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Automatic detection lung infected COVID-19 disease using deep learning (Convolutional Neural Network)

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Abstract

In late 2019, a virus appeared suddenly he claims Covid-19, which started in China and began to spread very widely around the world. And because of its effects, which are not limited to human life only, but rather in economic and social aspects, and because of the increase in daily injuries and significantly with the limited hospitals that cannot accommodate these large numbers, it is necessary to find an automatic and rapid detection method that limits the spread of the disease and its detection at an early stage in order to be treated more quickly. In this paper, deep learning was relied upon to create a CNN model to detect COVID-19 infected lungs using chest X-ray images. The base consists of a set of images taken of lungs infected with Covid-19 disease and normal lungs, as the CNN structure gave accuracy, Precision, Recall and F-Measure 100%.

Keywords: Deep learning, Convolutional Neural Network, COVID-19.

1. Introduction

The end of the year 2019 is considered one of the worst years in the current century due to the outbreak of what is known as the Corona virus. It appeared for the first time in the cities of Wuhan, China, and began to spread very widely around the world due to the lack of discovery of any treatment or vaccine that works to reduce the spread [9, 16]. Not only did it have effects on the

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health aspect of the human being, but rather, the movement of the world was stopped from carrying out various activities [17, 8]. In 2020 Huang et al. In January, a summary of this virus, as 41 people infected with this virus were studied. Symptoms of this virus are coughing, fever and shortness of breath. These are among the most important symptoms that he is infected with, and some other people do not show symptoms significantly only headache and body weakness. It can spread from one person to another through touch or close contact with an infected person [7, 2]. The disease is diagnosed through several methods, one of which is taking a image of the chest area and it is examined by experts, but it takes a long time in case there are hundreds of infected people. But with the advancement of technology and its use in all fields, it has been used in a rapid diagnosis of the disease. The use of deep learning represented by convolutional neural networks that take the image as an input and then diagnose whether the person is affected or not [4, 6, 1, 5].

Hassantabar & et al. (2020) Two models of neural networks were presented using convolutional deep learning, the first is convolutional and the other is the deep neural network. A database was used to image the lung region. The classification of the results shows that the CNN architecture rendered with higher accuracy (93.2%) and sensitivity (96.1%) outperforms the DNN method with an accuracy of 83.4% and sensitivity of 86% [15].

Wang & et al. introduced a system that detects Covid-19 disease by using convolutional neural networks for a set of chest X-ray images. The research worked on image analysis of the affected lungs and normal lungs, where the system's recognition accuracy was 93.3% [12]. Ali & et al. He 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 and the results were as follows: 96.1% accuracy for Dataset-1, 99.5% accuracy for Dataset2 and 99.7% accuracy for Dataset-3 [13].

Mohammad & et al. They 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. As the accuracy value for Covid-19 detection reached 99.56%, and the overall rate of all trained items was percentage [14].

2. Methodology

This part includes a detailed explanation of the components of the proposed system and the parts of a convolutional neural network.

2.1. Deep Learning

Deep learning is considered one of the most important fields that is spreading very widely due to its ability to create models that simulate nerve cells in humans and give the correct perception of the given problem. This part belongs to artificial intelligence. Most of the deep learning research focuses on analyzing 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 [10, 3].

2.2. Convolution Neural Network

CNN is a deep learning 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 in the neural network features, but in CNN the input is images, secondly, the hidden layers of the neural network are neurons and each neuron is connected to all the neurons in the neighboring hidden layer except in CNN each hidden layer is made of 3 dimensions width, height and depth and every neuron in each hidden layer are connected to a part of neighboring layer neurons. It cannot be considered a normal neural network consisting of many hidden layers only, it is intricately designed to simulate the brain and how it identifies between images. It can extract features rather than manually build them using many locally connected layers that can extract [10, 3, 11].

