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# Comparative Analysis of Deep Learning Models for Detection of COVID-19 from chest X-Ray Images

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***Abstract*—** The coronavirus disease is a viral infectious disease resulting from severe acute respiratory syndrome coronavirus. The new coronavirus, which began in China, in December 2019, has rapidly become pandemic and resulted to over 500000 deaths worldwide. Prompt detection of COVID-19 is necessary to prevent the transmission of COVID-19. In this research, we developed Deep Learning (DL) models for detection of COVID-19 from chest X-ray Images and evaluated the performance of the models by using accuracy, sensitivity and specificity. 401 COVID-19 chest X-ray images were obtained from open access database developed by Dr Cohen while 397 normal_and 390 pneumonia chest X-ray images were obtained from Kaggle repository. Modified Alexnet, Googlenet and SqueezeNet were used to classify the chest X-ray images. Transfer learning with Alexnet achieved an overall best performance of 100% accuracy, 100% sensitivity and 100% specificity on binary test dataset and 98.31% accuracy, 98.55% sensitivity and 99.37% specificity on three classes test dataset. The work will provide early detection of COVID-19 and thereby enhance medical decisions, treatments and management procedures.

***Keywords*—** Coronavirus; X-ray Images; Deep Learning; Convolutional Neural Network; Transfer Learning

## I. INTRODUCTION

The coronavirus disease (COVID-19) is an infectious disease caused by severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2). The coronavirus outbreak, which emerged in China, in December 2019 is now a pandemic affecting many countries globally. COVID-19 has affected all levels of the education system, fiancé industry, manufacturing and agriculture and oil sector [1,2]. The previous coronaviruses are known to cause respiratory infections which include Severe Acute Respiratory Syndrome (SARS) and Middle East Respiratory Syndrome (MERS) which was recorded in Saudi Arabia in 2012 resulted to over 800 death [3] while SARS reported in 2003 in China resulted to over 850 deaths [4]. SARS-CoV-2 is a member of the class of single-stranded RNA viruses called coronaviridae, which is the type of virus that affects mammals, birds and reptiles. The period of incubation of a coronavirus varies but is generally up to two weeks [5]. Clinical symptoms include dry cough, tiredness, headache aches, nasal congestion, conjunctivitis, sore throat and loss of taste or smell [6,7]. Although some antiviral drugs have been evaluated against COVID-19 which resulted in clinical recovery, there is no approved antiviral or vaccine available treatment.

Recently, many radiology images have been used for COVID-19 detection [8]. Images obtained from imaging techniques such as X-ray and CT scan contain important information that are useful for diagnosis. X-ray machines are usually use to scan the body for the detection of tumors, fractured bones, pneumonia, and lung infection. Although. CT scanning is the more sophisticated system to examine different body part, tissues and organs more clearly, X-ray imaging is cheaper and more available than CT [9]. The application of deep learning techniques for automatic detection in the medicine have newly gained popularity and has become a useful tool for clinicians. Deep learning, which is a branch of machine learning that enables the creation of end-to-end models to achieve result without the need for subset manual feature extraction [10]. Computer-aided diagnosis systems developed using deep learning could assist in the early detection of COVID-19 abnormalities and help to monitor the progression of COVID-19.

The rest of the paper is as follows: Section II contains the related works on the detection of COVID-19 from ultrasound thyroid images, Section III discuss the procedures for the development of the deep learning models, Section IV presents the results and discuss the results obtained and section V concludes the research work.

## II. RELATED WORK

In [7], The deep learning model known as COVIDX-NET was applied to detect COVID19 from X-ray images and an accuracy of 90% was obtained. Ozturk et al. [11] developed DarkNet model for the detection of COVID-19 X-ray. The dataset used was the combination of COVID X-ray dataset provided by Dr Joseph Cohen [12] and the Kaggle Chest X-ray images [13]. The dataset was divided into binary class (COVID vs. No-Findings) as well as multi-class classification (COVID vs. No-Findings vs. Pneumonia). 98.08% accuracy was obtained for binary classes while 87.02% accuracy was obtained for multi-class cases. Alom etal. [14] proposed an inception Residual Recurrent Convolutional Neural Network for COVID-19 detection and obtained a testing accuracy of 84.67% and 98.78% for X-ray and CT-images respectively. In [15], a deep neural network called COVID-Net with high architectural diversity and selective long-range connectivity was presented. The model was experimented on COVID-19 dataset and pneumonia detection dataset and achieved a testing accuracy of 83.5%.

