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Detection of COVID-19 in X-Rays by Convolutional Neural Networks

Ola N. Kadhim*¹, Fallah H. Najjar², Kifah T. Khudhair³

¹Al-Furat Al-Awsat Technical University, Technical Institute of Al-Mussaib, Iraq

²Al-Furat Al-Awsat Technical University, Technical Institute of Najaf, Iraq

³Al-Furat Al-Awsat Technical University, Technical College of Management, Kufa, Iraq

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Abstract:

Coronavirus is considered the first virus to sweep the world in the twenty-first century, it appeared by the end of 2019. It started in the Chinese city of Wuhan and began to spread in different regions around the world too quickly and uncontrollable due to the lack of medical examinations and their inefficiency. So, the process of detecting the disease needs an accurate and quickly detection techniques and tools. The X-Ray images are good and quick in diagnosing the disease, but an automatic and accurate diagnosis is needed. Therefore, this paper presents an automated methodology based on deep learning in diagnosing COVID-19. In this paper, the proposed system is using a convolutional neural network, which is considered one of the mostly prominent techniques used today for its reliability and ability to generate rapid results. The system was trained on a set of X-Ray images taken of the chest area of infected and uninfected people. The CNN structure gave accuracy, Precision, Recall and F-Measure 98%. This model is characterized by its ability to distinguish efficiently and adapt to different cases.

Keywords: Convolutional Neural Network, COVID-19.

الكشف عن كوفيد-19 بالأشعة السينية بواسطة الشبكات العصبية التلافيفية

غلا نجاح كاظم^{1*}، فلاح حسن نعمة²، كفاف طه خضير³

¹جامعة الفرات الأوسط التقنية، المعهد التقني، المسيب، العراق

²جامعة الفرات الأوسط التقنية، المعهد التقني، النجف، العراق

³جامعة الفرات الأوسط التقنية، الكلية التقنية الإدارية، كوفة، العراق

الخلاصة:

يعتبر فيروس كورونا أول فيروس يجتاح العالم في القرن الحادي والعشرين، ظهر في نهاية عام 2019. بدأ في مدينة ووهان الصينية وبدأ ينتشر في مناطق مختلفة حول العالم، بسرعة كبيرة ولا يمكن السيطرة عليها لقلة الفحوصات الطبية وعدم كفاءتها. لذا فإن عملية الكشف عن المرض تحتاج إلى تقنيات وأدوات كشف دقيقة وسريعة. صور الأشعة جيدة وسريعة في تشخيص المرض لكن تحتاج إلى تشخيص آلي ودقيق. لذلك، تقدم هذه الورقة منهجية آلية تعتمد على التعلم العميق في تشخيص COVID-19. في هذا البحث، استعملنا نظاماً مقترحاً لشبكة عصبية تلافيفية، والذي يُعد من أبرز التقنيات المستعملة حالياً لقدرته على تحقيق نتائج

*Email: ola.najah@atu.edu.iq

سريعة ويتم تمثيله بالاعتمادية. تم تدريب النظام على مجموعة من صور الأشعة السينية التي تم التقاطها لمنطقة الصدر للمصابين وغير المصابين. أعطت بنية CNN الدقة والدقة والاستدعاء والقياس 98%. يتميز هذا النموذج بقدرته على التمييز بكفاءة والتكيف مع الحالات المختلفة.

