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A new modification CNN using VGG19 and ResNet50V2 for classification of COVID-19 from X-ray radiograph images

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ABSTRACT

Coronavirus often called COVID-19 is a deadly viral disease that causes as a result of severe acute respiratory syndrome coronavirus-2 that needs to be identified especially at its early stages, and failure of which can lead to the further spread of the virus. Despite with the huge success recorded towards the use of the original convolutional neural networks (CNN) of deep learning models. However, their architecture needs to be modified to design their modified versions that can have more powerful feature layer extractors to improve their classification performance. This research is aimed at designing a modified CNN of a deep learning model that can be applied to interpret X-rays to classify COVID-19 cases with improved performance. Therefore, we proposed a modified convolutional neural network (shortened as modification CNN) approach that uses X-rays to classify a COVID-19 case by combining VGG19 and ResNet50V2 along with putting additional dense layers to the combined feature layer extractors. The proposed modified CNN achieved 99.24%, 98.89%, 98.90%, 99.58%, and 99.23% of the overall accuracy, precision, specificity, sensitivity, and F1-Score, respectively. This demonstrates that the results of the proposed approach show a promising classification performance in the classification of COVID-19 cases.

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1. INTRODUCTION

Coronavirus is also referred to as COVID-19, which began in the last month of 2019 that was originated in the Wuhan province of China [1], [2]. This COVID-19 is a viral type of the diseases that occurred as a result of severe acute respiratory syndrome coronavirus-2 (acronymically written as SARS-COV2) [3]. Countries like Brazil, China, Italy, India, and many other countries around the continents of world have been negatively affected by the rapid spread of coronavirus. Moreover, this kind of viral disease has no specific drug to cure the infected patients, and it has a fatality rate of 2% [4]. COVID-19 has symptoms that include breath difficulties, cold, headache, high fever, sore throat, fatigue, as well as muscle pain [5], [6]. The spread of the disease can be prevented by isolating the infected individual or quarantining any individual who has symptoms of COVID-19 at home [7]. It has been reported to have a total of 623,893,894 confirmed COVID-19 cases including 6,553,936 as a total number of confirmed deaths cases along with 12,814,704,622 vaccine doses that have been distributed throughout the glob [8].

A real-time reverse transcriptase polymerase chain reaction that is commonly called RRT-PCR is use as the golden standard method approach for diagnosing suspected infected COVID-19 persons [9]. Despite being the standard diagnosis procedure. However, the researches show that obtaining the results of the diagnosis after using the RRT-PCR is time-consuming [10], along with having low sensitivity of ranges between 60–70% [11], which could result in classifying COVID-19 patients as healthy persons. This indicates that it is inefficient and risky procedure to use the RRT-PCR tool for identifying the COVID-19 persons.

Different kinds of artificial intelligence methods have been applied to radiography imaging comprising X-rays, CT scans, MRI, and many others to find the solutions to medical classification problems in the healthcare aspect [12]-[14]. The X-rays are the most commonly used and the most popular kind of radiography imaging used for Pneumonia diagnosis [15], [16]. Additionally, it is also the cheapest kind of radiography imaging [17]. Using a manual approach on X-rays to classify COVID-19 cases is a difficult task, time-consuming, and erroneous even for expert medical doctors and radiologists.

A report shows that Deep learning is a complex tool that has the ability of learning and identifying intellectual and complicated or cognitive classification problems [18]. Various deep learning techniques have been applied by other researchers, and the results indicated promising results by interpreting X-rays to classify COVID-19 cases with better classification performance. In this study, we proposed to design a modified convolutional neural network (CNN) of the deep learning techniques that interprets X-ray radiograph images to classify COVID-19 cases. The most important contributions of our proposed approach are summarized:

- Designing a modified CNN that has the capability of interpreting human X-rays to classify COVID-19 cases.
- Our proposed approach can be used in medical sector by radiologists to diagnose COVID-19 patients because it is easy to use and very secure.
- The sensitivity of our proposed approach is better than the sensitivity of the RRT-PCR tool.
- The performance result of our proposed modified CNN technique has outperformed the individual performance of both VGG19 and ResNet50V2 models of the CNN.

