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Convolutional neural network in the classification of COVID-19

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ABSTRACT

Covid-19 spread out rapidly around the world, forcing many countries to full shutdown, and economical and social consequences. Resulting in rapid need for new and effective methods to deal with this crisis and control it. X-ray lung images is considered one of the most effective and safe method for diagnosing Covid-19, since it could provide solid proof of the existing of the disease, and it has limited effect on the health of the human comparing with other radiography methods. In this proposed work, CNN model is designed and trained to classify Covid-19 X-ray images, by using the COVID-19 Radiography Database, which is published and available online. This database is collected by researchers and experts from various universities around the world. The database contains total of 15153 lung x-ray images, divided into three classes. The classification classes are: *Normal*, *Covid-19*, and *Viral Pneumonia*. The model is trained and tested on publicly available dataset. The dataset is divided into three parts: training, validation, and testing datasets. The model is evaluated based on the three of these datasets. Totally, the evaluation metrics include Accuracy, F1-score, Area Under Curve (AUC), Precision, and Recall, with values of greater than 98% for all of the evaluation metrics. Comparing the results with state of arts publications, which used the same dataset, the proposed method outperformed the state of arts publications depending on the evaluation metrics. The number of the trainable parameters in the proposed CNN model is about 25.4 millions.

Keywords: CNN, Deep learning, Covid-19, X-ray, classification.

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1. Introduction

Coronavirus disease (Covid-19) is type of infection disease. Caused by SARS-CoV-2 virus. Infected people can spread the virus by coughing, sneezing, or just even breathing. The virus are transported in small liquid particles in the air, infecting other people, or laying down on surfaces. And could be spread further by touching the contaminated surface by healthy people [1]. Since the pandemic of Coronavirus and up to 20 October 2021, more than 242 million people are infected, and 4.93 million are dead [2]. Early diagnosis of Coronavirus is considered a critical and important factor in the treatment. There are different methods to diagnose Coronavirus. One of the most common and effective methods is the radiological imaging. Since they reveal the presence of the disease severity. The most common chest radiography imaging are chest X-ray and computed tomography (CT) [3, 4].
Deep Learning (DL) techniques showed high-level performance in many different tasks. Especially in medical images analysis and classification [5-7]. One prominent Deep Learning algorithm in the field of Computer Vision in general, and especially in medical images analysis is Convolutional Neural Network (CNN). Since CNN could extract features from the training images, without the need to the manually extract the features. This will lead to the potential of extracting hundreds of thousands or millions of features from training images. Moreover, it have what is called the “Dense layer”, which is responsible of classifying the images based on their extracted features [8, 9].

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2. Related works

In the last period, many publications contributed on how to classify Covid-19 disease from many different types of medical images. Including X-ray, Computed Tomography scan (CT), and others. Asif and other researchers in 2020 [10], proposed a method based on Convolutional Neural Network (CNN) to classify Covid-19 disease. The number of classes in their study is consisting of three classes, Normal, Covid-19, and other viral pneumonia chest disease. Their dataset is collected from online repository of Dr. Joseph Cohen and others [11]. Which contains 864, 1345, and 1341 images for Covid-19, Viral Pneumonia, and Normal classes respectively. They used the model Inception V3 with transfer learning as their model. They obtained training accuracy of 97% and validation accuracy of 93%. Wang and others researchers in 2020 [12], proposed a different CNN based model to train and classify Covid-19 from X-ray images. The total number of the dataset is 13962 images collected from five different resources. They are classified into three classes: Normal, pneumonia, and Covid-19, with images number of 8066, 5538, and 358 respectively. The total number of trainable parameters are 11.75 millions. And the testing accuracy is 91.0%. Besides X-rays, some researchers used CT scan to classify Covid-19 by using Deep Learning models. In 2020, Polsinelli and other researchers [13] trained and tested a CNN model that is based on SqueezeNet to classify Covid-19 in CT scan images. Total accuracy of 85.03% is gained, with little higher rates in some datasets. They used Zhao [14] and the Italian [15] datasets. The first dataset is consisting of 360 images of COVID-19, and 397 images of other kinds of diseases and/or healthy lungs. The second dataset is consisting of 100 Covid-19 images. In 2021, Chaddad and other researchers [16] developed a CNN based model to classify Covid-19 in CT scan images. Six pre-trained CNN models are used (which are: AlexNet, DenseNet, GoogleNet, NASNet-Mobile, ResNet18, and DarkNet). Two classes to classify, the Normal and Covid-19. Highest accuracy for CT scan images classification is 82%. The dataset is consisting of total of 846 images. 449 of Covid-19 images, and 397 of Normal images.