1. Introduction

In late 2019, a virus appeared in Wuhan, one of the Chinese cities, and this virus is called Covid-19 [1, 2]. It spread large and widely across Chinese regions, then began to move to the outside world. No cure was found at that time, so medical institutions began creating types of drugs in order to reduce this virus. The symptoms of this disease were fever, cough and severe shortness of breath, especially for the elderly and people who have chronic diseases [3]. Infections are still rising in other countries and in different regions around the world. They relied on several techniques in diagnosing COVID-19 disease, including a pharyngeal swab or a nasal swab through which nucleotides are diagnosed, but these traditional methods require time, especially if there are a very large number of infected people, in addition to a great effort. It requires medical professionals and may not lead to accurate results. There are other methods also depend on X-Ray images in detecting COVID-19, but the diagnosis may be inaccurate. The person may have other diseases, such as pulmonary tuberculosis, so the diagnosis by the specialist is incorrect. Speeding up the diagnosis and prompt access to treatment is important. At present time, trend towards artificial intelligence has become significant, especially in the processing of digital images. It is moving towards deep learning, which has strong advantages in the process of representing any problem. This technology can be used to treat medical images, which are X-Rays taken for lung area, and accurately diagnose them. The current trend in deep learning can be exploited, which is a convolutional neural network that deals with digital images that relies on image feature extraction and classification based on a training process for that image. In this paper, we propose a system based on convolutional neural networks to process medical images that are X-Ray images of patients with COVID-19 and those who are not infected to be distinguished between them based on the characteristics extracted through this neural network. This system was proposed in order to rely on automatic detection of COVID-19 disease quickly and accurately without resorting to nasopharyngeal and nasal swabs that require time and effort, in addition to the pain associated with the swab. Infected or not, a way that saves time and effort, in addition to the speed of detection that limits the spread of the disease, reduces it and treats it faster [4]. Where the accuracy of any system within deep learning depends on the amount of trained data, the larger it is and contains different possibilities and different directions for images, the better, especially in detecting the disease. More cases of patients, more accurate diagnosis, in addition to the accuracy of the base data. Figure (1) shows an illustration of the Corona virus. This paper is ordered in as following: part two includes Literature review. Methodology and proposed method in section three. While the fourth section introduces results and discusses techniques. Finally, the conclusion.



Figure 1: COVID Virus.**2. Literature Review**

Many researchers that worked on this field used deep learning in detecting COVID-19 disease, but the accuracy of results is different depending on the proposed system. We will mention some of them:

Hassantabar & et al. (2020) [5] presented two models of deep learning algorithms and applied them to a set of images taken for lung area. One of them is a Deep Neural Network (DNN) and other one is a Convolutional Neural Network (CNN). The first is a deep instruction, but for normal neural networks that take characteristics from images. As for the second model, the network used to take the complete images as an input. The classification of the results display that the proposed CNN rendered with large accuracy that equal (93.2%) and sensitivity with the value (96.1%) outperforms the DNN proposed with the value 83.4% and 86% that represented accuracy and sensitivity.

Wang & et al. [6] introduced a system that detects COVID-19 disease by using convolutional neural networks for a set of chest X-Ray images. The researchers worked on image analysis of infected and normal lungs, where the system's recognition accuracy was 93.3%.

Ali & et al. [7] presented five convolutional neural network models (ResNet50, ResNet101, ResNet152, InceptionV3 and Inception-ResNetV2) on three databases consisting of four categories: healthy lungs, lungs infected with COVID-19, and Viral pneumonia and bacterial pneumonia. The results were as follows: 96.1% accuracy for Dataset.

Mohammad & et al. [8] provided a convolutional neural network model to train a set of X-Ray images containing three categories normal, pneumonia, and COVID-19. The number of pictures infected with COVID-19 was 180. The total mean accuracy for whole classes is 91.4%

2. Methodology

The proposed system includes working on deep learning, which is a widespread field at the present time and convolutional neural networks that use a set of input images to distinguish. It will be explained.

2.1 Deep learning

It is a field of research that originated in 2006 that rely on machine learning. The techniques and algorithms of this field were developed after 2006, until they reached what they are today in terms of great development that have broadly affected various fields of topics that include digital signal processing, image processing, and others, and entered various fields. Neural networks are one of the algorithms that rely on deep learning, consisting of a group of cells that simulate the neuron cells of human mind, and these networks have been developed on these networks down to convolutional neural networks that process digital images. Most of the deep learning research focuses on analysing large data sets using linear and nonlinear variables. It is not necessary for every cell in the layer to be associated with all cells in the second layer [9,10].