The other sections of this article have been summarized as follows. The discussion of related studies is outlined in section 2 of the manuscript, the method is given in section 3 of the manuscript, the presentation, interpretation, and explanation of the results obtained are contained in section 4 of this article, and the research conclusion is contained in section 5 of the manuscript.

2. RELATED EXISTING REVIEW

Among the related existing studies, is the research of Rahimzadeh and Attar [19], where the authors proposed a modification approach that involved combining two CNN models including ResNet50V2 and Xception. A new training method was proposed that enables the architecture of the network of CNN to learn more features, in particular, when the X-ray dataset is not balanced. A total of 180 X-rays of positive COVID-19 patients were used in the study. It is through the application of this approach that the architecture of CNNs classifies the real COVID-19 patients instead of performing the wrong COVID-19 classification. The modified CNN approach achieved 91.40% for overall classification accuracy. The limitation here is that only a few X-ray images of positive COVID-19 cases have been used in the study. Additionally, there is still room for improving the performance of the modified system.

Singh *et al.* [20] suggested that COVID-19 has no medicine currently available to cure the disease, and the best method to get rid of the disease is through massive diagnosis along with practicizing the social distance. Therefore, a modified XceptionNet approach was proposed which is based on XceptionNet that uses separable-wise convolutions through the use of 1419 X-rays (out of which 132 are for COVID-19) for diagnosing COVID-19 individual patients. Similarly, this system contains six layers of convolution in the upper part as well as twelve depth-wise separable layers of the convolution in the middle. Finally, fully connected dense layers were built at the end without repeating any block of the convolution. The experimental results were evaluated, and it appeared that the modified system outperformed most of the existing studies with 95.80%, 96.16%, 95.60%, and 95.88% for accuracy, precision, sensitivity, and F1-score, respectively. However, the system uses only few numbers of X-rays for positive COVID-19 which might make the results to be misleading due to overfitting.

In the research of Redie *et al.* [21], the authors suggested that a RRT-PCR is the most currently used COVID-19 testing kits in most of the COVID-19 diagnosis centers in the world. Therefore, the authors proposed a modified DarkCovidNet that is based on CNN models to design a model that identifies COVID-19 automatically through the use of X-rays radiograph images that were obtained from various sources for binary classification and multiple classification tasks. The DarkCovidNet was modified by adding the numbers of the convolutional layers from 17 layers to 19 layers and leaving the pooling layers in the original DarkCovidNet unchanged. The system was trained on no fewer than ten thousand X-rays, and it has achieved 99.53% and 94.18% of accuracy for binary and multiple classifications, respectively. However, only 280 positive X-rays were used for testing the proposed system.

Anand *et al.* [22] proposed a modified VGGNet that uses X-rays for the purpose of classifying X-ray dataset into four classes. The system was formed by adding three different pooling layers to the existing VGGNet. These classes contain viral, coronavirus, bacteria, and normal which has been retrieved from Github online repository. This dataset comprises 1,345 radiograph images for viral, 231 radiograph images for COVID-19, 2,503 radiograph images for bacteria, and finally, 1,341 radiograph images for normal. The performance of this system was compared to the performance of other five models namely Inception-V4, VGGNet, AlexNet, DenseNet-201, and GoogLeNet. The results show that the proposed system achieved 98%, 100%, 89%, and 91% for accuracy, specificity, precision, and sensitivity, respectively. However, the system is associated with using few COVID-19 dataset.

