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FUTACOVNET: A Deep CNN Network for Detection of Corona Virus (Covid-19) using Chest X-ray Images

[1]Olabode O., [2]Akintola K.G., [3]✉Akinyede, R.O., [4]Adeyemi E., [5]Afeni B., [6]Akinbo R. and [7]Olabode A.

[1,2,3,6]The Federal University of Technology, Akure
[4,7]Federal Teaching Hospital Ido, Ekiti State, Nigeria
[5]Joseph Ayo-Babalola University, Arakeji
Emails of authors: oolabode@futa.edu.ng, kgakintola@futa.edu.ng, [3]✉roakinyede@futa.edu.ng, afenibo@futa.edu.ng

Abstract

In December 2019, WHO declared COVID-19 as morbidity and mortality rates continue to soar high with a global cumulative case of 460,280,168 and cumulative mortality of 6,050,018. The standard clinical golden tool mostly used for the diagnosis of COVID-19 is the Reverse transcription polymerase chain reaction (RT-PCR). It is adjudged to be very expensive, less-sensitive, not readily available in hospitals and most significantly, requires the services of a specialized medical expert. X-ray imaging is an easily accessible tool that can be an excellent alternative tool in COVID-19 diagnosis. This paper proposed a technique to automatically predict the presence of COVID-19 pneumonia from digital chest X-ray images using deep learning. Any technological tool that can help in the effective screening of the COVID-19 infection with high level of accuracy is highly required. In this research, the use of transfer learning approach in the rapid and accurate diagnosis of COVID-19 from chest X-ray images is carried out. A new CNN architecture that is trainable optimally while maximizing the detection accuracy is developed. A database was created by combining several public databases and also by collecting images from National Hospital, Abuja. The database contains a mixture of 3616 COVID-19 and 10,192 normal chest X-ray images. The X-ray images were used to train and validate the deep Convolutional Neural Network (CNN) model. The trained network was then used to classify the normal and COVID-19 patients. The proposed CNN classification accuracy, precision, recall and F1-Score of the model are 96.5%, 96%, 96% and 96% respectively. The model was then compared with the state-of-the-art CNN models and it outperformed all of them. The high accuracy of this model can significantly improve the speed and accuracy of COVID-19 diagnosis in our local hospitals. This would be extremely valuable during an outbreak of pandemic-related diseases when there are limited facilities and human resources for early diagnosis and management.

Keywords: X-Rays, COVID-19 pneumonia, Deep learning, transfer learning, pandemic and Diagnosis

1. Introduction

Coronavirus disease 2019 (COVID-19) is caused by the Severe Acute Respiratory Syndrome Coronavirus 2 (SARS-CoV-2). Coronaviruses are a family of viruses that can cause illnesses such as the common cold, severe acute respiratory syndrome (SARS) and Middle East respiratory syndrome (MERS). SARS-CoV-2 belongs to Beta coronavirus together with two highly pathogenic viruses, SARS-CoV and MERS-CoV. SARS-CoV-2 is an enveloped and positive-sense single-stranded RNA (+ssRNA) virus [3, 11]. The disease caused by SARS-CoV-2 was labeled as COVID-19 by the International Classification of Diseases (ICD) [4]. WHO declared COVID-19 a pandemic in December 2019. The COVID-19 virus spreads primarily through droplets of saliva or discharge from the nose when an infected person coughs or sneezes.

Covid-19 prevention is one way to reduce the spread of the virus infection. This can be achieved by maintaining social distancing, hand washing with sanitizers, isolation of

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infected person and so on. The diagnostic techniques based on viral RNA amplification, specifically qRT-PCR (quantitative real-time polymerase chain reaction), are the gold standard diagnostic methods for COVID-19 [5]. Unlike other molecular tests that do not have perfect diagnostic specificity, qRT-PCR is highly specific with a specificity of almost 100 % which has led to RT-PCR becoming the gold standard molecular diagnostic test [5]. This method however has its own shortcomings making it difficult to diagnose the disease very well. RT-PCR is time-consuming, complex, costly, and is a manual process. Also, it required costly laboratory kits which may be difficult or even impossible for many developing countries to afford during crises and epidemics [6]. Like all diagnostic and laboratory methods in healthcare systems, this method is not error-free and is biased. The method also requires an expert laboratory technician to sample the nasal and throat mucosa which is a painful process [7]. Many studies have shown false positive Polymerase Chain Reaction PCR testing [8]. Some other studies have indicated the low sensitivity of the RT-PCR test to be 30% to 60%, indicating a decrease in the accuracy of the diagnosis of COVID-19 in many cases. Some studies also pointed to its false-negative rate and contradictory results [9].