2.2 Convolution Neural Network

Convolution Neural Network (CNN) is a deep neural network that is used to recognize images. Convolution Neural Network is known as ConvNets, deep CNN (DCNN). The Convolution Neural Network differs from the normal neural network by several things such as

first input is neural network features, but in CNN the input is image , secondly, the hidden layers of the neural network are neurons and each neuron is connected to all the neurons in the neighbouring hidden layer but in CNN each hidden layer is made of 3 dimensions (width, height and depth) and every neuron in each hidden layer is connected to a part of neighbouring layer neurons. DCNN is not just a deep neural network containing many hidden layers, but a deep network designed to simulate how images are recognized by the brain. It can extract features rather than manually build them using many locally connected layers [11, 12, 13]. Figure 2 represents CNN components.

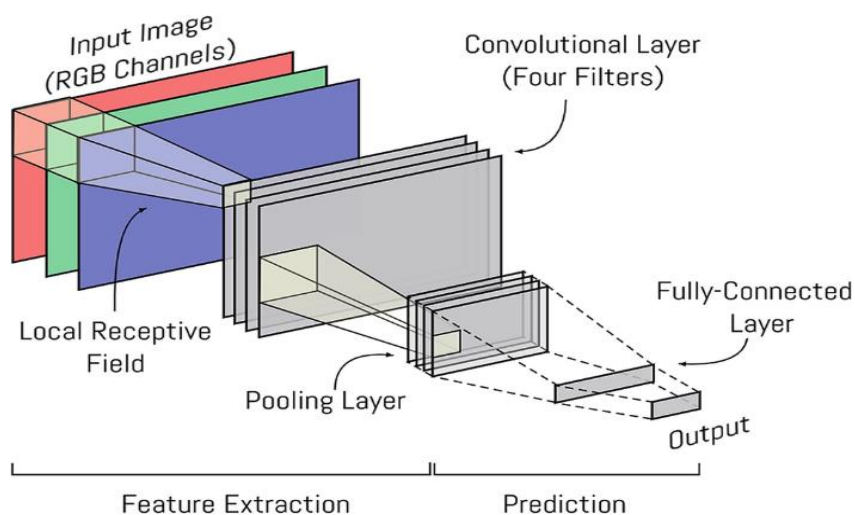


Figure 2: CNN components.

The components of the convolutional network (CNN) are:

- Input layer: the image is a 3D matrix (width × height × depth) of values ranging from 0-255.
- Convolution layer: Applied in convolution layer filter or kernel layer that would determine the presence of certain attributes or patterns in the original image (income), then several filters can be used in order to extract different attributes. Figures 3 and 4 refer to stride and convolution layer respectively.

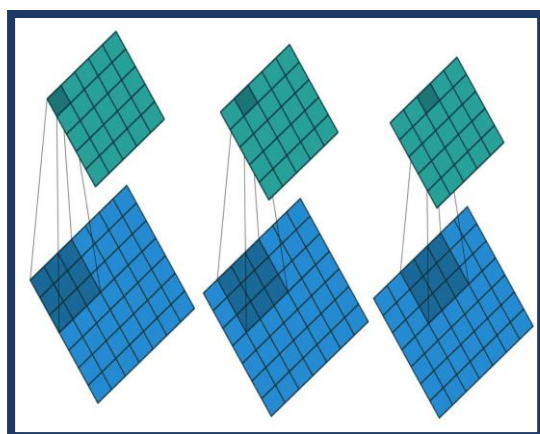


Figure 3: Stride Convolution.

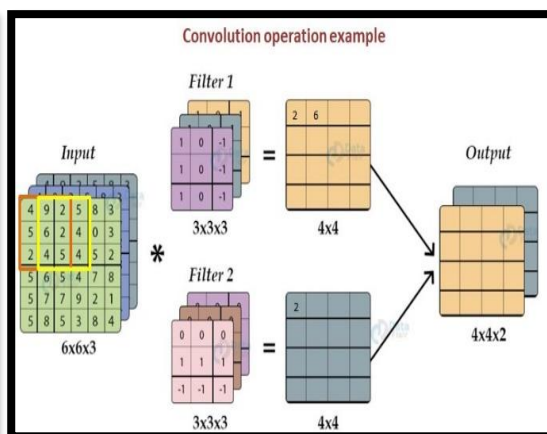


Figure 4: Convolution layer.