Agrawal and Choudhary [23] claimed that as the positive COVID-19 individual cases increases, the provision of adequate tools is vital in detecting the suspected COVID-19 cases. Therefore, a modification of the CNN model called FocusCovid was proposed which was built from the scratch for the COVID-19 detection by using X-rays. A total number of 2484 X-rays for normal as well as COVID-19 cases were used for binary classification for both the training and testing of the system. While a sum of 3829 X-rays were used in three-class classification for both the training and testing their proposed model. This system constitutes four separate blocks of residual as well as residual layers. The system achieved an overall average of 99.2%, 99.2%, 99.2%, and 99.2% for F1-score, precision, sensitivity, and accuracy, respectively. However, the system consumes a lot of time for training the system from the scratch.

Sanket *et al.* [24] claimed that over 172 million individuals have infected with COVID-19 globally, and as the infected cases increase rapidly, there is a need to have a fast COVID-19 diagnostic system to control its spreading. Consequently, the authors proposed a CovCNN of the CNN-based model for detection of coronavirus cases to help the medical practitioners to speed up the COVID-19 diagnostic task amongst the heavy workload conditions. The system involves the incorporation of multiple folds of the CNN. A total of 657 X-rays (where 219 are COVID while 438 are non-COVID-19 patients) were used in the experiments. The system achieved the best accuracy of 98.4%. However, their approach might be associated with a high rate of overfitting as a result of using few X-rays for model training purposes. It can be observed that none of the existing studies has considered using a modified CNN by combining both ResNet50V2 and VGG19 on X-ray radiographs for COVID-19 classification purposes. Moreover, the performance of the existing systems still needs improvement.

3. METHOD FOR OUR PROPOSED APPROACH

3.1. Process of X-ray radiograph image data collection

The X-ray samples of the individuals used in our experiments have been obtained and extracted from Kaggle [25], which happened to house the largest X-rays for positive COVID-19 individual patients that were obtained from different countries and sources that are now available for the public to use free of charges. Moreover, this Kaggle website has a database called COVID-19 radiography that contains 4 subfolders which include normal, lung opacity, pneumonia, and COVID-19. Out of these subfolders, we only considered Normal and COVID-19 which contained a total of 13,808 X-rays comprising 10,192 X-rays of Normal and 3,616 X-rays of COVID-19 patients that were later combined into a single folder containing an unbalanced number of X-rays. To create a balanced dataset that is preferable while designing a better classification system, we have randomly chosen the same number of Normal X-rays as the COVID-19 X-rays for the purpose of our experimentations. In this case, 3,600 X-rays of positive COVID-19 patients and other X-rays of Normal persons totaling 7,200 different X-rays have been considered. 80% of the selected X-ray dataset have been used for training and validating the proposed modified CNN, and 20% of the selected X-ray dataset sample was used for testing the proposed modified CNN system. All of the 7200 X-rays have been rescaled to the size 244×244 that is required by the architectures of VGG19, ResNet50V2, and the proposed modified CNN. An example of X-rays for normal and COVID-19 individuals is presented in Figure 1; the first row contains X-rays of COVID-19, while the second row represents X-rays of normal persons.