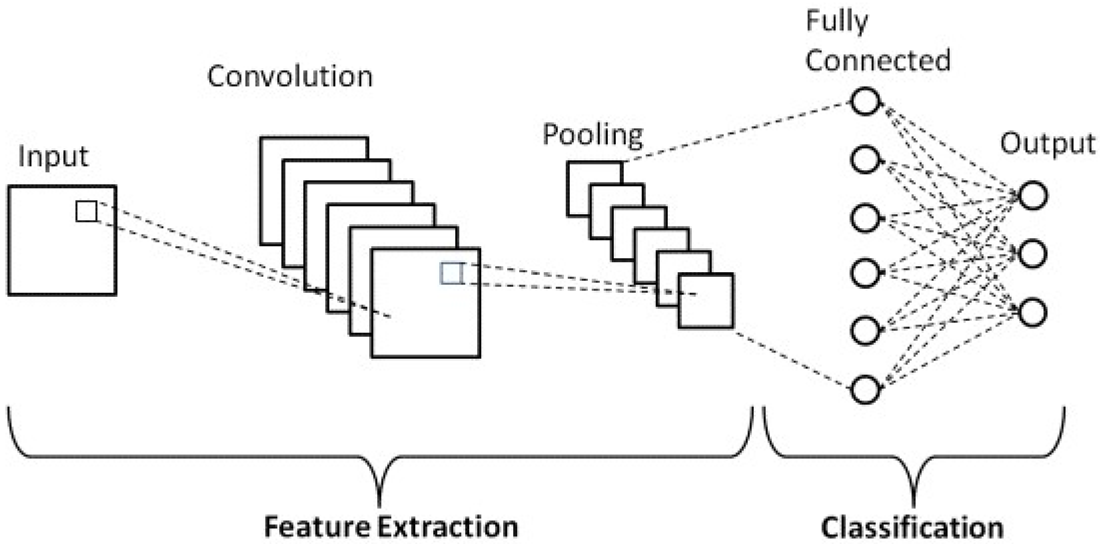


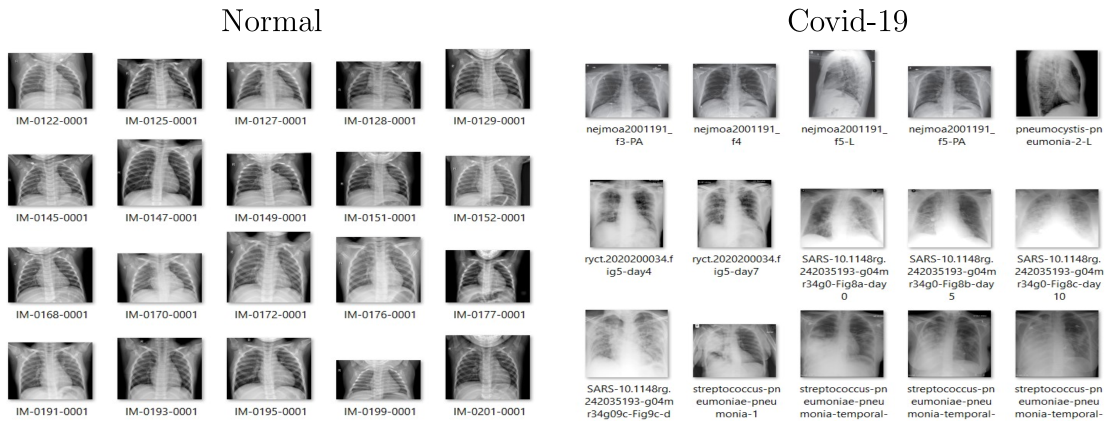
Figure 1: Convolution Neural Network

The components of the convolutional network CNN:

- 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.
- 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).
- 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 amount of calculations necessary, but also prevents you from falling into an overfitting state.
- Full contacted: 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 the two different layers are directly connected to the neurons within the fully connected layer.
- Output layer: After the Soft-Max layer this layer extracts data from the previous layer, and the difference between the real number and the resulting number from the network is greater, the error rate was greater. Where the error rate is a measure of the accuracy and efficiency of the neural network.

2.3. Dataset

A database was used that contains two categories, the first of which is Covid-19 and the other is normal. These images are taken for the chest area. This data was collected from websites on the Internet and part of it from a specialist radiology center. As the number of normal images reached 1600, the number of images infected with Covid-19 reached 1000. The base was divided into three parts: training, verification and testing [18, 19, 20].



2.4. Proposed Method

As we mentioned in the previous step, the components of the convolutional neural network and the database that we relied on requires us to divide the data into two groups, design and testing. The first group is trained on the network, and it is also divided into two parts, training and verification, and the bulk of the data includes 60%. First, a portion of the data is trained on the network, and then the results are validated. Then a set of data is tested after creating the final model that leads to high performance implementation.

The proposed system for the neural network consists of several layers, as I mentioned in the previous part. Each layer has its own features that depend on filters that represent weights that are applied to the image to extract features that pass 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. The proposed system includes two basic stages:

1. Pre-processing: At this stage, the images are filtered and noise removed. The images are also made of one size.
2. Lung recognition: In this stage, the convolutional neural network 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.