In [16], the performance of VGG19 and the MobileNet in the detection of Covid-19 were evaluated with 224 images of confirmed Covid-19 disease, 700 images of confirmed common bacterial pneumonia, and 504 images of normal conditions. The best accuracy and specificity obtained were 96.78% and 96.46% respectively. In [17], a machine learning approach was proposed for detection of COVID-19 from CT images. Images features were extracted by using Local Directional Pattern (LDP), Grey Level Co-occurrence Matrix (GLCM), Discrete Wavelet Transform (DWT) algorithms, Grey-Level Size Zone Matrix (GLSZM) and Grey Level Run Length Matrix (GLRLM). The extracted features were classified by Support Vector Machine (SVM) .The best accuracy of 98.77% was obtained by GLSZM feature extractor

.

Farooq and Hafeez [18] developed a deep learning model for detection of COVID-19 using ResNet-50 architecture. Data augmentation was used to prevent overfitting. An accuracy of 96.23% was achieved on a multi-class classification of normal, bacterial infection pneumonia and COVID-19. In [19], Inception ResNetV2, ResNet50 and InceptionV3 were proposed for classification of X –ray images to COVID and non-COVID images. The highest accuracy of 98% was obtained by ResNet50. In [20], deep anomaly detection model was developed for detection of COVID-19. The dataset consist of 70 COVID-19 images and 30 non COVID -19 images. The proposed model achieved an accuracy of 96%. Linda [21] developed a DCNN, called COVIDNet for the detection of COVID19 from the chest X-ray images and obtained an accuracy of 83.5%. Sethy and Behra [22] used the combination of Resnet 50 and Support Vector Machine (SVM) to detect COVID-19 images and obtained an accuracy of 95.38%.
In this research, we modified deep learning models for detection of COVID-19 from X-ray images using the same parameters and evaluated the performance of the models. Since the available COVID-19 dataset are not adequate to train deep neural networks, transfer learning with deep learning models are presented for detection of COVID-19.

## III. METHODOLOGY

### 3.1 Data Acquisition

401 COVID-19 X-ray images were obtained from open access database developed by Dr Cohen [11], which is constantly updated with images shared by various researchers. Furthermore, 397 normal and 390 pneumonia images were obtained from the Kaggle repository [12]. Samples of chest x-ray images are shown in Figure 1. For this study, COVID-19 and normal images classes are referred to a dataset 1 while COVID-19, normal and pneumonia images classes are referred to a dataset 2.

(a) COVID 19 (b) Normal (c) Pneumonia.
Figure 1 Chest X-ray images

### 3.2 Data Preprocessing

Histogram Equalization was used to enhance the image contrast while the noise was removed by using the adaptive filtering technique**.** The dataset was divided into training set (60%), validation set (20%), and test set (20%). The test set only contains samples from the original dataset, not augmented data. In order to prevent overfiting, the training images were augmented by rotating left and right and then flipped 70, 160 and 270 degrees.

### 3.3 Convolutional Neural Networks for Detection of COVID-19

Convolutional Neural Network (CNN) which is a deep learning algorithm was applied to detect COVID-19 from the chest X-ray images. CNN takes an input image, assign learnable biases and weights to various aspects in the image by using a pre-trained network. A pre-trained network is easier and faster than training a network from scratch since learned features can be applied to a new task with fewer training images. In this study, Alexnet, Googlenet and SqueezeNet were modified to detect COVID-19 from the chest X-ray images

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#### 3.3.1 COVID-19 Detection using Alexnet Transfer Learning Network

The X-ray images were classified by a modified Alexnet into two classes as well as three classes: COVID -19 positive and Normal, then COVID-19 positive, Normal and Pneumonia. Alexnet is a pre-trained convolutional neural network, which was developed by krizhevsky *et al.*,[23]. The network has been trained on over a million images the imagenet database [24] and can classify images into 1000 classes. AlexNet consist of 5 convolutional layers and 3 fully connected layers with 60 million parameters. AlexNet has 227-227 image input size and uses Rectified Linear Unit (ReLu) for the non-linear part which trains faster than Tanh or sigmoid function .