Fast, accessible, affordable and reliable identification of COVID-19 diagnoses method is key to slowing the transmission of COVID-19 infection [10]. Other alternative testing approaches include imaging-based approaches which include computed tomography (CT) imaging, X-Ray imaging based and Ultrasound imaging. The radiological imaging such as chest X-ray and chest CT-scan can be helpful to isolate the infected persons timely and control this epidemic situation. But the major challenge is the limited n umber of radiologists available in hospitals to conduct accurate and efficient analysis on the radiographic images [11]. Chest X-ray is an imaging procedure that uses a very small amount of radiation, which quickly goes through the body in order to capture an internal image of the chest [11]. A chest X-ray helps to indicate abnormal formations or a large variety of chest diseases such as pneumonia, cystic fibrosis, emphysema, cancer and so on [11]. In addition, a chest X-ray is often used for an emergency diagnosis due to its fast and easy usage. These techniques can easily detect the radiological characteristics of COVID-19. The best choice of radiologists is the chest X-ray as some of the hospitals are equipped with X-ray machines. Chest radiography (CXRs) is a common diagnostic imaging technique that uses X-rays to produce images of the chest. It is a valuable tool in the evaluation of various conditions affecting the lungs, heart, and surrounding structures. They are the preferred initial imaging modality when pneumonia is suspected and the radiation dose of CXR (0.02 mSv for a Posterior-Anterior (PA) film) is lower than the radiation dose of chest CT scans (7 mSv), putting the patients less at risk of radiation-related diseases such as cancer [13]. In addition, CXR are cheaper than CT scans, making them more viable financially for healthcare systems and patients. Finally, portable CXR units can be wheeled into ICU as well as emergency rooms (ER) and are easily cleaned afterwards, reducing impact on patient flow and risks of infection [13].

Deep learning models are emerging and powerful tools that have been used for diseases diagnosis and medical image analysis [14]. Deep learning mode has also shown promising results in diagnosis of COVID-19. Various deep learning models have exploited in automated COVID-19 diagnosis in X-ray images. However, many of the reported works made use of existing CNNs designed to classify natural images. Natural images however possess characteristics that are different to that of COVID-19 radiographic patterns. There is the need to fine tune or develop a new CNN model that will make use of COVID-19 radiographic patterns of region-homogeneity, textual variation, boundaries, and so on which can result in enhanced COVID-19 detection [14, 16, 17]. Recent studies show that CT and X-ray, contain salient information about COVID-19 virus and could be used as an alternative diagnosis method [23]. In addition, most of the existing works made use of a single and small dataset source with a limited number of images for model training and evaluation. The use of small dataset can lead to the poor model performance.

2.0 Literature Reviews

Das *et al*., [2] observed that since the outbreak of COVID-19, the number of confirmed cases of COVID-19 and deaths kept increasing globally. The review of Bao *et al*., [12] discussed the state-of-the-art studies about fighting the disease. It summarizes the current strategies and recent advances in detecting, preventing, and treating COVID-19 and interprets the underlying mechanisms in detail.

Girshick *et al*., [18] proposed a simple and scalable detection algorithm that improves mean average precision (mAP) by more than 30% relative to the previous best result on VOC 2012. The approach combines two key insights: (1) application of high-capacity convolutional neural networks (CNNs) to bottom-up region proposals in order to localize and segment objects and (2) supervised pre-training for an auxiliary task, followed by domain-specific fine-tuning for small training data, yields a significant performance boost. R-CNN decomposes the overall detection problem into two subproblems: to first utilize low-level cues such as color and super pixel consistency for potential object proposals in a category-diagnostic fashion, and to then use CNN classifiers to identify object categories at those locations.

Shin [15] implemented a Deep Convolutional Neural Networks for Computer-Aided Detection. The study first explored and evaluated different CNN architectures. The study also examined when and why transfer learning from pre-trained ImageNet can be useful. The study focused on two specific computer-aided detection (CADe) problems: thoraco-abdominal lymph node (LN) detection and interstitial lung disease (ILD) classification. The research achieves the state-of-the-art performance.

The study of Mohammad-Rahimi *et al*., [20] reviewed machine and deep learning methods used on chest X-ray images and CT scans for COVID-19 diagnosis and compared their performance. The accuracy of these methods ranged from 76% to more than 99%, indicating the applicability of machine and deep learning methods in the clinical diagnosis of COVID-19Click or tap here to enter text..

The study of Apostolopoulos and Mpesiana, [19] presents the automatic detection of Covid-19 from X-ray images utilizing transfer learning with convolutional networks. The motivations for this work are to detect COVID-19 early for timely referral of patients to quarantine, to cut the cost of testing, availability of X-ray images of normal and COVID-19 patients and the development in the field of machine learning.

Five models of CNN were trained at the lower level excluding the neural nature top level. These models are the VGG19, MobileNet, Inception, Xception and Inception Resnet. Due to small sample of dataset, transfer learning was used to train the models. Then, the classifier layer which is the neural network layer placed at the top of the model is tuned on the number of nodes and the number of hidden layers. A total of 1427 thoracic X-ray images is first collected. The images include 224 COVID-19, 700 images of common bacteria pneumonia and 504 images of normal patients. Secondly, another dataset that contains 224 Covid- 19 diseases, 714 images with confirmed bacterial and viral pneumonia and 504 normal patients is also used. The X-ray images were re-scaled to a size of 200 x 266. The training was conducted for ten epochs and a batch size of 64. Metrics such as accuracy, sensitivity and specificity were used to evaluate the models. It was noted that two models performed best on dataset1. These are the VGG16 and MobileNet. The MobileNet model was then used to classify the dataset2 and it achieved the accuracy of 94.73.

