Int. J. Nonlinear Anal. Appl. 14 (2023) 1, 941–951
ISSN: 2008-6822 (electronic)
http://dx.doi.org/10.22075/ijnaa.2022.6878

Identifying the infection rate of covid-19 and using artificial intelligence to distinguish between covid-19 and pneumonia

Rusul Saad Alsabea, Asaad Noori Hashim*

Department of Computer Science, Faculty of Computer Science and Mathematics, University of Kufa, Najaf, Iraq

(Communicated by Ehsan Kozegar)

Abstract

There is a growing trend in early detection and diagnosis of COVID-19 for effective and accurate treatment. Several specialized studies have been conducted to develop programs that help in accurate diagnosis and reduce the burden on experts and specialists in this field. This paper describes an automated detection method for COVID-19 using deep learning techniques and computerized tomography images of the chest region. The images were initially optimized as a first step, and then a diagnostic process was performed to determine whether the lung had pneumonia, COVID-19, or healthy using the CNN algorithm. In addition to diagnosing the infection, the lung area was subsequently separated from the CT images for use in performing the final stage of determination of the ratio of COVID-19 infection in the lung and classified according to the ratio of infection rate to three stages (mild, moderate, severe). It is worth mentioning that the proposed system was trained on a database that contained 10,000 images of COVID-19, 10,000 pneumonia, and 10,000 healthy lungs. The proposed system diagnosed COVID-19 with an accuracy of 99.7 and an F1 score of 99.7.

Keywords: Diagnosis Covid-19, CNN, Segmentation Lung, Deep learning, The ratio of Covid-19
2020 MSC: 68T07

1 Introduction

COVID-19 is a novel Coronavirus-related illness related to the same family viruses responsible for the common cold and severe acute respiratory infection (SARS). Coronaviruses are "positive-sense single-stranded RNA enveloped viruses" [11]. On December 31, 2019, the Coronavirus first infected a person in the Chinese city of Wuhan, from where it spread widely to the rest of China and then to the whole world. The virus spreads through small liquid particles released from people infected with mouths or noses when they talk, cough, breathe, sneeze, or sing. The volume of these particles ranges from large respiratory droplets to very small aerosols [9]. COVID-19 has had a significant impact on humans. The plurality of infected patients has mild to medium symptoms and recover without needing to be admitted to the hospital. But some may have a severe illness and develop different symptoms, and symptoms differ from one person to the next Fever, cough, tiredness, and a loss of taste or odour are the most common signs and symptoms. Sore throat, pains, headache, aches, rash, airhead, or discolouration of the fingers or toes are all possible symptoms. Breathing difficulties or shortness of breath, loss of speech or mobility problems, confusion, and chest

*Corresponding author
Email addresses: rusuls.alsabe@student.uokufa.edu.iq (Rusul Saad Alsabea), asaad.alshareefi@uokufa.edu.iq (Asaad Noori Hashim)

Received: June 2022 *Accepted:* August 2022

discomfort are the most difficult symptoms [13]. Coronavirus is one of the most dangerous viruses because of its speed of spread among individuals and the severity of its effects on who becomes infected. In February, listed as a pandemic from (WHO) the World Health Organization, early detection and diagnosis are imperative to prevent infections from worsening, escalating and getting out of control [1]. Early detection of infection with the Coronavirus is the first and most important step in confronting the disease because of its impact on limiting the prevalence of the virus through quarantining the infected person and starting to receive appropriate treatment. There are multiple ways to detect the disease, including a nasal or oral swab and (RT-PCR), but it takes an extended time to show the results. In addition to the high cost, the high cost of the set of laboratories used for diagnosis, especially in developing countries. It was necessary to think of an alternative solution that would be less costly and give high precise results [15]. Using medical imaging tools, whether X-rays or computed tomography scans, is another way to detect coronavirus 19, as these tools are essential for people with confirmed or suspected of being infected [19]. But the most important factor in underestimating the diagnostic value of using X-rays to detect COVID-19 is that the disease cannot be diagnosed until an infected person's infection has advanced. On the contrary, with regard to tomography, where the disease can be diagnosed in its early stages, and this is a key point in preferring computed tomography over x-rays, the earlier the diagnosis of the disease, the sooner the necessary procedures for treatment are taken, and thus not to worsen the injury and symptoms in the affected person [18]. Despite the great role that computed tomography plays in diagnosing infection with Covid-19, the greatest effort falls on the radiologist in terms of visual scanning of the details in the computed tomography images. In addition, a significant number of computed tomography pictures must be analyzed in a short time, posing a high risk of errors and necessitating the use of intelligent technologies that can automatically classify CT images.