3. Convolutional neural network (CNN)

Convolutional Neural Network (CNN) is Deep Neural Network, that is used mainly for images, due to its powerful performance in visual tasks such as image classification, segmentation, object detection, and others. The way the CNN works, is by training different types of layers, that are combined are capable of extracting visual features from the images. These features are processed later in different tasks such as classification or segmentation [8]. The most fundamental layer in CNN is the convolutional layer. Which is trainable filter (kernel), which its values are learned through the training process to extract the required features [8]. Figure 1 shows how the convolutional layer works.

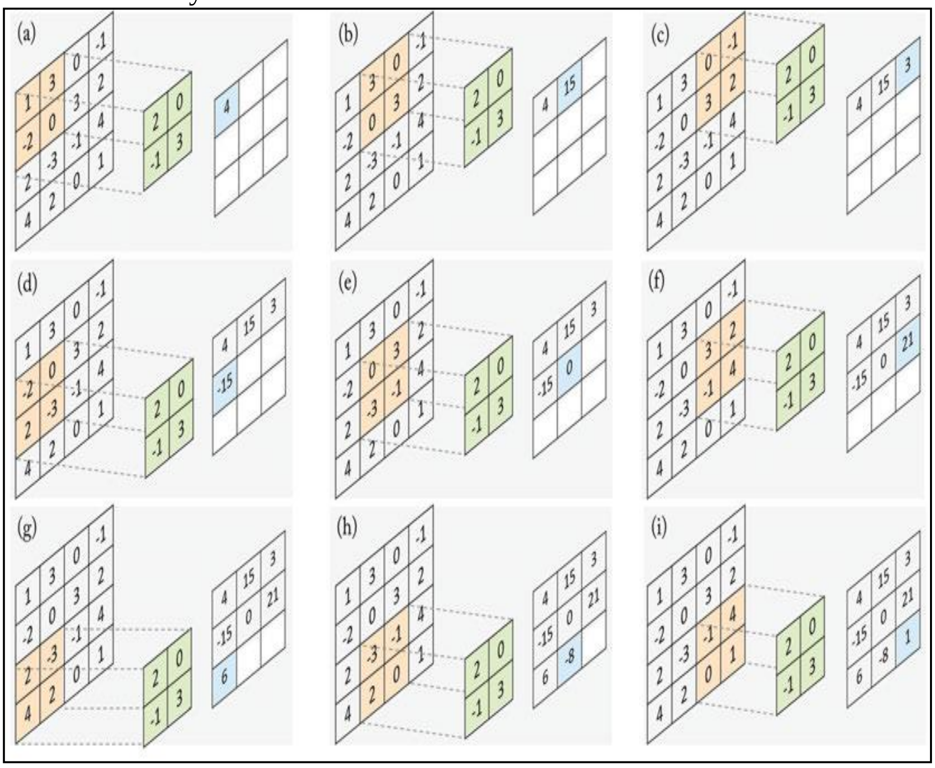

Figure 1. Convolutional Layer in CNN [8]

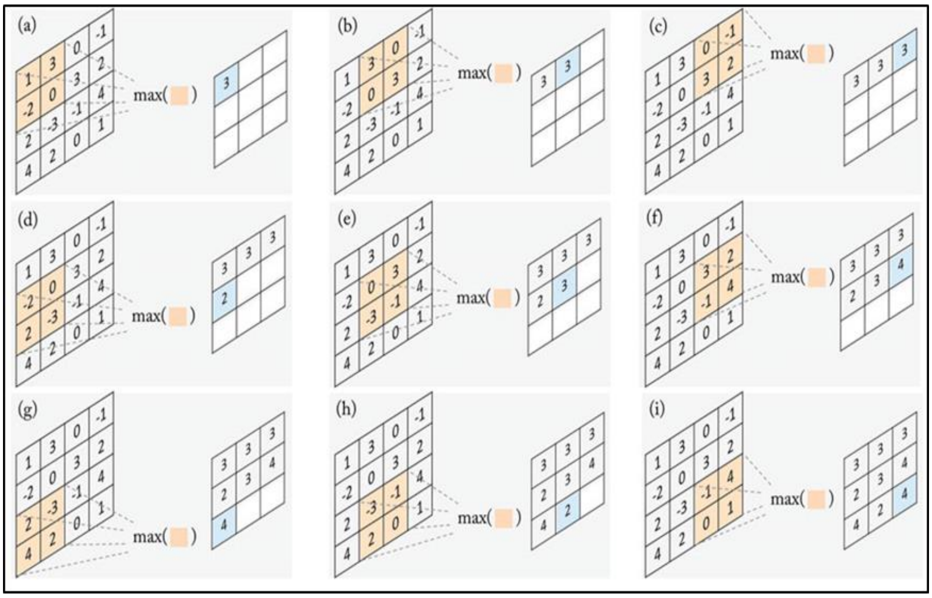

Figure 2. Max-pooling layer in CNN [8]

