PREDICTING COVID-19 FROM CHEST X-RAY IMAGES USING OPTIMIZED CONVOLUTION NEURAL NETWORK

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ABSTRACT

Machine learning is emerging as a unique powerful method to improve the diagnosis and prognosis of several multifactorial diseases, including COVID-19. The COVID-19 pandemic is a major threat, and it has severe impact on the health and life of many people worldwide. The recent advances in computer vision made possible by various computational method has paved the way for computer assisted diagnosis in fighting COVID-19. Early detection of the COVID-19 through accurate diagnosis, may decrease the patient's mortality rate. Chest X-ray images are crucial and mostly used for the diagnosis of this disease. Thus, this study used optimized Convolution Neural Network (OCNN) to support the diagnosis of COVID-19 using chest x-ray. Particle Swarm Optimization (PSO) was applied to optimize the network of CNN for improved performance. The dataset used in this study was acquired from Kaggle repository. The dataset contains the Chest X-Ray images of COVID-19 patients and normal patients. The model is created, and the results have been evaluated by using the various evaluation metrics, i.e., sensitivity, false positive rate, precision, accuracy, and prediction time. The approach adopted in this study enhances CNN by making it free from iterative adjustment of weights which increases the computational speed to a higher extent. The experimental results reveal that the proposed technique achieved an improved performance which indicates the very high accuracy of the proposed model.

Keywords: *Convolution Neural Network, Particle Swarm Optimization, Deep learning, COVID-19, Chest X-Ray.*

INTRODUCTION

Covid-19, generally described to as coronavirus disease-19 is putting even the best healthcare systems across the world under tremendous pressure (Kumar *et al.,* 2020). Covid-19 has become apparent as a fatal severe acute respiratory syndrome (SARS) infection over the past few months (Zhu *et al.,* 2020, Lai *et al.,* 2020). It has seriously threatened human life and health worldwide. Severe disease onset might result in death due to massive alveolar damage and progressive respiratory failure (Xu *et al.,* 2020). The early detection of this type of virus will help in relieving the pressure of the healthcare systems (Prem *et al.,* 2020, Kumar *et al.,* 2020). Furthermore, early and automatic diagnosis of Covid-19 may be beneficial for countries for timely referral of the patient to quarantine, rapid intubation of serious cases in specialized hospitals, and monitoring of the spread of the disease (Apostolopoulos and Mpesiana, 2020).

In handling and fighting against Covid-19, the most critical step is to effectively screen and diagnose infected patients. Among them, chest X-ray imaging technology is a valuable imaging diagnosis method. The use of computer-aided diagnosis to screen X-ray images of COVID-19 cases can provide experts with auxiliary diagnosis suggestions, which can reduce the burden of experts to a certain extent (Wang *et al.,* 2020). In March 2020, there has been an increase in publicly available X-rays from healthy cases, but also from patients suffering from Covid-19. This enables researchers to study the medical images and identify possible patterns that may lead to the automatic diagnosis of the disease (Ola *et al.,* 2020).

The detection of Covid-19 using chest X-ray images has life-saving importance for both patients and doctors. In addition, in countries that are unable to purchase laboratory kits for testing, this becomes even more vital (Sekeroglu and Ozsahin, 2020). Considering the time required for diagnosis and the financial costs of the laboratory kits used for diagnosis, artificial intelligence (AI) and deep learning research and applications have been initiated to support doctors who aim to treat patients and fight the illness (Apostolopoulos and Mpesiana, 2020; Ogundepo *et al.,* 2022). This is significant because, currently, the pandemic is still rampant in various part of the world, and therefore effective diagnosis is critical. Therefore, the use of AI-based automated high-accuracy technologies may provide valuable assistance to doctors in diagnosing Covid-19.

Deep Learning is a combination of machine learning methods mainly focused on the automatic feature extraction and classification from images, while its applications are broadly met is object detection tasks, or in medical image classification tasks (Apostolopoulos and Mpesiana, 2020). Machine learning and deep learning have become established disciplines in applying artificial intelligence to mine, analyze, and recognize patterns from data. Reclaiming the advances of those fields to the benefit of clinical decision making and computer-aided systems is increasingly becoming nontrivial, as new data emerge (Greenspan *et al.,* 2016).