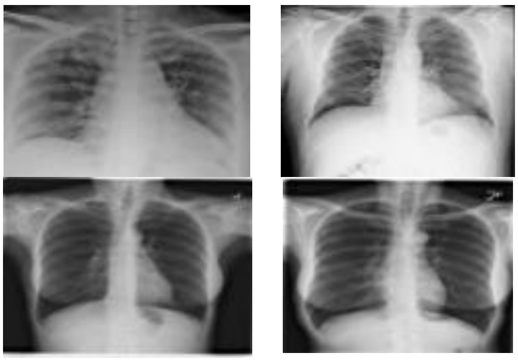


Figure 1. An exemplary of medical X-rays

3.2. Research design and method

A scientific notebook called Jupiter, which is a python notebook that uses K-neural networks application programming interface (API) that has beenbuilt to use a backend called Tensorflow was used for performing our experiments. Both the VGG19 and ResNet50V2 are executed concurrently by the use of extracted preprocessed training X-ray radiograph dataset. We then removed their top layers and then use their feature layer extractors to combine the two models of the CNN. A dense layer with a Relu (an acronym for a "Rectified linear unit) activation function was added to the combined model of the CNN. We have added 50% of the dropout to deal with problems related to the overfitting. Finally, a dense layer that serves as an output layer with two outputs for making binary-class classification alongside with a Softmax activation function were added to complete the design of our modified CNN for COVID-19 classification purpose. Framework architecture of our proposed modified CNN version is illustrated in Figure 2. Our modified CNN contains a total of 48,721,962 parameters consisting 48,621,994 trainable parameters and 99,968 non-trainable parameters. Moreover, the configuration settings shown in Table 1 have been applied in the experiments.