Another important layer is the Pooling layer. Which is used in reducing the massive size of the generated feature maps. There are two main Pooling layers. First the max pooling layer, in which only the largest value in the predefined size of the filter is selected. Keeping the most prominent values. The other pooling layer is the average polling, in which the average (mean value) of the selected values is set to represent the filter [8]. Figure 2 shows how the Max Pooling layer works. Another important layer is the DropOut layer. Which is used as regularization layer, to prevent the problem of overfitting. This problem occur when the model is over-trained on the training datasets, and its not capable of performing well on the testing and deployment data. DropOut layer will omit randomly some of the neurons in the model, to guide the learning process to be capable of handling noisy and unexpected inputs [8]. The Dense layer (or fully connected layer). Which is a traditional Neural Network, that takes the final feature map of the CNN model as input, and classify the image as an output. These different layers are designed by the programmer, depending mainly on the problem itself and the dataset, besides some experience and trial and error. The final model will be trained, and the values of the filters and weights will be adjusted by the Back-Propagation operation and the optimizer.

4. Dataset

The training and testing dataset used in this work is the COVID-19 Radiography Database [17, 18]. The dataset is collected by a researchers and doctors from Qatar University – Qatar, University of Dhaka – Bangladesh, and other collaborators from Pakistan and Malaysia. The dataset is downloaded from Kaggle [18]. The original dataset contains three classes. Which are Normal to represents the healthy lung x-rays, Covid to represent the lungs having Covid-19 disease, and Viral Pneumonia to represents other types of Pneumonia than Covid-19. Table 1 shows the numbers of x-ray images for each class.

Table 1. COVID-19 Radiography Database distribution

Class	N
Normal	10192
Covid-19	3616
Viral Pneumonia	1345
Total	15153

5. Materials and methods

Deep learning will be used to build the model to predict the class of the x-ray lung image. Convolutional Neural Network (CNN) will be used to train the prediction model. To build and train the model the following steps are carried out.

5.1. Data collection

Dataset collection: in the original dataset, the number of classes are showed in Table 1. However, due to the high number of images, and since they are imbalanced in number, only 3900 images are considered. The dataset is split into training, validation, and testing datasets. Table 2 shows the data distribution of the different classes among each of the datasets.

Table 2. Data distribution and classes used in this paper

Dataset	**Total Number (%)**	**Class**		
		Normal	Covid-19	Pneumonia
Training	2100 (53.84 %)	704	706	690
Validation	900 (23.07 %)	276	303	321
Testing	900 (23.07 %)	276	303	321