• Activation function: These functions are used in the neural network in many places, including those used after the convolution layer and those used after fully connected such as (Sigmoid, RELU, Soft-Max). Figure 5 explains activation function ReLU.

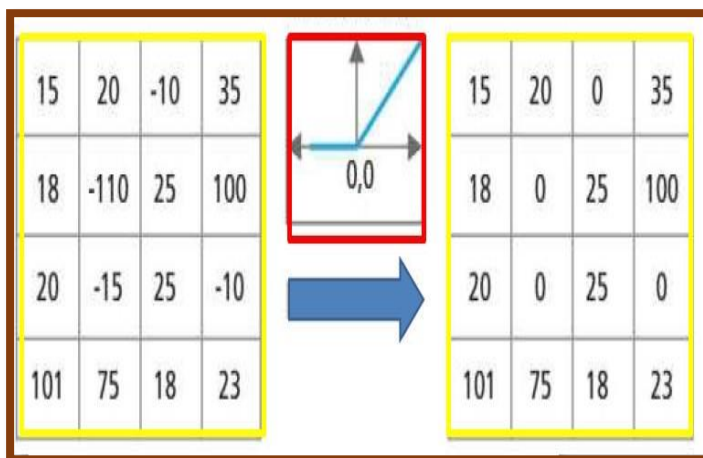


Figure 5: RELU Function.

• Pooling layer: The expensive pooling layer reduces the size of activation maps (maps for the possibility of using more than one filter). This not only reduces the number of necessary calculations, but also prevents falling into an overfitting state. Figures 6 explain types of pooling layer.

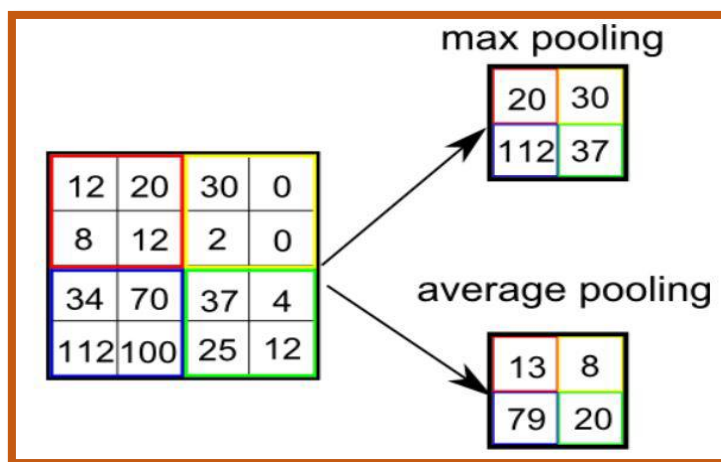


Figure 6: Pooling layer.

• Full Connected: After repeating the previous layers several times, all features assemble as a flatten vector until the data enters the final layer of the neural convolution network, which is the fully connected layer. The neurons in two different layers are directly connected to the neurons within the fully connected layer. Figure 7 explain fully connected layer.

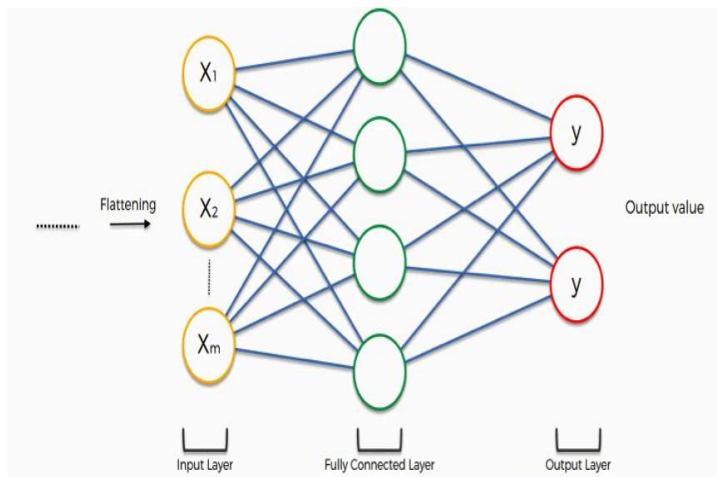


Figure 7: Full connected layer.