Some researchers: Song [21] and Shrada *et al*., [22] develop an accurate computer-aided method to assist clinicians to identify COVID-19-infected patients by CT images. The study of Song [21] develops an accurate computer-aided method to assist clinicians to identify COVID-19-infected patients by CT images. CT scans of 88 patients diagnosed with COVID-19 were collected from hospitals of two provinces in China, 100 patients were infected with bacteria pneumonia, and 86 healthy persons for comparison and modeling. Based on the data, a deep learning-based CT diagnosis system was developed to identify patients with COVID-19. The research established a deep learning-based CT diagnosis system to detect the COVID-19 causing pneumonia and to localize the main lesions. The fully automated lung CT diagnosis system was developed by three main steps. First, the main region of the lung was extracted and filled the blank of lung segmentation with the lung itself to avoid noises caused by different lung contours. Then, designed a Details Relation Extraction neural network (DRENet) to obtain the image level predictions. Finally, the image-level predictions were aggregated to achieve person-level diagnoses.

The experimental results showed that the model could accurately discriminate the COVID-19 patients from the bacteria pneumonia patients with an AUC of 0.95, recall (sensitivity) of 0.96, and precision of 0.79. When integrating three types of CT images, their model achieved a recall of 0.93 with precision of 0.86 for discriminating COVID-19 patients from others. Moreover, the model could extract main lesion features, especially the ground-glass opacity (GGO), which are visually helpful for assisted diagnoses by physicians.

The work of Qi *et al.*, [25] designed a novel multi-feature convolutional neural network (CNN) architecture for multi-class improved classification of COVID-19 from CXR images. CXR images are enhanced using a local phase-based image enhancement method. The enhanced images, together with the original CXR data, are used as an input to the proposed CNN architecture. Using ablation studies, they showed the effectiveness of the enhanced images in improving the diagnostic accuracy. The work provided a quantitative evaluation on two datasets and qualitative results for visual inspection. Quantitative evaluation is performed on data consisting of 8851 normal (healthy), 6045 pneumonia, and 3323 COVID-19 CXR scans. In Dataset-1, the model achieves 95.57% average accuracy for a three classes classification, 99% precision, recall, and F1-scores for COVID-19 cases. For Dataset-2, they obtained 94.44% average accuracy, and 95% precision, recall, and F1-scores for detection of COVID-19.

Khan *et al.*, [14] developed a CNN architecture STM-RENet to interpret the radiographic patterns from X-ray images. The STM-RENet is a block-based CNN that employs the idea of split–transform–merge in a new way. A new convolutional block STM that implements the region and edge-based operations separately and jointly is proposed. The learning capacity of STM-RENet was further enhanced by developing a new CB-STM-RENet that exploits channel boosting and learns textural variations to effectively screen the X-ray images of COVID-19 infection. The good detection rate (97%), accuracy (96.53%), and reasonable F-score (95%) of the technique suggest that it can be adapted to detect COVID-19 infected patients,

Research was taken to investigate the utility of artificial intelligence (AI) in the rapid and accurate detection of COVID-19 from chest X-ray images Chowdhury, [26]. The aim of the work is to propose a robust technique for automatic detection of COVID-19 pneumonia from digital chest X-ray images applying pre-trained deep-learning algorithms while maximizing the detection accuracy. A public database was created by combining several public databases and also by collecting images from recently published articles. The database contains a mixture of 423 COVID-19, 1485 viral pneumonia, and 1579 normal chest X-ray images.

The networks were trained to classify two different schemes: i) normal and COVID-19 pneumonia; ii) normal, viral and COVID-19 pneumonia with and without image augmentation. The classification accuracy, precision, sensitivity, and specificity for both the schemes were 99.7%, 99.7%, 99.7% and 99.55% and 97.9%, 97.95%, 97.9%, and 98.8%, respectively. The high accuracy of this computer-aided diagnostic tool can significantly improve the speed and accuracy of COVID-19 diagnosis. They concluded that their work would be extremely useful in this pandemic where disease burden and need for preventive measures are at odds with available resources

The research work of Aboutalebi *et al.*, [24], introduced the COVID-Net CXR-S, a convolutional neural network for predicting the airspace severity of a SARS-CoV-2 positive patient based on a CXR image of the patient's chest. The work leveraged transfer learning to transfer representational knowledge gained from over 16,000 CXR images from a multinational cohort of over 15,000 SARS-CoV-2 positive and negative patient cases into a custom network architecture for severity assessment. Experimental results using the RSNA RICORD dataset showed that the proposed COVID-Net CXR-S has potential to be a powerful tool for computer-aided severity assessment of CXR images of COVID-19 positive patients.