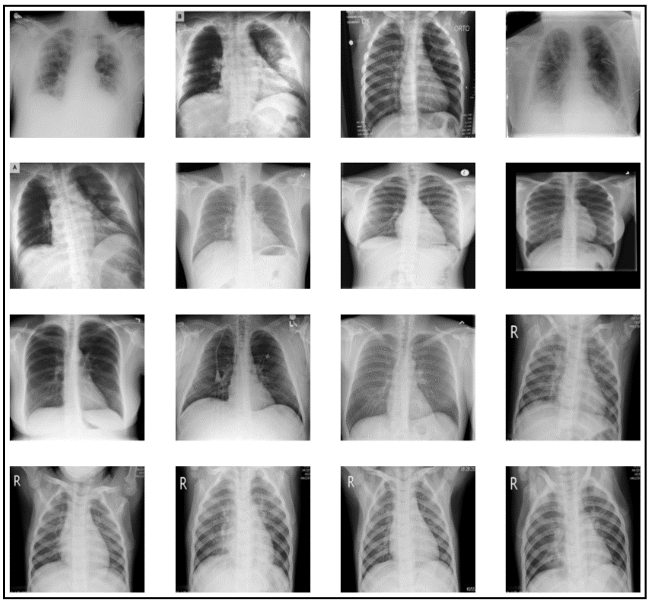

Figure 3. Sample images after applying Grey-scaling filter

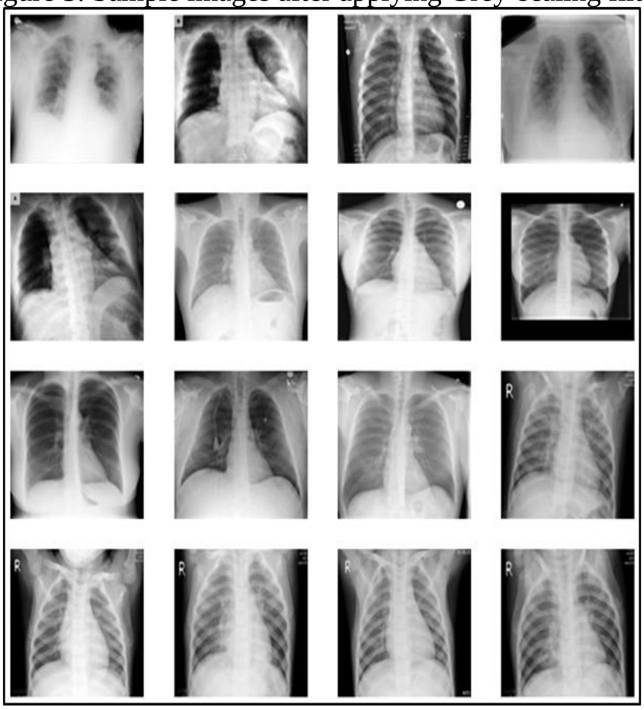

Figure 4. Sample images after applying Median filter

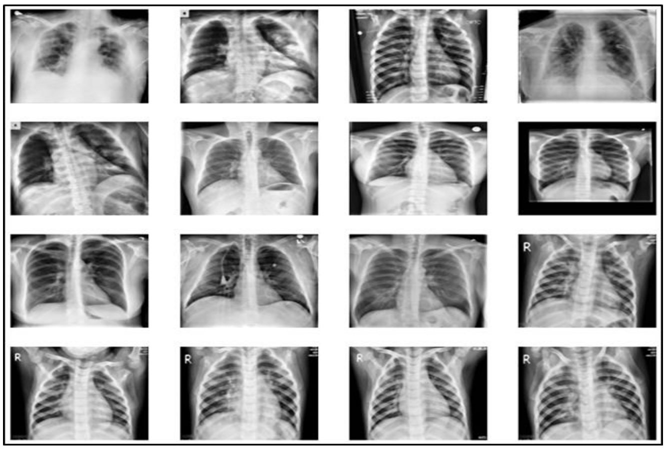

Figure 5. Sample images after applying CLAHE

5.2. Data Pre-processing

In order to make the images proper to extract and classify them, based on their features, pre-processing steps are required. The conducted pre-processing steps are:

- **Grey scaling:** Although the images are looking in grey scale, but they are saved as three channels instead of one (i.e. RGB instead of grey scale). Meaning, using one channel will hold the same features as three channels. Therefore, the images are converted into greyscale (i.e. one channel). This will reduce the time required to train the images. Figure 3 shows sample of images after reading and converting them into greyscale.
- **Median filtering:** Is widely used filter to remove noise from images, because it removes the noises while preserving the edges. It works by going through each pixel in the image, and replace it with the median value of its neighbors. In this work, a kernel size of 5 is used. Figure 4 shows sample of images after applying median filter [19].
- **Contrast Limited Adaptive Histogram Equalization (CLAHE):** Is a filter to improve contrast in digital images. Instead of using the entire image to equalize the contrast in the normal contrast equalizer, CLAHE works on small parts of the image named tiles. The used tile in this work is 8*8. And the clip limit is set to 2. Clip limit represents the highest level of the histogram each part of the image could reach [20]. Figure 5 shows sample of images after applying CLAHE filter.
- **Image resize:** the images in the original dataset are 299 * 299 pixels. However, reducing the image size is essential to increase the training time. But the new size should be small enough to keeps the important image features. Therefore, the images in this work are resized into 223 * 223 pixels.

5.3. CNN model structure

Table 3 shows the structure of the CNN model. In the Feature Extraction part, the Convolutional layers are used in extracting features from the images. The padding in convolutional layers are set to “same”. Meaning the input matrix and the output feature map for the convolutional layer have the same size. Notice that the generated feature maps are getting denser while they are getting deeper. The Max-pooling layers are used to reduce the feature maps, and thus small irrelevant details will be omitted, and less time is required to train. The stride value for the Max-pooling layers are all set to 2*2. Furthermore, the Drop-out layers are used too to reduce the overfitting problem. Notice that all the Drop-out layers have 10% drop out rate. The classification part have 373248 inputs, two hidden layers (each have 64 nodes) and an output layer. Notice that the used Activation Function is ReLU for all Convolutional and Dense layers in the model, except for the last dense layer, which Softmax is used.

