificity	$TN/(TN + FP)$
4	Precision	$TP/(TP + FP)$
5	F1-Score	$2 \times ((Precision \times Recall)/(Precision + Recall))$

- False Positive (FP): which specifies the number of negative instances samples that were incorrectly classified.
- True negative (TN): which specifies the number of negative instances samples that were correctly classified.

5. Conclusion

Infectious COVID19 shocked the entire globe and remains threatening for the lives of billions of the people. In the present work, Comparison of results that have been obtained from state-of-art approaches was listed in (Table1) for identification best method of deep learning for the classification of the COVID-19 patients from the normal ones through the use of CXR and CT images. Show performance evaluations to methods in Table 1 that the RestNet50 pre-trained and DCNN model gives better results in comparison with other available approaches with about 98% accuracy. However, the studies (mentioned previously) carried out their experimentations on much smaller number of the images (size of Covid-19 samples is small), which possibly could not have enough variability, and Another limitation is that the algorithms in these studies mentioned above took more time to train the data.

For the future works, we intend to make our model in the next article more accurate and robust by overcome limitations through using more Covid-19 images from the local hospitals, reduce the time used for training and build a model consisting of a large number of layers.

CRediT authorship contribution statement

Hanaa Mohsin Ahmed: Conceptualization, Methodology, Software, Data curation, Investigation, Supervision, Software, Validation. **Basma Wael Abdullah:** Writing - review & editing, Writing - original draft, Visualization.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Further reading

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