In the study of Horry, [27], it was demonstrated how transfer learning from deep learning models can be used to perform COVID-19 detection using images from three most commonly used medical imaging modalities X-Ray, Ultrasound, and CT scan. The aim of the research work is to provide over-stressed medical professionals an alternative method of using intelligent deep learning image classification models. The research first identified a suitable Convolutional Neural Network (CNN) model through initial comparative study of several popular CNN models. The optimization of the selected VGG19 model was carried out. The results indicate that Ultrasound images provide superior detection accuracy compared to X-Ray and CT scans. The experimental results highlight that with limited data, most of the deeper networks struggle to train well and provides less consistency over the three imaging modes used. The selected VGG19 model, which is then extensively tuned with appropriate parameters, performs in considerable levels of COVID-19 detection against pneumonia or normal for all three lung image modes with the precision of up to 86% for X-Ray, 100% for Ultrasound and 84% for CT scans.

2.1 Dataset Sources and Development

As shown in figures 1 and 2, the dataset combined several dataset from publicly available datasets. The COVID-19 chest X-Rays were obtained from the publicly accessible COVID-19 Image Data Collection reported in Bhuvana *et al*., [6] and Cohen *et al*., [13]., Aboutalebi *et al*., [24].

3.0 Methodology

3.1 Preprocessing

The dataset was preprocessed to resizing the X-Ray images to 50 x 50 pixels in order to fit the input image-size of the developed model.

3.2 Research Workflow

Figure 3 shows the workflow of the framework. It consists of getting the X-ray of Covid and Normal patients to derive the dataset, preprocessing the dataset, training of the CNN models, testing of the CNN models and evaluating the performance of the CNN models.

The architecture of the proposed Convolutional Neural Network Model for the Covid-19 detection is shown in Figure 4. The model has five convolution layers and five Maxpooling layers with each layer interleaved with a convolutional layer. I have one flatten layer, three dense layers and one output layer with Softmax activation function. The convolutional is used for feature extraction. It performs convolution with filters followed by activation using the ReLU and lastly pooling using the Max-pooling function. The fully connected layer performs the classification of the input images into the Covid or non-Covid classes.

The following section presents a brief description of the layers.

3.3 The Convolutional Layer

In this layer, the x-ray images are convolved with kernels to extract features from the image. This is followed by activation using the ReLU activation function. The Convolution at a pixel point is given by:

$$O(i,j) = k * I(i,j) = \sum_{j=-q}^{q} \sum_{i=-q}^{q} k(i,j) * I(i,j) \qquad (1)$$

where k is the filter or kernel, $k(i,j)$ is the value of the kernel at position i, j, of an image. An activation function is used to transform the computation to acceptable range in order to aid convergence of gradient decent. The ReLU activation function is given by:

$$y = \max(0, x) \qquad (2)$$

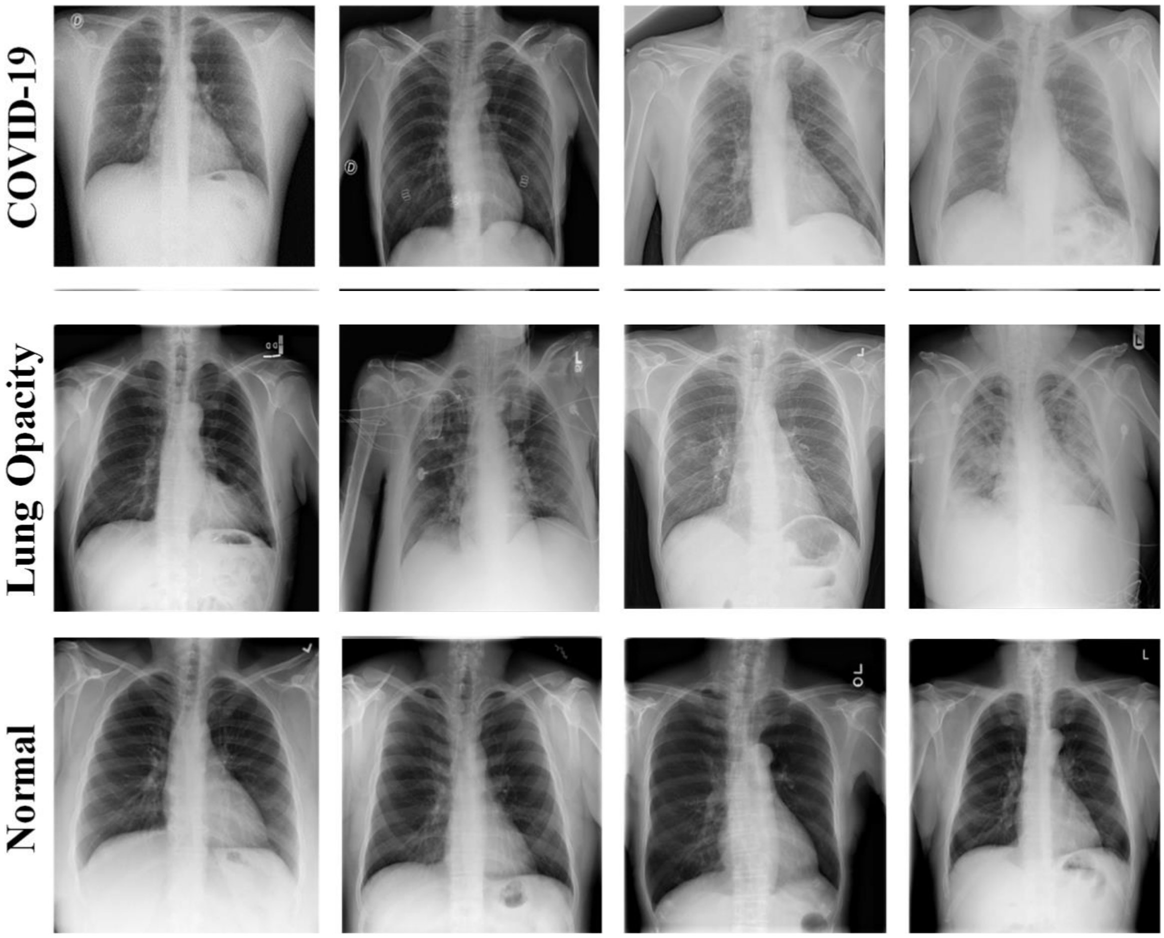

Figure 1: CXR image samples from different datasets: (A) COVID-19, (B) non-COVID Lung Opacity, (C) and Normal (Source: Rahman, [28])

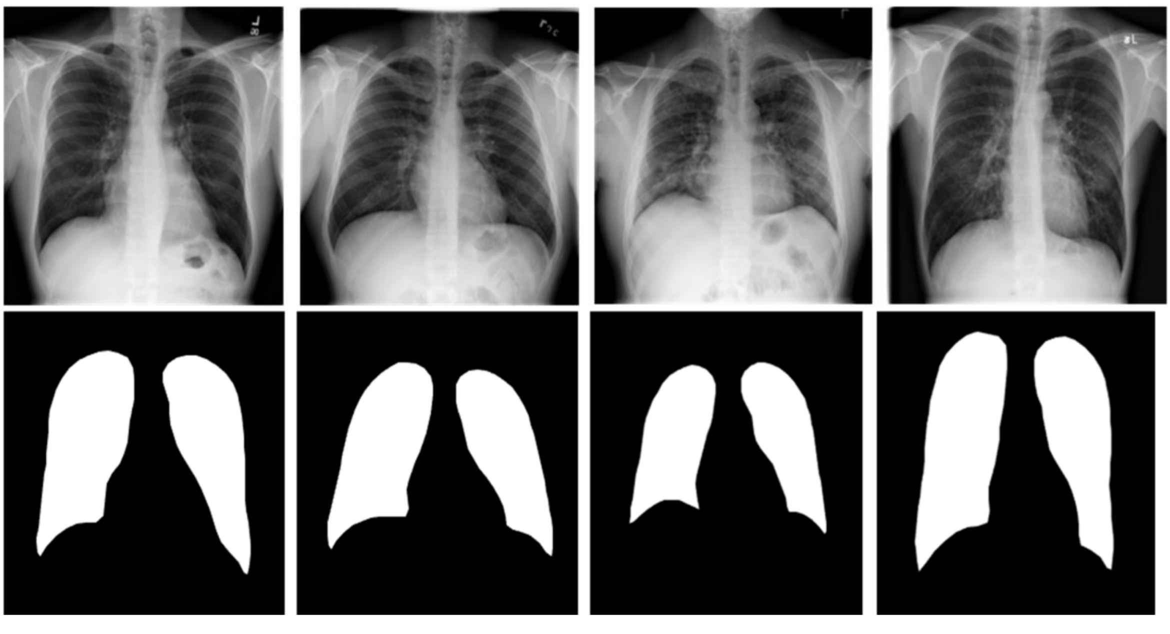

Figure 2: Samples of CXR and their ground truth masks of the dataset (Source: Rahman, [28]**).**