Table 3. Proposed CNN structure

Layer	**Output Shape**	**Number of parameters**	
layer_1 (Conv2D)	(223, 223, 16)	160	Feature Extraction
layer_2 (Conv2D)	(223, 223, 32)	4640	
layer_3 (MaxPooling2D)	(111, 111, 32)	0	

layer_4 (Conv2D)	(111, 111, 64)	18496	
layer_5 (Dropout)	(111, 111, 64)	0	
layer_6 (Conv2D)	(111, 111, 128)	73856	
layer_7 (Conv2D)	(111, 111, 256)	295168	
layer_8 (MaxPooling2D)	(55, 55, 256)	0	
layer_9 (Dropout)	(55, 55, 256)	0	
layer_10 (Conv2D)	(55, 55, 512)	1180160	
layer_11 (MaxPooling2D)	(27, 27, 512)	0	
layer_12 (Dropout)	(27, 27, 512)	0	
flatten (Flatten)	(373248)	0	
layer_13 (Dense)	(64)	23887936	Classification
layer_14 (Dense)	(64)	4160	
layer_15 (Dense)	(3)	195	
Total number of trainable parameters: 25,464,771			

5.4. Model training

In order to train the model, two main things must be selected. Which are the Loss Function, and the optimizer. The used Loss Function is Sparse Categorical Cross-Entropy. It is used since the problem is categorical. And it is preferred over the normal Categorical Cross-Entropy to reduce the computation time. Since Sparse Categorical Cross-Entropy uses single truth label instead of one-hot encoded vector in Categorical Cross-Entropy [21, 22]. And Adam optimizer is used too, due to its high performance in many deep learning models [23].

5.5. Model regulation

During the training process, overfitting problem appeared. The overfitting problem is when the model is "over trained". Meaning it is performing very good on the training phase. However, when testing the model the results are not good. This is because the model starts to extract incorrect features that doesn't generalize what we are expected from it. Generally, this problem could be spotted by comparing the difference between the training and testing performance. To overcome this problem, two methods are used in this work. The first one is the use of DropOut layers that are explained previously in this paper. Second method is the use of Early Stopping. After the model is trained in each epoch, it is tested on the validation dataset. If the error rate between the training and validation is high, it is a sign of overfitting. Meaning that the model performance in the training was good, but when tested on unseen data its performance is declined. So the training will be stopped since it docent generalize anymore (Song et al., 2019). Figure 6 shows the idea behind Early Stopping.

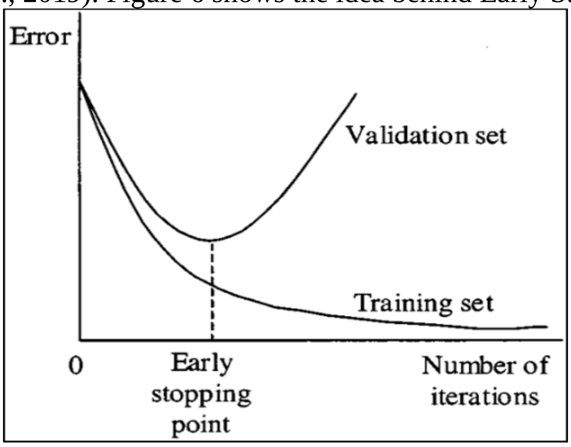

Figure 6. Early Stopping [24]

6. Results

The model performance is measured based on its performance during training and testing. during training, each epoch the model is trained on training dataset, and then its evaluated by using validation dataset. Figure 7 shows the process of training and validation based on the accuracy and loss values. Figure 8 shows the confusion matrix of the validation phase. And Table 4 shows the evaluation metrics during the validation phase. With total classification accuracy for validation phase of 0.98, and Area Under the Curve (AUC) of 0.9758.