To the best of our knowledge, deep learning (DL) architecture has been used in many CAD frameworks and in numerous medical imaging applications, such as for COVID-19 (Kang *et al.,* 2020, Narin *et al.,* 2021, Goel *et al.,* 2021). In recent years, the convolutional neural network (CNN) has yielded the most promising results in classifying radiological images. CNNs are DL algorithms and have been used in many applications, including image classification. These advantages motivated our attempt to propose a CNN algorithm for COVID-19 diagnosis in this study. The hyperparameters of CNNs have a significant impact on the network's performance, so they directly control the training process. The selection of suitable hyperparameters plays an important role in the training of the CNN network. This is because if the learning rate is high the network may converge too quickly but if the learning rate is too low it may lead the network to lose important details in the data. CNN suffers from the hyperparameter problem and can be solved using an optimization technique (Kumar *et al.,* 2020, Goel *et al.,* 2021).

Consequently, there is a need to optimize the hyperparameters of CNNs for suitable training and optimum performance results. The main contributions presented for the Covid-19 prediction and classification is specified as follows:

1. Firstly, transfer learning (VGG16) is adopted to overcome the overfitting problem caused by the limited number of training images in deep learning.
2. The hyperparameters of the CNN are optimized using PSO to determine the best accurate results

in diagnosing healthy patients and Covid-19 patients from X-ray images.

3. An optimized CNN model is proposed for the automatic diagnosis of COVID-19 using X-ray images with an accuracy of 99.20%.
4. The evaluation in terms of different performance metrics such as accuracy, sensitivity, precision, false-positive rate, false-negative rate, and prediction time.

Next, section 2 showcases the literature review, section 3 depicts the detailed research method while the results are given in section 4. Section 5 concludes the study and contains the recommendation for further studies.

LITERATURE REVIEW

Convolutional Neural Networks

Convolutional neural network is a deep learning neural network that models animal's visual cortex. CNN based models have been widely proposed to solve various computer vision problems including complex image segmentation and classification, object detection and optical character recognition (Krizhevsky *et al.,* 2012). The main power of a CNN lies in its deep architecture (Szegedy *et al.,* 2012, LeCun *et al.,* 1998*)*, which allows extracting a set of discriminating features at multiple levels of abstraction.

Each of the convolution layer is composed of linear filtering (convolution), non-linearity and feature pooling stages (Tajbakhsh *et al.,* 2016). Due to strong image recognition capabilities, in the past few years, CNNs are used across variety of applications including natural language processing, hyperspectral image processing and identifying different diseases in radiographic images (Sun *et al.,* 2017, Sinha *et al.,* 2017). Three types of layers are usually created to develop a CNN: convolutional layers, pooling layers and fully connected layers. Most of computation is done in the convolutional layer.

1. **Convolutional Layer:** The convolutional layer is the first operational step after the data is entered into the CNN. When convolving, there are three parameters that control the dimensions of the output matrix, namely: the size, stride, and fill of the filter.
   i. **Filter**: Usually, size 3×3 or 5×5 filters are chosen, the filter size is still determined by the image size of the input data.
   ii. **Stride**: The distance the filter moves is the stride, which controls the filter input for convolution calculations.
   iii. **Padding:** Before the convolution process, it is necessary to fill in the fixed data (such as 0) around the input data.
2. **Pooling Layer:** It uses the image local correlation to downsize image to reduce the spatial dimension and highlight useful feature information. The most common pooling layer is the Max-Pooling which continues to select the maximum pixel value in the winding area, and the final output image matrix is composed of the maximum pixel values of each area.
3. **Fully-Connected Layer:** Many CNN models use fully connected layer to learn more information in the last few layers. It is the same as the traditional ANN, and each neuron is connected to all neurons in the previous layer.
4. **Activation Function:** The activation function plays a key role in passing messages to the next layer of neurons to learn or simulate nonlinear complex problems, find features that represent the characteristics of the data, and solve the problem of linear models' inability to describe complex data. In the choice of the activation function, more discussed now is the Rectified Linear Units (ReLU) as shown in Equation (1):

$$f(x) = max\,(0, x) \qquad (1)$$

5. **Loss function:** The loss function is an indicator to determine whether the current neural network and training materials are suitable and consistent with the training materials.