2 Related Work

This section includes a set of works related to this field:

Shubham Chaudhary et al. 2021 presented a technique that uses the gyrus network and computed tomography pictures of the chest region to identify COVID-19 infection and Pneumonia. The system had two stages: the first utilized the Dense Net structure to identify disease, whether it was Covid-19 or Pneumonia, and the second used the Efficient Net structure to achieve a three-dimensional fine-grained classification of three species: COVID-19 infected, normal, or Pneumonia infected. The suggested system's first step obtained a 94% accuracy, while the second stage earned an 89.3% accuracy. According to cross-sectional pictures, the mechanism has been put in a database consisting of 80 patients, 55 had Pneumonia, and 25 had COVID-19 [3].

Stephanie A. Harmon et al. 2020 A presented study that used data from several international organizations and institutions to analyze the effectiveness of artificial intelligence systems for identifying COVID-19 infections. The research demonstrated a lung segmentation method that used the AH-Net architecture to use the lung region as input for CT-based prediction and various classification models, including 3D classification. An accuracy of 90% was achieved on different data sets[5].

Feng Shit et al. 2020 research presented included a classification for using infection volume to distinguish COVID-19 infection from Pneumonia. First, all images were pre-processed to generate segmentation of lung domains for feature extraction. Then subjects were automatically classified with different ranges based on lesion sizes. iSARF was used to do this. Finally, the proposed approach was used to test a database of 1658 patients with COVID-19 and 1027 patients with Pneumonia. The accuracy of the proposed system was 0.879 [16].

Ouyang Xi et al. 2020 He suggested a technique based on computed tomography images and a double-sampled attention network for identifying COVID-19 from Pneumonia. The focus was on the afflicted portions of the lungs to diagnose using an Internet-based novel unit of interest using a three-dimensional gyrus neural network, based on the fact that sizes of the infection areas between COVID-19 and Pneumonia are uneven. The validity of the training was verified using 2186 cross-sectional pictures from several centres, and the test was conducted using 2057 images independent that were not part of the training. The suggested system had a precision of 87.5% [10].

Xiaowei Xu et al. 2019 Suggest a system to distinguish between infection with influenza-A viral pneumonia LAVP or infection with Covid-19. After performing the automatic extraction of the characteristics of the excised area from the images used for the chees, the proposed system classifies it as infected with COVID-19 or LAVP. The proposed system has been applied to the database used, which consists of 618 images only. It should be noted that the sensitivity achieved by the proposed method was 98% [22].

Dilbag Singh et al. (2020) suggested a system for early diagnosis of COVID-19 through tomography based on MODE, where the images entered into the system (COVID+19, COVID-19) are classified through a network application (CNN) whose parameters are adjusted with MODE. In addition, MODE is also used to perform mutation, intersection, and selection operations. The proposed system achieved an accuracy of 92% [17].

Jin et al. (2020) proposed a multi-directional classification system capable of diagnosing COVID-19 or influenza-A/B in addition to acquired Pneumonia CAP. The disease classification process is based on a deep two-dimensional network built on Res Net 152. The proposed system achieved high performance in classification, with an accuracy of 97% for the base case. The data used is more than 10 thousand CT volumes, and testing perform on 3,199 scans [7].

3 Methodology

There are three phases to the suggested approach: The first stage is pre-processing, which applies a normalization technique to the CT images to improve them, followed by edge sharpening to enhance the edges. Then CNN is utilized to extract deep features and identify COVID-infected CT samples. Finally, lungs are segmented from patients' CT scans to quantify lung infection with COVID-19.

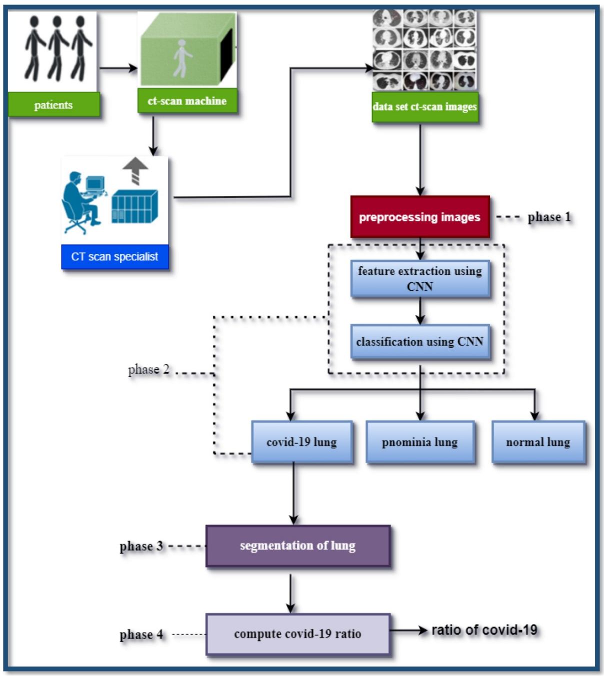


Figure 1: The proposed system

3.1 Dataset

COVID is diagnosed using computer-generated software based on pictures of the lungs. X-rays or computed tomography (CT) equipment creates the images. This paper used CT scan images from the open-source Kaggle repository. A dataset containing images of COVID-19-infected lungs and other healthy lungs and images of pneumonia-infected lungs. The database also contains patient data such as identity, source, country, gender, age, and presentation. 10,000 images of lungs infected with COVID-19, 10,000 of normal lungs, and 10,000 of lungs infected with Pneumonia were selected from the base mentioned above. It was divided between training, validation, and testing, as shown in Table 1. Figure 2 shows a database sample that was used.