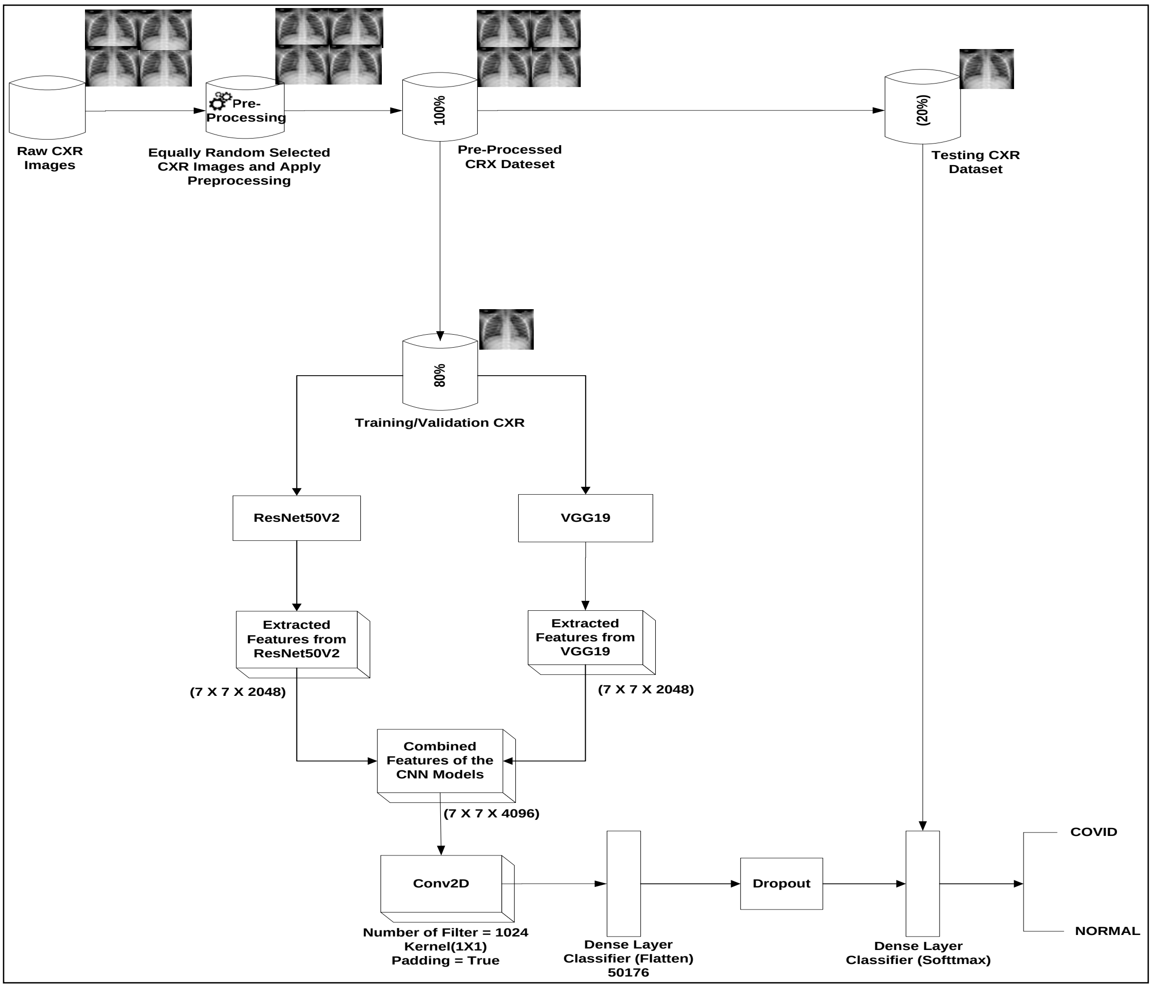


Figure 2. Schematic system framework

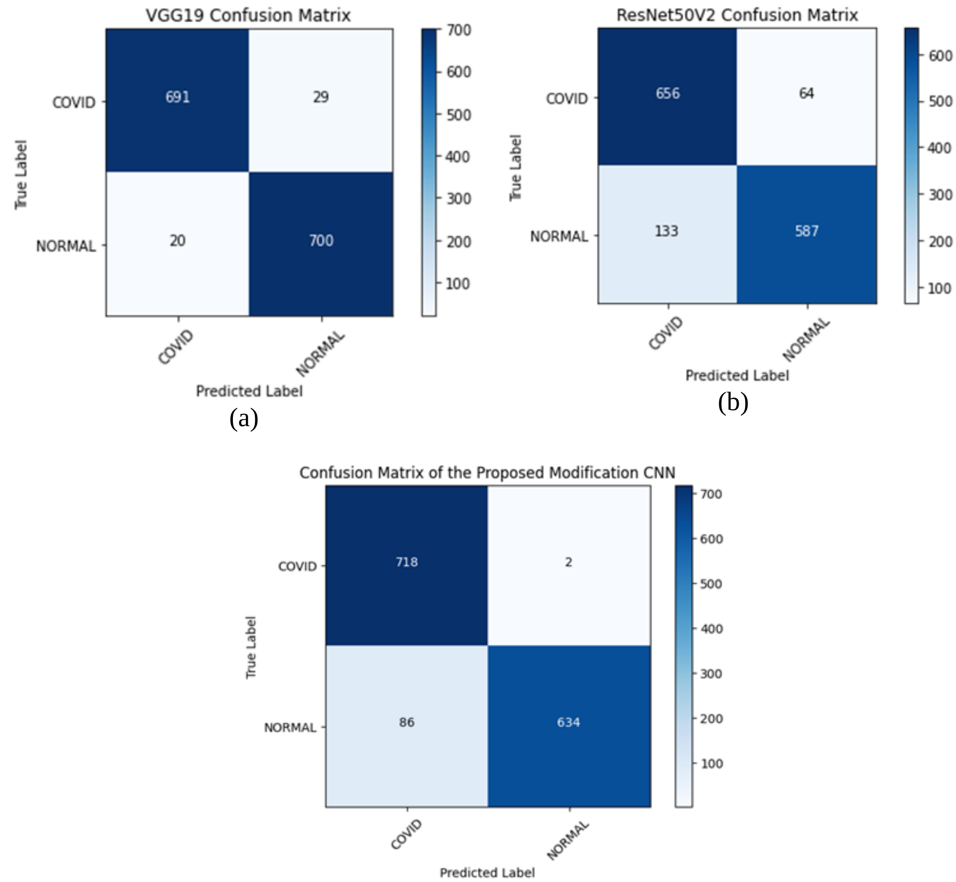
Table 1. Configuration settings used for our experimentations

Configuration	Type/Quantity
Number of epochs	30
Number of batch sizes	30
Activation function	Relu
Learning rate	0.0001
Dropout	50%
Activation function used by dense classifier layer	Softmax