Classification section in CNN

There are two layers in the classification section: dense layers and dropout layers. The dense layer is also referred to as fully connected layers consisting of different neurons or units where the last dense layer is made up of several neurons that resemble the number of types. The activation layer is added after the completion of each dense layer. The activation function is used for the final dense layer output, which is entirely different from the dense layer in which the sigmoid or softmax function is usually used. In the multi-classification jobs, the Softmax layer is used to assign decimal probabilities for all types, and the target category can have a high-value probability. The softmax of the *jth* output unit numerically evaluated by the below equation.

$$\hat{b}_j = \frac{e^{a_j}}{\sum_j^M e^{a_j}} \qquad for\ j = 1,2,3,\dots,M \qquad (2)$$

From the above equation, a_j indicates the output of the *jth* dimension, the number of dimensions is represented by *M* that is equal to the category numbers, and the probability linked with the *jth* category is indicated as $\hat{b}_j$. Once the prediction has been made, the sample will be assigned to the kind that has a high value for likelihood as shown below:

$$\hat{b}_j = \max_{j\in[1,M]} \hat{b}_j \qquad (3)$$

The sigmoid function is employed in the tasks of binary classification. It receives any number of ranges values and returns the value falling within the [0,1] interval. The following equation numerically measures this sigmoid function:

$$Sigmoid\ (a) = \frac{1}{1+e^{-a}} \qquad (4)$$

Dropout layers are the regularization methods implemented only in the network training to prevent it from the problem of overfitting by dropping the subset of the entered neurons and their links momentarily from the last dense layer. The dropout layer normally pursues the dense layers apart from the last dense layer that generates the kind-particular probabilities.

Transfer learning

These kinds of learning from the pre-trained model mean that the pre-trained model is provided and integrated into the new database and it is the regular approach used to build a new scrape approach. Various CNN methods are often employed as the pre-trained approach namely VGG. VGG has two types: VG G16 and VGG19. VGG16 is a 16-layer network of 13 convolutionary layers, 5 max-pooling layers, and 3 dense layers. VGG19 consists of 16 convolutional layers, 5 max-pooling layers, and three dense layers. VGG 19 architecture in this study is used for the classifying of x-ray chest images (Kim *et al.,* 2018).

Particle Swarm Optimization (PSO)

PSO is a population-based optimization technique inspired by the behaviour of schools of fish, herds of animals or flocks of birds (Eberhart & Kennedy, 1995). In PSO, a solution is represented as a particle, and the population of solutions is called a swarm of particles. Each particle consists of two main attributes: the position and the velocity (Wisittipanich *et al.,* 2021; Ola *et al.,* 2019). The main ideology behind PSO is that each particle is well known of its velocity and the best configuration achieved in the past (pBest), and the particle which is the current global best configuration in the swarm of particles(gBest) (Adetunji *et al.,* 2015; Adetunji *et al.,* 2018). Hence, at every current iteration, each particle updates its velocity in such a way that its new position will be close enough to global gBest and its own pBest at the same time (Sahu *et al.,* 2012). The velocity and particle vector are adjusted based to the following equations (5) and (6) respectively:

$$v_{id}(t+1) = w * v_{id}(t) + c_1 * r_1 * (P_{id} - x_{id}(t)) + c_2 * r_2 * (P_{gd} - x_{id}(t)) \qquad (5)$$

$$x_{id}(t+1) = x_{id}(t) + v_{id}(t+1) \qquad (6)$$

where v_{id} indicates the velocity of *ith* particle in the *dth* dimension, x_{id} indicates the position of *ith* particle in the *dth* dimension, P_{id} and P_{gd} represents the local best and the global best in the *dth* dimension, r_1 and r_2 are the random numbers between the range 0 and 1, c_1 , c_2 and w, are acceleration coefficient for exploitation, acceleration coefficient for exploration and inertia weight respectively.

Related Works

Kumar *et al.,* (2020) predicted COVID-19 using chest x-ray images through deep feature learning model with smote and machine learning classifiers. Deep features using ResNet152 with Random Forest and XGBoost classifiers was used. Experimental results shows that the Random Forest and XGBoost classifiers achieve accuracy of 97.3%and 97.7% respectively.

Apostolopoulos and Mpesiana (2020) proposed an automatic detection of Covid-19 from X-ray images. Transfer learning (MobileNet v2) with convolutional neural networks was adopted. Experimental results revealed that accuracy, sensitivity, specificity of 98.66%, 96.78% and 96.46% was achieved respectively. Furthermore, Castiglioni *et al.,* (2021) proposed diagnosis of COVID-19 based on machine learning techniques applied on chest x-ray. Convolutional neural network was adopted in the study. The performance of the system was evaluated and was found to achieve a sensitivity, specificity and AUC of 80%, 81% and 81% respectively.