Table 1: Dataset is divided into train, test and validation sets

	COVID 19	Nonovoid-19	Pneumonia	Total
Train set	5600	5600	5600	16800
Validation set	1400	1400	1400	4200
Test set	3000	3000	3000	9000
Total	10000	10000	10000	30000

Figure 2: Samples from Database

3.2 Pre-processing CT Image

Images obtained from medical equipment are prone to blurring, whether due to the medical devices' nature or the environment's illumination. Because the blur affects the diagnostic process, defogging the photographs is the first step in determining the diagnosis. The blur added to the image is the consequence of the values being spread and their distance from the mean, so the optimization process used consists of two steps:

3.2.1 Normalization

When there is a large disparity between certain values, this disparity causes an error in the analysis of those values. In order to address this disparity, these values must be converted within a specific range so that they are convergent. The normalization process is used in many fields, including data mining and analysis, image processing, and others [4]. Unfortunately, the images resulting from the medical devices are blurry, and the values are scattered. Images result makes the analysis process of the image with error results. In this paper, we used the normalization process for the color values of the image to be converted between zero and one using the formula below [14]:

$$M = \left(\frac{V - \min}{\max - \min} * \left(\max_n - \min_n \right) + \min_n \right) \tag{3.1}$$

Since the image values are grayscale 0-255, they must be converted to another Color space with a value between 0-1. Other Color spaces need images consisting of three layers so that the grey layer will be duplicated into three layers. Then the image will be converted to NTSC Color space, which makes the image's Color values between 0 and 1.

In this Color model, there are three elements: luminance (Y), with two Color difference signals (I) and saturation (Q). The conversion from RGB to YIQ is carried out using the formula below [20]:

$$\begin{bmatrix} Y \\ I \\ Q \end{bmatrix} = \begin{bmatrix} 0.299 & 0.587 & 0.114 \\ 0.595 & -0.274 & -0.321 \\ 0.211 & -0.522 & 0.311 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix} \tag{3.2}$$

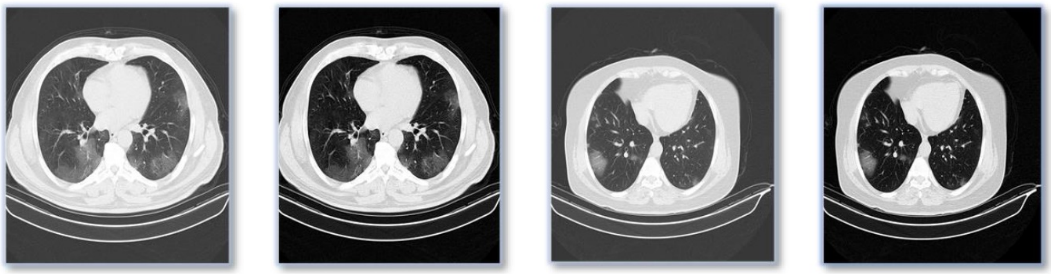
After converting the image to NTSC Color space and applying the normalization process, the smallest value in the image is denoted by min, the image's maximum value is represented by max, and V represents the image's pixel values. Then the image is returned to the RGB Color space.

The figure below shows the enhancement of the images:

Algorithm 1 CT-Scan Image Enhancement

Input: Bluer CT-Scan Image.
Output: Remove image blur.

1: Begin:
2: Read the grey image
3: Resize images to the same size.
4: Replicate the image with three layers to convert it from grey to RGB.
5: Convert the image in step 3 from RGB color space to NTSC color space.
6: Optimize the level of the varying values of the images generated from step 4 by applying the normalization equation to make them between zero and one.
7: show the final image.
8: End



(a) (b) (c) (d)

Figure 3: (a) and (c) represent the normal and COVID images before enhancement. (b) and (d) represents a normal and COVID image after enhancement.