Algorithm (1): Proposed Method

Requires: Dataset images $Im = \{M1, M2, I3 \ldots Mn\}$, number of epochs.
Training stage:

1. divide Im into two part $(design_{set}, test_{set})$.
2. Split design_set into two part Training (tr_{set}) and Validation (val_{set}).
3. $I_{Train} \leftarrow Train\ (Proposed\ \ Network, tr_{set}, val_{set})$.
   a) Initialize the weights at adequate values.
   b) Take the input from the training data tr_{set} of $\{input, correctoutput\}$ and enter it to the proposed layer.
   c) Computing the error of the output

$$\textbf{a.}\quad \textbf{Error} = \frac{\mathbf{1}}{\mathbf{2}}(\textbf{desired-predicated})^{\mathbf{2}}$$

   d) Computing the weight updates according to ADAM
   e) Executed Steps b - d for all training data.
   f) Repeat Steps b- e until the error reaches an acceptable tolerance level.
   g) Estimate the tr_{set} using val_{set} for each epoch.
4. When we reach high performance accuracy, the training phase is terminated.
5. Return: Trained Proposed $\rightarrow I_{Train}$.
   Testing step:
6. Extract features from $test_{set}$.
7. Use the trained classifier I_Train to predict the label for $test_{set}$.
8. Get the known labels for $test_{set}$.
9. Display the mean accuracy.
10. Evaluation Proposed Network by using metrics.

End

Table.1 below, details the layers used in CNN:

3. Performance Evaluation

After building the system and training 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, he will use a set of measures that determine the number of correctly and incorrectly diagnosed images. Measures such as accuracy, precision, recall, F1-score.

$$Accuracy = \frac{TP + TN}{Total} \times 100\% \tag{3.1}$$

$$Recall = \frac{TP}{TP + FN} \times 100\% \tag{3.2}$$

$$Precision = \frac{TP}{TP + FP} \times 100\% \tag{3.3}$$

Table 1: CNN Parameter

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None,100,100,64)	4864
activation (Activation)	(None,100,100,64)	0
max_pooling2d (MaxPooling2D)	(None,50,50,64)	0
conv2d_1 (Conv2D)	(None,50,50,128)	204928
activation_1 (Activation)	(None,50,50,128)	0
conv2d_2 (Conv2D)	(None,25,25,128)	409728
activation_2 (Activation)	(None,25,25,128)	0
max_pooling2d_1 (MaxPooling2D)	(None,12,12,128)	0
conv2d_3 (Conv2D)	(None,6,6,256)	819456
activation_3 (Activation)	(None,6,6,256)	0
max_pooling2d_2 (MaxPooling2D)	(None,3,3,256)	0
conv2d_4 (Conv2D)	(None,2,2,256)	1638656
activation_4 (Activation)	(None,2,2,256)	0
max_pooling2d_3 (MaxPooling2D)	(None,1,1,256)	0
conv2d_5 (Conv2D)	(None,1,1,64)	0
activation_5 (Activation)	(None,1,1,64)	0
flatten (Flatten)	(None,64)	0
dense (Dense)	(None,64)	4160
activation_6 (Activation)	(None,64)	0
dense_1 (Dense)	(None,1)	65
activation_7 (Activation)	(None,1)	0

$$F1_score = 2 \times \frac{Recall \times Precesion}{Precesion + Recall} \times 100\% \tag{3.4}$$

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.

Table 2: Actual Class.

Predicted class			
		Class=**True**	*Class*=**False**
Actual class	*Class*= **Covid-19**	*True* **Positive**	*False* **Negative**
	Class= **Normal**	*False* **Positive**	*True* **Negative**

4. Performance Experiment

In this paper, they used a rule consisting of two groups, infected and uninfected, and the results were verified using a set of M scales, as well as calculating the time taken. The base was divided into two parts, 80% design and 20% testing. Divide the design data into two parts: 60% training and 20% validation. Measures such as measured as that of accuracy, precision, recall, F1-score. Various cases have been studied that include changes in system parameters, as shown in Table 3.