Three recent studies that propose innovative approaches for the early detection and diagnosis of lung diseases, with a specific focus on COVID-19 infection. Kandati and Gadekallu (2023) introduce a federated learning approach using particle swarm optimization for the early detection of chest lesions caused by COVID-19 infection. Wang *et al.* (2023) propose PSTCNN, a self-tuning convolutional neural network guided by particle swarm optimization, for explainable COVID-19 diagnosis. Rajagopal *et al.* (2023) present a deep convolutional spiking neural network optimized with Arithmetic optimization algorithm for lung disease detection using chest X-ray images. These studies demonstrate the potential of advanced techniques in improving accuracy and optimizing the diagnostic process. The findings underscore the significance of these methodologies in enhancing lung disease detection and their potential impact on early diagnosis and effective treatment (Kandati & Gadekallu, 2023; Wang *et al.,* 2023; Rajagopal *et al.,* 2023).

METHODOLOGY

The X-ray images including normal and covid-19 cases were first acquired. Then, the images were pre-processed to obtain the desired image quality for further processing. This is followed by segmenting the pre-processed images and the result is subsequently presented to optimized CNN feature extraction and classification. Figure 1 depict the scheme of the proposed technique in this study.

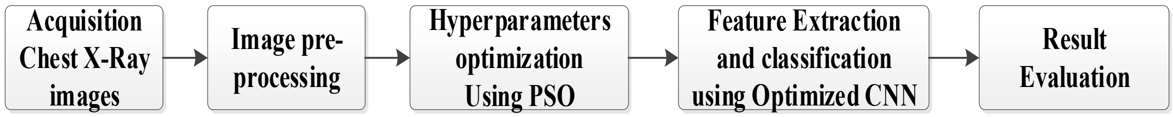

Figure 1

Image acquisition

The dataset used in this study was acquired from Kaggle repository. The dataset contains the Chest X-Ray images of COVID-19 patients and normal patients. Figure 2 depicts some of the Chest X-Ray images acquired from Kaggle database.

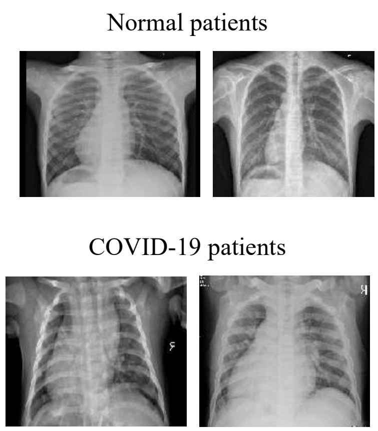

Figure 2: Chest X-Ray images

1560 Chest X-Ray images were used in the study; 930 were used for training while 624 were used for testing. The test data comprises of 390 Normal patients and 234 Covid-19 Patient.

Image Pre-processing

The acquired images were pre-processed. The Preprocessing techniques were applied: image resizing, segmentation and data augmentation. Segmentation was achieved using the fuzzy c-means clustering algorithm by Bezdek *et al.,* 1984. Images was resized to 224 X 224 pixels to make it suitable with the VGG-16 model, data augmentation was employed to increase training data and to reduce overfitting problems. The augmentation techniques include rotation, shearing, zooming, width shifting, height shifting, and horizontal flipping. Figure 3 depicts the pre-processed images.

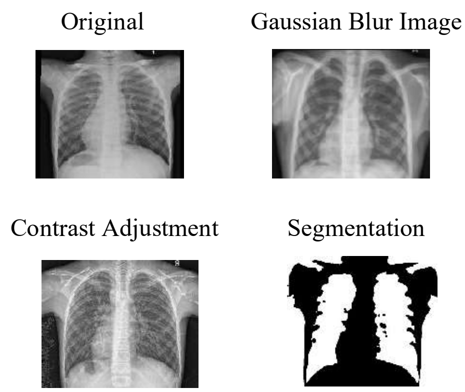

Figure 3: The pre-processed images.

Feature Extraction and Classification using Optimized CNN

The main aspect of this scheme is to create the method for the classification of Chest X-Ray images using deep learning Convolutional neural networks. The Chest X-Ray images are classified as either normal patient or Covid-19 patient. These Chest X-Ray images are given as the input to this scheme and the output could be the exact classified image. CNN is fine-tuned by using the PSO algorithm. By using this optimization approach, CNN is retrained with Chest X-Ray images to achieve the exact classification output.