The improvement shown in the images can be seen through the initial processing steps that were made in Figure 3 and to measure the improvement effect on the images more accurately

3.2.2 Proposed Method

Deep learning(DL) is a collection of methods that permit feeding raw data to a machine and automatically detecting representations needed for detection or classification. DL ways are representational learning ways with multiple levels of representation, acquired by authoring a non-linear but short work. A (CNN) is a method that uses deep learning to deal with images. For example, the input to this network is an image, and the output is a classification [8]. A CNN was used to extract the features needed to diagnose COVID-19 from computerized tomography images. The proposed network for the used system is shown in the table below:

Table 2: Layers of CNN for the proposed method

Id	Layers	Input Size	Kernel size	No. of Filters	Stride	Padding
1	Input Layer	$200 * 200 * 3$	–	–	–	–
2	convolution2dLayer	$200 * 200 * 3$	$5 * 5$	30	1	same
3	Batch Normalization Layer	$200 * 200 * 3$	–	–	–	–
4	ReLU	$200 * 200 * 3$	–	–	–	–
5	maxPooling2dLayer	$200 * 200 * 3$	$2 * 2$	–	2	same
6	convolution2dLayer	$100 * 100 * 3$	$5 * 5$	60	1	same
7	Batch Normalization Layer	$100 * 100 * 3$	–	–	–	–
8	ReLU	$100 * 100 * 3$	–	–	–	1
9	maxPooling2dLayer	$100 * 100 * 3$	$2 * 2$	–	2	same
10	convolution2dLayer	$50 * 50 * 3$	$5 * 5$	90	1	same
11	ReLU	$50 * 50 * 3$	–	–	–	–
12	maxPooling2dLayer	$50 * 50 * 3$	$2 * 2$	–	2	same
13	Fully connected (400)	1875	–	–	–	–

14	FC-Activation function (tanh)	400	–	–	–	–
15	Dropout Layer(0.2)	400	–	–	–	–
16	FC-Dense layer (3)	320	–	–	–	–
17	Softmax output layer	3	–	–	–	–

3.2.3 Segmentation of Lung

Usually, when an image of the lung area is taken using a CT scan, parts other than the Lung will appear, such as bones and blood vessels and the soft tissues inside the body. Therefore, it is necessary to cut only the part of the Lung and separate it from the rest of the components of the image. The algorithm below shows a segment of Lung:

Algorithm 2 Segmentation of Lung

Input: CT-Scan Image of the Lung.
Output: Segment of Lung.

1: Begin:
2: Read the CT-Scan image.
3: Convert a grayscale image to a binary image using a threshold.
4: Complementation of the image resulted from (step 2).
5: Remove the border from the image that results from (step 3).
6: Apply the morphology operation to the image resulting from step 4.
7: Fill the holes in the image (step 4).
8: Replace binary value with origin value of Lung accept background.
9: End

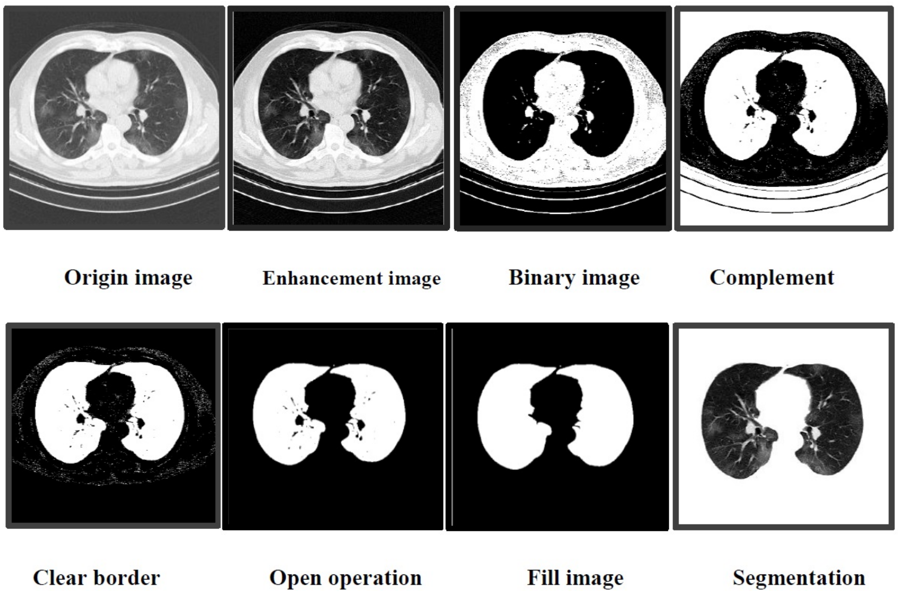


Figure 4: Step of Segmentation and compute the ratio.