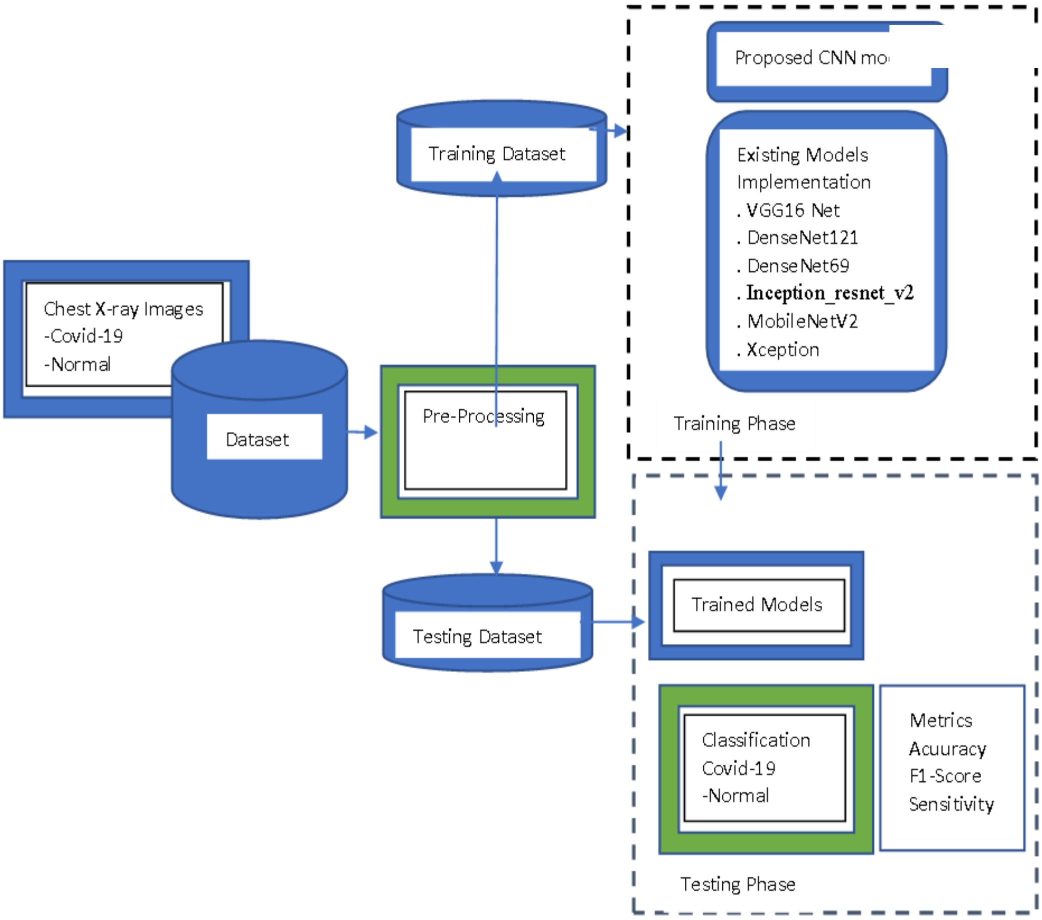

Figure 3: The Workflow of the framework

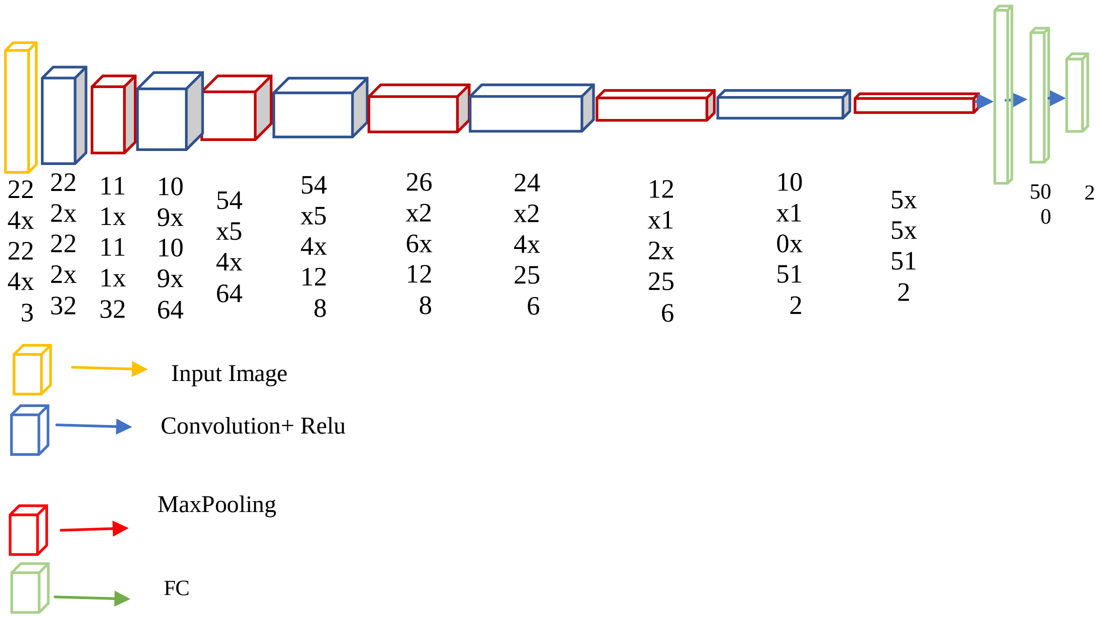

Figure 4: Architecture of the FUTACOVNET

3.4 The Pooling Layer

The pooling layer is used to down-sample an input image. This is performed after the ReLU operation. The Maximum Pooling (Max-pooling) operation is adopted in this research.

3.5 The fully Connected Layer (Softmax Activation)

The fully connected layer is used to classify the input images into Covid and No-Covid classes. The Softmax activation function is used on the output of the last layer of the fully connected layer. It returns values between 0 and 1. The Softmax Equation is given as:

$$\sigma(\vec{z})_i = \frac{e^{z_i}}{\sum_{j=1}^{K} e^{z_j}} \qquad (3)$$

where $\vec{z}$ is the input vector made up of values $z_0, \ldots, z_k$, e^{z_i} is the exponential of each vector and K is the number of classes in the classifier denotes the correctly predicted normal cases, and FN denotes the COVID-19 cases that are misclassified as Normal. The total trainable parameters of the model are 14,871,078. Table 1 shows the parameters of the CNN model layer by layer. Finally, the total trainable parameters of the model which is 14,871,078 is gotten by summing all the parameters in each layer together,

4.0 Experimental Result Analysis

4.1 Experiment Setup

To carry out this experiment, the dataset was split into training and testing. A total of 13608 data items was used for training while 200 data items were used for testing. The CNN Model was trained with a batch size of 16 with maximum epoch number of 50 using the Adam optimizer function and the learning rate of 0.001. The networks models were implemented using Python and the Keras package with TensorFlow2 on an Intel(R) Core(TM) i7- 6600U 2.60 GHz processor.