Table 3: Evaluation Metrics of CNN-COVID-19

Size of images	Size filter	Epochs	Accuracy	Precision	Recall	F-measure	Timeh:m: s
180*180	5*5	100	99.57%	98.70%	100.00%	99.35	1:16:37
180*180	5*5	90	93.91%	96.10%	87.06%	91.36	0:58:18
180*180	5*5	80	97.83%	95.51%	100.00%	96.64	1:6:14
180*180	5*5	70	97.83%	94.81%	98.85%	96.69	1:2:24
180*180	4*4	100	98.26%	94.81%	100.00%	97.33	0:55:53
180*180	4*4	90	99.57	98.70%	100.00%	99.35	0:51:8
180*180	4*4	80	100.00%	100.00%	100.00%	100.00	1:19:48
180*180	4*4	70	98.70%	96.10%	100.00%	98.01	0:44:51
180*180	3*3	100	97.39%	93.51%	98.63%	96.00	0:36:54
180*180	3*3	90	98.26%	94.81%	100.00%	97.33	0:33:41
180*180	3*3	80	98.26%	98.70%	96.20%	97.44	0:31:53
180*180	3*3	70	98.70%	96.10%	100.00%	98.01	0:47:13
180*180	2*2	100	97.39%	92.21%	100.00%	95.95	0:26:25
180*180	2*2	90	96.52%	100.00%	90.59%	95.06	0:24:26
180*180	2*2	80	96.09%	97.40%	91.46%	94.34	0:23:30
180*180	2*2	70	97.39%	93.51%	98.63%	96.00	0:18:57
190*190	5*5	90	96.09%	88.31%	100.00%	93.79	0:59:0
200*200	5*5	90	100.00%	100.00%	100.00%	100.00	1:13:45
210*210	5*5	90	47.39%	97.40%	38.66%	55.35	1:11:15
220*220	5*5	90	96.96%	96.10%	94.87%	95.48	1:19:24
200*200	4*4	90	99.57%	98.70%	100.00%	99.35	0:50:41
200*200	3*3	90	98.70%	96.10%	100.00%	98.01	0:32:26
200*200	2*2	90	96.96%	97.40%	93.75%	95.54	0:23:13
200*200	5*5	60	95.65%	87.01%	100.00%	93.06	0:50:17
200*200	5*5	70	97.83%	93.51%	100.00%	96.64	0:53:71
200*200	5*5	80	99.13%	97.40%	100.00%	98.68	1:06:13
200*200	5*5	90	100.00%	100.00%	100.00%	100.00	1:13:45
200*200	5*5	100	100.00%	100.00%	100.00%	100.00	1:21:13
200*200	5*5	110	100.00%	100.00%	100.00%	100.00	1:26:17
200*200	5*5	120	99.13%	97.40%	100.00%	98.68	1:31:37

Case 1: Lung CT Image Size Adjusting

In this case the size of the image was changed between of (180*180) to of (200*200) and began with the volumes of (180*180) because the network does not take the size of an image less than 180 because the processes that are carried out on the input image are many and that the network is deep and decreases in size in each layer because Convolution and max pooling reduce image size and in volumes (180*180 ,190*190 ,200*200 ,210*210 ,200*220) the best result was size of (200*200) because of the lack of pixels lost. as shown in Table (3).

Case 2: Filters Dimension used in the Convolution Layer

In this case the size of the filter (5*5) was used because this filter fits the size of the image as the number of pixels distress is low, but this filter has more calculations and takes longer in the convolution process but the filter (2*2,3*3, 4*4) that has been used does not give more accurate results than the filter results (5*5) because it contains more lost pixels. as shown in Table (3).

Case 3: Number of Epochs in CNN Training Model

In this case, it has a significant impact on accuracy and time, as their number has a significant impact on the results, as each Epoch is trained network and weights are changed according to the results extracted to the best results, after which the examination process is conducted to investigate the accuracy of the results in this network the best results obtained are in epoch 90,100,110 because they are well trained and the results of 80,70,60 network are not well trained. Since epoch's number is small and does not give accurate results, but in less time than Epoch 90, the results in Epoch

120,130,140 the network was inflexible and did not accept changes in the input images and Nose in which they give inaccurate results and that the best number Epoch was inferred is 90 and this is because it reveals the images in a series (flexible) and in less time. as shown in Table (3).

5. Conclusion

Deep learning is a popular part today for its proficiency and speed at classifying data. Therefore, this system has been proposed to detect Covid-19 early and reduce the efforts of doctors. The system adopts chest X-rays taken for infected and uninfected people. The results obtained accuracy, Precision, Recall and F-Measure 100%, meaning that the diagnosis was correct for each image. In light of the results obtained, this system will help doctors in the correct diagnosis of patients accurately and quickly. The efficiency of the system can also be increased by increasing the number of the database to include other infections or other forms.