3.3. Results obtained from experiments and their discussions

As we mentioned in the preceding sub-section, a Jupiter notebook was used in conducting all the experiments which happened to be a Python scientific notebook in which Keras API that uses TensorFlow as its backend is considered. Our randomly constructed database folder comprising X-rays for COVID-19 along with X-rays for normal cases were used by our proposed modified CNN to classify the COVID-19. This COVID-19 classification was also been conducted to classify the same dataset as with our proposed modified CNN by using a single VGG19 and ResNet50V2. Figure 3 represents a 2×2 confusion matrix that expresses the performance of the model of the CNN. Where Figure 3(a) illustrates the result obtained from the VGG19 of the CNN. It implies that our system has classified 691 X-ray radiographs for COVID-19 cases. In addition, a total of 29 X-rays for COVID-19 cases have been misclassified as normal cases. When we consider the other hand, it shows that 700 X-rays for Normal cases have been classified correctly by the VGG19 model of the CNN. However, the VGG19 failed to correctly classify a total of 20 X-rays for Normal cases. In terms of the overall classification accuracy, 96.60% of accuracy has been achieved. Similarly important, Figure 3(b) represents the result obtained after applying ResNet50V2 to our combined COVID-19 and Normal dataset. It infers that the ResNet50V2 of the CNN has classified 656 COVID-19 cases correctly, while the sum of 64 COVID-19 cases is classified as normal cases. Contrarily, 587 Normal cases have been correctly identified, while 133 Normal cases were misclassified as COVID-19 cases. The ResNet50V2 achieved an overall classification of 86.32%.

Finally, considering Figure 3(c) that represents the result of the confusion matrix obtained after our modified CNN is applied to our combined dataset. It can be noticed that 712 COVID-19 cases have been identified correctly, while only 8 COVID-19 cases have been misclassified as normal cases. Contrariwise, 717 X-ray radiographs for normal cases have been classified correctly. While only 3 X-ray radiographs for Normal cases were misclassified as COVID-19 cases. An overall classification accuracy of 99.24% was achieved by our modified CNN. Table 2 is the summary of results obtained from the three models after conducting our experiments. It is important to noted that all the experiments were conducted using the most commonly used performance metrics which include accuracy, F1-score, specificity, precision, and sensitivity are used for measuring the effectiveness of the proposed approach [26]-[28].



(a) (b) (c)

Figure 3. Confusion matrices for (a) VGG19, (b) ResNet50V2, and (c) modified CNN

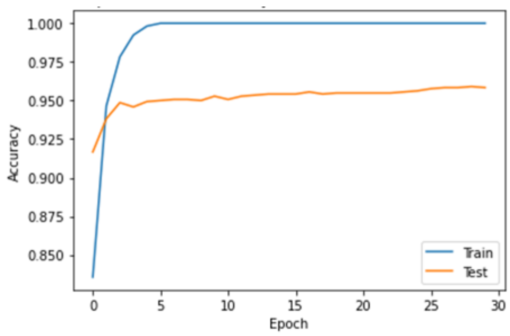
Table 2. Summary of results obtained from the proposed modified CNN Vs VGG19 and ResNet50V2

Model of the CNN	Accuracy	Sensitivity	Specificity	Precision	F1-score
VGG19	96.60%	95.97%	97.22%	97.19%	96.58%
ResNet50V2	86.32%	91.11%	81.53%	83.14%	86.94%
Proposed modified CNN	99.24%	98.89%	99.58%	99.58%	99.23%

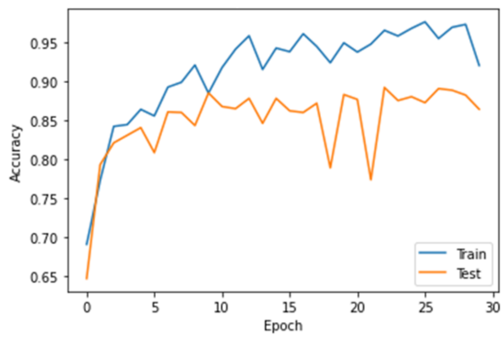
From the plots shown in Figure 4, it inferred that Figures 4(a)-(c) deficit the accuracy graphs representing VGG19, ResNet50V2, and the proposed modified CNN, respectively. After observing the three accuracy graph plots, it indicates that our proposed modified CNN shown in Figure 4(c) performed better than both the VGG19 as well as ResNet50V2 in terms of accuracy performance.