This proposed approach is an efficient way of improving the CNN network's efficiency by pre-trained CNN networks, i.e. VGG-19. To achieve the best performance of the proposed approach, the hyper-parameters of the CNN is optimized using PSO algorithm. The proposed approach has five stages as shown in Figure 1 above.

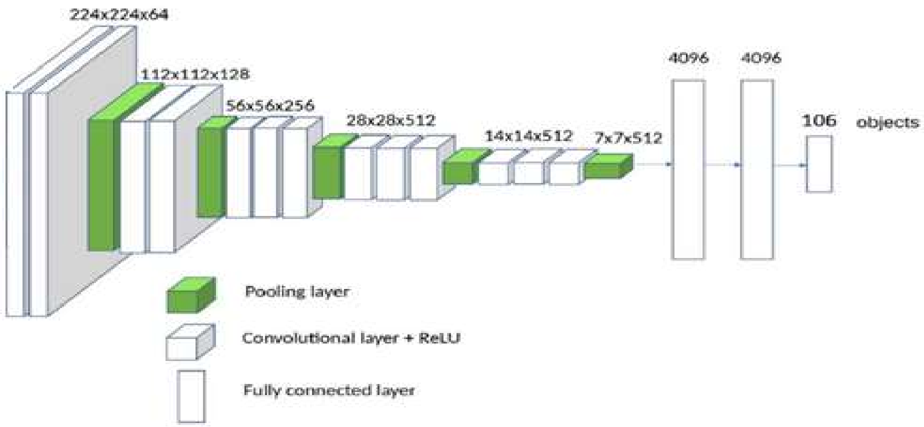

Figure 4 The VGG-19 network architecture.

After the Convolutional and pooling layers, fully connected layers are located to merge the features obtained and in the last, i.e., the SoftMax layer the output is computed.

The strategy was to combine fully connected layers blocks with studying a nonlinear mixture of the extracted features and also to execute the resultant classification. Figure 4 illustrates the summary of the VGG-19 network architecture.

The VGG-19 architecture composed of 16 Convolutional layers arranged in blocks. Every block consists of two or three Convolutional layers. The network consists of five max-pooling layers and three dense layers. The classification structure of the proposed approach for the detection of Covid-19 using Chest X-Ray images is shown in Figure 5.

The optimization of Hyper-parameter

The pre-trained CNN architectures have several limitations. The noted limitations are that most of the hyper-parameters of any such pre-trained CNN cannot be modified and has some of the hyper-parameters which require adjustment namely, the mini-batch size and also the unit numbers in every dense layer and the dropout layer. In this paper, the PSO algorithm was employed in the CNN architecture models classifier section to optimize the mini-batch size and dropout layer rate.

Learning phase

In the learning phase, the CNN architecture models were used to classify the Chest X-Ray images. Hence, the feature extraction and the fine-tuning were employed to adjust the VGG-19 network model to the current database used for this work. The Convolutional layer was stuck within the feature extraction process, while the classifier segment was swapped by the corresponding one.

There are several layers in the current classifier: the fully connected layers consist of a dropout layer, flatten layer, batch normalization layer, and two dense layers. The first fully connected layer consists of neuron groups with a rectified linear unit and the second fully connected layer consists of four function units of SoftMax. After training the classifier for the number of iterations the fine-tuning was achieved by reactivating the Convolutional last two layers and retraining with the classifier as shown in Figure 5.

Once the training process is completed all these were merged to create the final prediction of Covid-

19 using Chest X-Ray images which averages their posteriors of SoftMax class.