3.2.4 Determine the COVID Ratio

After lung extraction, the incidence of COVID is determined by the equation below:

$$Covid_{Rate} = \frac{\sum_{i=1}^{\text{No.of Images}} \left(\frac{\text{the number of pixels in a COVID}}{\text{the number of pixels in a norml+the number of pixels in a COVID}} \right)}{\text{number of images}} \tag{3.3}$$

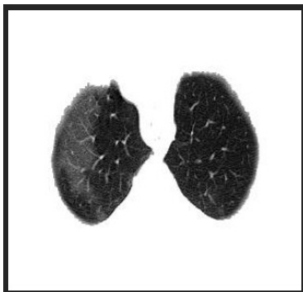
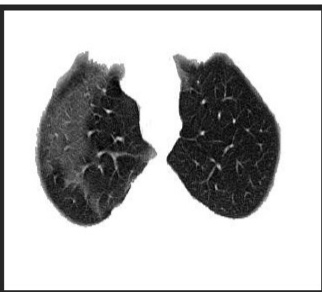
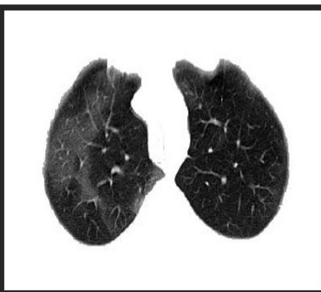
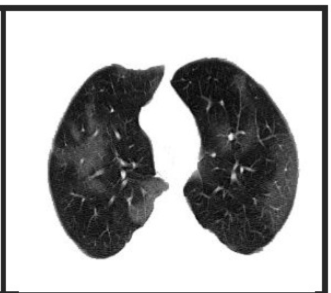
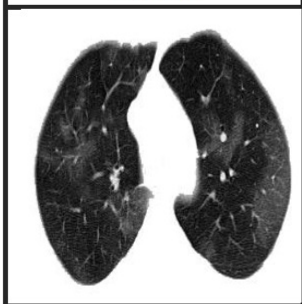
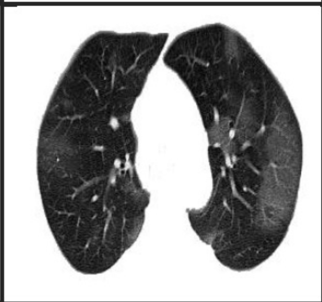
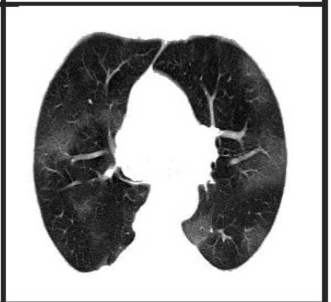
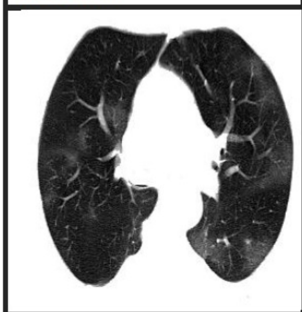
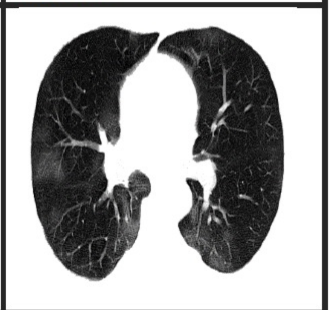
The lung was divided into three regions, so the pixels within the lung were of three types. If the pixel values are less than 70, it represents a normal, uninjured lung. If pixel values are less than or equal to 170 and greater than or equal to 70, they represent Covid infection values. Finally, if it is greater than 170, it represents the veins of the lung.

Usually, 12 to 20 images of the lung area are taken in different directions, so the injury is calculated for each image. Then, the sum of the injuries extracted from all images is divided by the number of images.

Three types of ratios:

1. The type is mild if the ratio is less than or equal to 25.
2. The type is moderate if the ratio is greater than 25 and less than or equal to 50.
3. The type is severe if the ratio is greater than 50.

Table 3: The results of computing the ratio of covid-19 for the patient.

			
26.453	27.304	22.968	22.755
			
26.313	27.755	32.180	29.558
			
17.702	12.821	8.878	16.4566
22.595 Mild			

4 The Expected Results and Performance Analysis

The proposed method was implemented using a MATLAB environment within an Intel Core i7 computer specification with 20-GB RAM. Splitting the data into training and testing was cross-validation randomly to avoid overfitting problem—division as mentioned in the methodology part. The proposed method was implemented on the dataset that includes Covid-19 ,normal lungs, and Pneumonia. The results indicated an accuracy rate of 99.488 for the proposed network, suggesting a great ability to distinguish between Covid and Pneumonia. Figure 5 shows the training process for the dataset, where the blue Color represents the percentage of accuracy of the correct diagnosis of the rule. The red Color represents the amount of error. Both accuracy and error start from an unacceptable level. As the training process continues, they improve until the accuracy becomes maximum and the error becomes as tiny as possible.