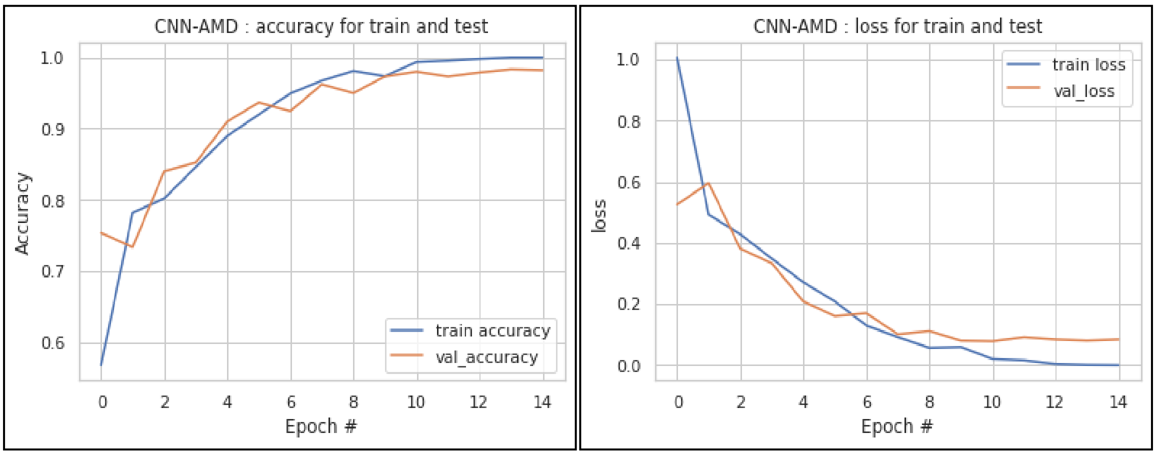

Figure 7. training and validation based on the accuracy and loss values

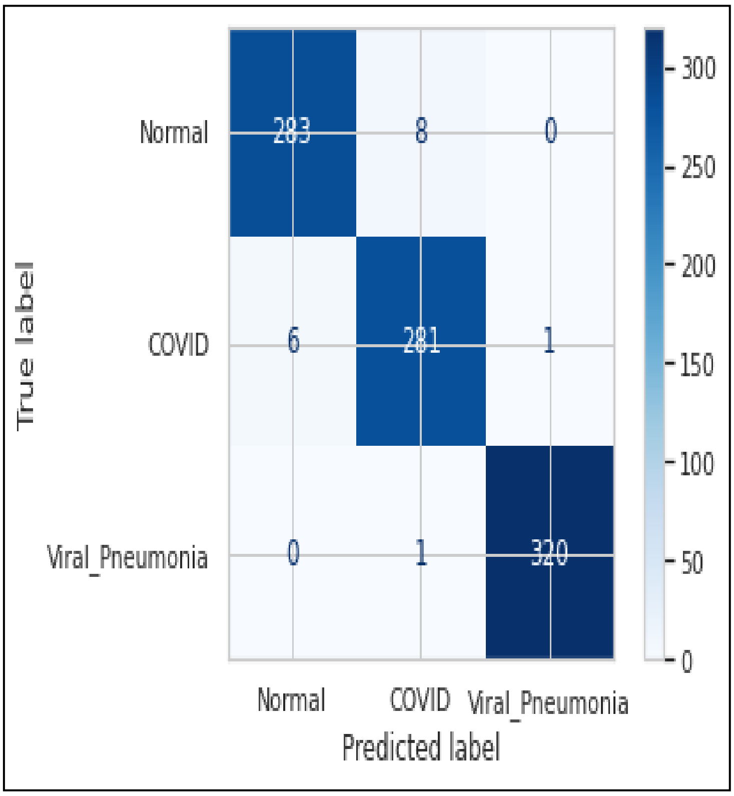

Figure 7. Confusion matrix of validation phase

Table 4. Evaluation metric for the validation phase

Class	Precision	Recall	F1-score	Number of images
Normal	0.98	0.97	0.98	291
Covid	0.97	0.98	0.97	288
Viral Pneumonia	1.0	1.0	1.0	321
Average	0.98	0.98	0.98	