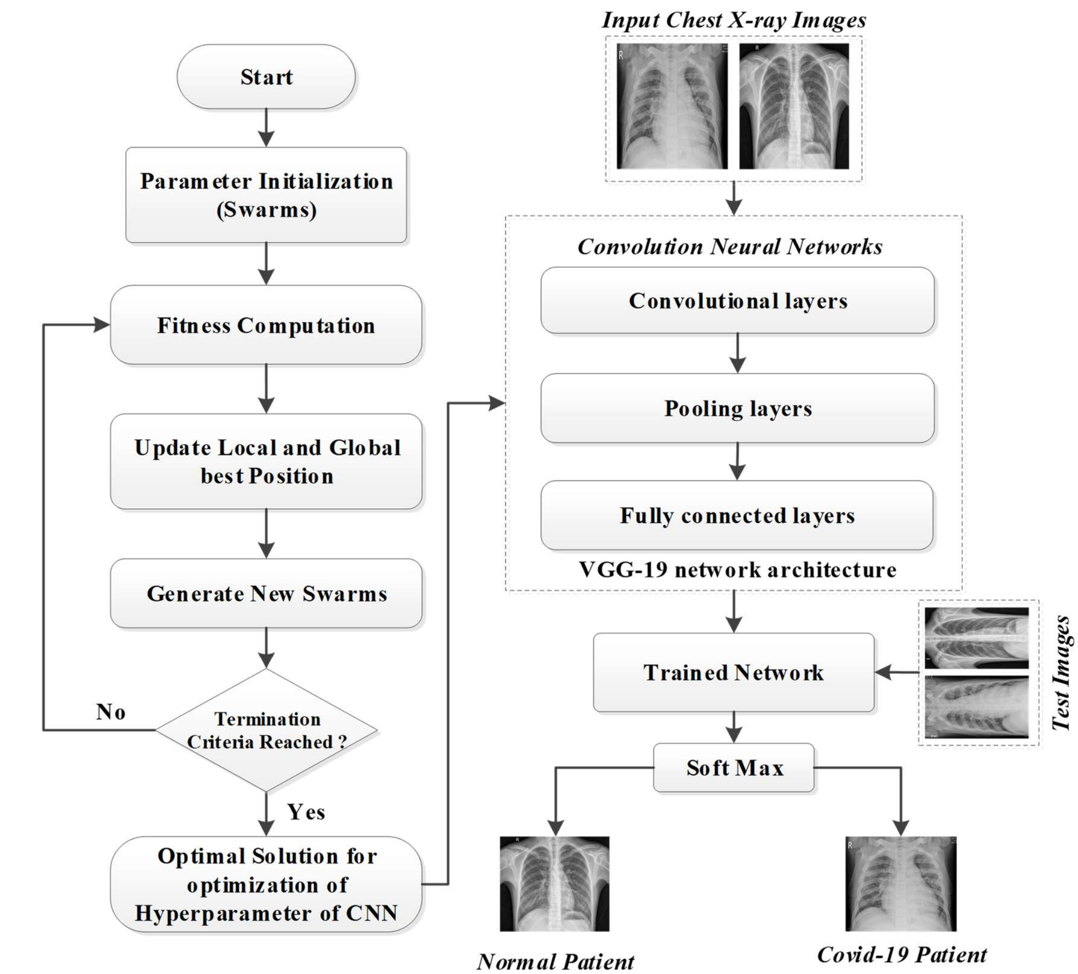

Figure 5: Flow diagram of optimized CNN for COVID-19 diagnosis

Evaluation

The performance of the techniques under study for the prediction of Covid-19 was evaluated based on accuracy, False Positive Rate (FPR), sensitivity, specificity, precision, accuracy and prediction time. Confusion matrix was used to determine the values of the performance metrics. It contains "True Positive (**TP**), False Positive (**FP**), False Negative **(FN)** and True Negative **(TN)**."

$$\text{False Positive Rate (FPR)} = \frac{\text{FP}}{\text{TN} + \text{FP}} \quad (7)$$

$$\text{Sensitivity} = \frac{\text{TP}}{\text{TP} + \text{FN}} \quad (8)$$

$$\text{Specificity} = \frac{\text{TN}}{\text{TN} + \text{FP}} \quad (9)$$

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \quad (10)$$

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \quad (11)$$

RESULTS AND DISCUSSIONS

The techniques for the prediction of Covid-19 in this study were implemented using MATLAB R2018 on Windows 10 64-bit operating system, Intel®Core™ i5-2540M CPU@2.60GHz Central Processing Unit, 6GB Random Access Memory and 500GB hard disk drive. The application was designed to run across different platforms.

A total number of 624 Chest X-Ray images were used to test the techniques; the dataset comprises of 390 normal and 234 were abnormal (Covid-19).