Observing the curves of the graphs shown in Figure 5 comprising the three loss plots namely Figures 5(a)-(c) whose curves diagnose the problems associated with learning such as overfitting problems, underfitting problems, or well-fitting problem, along with whether the training, as well as the validation datasets, is well expressed. The Figure 5(a) indicates that the VGG19 of the CNN model performed moderately on the combined X-rays for the COVID-19 classification task. While from Figure 5(b), it can observe that the ResNet50V2 of the CNN models performs very poorly on the combined X-ray dataset. Finally, it can be noticed that the training losses towards the end of the curve of the modified CNN shown in Figure 5(c) decrease and keep decreasing. This indicates the suitability of our approach on the combined X-ray dataset towards classifying COVID-19 than when applying both VGG19 and ResNet50V2. We can conclude that our proposed approach is suitable for both training and validation datasets for COVID-19 classification.

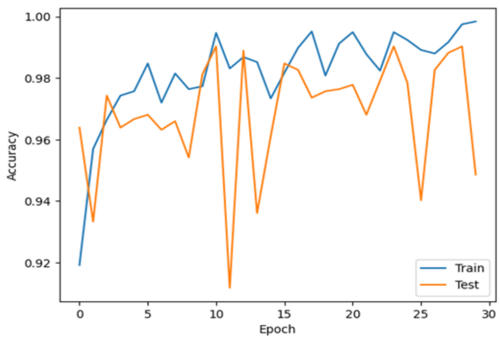
Observing Table 3, it can be noted that our proposed modified CNN approach attained a classification performance accuracy of 99.24% along with a sensitivity of 98.89% which are better than most of the referenced existing classification systems except for [23] where 99.20% of sensitivity was obtained, and for where accuracy of 99.58% was achieved, but our approach has the highest precision of 99.58%. The classification performance achieved in [19] performed very poorly than all of the other modified CNNs. Despite the fact that our approach achieved lesser sensitivity performance than the one obtained from [23]. However, our modified CNN performed better in terms of the performance of other metrics including accuracy obtained from the referenced studies. This shows that our proposed modification CNN base on combining VGG19 and ReNet50V2 can be applied to X-rays to perform classification of COVID-19 with promising results. Therefore, our proposed approach can be used for COVID-19 classification with a better classification than the single model and the modified CNN techniques used in many of the existing studies.



(a)



(b)



(c)

Figure 4. Accuracy graph of the CNN models for (a) VGG19, (b) ResNet50V2, and (c) modified CNN