Table 1: Parameters of the CNN model

Number of Layer	Layer Type	Kernel	Output Shape	Number of Trainable Parameters
1	Conv2D	3x3	(32,222, 222)	896
2	MaxPooling	2x2	(32,111,111)	-
3	Conv2D	3x3	(64,109,109)	18496
4	MaxPooling	2x2	(64,54,54)	-
5	Conv2D	3x3	(128,52,52)	73856
6	MaxPooling	2x2	(128,26, 26)	-
7	Conv2D	3x3	(256,24,24)	295168
8	MaxPooling	2x2	(256,12,12)	-
9	Conv2D	3x3	(512,10, 10)	1180160
10	MaxPooling	2x2	(512,5, 5)	-
11	Flatten	-	12800	-
12	Dropout	-	12800	-
13	FC1	-	1000	12801000
14	Dropout	-	1000	-
15	FC2	-	500	500500
16	FC3	-	2	1002

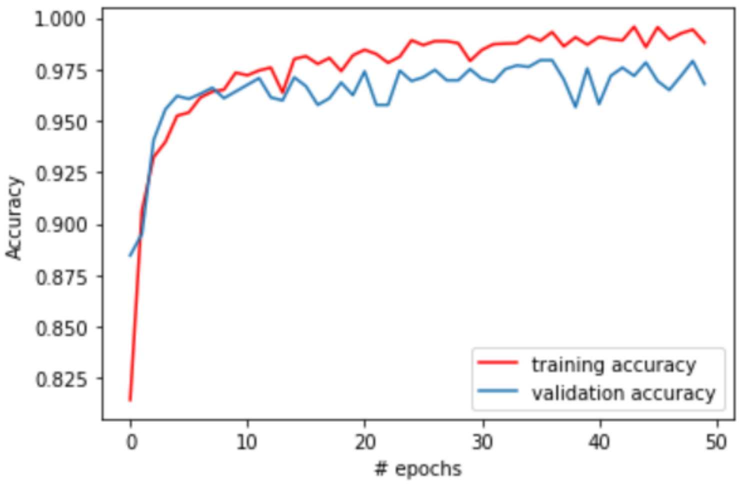

Figure 5 Training Curve showing accuracy vs number of epochs

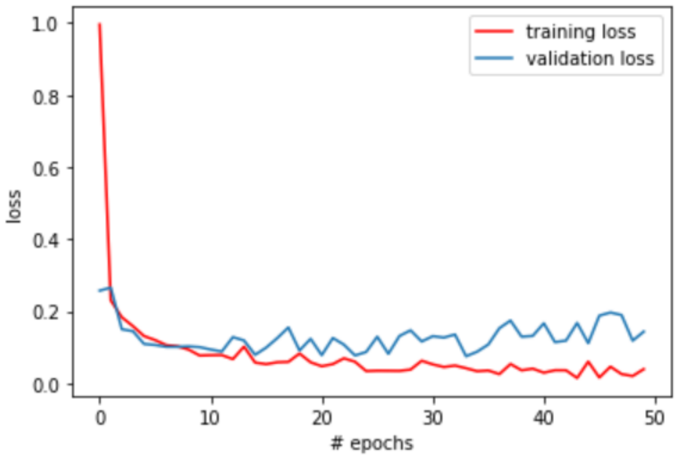

Figure 6. Training Curve showing loss vs number of epochs

4.2 Results

Figure 5 shows the graph of the performance of the CNN model with accuracy of the training and validation set. The training and validation accuracies are 98.79% and 96.78%, respectively, at epoch 50. Further, Figure 6 depicts the cross-entropy (loss) in the training and validation set. The obtained training and validation loss for the CNN model are 0.0396 and 0.1436 respectively at epoch 50. Table 2 shows the accuracy, specificity, sensitivity, and F1-score for the CNN model. This is graphically shown in Figure 8. The CNN model achieved 95% Accuracy, 93% Precision, 95% Recall, and 94% F1-score for the COVID-19 cases. For the Normal classification, it recorded 97% Accuracy, 98% Precision, 97% Recall, and 98% F1-score.
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Figure 7 shows the confusion matrix of the test result of the proposed CNN model. Out of 59 Covid-19 images, 3 were misclassified while out of 141 Normal images, 4 was misclassified. Among the total 200 images only 7 was misclassified thereby achieving the recognition accuracy of 96.5%.

A comparison between existing CNN models and our proposed model shows that the proposed CNN model outperforms all the other models in terms of accuracy, precision, recall and f1-score but shows the same accuracy with VGG16 model. But in terms of computational time, the proposed model outperforms four of the considered CNN models as shown in Table 3 and graphically in Figure 9.