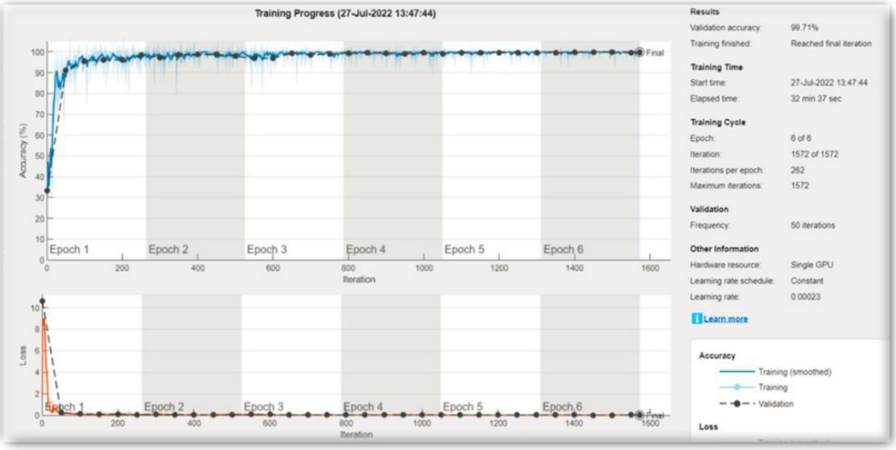


Figure 5: The training process with accuracy and error

As for the dataset that includes Covid and Pneumonia in addition to normal lungs, the classification process was excellent with a tiny amount of error as it was placed in a confusion matrix. This system has high accuracy in distinguishing between Covid and Pneumonia according to the extracted characteristics of each type.

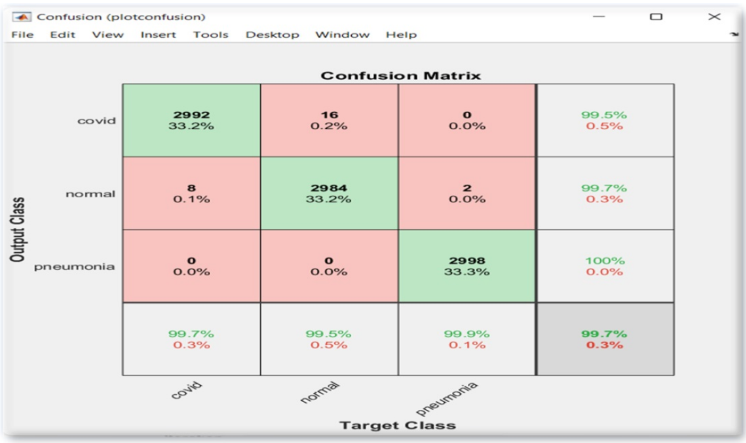


Figure 6: The training process with accuracy and error

Table 4 gives details of all cases studied on this base (C, N, P), where N represents normal Lung, C represents Covid lung, and P represents Pneumonia.

Table 4: Details of all cases studied

No. Layer	Size image	No. Filter	Size Filter	No. Epoch	Val accuracy	Accuracy	Precision	Recall	F1	Time/ minute
Change the size of the image										
3	$160*160*3$	30, 60, 90	$5*5$	6	98.10	98.200	98.200	98.200	98.200	19
3	$180*180*3$	30, 60, 90	$5*5$	6	98.90	98.444	98.957	98.944	98.950	28
3	$200*200*3$	30, 60, 90	$5*5$	6	99.71	99.711	99.711	99.711	99.711	32
3	$200*200*3$	30, 60, 90	$5*5$	6	98.00	98.355	98.368	98.355	98.361	34
Change the size of the filter										
3	$200*200*3$	30, 60, 90	$3*3$	6	99.24	99.144	99.150	99.144	99.149	22
3	$200*200*3$	30, 60, 90	$5*5$	6	99.71	99.711	99.711	99.711	99.711	32
3	$200*200*3$	30, 60, 90	$7*7$	6	99.213	99.211	99.213	99.211	99.212	39
3	$200*200*3$	30, 60, 90	$9*9$	6	98.91	98.912	98.912	98.913	98.912	44
Change of Learning Rate										

3	$200*200*3$	30, 60, 90	$5*5$	6	0.001	93.24	93.243	93.242	93.242	42
3	$200*200*3$	30, 60, 90	$5*5$	6	0.002	93.633	93.999	93.633	93.816	40
3	$200*200*3$	$200*200*3$	$5*5$	6	0.0002	98.143	98.199	98.200	98.199	36
3	$200*200*3$	$200*200*3$	$5*5$	6	0.00021	99.311	99.377	99.381	99.377	33
3	$200*200*3$	30, 60, 90	$5*5$	6	0.00023	99.711	99.711	99.711	99.711	32
3	$200*200*3$	30, 60, 90	$5*5$	6	0.000001	99.322	99.115	99.116	99.115	31
Change of Epoch										
3	$200*200*3$	30, 60, 90	$5*5$	4	99.07	99.233	99.239	99.233	99.236	19
3	$200*200*3$	30, 60, 90	$5*5$	5	99.19	99.227	99.279	99.277	99.278	24
3	$200*200*3$	30, 60, 90	$5*5$	6	0.00023	99.711	99.711	99.711	99.711	32
3	$200*200*3$	30, 60, 90	$5*5$	7	99.32	99.311	99.311	99.321	99.311	41
Change of No. Layer										
2	$200*200*3$	30, 60, 90	$5*5$	6	97.21	99.277	99.276	99.277	97.277	56
3	$200*200*3$	30, 60, 90	$5*5$	6	99.71	99.711	99.711	99.711	99.711	32
4	$200*200*3$	30, 60, 90	$5*5$	6	99.52	99.522	99.521	99.522	99.522	27