- Output layer: After the Soft-Max layer this layer extracts data from the previous layer. If difference between real number and resulting number (from the network) is big, that means the error rate will be big. Where the error rate is a measure of the accuracy and efficiency of the neural network.

2.3 Database

The database was collected from the Internet. The base consists of two parts, an image of a lung infected with COVID-19 disease, which forms a total of 1000 images, 800 images used for training and 200 for testing. In the other part, 1000 images of a normal lung were used. 800 images used for training and the rest (200) used for testing. The images type is a color image with a jpg extension [14, 15, 16] see Figure 8.

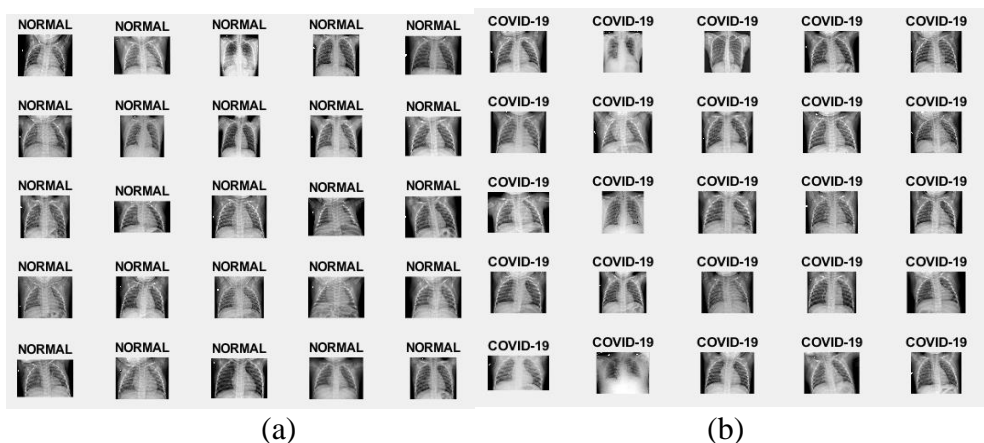


Figure 8: Image Dataset: (a) Normal lung and (b) Lung infected with covid-19 disease.

2.4 Proposed Method

Usually, any system consisting of CNNs, the input is a complete image that contains certain characteristics, and the output is a differentiation of that image according to the database used. The database is divided into two parts, one for design and the other for testing. The design part is also divided into two groups, one is training and the other is verification. CNN begins with training the data for a training group, and after completing a training, it validates the model’s ability to distinguish. Using verification data to find the accuracy of the model and to know the extent of the network's ability to learn and store the ideal weights at the lowest possible error.

After verifying the accuracy of the model and its ability to distinguish, role of testing group comes, through which a decision is made whether the lung is infected with COVID-19 or not.

The proposed system for the neural network consists of several layers, as mentioned in the previous part. Each layer has its own features that depend on filters represent weights that are applied to the image to extract features passing to the last layer, which is the basis for giving the decision. The last layer relies on backpropagation algorithm to update the weights and mounts to ideal weights. Where the error is calculated each time to obtain the lowest possible error in distinguishing the data. Figure 9 shows the structure of CNN.