Table 1: Contingency table for classification using Optimized CNN and CNN

Techniques		Optimized CNN		CNN	
		Predicted Class		**Predicted Class**	
		Normal	**Covid-19**	**Normal**	**Covid-19**
Actual Class	**Normal (390)**	386 (TP)	4 (FN)	378 (TP)	12 (FN)
	Covid-19 (234)	1 (FP)	233 (TN)	9 (FP)	225 (TN)

Table 2: Results obtained by Optimized CNN and CNN

Technique	FPR (%)	Sensitivity (%)	Specificity (%)	Precision (%)	Accuracy (%)	Prediction Time (sec)
Optimized CNN	0.43	98.97	99.57	99.74	99.20	455.54
CNN	3.85	96.92	96.15	97.67	96.63	565.02

The performance of optimized CNN was evaluated and compared with that of the standard CNN technique. Table 1 presents the contingency table for the classification Chest X-Ray images using Optimized CNN and CNN.

The result shown in Table 1 reveals that the optimized CNN features correctly classified 386 of the normal Chest X-Ray image datasets as normal as against the recorded 378 for CNN. The optimized CNN performed better in terms of the corresponding false negatives as recorded. Similarly, the for the classification of the abnormal Covid-19 dataset, the optimized CNN performed better by correctly identifying 233 of the abnormal Covid-19 datasets as abnormal as against the 255 recorded for CNN. The optimization of CNN ensured reduced false positives.

Furthermore, Table 2 depicts the performance of optimized CNN feature for validation measures; false-positive rate, sensitivity, specificity, precision, accuracy and prediction time. The result obtained in Table 2 shows that the optimized CNN technique achieved FPR, sensitivity, specificity, precision and accuracy of 0.43%, 98.97%, 99.57%, 99.74% and 99.20% at 455.54 seconds, respectively. Also, the CNN technique achieved FPR, sensitivity, specificity, precision and accuracy of 3.85%, 96.92%, 96.15%, 97.67% and 96.63% at 565.02 seconds. It can be inferred from the results based on the performance metrics that the optimized CNN model gave an increased 2.57% accuracy, 2.05% sensitivity, 3.42% specificity, 2.07% Precision and a decreased FPR of 3.42% over the CNN model. The outcome of this research reveals that the optimized CNN model outperformed the CNN model in prediction of Covid-19 using chest x-ray.

The results suggest that the optimized CNN model achieve the best classification accuracy over the standard CNN model. Due to the imbalance of the dataset, all the CNNs perform seemingly well in terms of accuracy, false-positive rate, sensitivity, specificity, precision and accuracy. However, as those metrics depend heavily on the number of samples representing each class, their unilateral evaluation leads to incorrect conclusions (Ola *et al.,* 2020).

While optimized CNN model achieves better accuracy, it is clear that in terms of the particular disease, the optimal results are those with the lowest number of false negative and false positive. A real-life interpretation of a false negative instance would result in the mistaken assumption that the patient is not infected with what this entails for the spread of the virus and public health. False positive on the other hand would result in the mistaken assumption that the patient who is not infected is infected which can likely subject such patient to serious health issues as a result of treatment of covid-19. It is evident from the result achieved that the performance of the optimized CNN solution outperformed CNN model and other state of art methods in (Kumar *et al.,* 2020, Apostolopoulos and Mpesiana, 2020, Castiglioni *et al.,* 2021). Also, it gives a consistently high value of sensitivity, accuracy, precision for both patient with Covid-19 positive and negative cases. The fact that the proposed model achieved reduced false negatives and positive demonstrates the robustness of the model. Its performance could be improved by training on larger multi-institutional and multi-geographical datasets, and the role of the algorithm as the second reader of chest x-ray images could be assessed in different instances in patients suspected of SARS-CoV-2 infection, especially as several countries are facing repeated waves of the Covid-19 pandemic. This deep learning tool may help guide the clinical workflow.

CONCLUSION

This research work has been done to detect the Covid-19 positive patients from Chest X-Ray images. Fast and timely detection of Covid-19 positive patients is necessary to avoid spreading the disease and keeping it in control. The optimization of parameters of CNN is justified in that it achieved a reduced FPR and improved prediction rate. Also, it reduces the computational complexity associated to deep learning technique. It was evident that the performance of optimized CNN model was well matched to some other existing technique. Hence, it will achieve a more accurate and computationally efficient CAD system which will help radiologists' interpretation and classification of chest X-ray in diagnosing Covid-19. The proposed technique is recommended for use in clinical practices for quick and accurate diagnosis of the disease.

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