Table 5 compares our proposed system for diagnosing COVID-19 with other systems based on deep learning and computed tomography images. The proposed system achieved a performance that exceeded the performance of other systems for several reasons, and the most important of these reasons is the use of the database consisting of 30 thousand images, on which the convolutional neural network was trained, which helped the network to extract all the features necessary to classify the injury, whether it was Covid or Pneumonia, in addition To the appropriate improvement that was made to the images as a first step to increase the clarity of the images. Furthermore, as can be seen, the convolutional neural network was distinguished by selecting the ideal input picture size of $200*200$, choosing the appropriate number of filters (30, 60, 90), the best filter size $(5*5)$, in addition to the number of layers represented by three layers. The other aspects that distinguished the proposed system from the previous systems contributed to the most excellent diagnosis accuracy of 99.71% and the fastest diagnostic time of 32 seconds.

Table 5: Comparison of the proposed method with other methods.

Study	Methodology	Size of Dataset	Types of Diseases	Accuracy
Chaudhary et al. [3]	Dense Net, Efficient Net	80	(C., P.)	94%
Harmon et al. [5]	AH-Net, 3D model based on Dense Net 121	2724	(C., P.)	90.8%
Shi et al. [16]	Size Aware Random Forest	2785	(C., P.)	87%
Ouyang al. [10]	CNN	4261	(C., P.)	94%
Xu et al. [22]	CNN	618	(N., C.)	86.7%
Singh et al. [17]	CNN & MODE	—	(N., C.)	92%
Jin et al. [7]	CNN depend (Res Net 152)	3199	(N., C.)	92.9%
Bhansali et al. [2]	CNN	743	(N., C.)	97%
Wu et al. [21]	Multi-Vision Fusion Model	450	(N., C.)	76%
Pu et al. [12]	3D NN	498	(N., C.)	70%
Jaiswal et al. [6]	DTL based on Dense Net 201	2492	(N., C.)	97%
Proposed system	CNN	30000	(N., C., P.)	99.7%

5 Conclusion

Much research has been done on automatic diagnosis based on deep learning, especially on CNN. It is considered the most critical area to deal with and fully process images. First, it is necessary to compute the percentage to determine the correct treatment. In this study, the injury ratio was calculated from the CT images of the injured person. Then the patient's condition is classified according to the level of his injury (mild, moderate, and severe). The idea of determining the infection rate is new. It has a minimal error rate, and this is due to the presence of some lung veins with colour values similar to those of infection, representing Covid in the Lung. Diagnostic rates were very high, as there is a high possibility of diagnosing any external images.

Acknowledgement

I'd like to express my gratitude to Dr Musa Mohamed Amin, M.B.CH.B specialized radiology, for his advice and instructions, which helped us improve our proposal for identifying infection with Covid-19 and calculating the proportion of infection using computed tomography pictures of the lungs.

References

[1] M. Alzubaidi, H.D. Zubaydi, A.A. Bin-Salem, A.A. Abd-Alrazaq, A. Ahmed and M. Househ, *Role of deep learning in early detection of COVID-19: Scoping review*, Comput. Meth. Prog. Biomed.Update **1** (2021), 100025.

[2] R. Bhansali, R. Kumar and D. Writer, *CoronaNet: A novel deep learning model for covid-19 detection in CT scans*, J. Student Res. **9** (2020), no. 2.

[3] S. Chaudhary, S. Sadbhawna, V. Jakhetiya, B.N. Subudhi, U. Baid and S.C. Guntuku, *Detecting covid-19 and community acquired pneumonia using chest CT scan images with deep learning*, ICASSP 2021-2021 IEEE Int. Conf. Acoustics, Speech and Signal Process. (ICASSP), IEEE, 2021, pp. 8583–8587.

[4] S. Gopal Krishna Patro and K.K. Sahu, *Normalization: A pre-processing stage*, arXiv preprint arXiv:1503.06462, (2015).

[5] S.A. Harmon, T.H. Sanford, S. Xu, E.B. Turkbey, H. Roth, Z. Xu, D. Yang, A. Myronenko, V. Anderson, A. Amalou and M. Blain, *Artificial intelligence for the detection of COVID-19 pneumonia on chest CT using multinational datasets*, Nature Commun. **11** (2020), no. 1, 1–7.