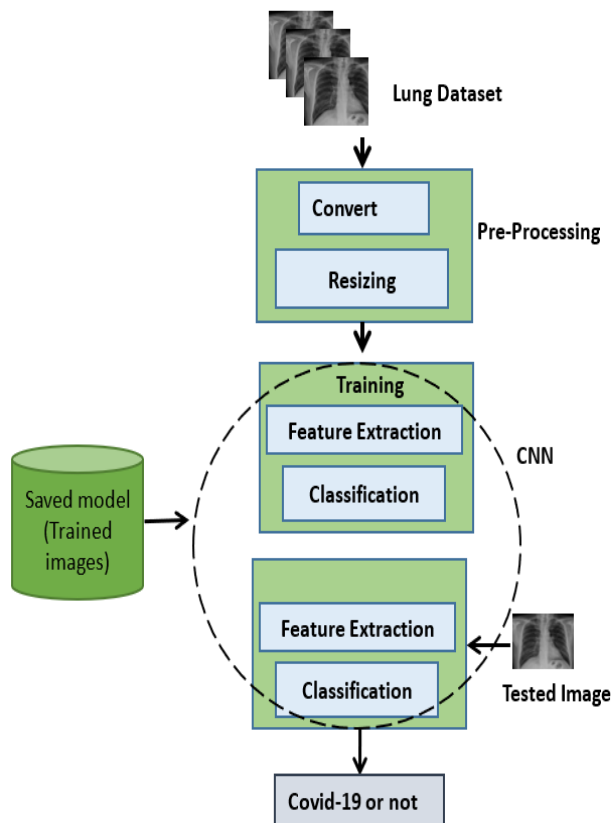


Figure 9: CNN-COVID-19 Model.

The model includes two stages:

- 1.Pre-processing: Images are selected from different sites so there are differences in image sizes and extensions. At this stage, images are converted into one extension and one size. In addition, the noise is removed from images by using the equalizer filter.
- 2.Lung recognition: In this stage, CNN automatically extracts features and trains the network on them. Where images of both normal and infected lungs are trained with COVID-19. Then, they are classified according to the characteristics of each base. The following Table 1 details the layers used in CNN:

Table 1: Parameters of the proposed model

Layers Indexes	Layer name	Kernel size	Stride	padding
1	Input layer	200*200*3	-	-
2	Convolution1	100*100*64	2	1
3	ReLU	100*100*64	-	-
4	Max pooling	50*50*64	-	-
5	Convolution2	50*50*64	2	1
6	ReLU	50*50*64	-	-
7	Convolution3	25*25*128	2	1
8	ReLU	25*25*128	-	-
9	Max pooling	12*12*256	-	-
10	Convolution4	6*6*256	2	1
11	ReLU	6*6*256	-	-
12	Max pooling	3*3*256	-	-
13	Convolution5	2*2*64	2	1
14	ReLU	2*2*64	-	-
15	Max pooling	1*1*256	-	-
16	Convolution6	1*1*256	2	1
17	ReLU	1*1*256	-	-

The essential steps of the training process methodology:

Algorithm 1: The training process using CNN
Input: Database for lung image. Output: Training and classification images. Begin: 1. Divide the database into three groups: first group training, second group validation, and third group testing. 2. Determine the parameter and the architecture of CNN. 3. Training proposed method using a training group. 4. Estimate the training proposed method using the validation group. 5. For N epochs, do steps 3 to 4. 6. Choose the best parameter for proposed method with minimal error on the validation group. 7. Estimate the selection proposed method using the test group.

2.5 Performance evaluation

After building the system and trained using the database, it must be confirmed that the system is correct and what percentage of it distinguishes infected and non-infected images. In order to achieve the accuracy of the results, a set of measures that determine the number of correctly and incorrectly diagnosed images will be used. Measures such as accuracy (A), precision (P), recall (R), and F1-score (F1).

$$A = \frac{TP+TN}{Total} \times 100\% \tag{Eq. 1}$$

$$R = \frac{TP}{TP + FN} \times 100\% \tag{Eq. 2}$$

$$P = \frac{TP}{TP + FP} \times 100\% \quad \text{Eq. 3}$$

$$F1 = 2 \times \left(\frac{R \times P}{P + R} \right) \times 100\% \quad \text{Eq. 4}$$

True Positive (TP): correctly that mean the actual class is true and model predicate true.
 True Negative (TN): The model predicated negative and classified correctly that mean the actual class is false and model predicate false.