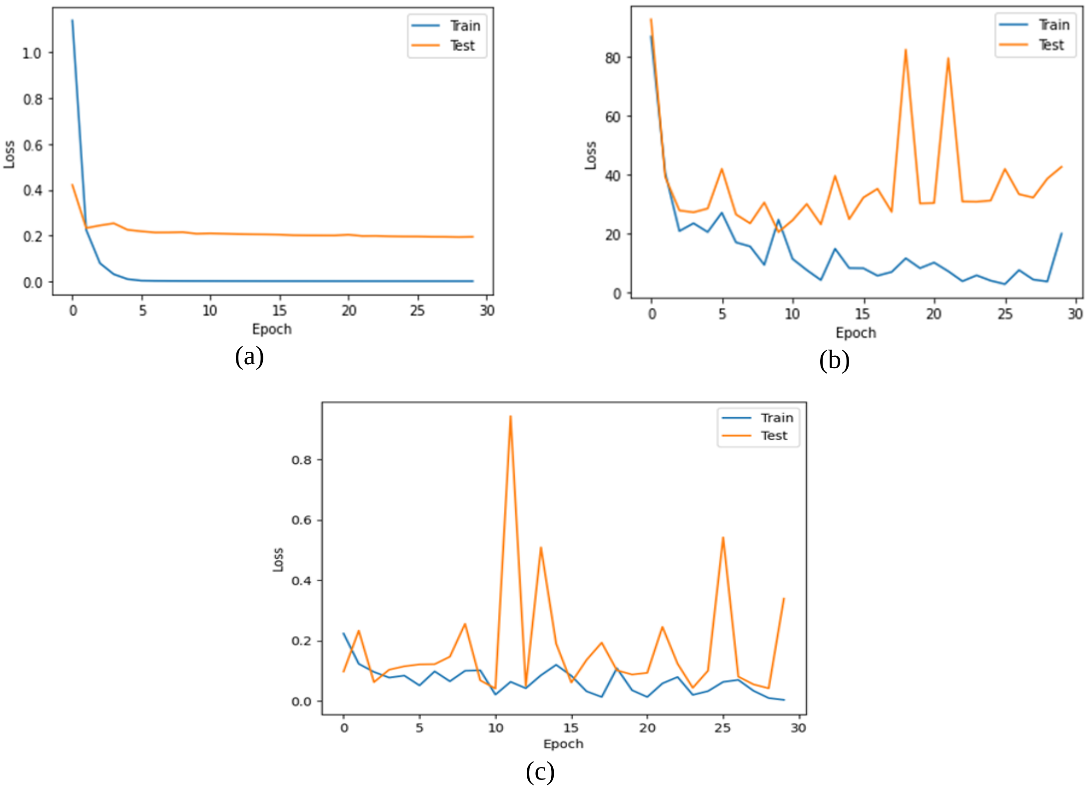


Figure 5. Loss graph of the CNN models for (a) VGG19, (b) ResNet50V2, and (c) modified CNN

Table 3. Comparison of the proposed modified CNN against some various existing CNN models

Model of the CNN	Accuracy	Sensitivity	Specificity	Precision	F1-score
Rahimzadeh and Attar [19]	91.40%	-	-	-	-
Singh *et al.* [20]	95.80%	95.60%,	-	96.16%	95.88%
Agrawal and Choudhary [23]	99.20%	99.20%	-	99.20%	99.20%
Rajpal *et al.* [29]	97.4 ± 0.02%	98.7 ±0.05%	-	-	-
Siddhartha and Santra [30]	99.58%	-	-	-	-
Yildirim *et al.* [31]	99.05	-	-	-	-
Duong *et al.* [32]	98.08%	-	-	-	-
Mousavi *et al.* [33]	>90.00%	-	-	-	-
Proposed Modified CNN	99.24%	98.89%	99.58%	99.58%	99.23%

4. CONCLUSION

In this study, we have designed a modified CNN using VGG19 and ResNet50V2 that classifies COVID-19 from the X-rays. After conducting a series of experimentations that involved the application of VGG19, ResNet50, and our proposed Modified CNN of the models to X-ray radiograph images, the results indicated that our proposed modified CNN achieved the highest COVID-19 classification accuracy of 99.24% which is better than the results of both the VGG19 and ResNet50V2. The result of our approach was also better than some of the results of existing modified CNNs. This indicated that our approach is promising in COVID-19 classification. Our research contributes toward designing a modified version of CNN that interprets X-rays to classify COVID-19 cases. It is also significant because it can be used by radiologists to diagnose COVID-19 patients due to it is easy to use capability and possession of higher sensitivity than that of the RRT-PCR tool. Despite with the contributions offered by our proposed modified CNN. However, it still uses a few positive X-rays for COVID-19. Additionally, the sensitivity still needs to be improved. In our future research, a hybrid modified CNN of the deep learning model will be designed. Moreover, more positive X-rays for COVID-19 are to be incorporated into the dataset. Finally, the ensemble concept will also be explored.

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