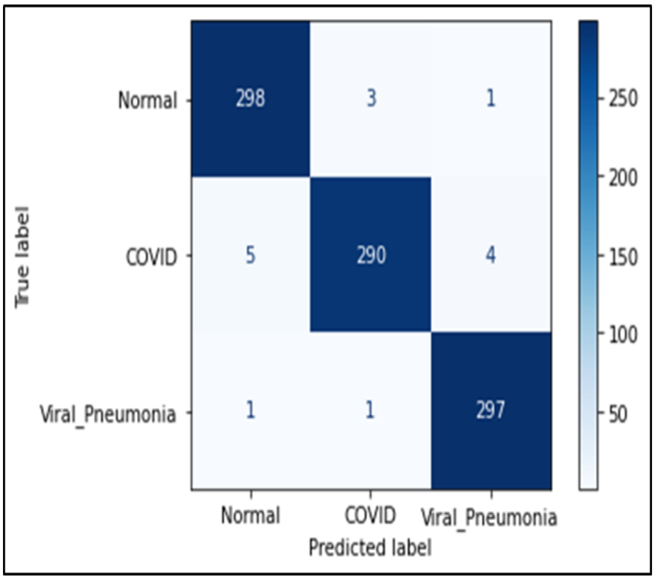

Figure 8. Confusion matrix of testing phase

Table 5. Evaluation metric for the testing phase

Class	Precision	Recall	F1-score	Number of images
Normal	0.98	0.99	0.98	302
Covid	0.99	0.97	0.98	299
Viral Pneumonia	0.99	0.99	0.99	299
Average	0.98	0.98	0.98	

Figure 9 shows the confusion matrix for testing phase. Table 5 shows the evaluation metrics for testing phase. With total classification accuracy for testing phase of 0.98, and Area Under the Curve (AUC) of 0.9865.

Table 6 shows a comparison of the proposed method with other state of art publications. All the other publications used the same dataset used in this work.

Table 6. Comparison between the results of the proposed method and other art of state publications

Paper	Year	Dataset(s)	Method	Evaluation metrics	
[25]	2021	COVID-19 Radiography Database	Pre-trained VGG16	Accuracy	0.987
				F1-score	0.975
				Precision	0.964
				Specificity	0.987
				Sensitivity	0.987
[26]	2021	COVID-19 Image Data Collection (Cohen, Morrison, Dao, et al., 2020), COVID-19 Chest X-ray Dataset Initiative , Actualmed COVID-19 Chest X-ray Data Initiative, RSNA Pneumonia Detection Challenge Dataset, COVID-19 Radiography Database	CNN	Accuracy	0.912
[27]	2021	COVID-19 Radiography Database	Single Shot Detection MobileNet	Accuracy	0.875

[28]	2021	COVID-19 Image Data Collection (Cohen, Morrison, Dao, et al., 2020), RSNA Pneumonia Detection Challenge (Pan et al., 2019), COVID-19 Radiography Database	Modified DenseNet201	Accuracy	0.921
				AUC	0.976
Proposed method	2022	COVID-19 Radiography Database	CNN	Accuracy	0.98
				F1-score	0.98
				AUC	0.9865
				Precision	0.98
				Recall	0.98

7. Conclusion

CNN is proved to be an efficient method for computer vision tasks. However, many configurations and designs could be set. In this proposed research, deeper CNN was able to extract sophisticated features, and thus better performance.

References

[1] T. Velavan and C. Meyer, "La epidemia de COVID-19," *Trop Med Int Health*, vol. 25, no. 3, pp. 278-280, 2020.

[2] WHO, "Coronavirus disease (COVID-19) pandemic.," *World Health Organization*, 2020. [Online]. Available: https://www.who.int/emergencies/diseases/novel-coronavirus-2019.

[3] G. Pascarella *et al.*, "COVID-19 diagnosis and management: a comprehensive review," *Journal of internal medicine*, vol. 288, no. 2, pp. 192-206, 2020.

[4] H. Salim, S. Abbood, M. Rahim, and A. M.Alaidi, "DR-LL Gan: Diabetic Retinopathy lesions synthesis using Generative Adversarial Network," *International journal of online and biomedical engineering*, vol. 18, no. 3, pp. 151-163, 2022.

[5] G. Litjens *et al.*, "A survey on deep learning in medical image analysis," *Medical image analysis*, vol. 42, pp. 60-88, 2017.

[6] N. Alseelawi, H. T. Hazim, and H. T. S. ALRikabi, "A Novel Method of Multimodal Medical Image Fusion Based on Hybrid Approach of NSCT and DTCWT," *iJOE*, vol. 18, no. 03, p. 115, 2022.

[7] I. A. Aljazaery, H. T. S. ALRikabi, and A. H. M. Alaidi, "Encryption of Color Image Based on DNA Strand and Exponential Factor," *iJOE*, vol. 18, no. 03, p. 101, 2022.

[8] S. Khan, H. Rahmani, S. A. A. Shah, and M. Bennamoun, "A guide to convolutional neural networks for computer vision," *Synthesis Lectures on Computer Vision*, vol. 8, no. 1, pp. 1-207, 2018.