False Positive (FP): The model predicated incorrectly that mean the actual class is false and model predicate true.

False Negative (FN): The model predicated incorrectly that mean the actual class is true and model predicate false.

3. Performance Experiment

This section presents the experimental results of using supervised deep convolutional neural network in the COVID-19 recognition system. The proposed system has been implemented by utilizing a personal laptop using Python. Then presents measures such as accuracy, precision, recall, F1-score.

Figure 10 represents the training process database for the proposed system. It consists of two parts, first representing the blue color, which includes the accuracy of the correctly classified data, starting from 70 to 98, the more trained the network, the greater the percentage of correct diagnosis.

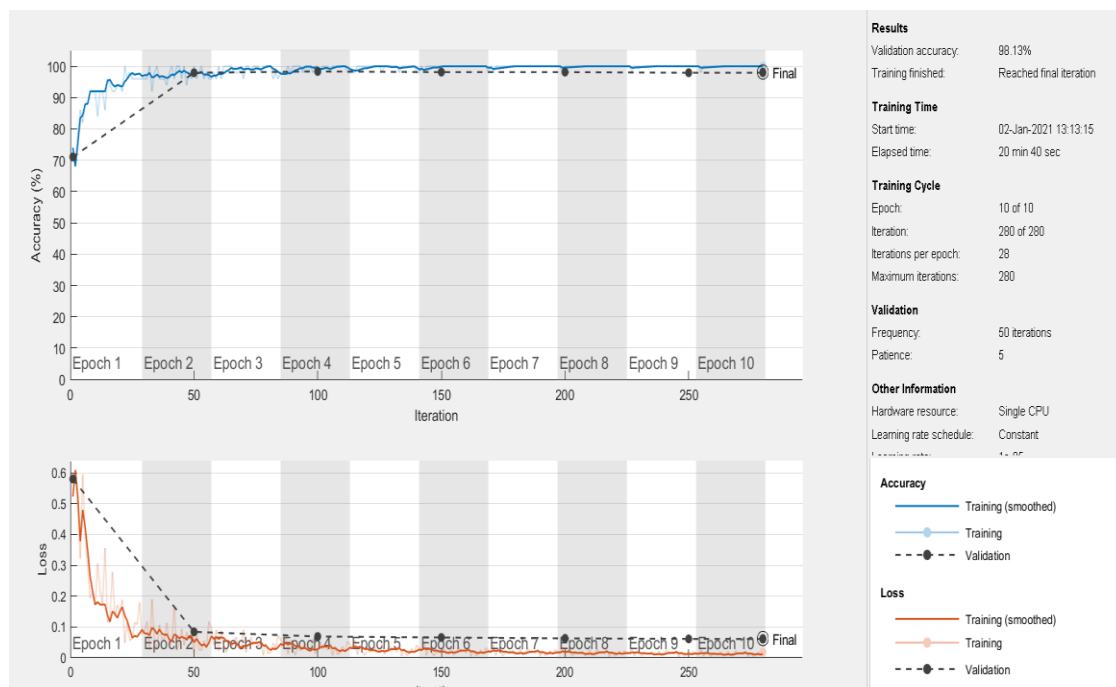


Figure 10: CNN-COVID-19 model of 80% training and 20% testing.

Corresponding to the lower part, which represents the red color, is the amount of error that occurred in the diagnosis (the difference between the expected results and the extracted results), the ratio started from 0.6 down to 0.

The accuracy of the results depends on a number of factors including the number of Epochs, the size of the input image, the number of filters and its size, the number of images used for training and testing, and other parameters within the network.

Many cases were studied, and each case had different results, reaching the current system, which gave the highest percentage, and relied on it. Among them, the size of the input images was changed between 100 and 300, as well as the number of different Epochs was taken. But in return, the time will increase, as it ranges from one to two hours. The reason for this is because each layer of CNN consists of a different number of filters and parameters, and each input image consists of three layers. These filters must be applied to each layer. As for the size of the filters, it has a clear effect on the results of the best size of the $5 * 5$ filters within this system.