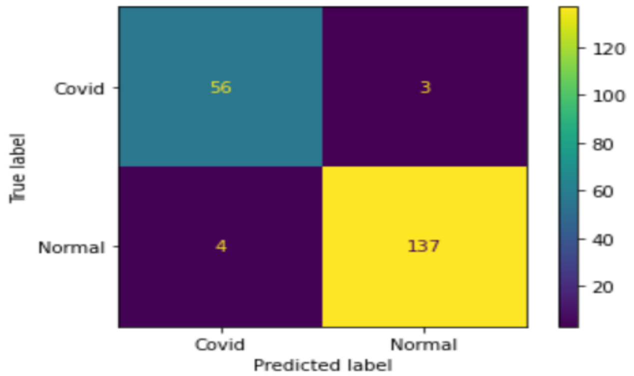

Figure 7 Confusion Matrix of the proposed CNN model

Table 2 Performance of the proposed CNN Model

Class	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Covid-19	95	93	95	94
Normal	97	98	97	98

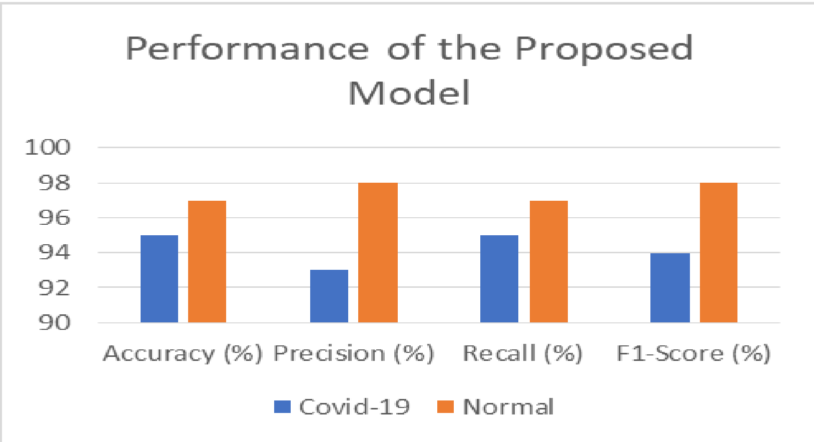

Figure 8 Performance of the CNN model

Table 3 Comparative with other models

S/N	Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	Training Time (s)
1	DenseNet121	93.5	92	93	93	153500
2	VGG-16	96.5	96	95	95	196250
3	DenseNet69	94	93	92	93	256700
4	MobileNetV2	94	95	88	91	20750
5	Inception_resnet_v2	93	94	88	90	184400
6	Xception	93	94	88	90	47050
7	**FUTACOVNET**	**96.5**	**96**	**96**	**96**	**54400**

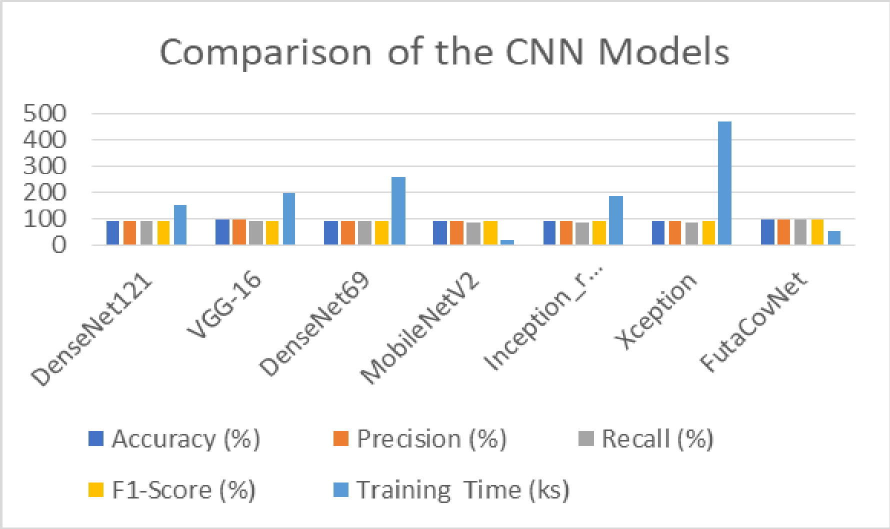

Figure 9 Comparative Analysis of the CNN models

5.0 Conclusion

As COVID-19 become entrenched in the society, hospitals in Nigeria are lacking tools for early detection of the disease. Hence, there is the need for alternative tools that can detect COVID-19 on time. There are availability of X-ray Images in Nigeria hospitals, hence, this research project provides a scalable deep CNN model for the diagnosis of novel COVID-19 from X-ray images. The performance of the proposed model in terms of Accuracy and computational time is achieved by using a mix of convolution and max-pooling operations. The model achieved an accuracy of 96.5%, precision of 96%, recall of 96%, and F1-score of 96%. The proposed CNN and some state-of-the-art CNN models were compared using the same dataset. The results showed that the proposed model outperforms all the competitive CNN models. The suggested model operates within an average computational timeframe. There is confidence that it could be employed in Nigerian hospitals for COVID-19-related diagnoses, thus alleviating the challenges associated with the conventional medical diagnostic process for the disease. The limitation of this proposed model is the size of the training data. As more data becomes available in future, the model is expected to perform better.

Declaration

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