References

[1] M. Akagi, Y. Nakamura, T. Higaki and et al., *Correction to: Deep learning reconstruction improves image quality of abdominal ultra-high-resolution CT[J]*, European Radiology, 29 (2019).

[2] J. Chan, S. Yuan, K.H. Kok and et al., *A familial cluster of COVID-19 associated with the 2019 novel coronavirus indicating person-to-person transmission: a study of a family cluster[J]*, Lancet. 2020 Jan 24. pii: S0140-6736(20)30154-9. doi: 10.1016/S0140-6736(20)30154-9.

[3] A. Gad, *Practical Computer Vision Applications Using Deep Learning with CNNs*, (2018).

[4] B. Gharbi, S. Michaël, J. Chen, J. Barron and et al., *Deep Bilateral Learning for Real-Time Image Enhancement[J]*, Acm Transactions on Graphics, 36 (2017) 118.

[5] S. Hassantabar, M. Ahmadi and A. Sharifi, *Diagnosis and detection of infected tissue of COVID-19 patients based on lung X-ray image using convolutional neural network approaches*, Chaos, Solitons and Fractals, 140 (2020) 110170.

[6] M. Hesamian, W. Jia, X. He and et al., *Deep Learning Techniques for Medical Image Segmentation: Achievements and Challenges[J]*, Journal of Digital Imaging, 32 (2019).

[7] C. Huang, Y. Wang, X. Li and et al., *Clinical features of patients infected with 2019 novel coronavirus in Wuhan, China[J]*, Lancet. 2020 Jan 24. pii: S0140-6736(20)30183-5. doi:10.1016/S0140-6736(20)30183-5.

[8] Q. Li, X. Guan, P. Wu and et al., *Early Transmission Dynamics in Wuhan, China, of Novel Coronavirus-Infected COVID-19[J]*, N Engl J Med. 2020 Jan 29. doi: 10.1056/NEJMoa2001316.

[9] P. Liu, L. Shi, W. Zhang, J. He, C. Liu, C. Zhao and L. Hu, *Prevalence and genetic diversity analysis of human coronaviruses among cross-border children.* Virology journal, 14 (2017) 1-8.

[10] B. Moons, D. Bankman and M. Verhelst, *Embedded Deep Learning*, (2018).

[11] J. Nagi, F. Ducatelle, G. Di Caro, D. Cireşan, U. Meier, A. Giusti and L. Gambardella, *Max-pooling convolutional neural networks for vision-based hand gesture recognition*, IEEE International Conference on Signal and Image Processing Applications (ICSIPA), (2011) 342-347.

[12] A. Narin, C. Kaya and Z. Pamuk, *Automatic detection of coronavirus disease (covid-19) using x-ray images and deep convolutional neural networks*, arXiv preprint arXiv:2003.10849, (2020).

[13] A. Narin, C. Kaya and Z. Pamuk, *Automatic detection of coronavirus disease (covid-19) using x-ray images and deep convolutional neural networks*, arXiv preprint arXiv:2003.10849.A. F. Gad, Practical Computer Vision Applications Using Deep Learning with CNNs, 2018.

[14] M. Rahimzadeh and A. Attar, *A new modified deep convolutional neural network for detecting COVID-19 from X-ray images*, arXiv preprint arXiv:2004.08052, (2020).

[15] L. Wang, Z. Lin and A. Wong, *Covid-net: A tailored deep convolutional neural network design for detection of covid-19 cases from chest x-ray images*, Scientific Reports, 10 (2020) 1-12.

[16] A. Zhavoronkov, V. Aladinskiy, A. Zhebrak and et al., *Potential COVID-2019 3C-like protease inhibitors designed using generative deep learning approaches*, Insilico Medicine Hong Kong Ltd A 307 (2020): E1.

[17] N. Zhu, D. Zhang, W. Wang and et al., *A Novel Coronavirus from Patients with COVID-19 in China, 2019[J]*, N Engl J Med. 2020 Jan 24. doi: 10.1056/NEJMoa2001017.

[18] `https://www.pyimagesearch.com/2020/03/16/detecting-covid-19-in-x-ray-images` learning/?fbclid=IwAR0UNoeVISUBISFDyJi5UX9KGFGn4dJA$_HHW2AvCz6ILXcv6dwLH8QBsG$18].

[19] https://www.kaggle.com/paultimothymooney/chest-xray-COVID-19
[20] https://github.com/ieee8023/covid-chestxray-dataset