The table below explains values of measures. The measure ratios of the proposed system amounted to 98%. There are a few images that were not properly diagnosed.

Table 1: Values of measures for training process.

Metrics	Results
Accuracy	98.75
Precision	98.76
Recall	98.47
F-Measure	98.61

Several test cases were made and the number of layers changed. There were several results, all the way to this model, which gave 98%, where the following is noted:

1. One of the reasons that the results depend on is the size of the image. Took different sizes of the images, so the least supported size within this system was $150 * 150$. It is not possible to take less than this size because of the network transactions that depend on the convolution process, so the image size is less than the original size to extract the characteristics. Then started to gradually increase the size up to $300 * 300$, the best results were when the size was $200 * 200$.

2. The size and number of transactions used in the network also have an impact on the results, as the transactions used in this system came based on the experience of many different cases, leading to these appropriate transactions with the images entered and arriving at an accurate discrimination case. Increasing or decreasing the number of filters does not have a big role, but it is necessary to consider the effect of each parameter on the input data. It is possible to use a small number of filters, which represent network parameters that have ability to extract characteristics better from many parameters. After an experiment in increasing the number of transactions, we noticed that the percentage began to decrease gradually.

3. Increasing the number of epochs also has a negative and positive effect on the results. Many expect that increasing the number of epochs means better results by increasing the training period, and this is not true. Through the proposed model, the training period was gradually increased. At first, the results were bad, and when they increased to 100, the accuracy

became good, but with increasing training, the results began to decrease below the mentioned limit. Epochs have a significant impact on the accuracy of the final results of the model. Table 2 represent difference cases.

Table 2: Difference cases for proposed method

Size of images	Size filter	Epochs	Accuracy	Precision
150*150	5*5	105	82.8%	82.12%
150*150	4*4	100	81%	80.15%
150*150	3*3	100	79.88%	82.3%
150*150	7*7	90	75.5%	73.12%
190*190	5*5	105	89.66%	90.81%
190*190	4*4	100	88.8%	90.11%
190*190	3*3	100	81.98%	88.34%
190*190	7*7	90	80.66%	79.3%
210*210	5*5	105	95.39%	93.81%
210*210	4*4	100	91.5%	94.81%
210*210	3*3	100	89.8%	87.3%
210*210	7*7	90	91.1%	96.10%
250*250	5*5	105	93.3%	92.21%
250*250	4*4	100	87.7%	92.99%
250*250	3*3	100	89.2%	93.76%
250*250	7*7	90	80%	82%
270*270	5*5	105	85%	88.33%
270*270	4*4	100	93%	89%
270*270	3*3	100	93.1%	90.22%
270*270	7*7	90	92.86%	92.15%
300*300	5*5	105	91.5%	90.11%
300*300	4*4	100	90%	96.10%
300*300	3*3	100	89%	90.5%
300*300	7*7	90	90%	87.01%

4. Conclusions

From the results that were referred to in the results section, note that the system has a high ability to distinguish between healthy lungs and lungs infected with COVID-19 disease, based on deep learning of a set of X-Ray images taken from a hospital and from the mentioned sites. The system works on images that are color or gray, even in the presence of noise, it has the ability to distinguish. Where this method proved its efficiency in the speed of treatment and correct diagnosis in a short time and high accuracy compared to the other methods mentioned, where the percentage of correct diagnosis of this system reached 98%. The amount of trained data has a very important role in increasing the accuracy of the system. It is possible to improve this system by increasing the number of X-Ray images in cooperation with hospitals and health centers. The work can also be improved by working on other types of diseases, such as pulmonary tuberculosis, and distinguishing it from healthy lungs and lungs infected with COVID-1

Conflicts of Interest

The authors declare no conflict of interest.

Author Contributions

The paper investigation, resources, and data curation have been done by Ola N. Kadhim; conceptualization, methodology, and implementation writing - original draft preparation, have been done by the Ola N. Kadhim; writing - review, editing, supervision, and funding acquisition, have been done by Fallah H. Najjar.

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