[6] A. Jaiswal, N. Gianchandani, D. Singh, V. Kumar and M. Kaur, *Classification of the COVID-19 infected patients using DenseNet201 based deep transfer learning*, J. Biomol. Struct. Dyn. **39** (2021), no. 15, 5682–5689.

[7] C. Jin, W. Chen, Y. Cao, Z. Xu, Z. Tan, X. Zhang L. Deng, C. Zheng, J. Zhou, H. Shi and J. Feng, *Development and evaluation of an artificial intelligence system for COVID-19 diagnosis*, Nature Commun. **11** (2020), no. 1, 1–14.

[8] Q. Li, W. Cai, X. Wang, Y. Zhou, D.D. Feng and M. Chen, *Medical image classification with convolutional neural network*, 13th Int. Conf. Control Autom. Robot. Vision (ICARCV), IEEE, 2014, pp. 844–848.

[9] H. Liu, F. Liu, J. Li, T. Zhang, D. Wang and W. Lan, *Clinical and CT imaging features of the COVID-19 pneumonia: Focus on pregnant women and children*, J. Infect. **80** (2020), no. 5, 7–13.

[10] X. Ouyang, J. Huo, L. Xia, F. Shan, J. Liu, Z. Mo, F. Yan, Z. Ding, Q. Yang, B. Song and F. Shi, *Dual-sampling attention network for diagnosis of COVID-19 from community acquired pneumonia*, IEEE Trans. Med. Imag. **39** (2020), no. 8, 2595–2605.

[11] A. Panday, M.A. Kabir and N.K. Chowdhury, *A survey of machine learning techniques for detecting and diagnosing covid-19 from imaging*, arXiv preprint arXiv:2108.04344, (2021).

[12] J. Pu, J. Leader, A. Bandos, J. Shi, P. Du, J. Yu, B. Yang, S. Ke, Y. Guo, J.B. Field and C. Fuhrman, *Any unique image biomarkers associated with COVID-19?* Eur. Radiol. **30** (2020), 6221–6227.

[13] B. Saloner, K. Parish, J.A. Ward, G. DiLaura and S. Dolovich, *COVID-19 cases and deaths in federal and state prisons*, Jama **324** (2020), no. 6, 602–603.

[14] C. Saranya and G. Manikandan, *A study on normalization techniques for privacy preserving data mining*, Int. J. Eng. Technol. **5** (2013), no. 3, 2701–2704.

[15] M.S. Satu, K. Ahammed, M.Z. Abedin, M.A. Rahman, S.M.S. Islam, A.K.M. Azad, S.A. Alyami and M.A. Moni, *Convolutional neural network model to detect COVID-19 patients utilizing chest x-ray images*, medRxiv, (2021). doi: https://doi.org/10.1101/2020.06.07.20124594

[16] F. Shi, L. Xia, F. Shan, B. Song, D. Wu, Y. Wei, H. Yuan, H. Jiang, Y. He, Y. Gao and H. Sui, *Large-scale screening to distinguish between COVID-19 and community-acquired pneumonia using infection size-aware classification*, Phys. Med. Biol. **66** (2021), no. 6, 65031.

[17] D. Singh, V. Kumar and M. Kaur, *Classification of COVID-19 patients from chest CT images using multi-objective*

differential evolution–based convolutional neural networks, Eur. J. Clinical Microbio. Infect. Diseases **39** (2020), no. 7, 1379–1389.

[18] C.H. Sudre, B. Murray, T. Varsavsky, M.S. Graham, R.S. Penfold, R.C. Bowyer, J.C. Pujol, K. Klaser, M. Antonelli, L.S. Canas and E. Molteni, *Attributes and predictors of long-COVID: Analysis of COVID cases and their symptoms collected by the Covid symptoms study app*, medRxiv 2020.10. 19.20214494, J. R. Soc. Interface, 6 (2020).

[19] D.N. Vinod, B.R. Jeyavadhanam, A.M. Zungeru and S.R.S. Prabaharan, *Fully automated unified prognosis of Covid-19 chest x-ray/CT scan images using deep Covix-Net model*, Comput. Boil. Med. **136** (2021), p. 104729.

[20] I. Vlad, *Using the NTSC color space to double the quantity of information in an image*, Stanford Exploration Project, Report 110, 2001.

[21] X. Wu, H. Hui, M. Niu, L. Li, L. Wang, B. He, X. Yang, L. Li, H. Li, J. Tian and Y. Zha, *Deep learning-based multi-view fusion model for screening 2019 novel coronavirus pneumonia: A multicentre study*, Eur.J. Radiol. **128** (2020), 109041.

[22] X. Xu, X. Jiang, C. Ma, P. Du, X. Li, S. Lv, L. Yu, Q. Ni, Y. Chen, J. Su and G. Lang, *A deep learning system to screen novel coronavirus disease 2019 pneumonia*, Engin. **6** (2020), no. 10, 1122–1129.