[9] R. M. Al_airaji, H. ALRikabi, and J. Qateef, "Face Patterns Analysis and recognition System based on Quantum Neural Network QNN," *International Journal of Interactive Mobile Technologies (iJIM)*, vol. 16, 2022.

[10] S. Asif, Y. Wenhui, H. Jin, and S. Jinhai, "Classification of COVID-19 from chest X-ray images using deep convolutional neural network," in *2020 IEEE 6th international conference on computer and communications (ICCC)*, 2020: IEEE, pp. 426-433.

[11] J. P. Cohen, P. Morrison, L. Dao, K. Roth, T. Q. Duong, and M. Ghassemi, "Covid-19 image data collection: Prospective predictions are the future," *arXiv preprint arXiv:2006.11988*, 2020.

[12] L. Wang, Z. Q. 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*, vol. 10, no. 1, pp. 1-12, 2020.

[13] M. Polsinelli, L. Cinque, and G. Placidi, "A light CNN for detecting COVID-19 from CT scans of the

chest," *Pattern recognition letters*, vol. 140, pp. 95-100, 2020.

[14] X. Yang, X. He, J. Zhao, Y. Zhang, S. Zhang, and P. Xie, "COVID-CT-dataset: a CT scan dataset about COVID-19," *arXiv preprint arXiv:2003.13865*, 2020.

[15] C. R. n. d. Italiana, "Societa Italiana di Radiologia Medica e Interventistica, Sirm dataset of COVID-19 chest CT scan," *https://sirm.org/category/senza-categoria/covid-19/*, vol. 2, 2021.

[16] A. Chaddad, L. Hassan, and C. Desrosiers, "Deep CNN models for predicting COVID-19 in CT and x-ray images," *Journal of medical imaging*, vol. 8, no. S1, p. 014502, 2021.

[17] M. E. Chowdhury *et al.*, "Can AI help in screening viral and COVID-19 pneumonia?," *IEEE Access*, vol. 8, pp. 132665-132676, 2020.

[18] T. Rahman *et al.*, "Exploring the effect of image enhancement techniques on COVID-19 detection using chest X-ray images," *Computers in biology and medicine*, vol. 132, p. 104319, 2021.

[19] V. s. processing, "In Digital Video and HD," *https://doi.org/10.1016/B978-0-12-391926-7.50031-X*, pp. 377–388), 2012.

[20] S. Sonali, "S., Singh, AK, Ghrera, SP, & Elhoseny, M.(2018). An approach for de-noising and contrast enhancement of retinal fundus image using CLAHE," *Optics and Laser Technology*.

[21] K. E. Koech, "Cross-entropy loss function," *Medium: towards data science*, 2020.

[22] S. Jadon, "A survey of loss functions for semantic segmentation," in *2020 IEEE Conference on Computational Intelligence in Bioinformatics and Computational Biology (CIBCB)*, 2020: IEEE, pp. 1-7.

[23] I. K. M. Jais, A. R. Ismail, and S. Q. Nisa, "Adam optimization algorithm for wide and deep neural network," *Knowledge Engineering and Data Science*, vol. 2, no. 1, pp. 41-46, 2019.

[24] R. Gençay and M. Qi, "Pricing and hedging derivative securities with neural networks: Bayesian regularization, early stopping, and bagging," *IEEE Transactions on Neural Networks*, vol. 12, no. 4, pp. 726-734, 2001.

[25] M. M. Taresh, N. Zhu, T. A. A. Ali, A. S. Hameed, and M. L. Mutar, "Transfer learning to detect covid-19 automatically from x-ray images using convolutional neural networks," *International Journal of Biomedical Imaging*, vol. 2021, 2021.

[26] C. B. Maior, J. M. Santana, I. D. Lins, and M. J. Moura, "Convolutional neural network model based on radiological images to support COVID-19 diagnosis: Evaluating database biases," *Plos one*, vol. 16, no. 3, p. e0247839, 2021.

[27] F. Arifin, H. Artanto, and T. S. G. Nurhasanah, "Fast COVID-19 Detection of Chest X-Ray Images Using Single Shot Detection MobileNet Convolutional Neural Networks," *Journal of Southwest Jiaotong University*, vol. 56, no. 2, 2021.

[28] J. Manokaran, F. Zabihollahy, A. Hamilton-Wright, and E. Ukwatta, "Detection of COVID-19 from chest x-ray images using transfer learning," *Journal of Medical Imaging*, vol. 8, no. S1, p. 017503, 2021.