The block diagram for the classification of the chest X-ray images using modified Alexnet is as shown in Figure 2. Since Alexnet network requires the size of an input image to be the same as the input size of the network, each X-ray image was changed to 227× 227. Furthermore, Alexnet requires 3-channels input data, therefore, the X-ray images were converted from grayscale to RGB (227 × 227 ×3) by concatenating their channel three times. In order to set the layers to classify chest X-ray images, the last three layers were replaced with a fully connected layer, a softmax layer, and a classification output layer. A max pooling layer was applied after each convolution layer to reduce the network size. Dropout was also applied to avoid overfitting by setting the output of each hidden neuron zero with probability of 0.5. The training options were specified and the Alexnet was trained with training X-ray images. Training options and network configuration were altered until the most impressive results were obtained.

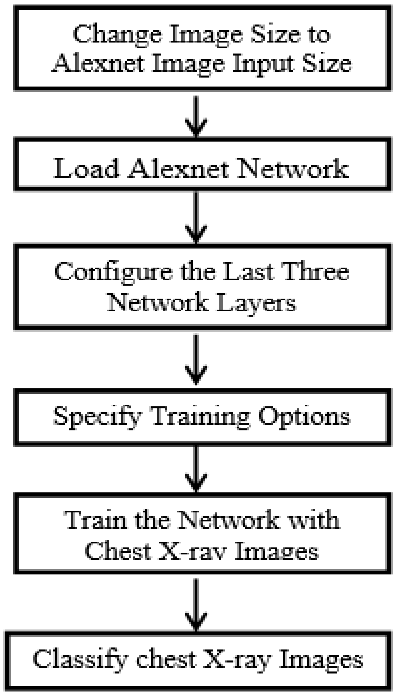


Figure 2: Block Diagram for the Classification of Chest X-ray Images using modified Alexnet

### 3.3.2 COVID-19 Detection using GoogLeNet Transfer Learning Network

Szegedy *et* al [25] designed a convolutional neural network that is 22 layers deep known as Googlenet (Inception-v1). The network has been trained on ImageNet and can classify images into 1000 object categories. Googlenet has an image input size of 224-by-224 with 5 million parameters. The network was built using dense modules (blocks) instead of stacking convolutional layers.

The flow diagram for the classification of the chest X-ray images using modied GoogLeNet is as shown in Figure 3 The X-ray images were loaded as an image datastore and the images size were changed to 224-by-224-by-3, which is the GoogLenet input image size. The weights of the earlier layers in the GoogleNet network was freeze by setting the learning rates in those layers to zero. The fully connected layer (lost classifier layer) was replaced with the layer that correspond to the numbers of filters equal to two classes for dataset 1 and three classes for dataset 2 while the classification layer (output layer), which specifies the output classes of the network was replaced with a new one without class label. The network automatically sets the output classes of the layer at training time. The fine-tuned network classified the validation images and determined the classification accuracy.

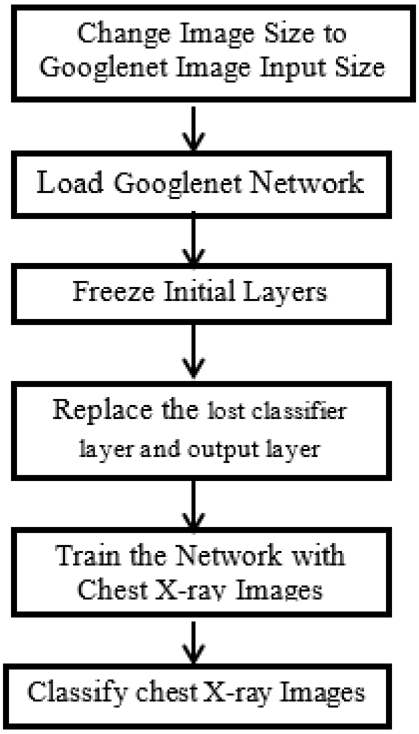


Figure 3: Block Diagram for the Classification of Chest X-ray Images using modified GoogLeNet

### 3.3.3 COVID-19 Detection using SqueezeNet Transfer Learning Network

SqueezeNet is a neural network that was designed to create a smaller network with fewer parameters maintaining the same level of accuracy with AlexNet [26]. The network is 18 layers deep and the number of parameters is 50×fewer than AlexNet. The convolutional layers of the network extract image features that the last learnable layer and the final classification layer can use to classify input image.

The flow diagram for the classification of the chest X-ray images using modified SqueezeNet is as shown in Figure 4 . In order to modify SqueezeNet to detect COVID-19, the training images were resized to 227-by-227-by-3, which is the SqueezeNet input image size. 'Conv10' and'

ClassificationLayer_predictions' are the layers in SqueezeNet that has features combination information that is extracted by the network into group probabilities, predicted labels and a loss value. The two layers were replaced with new layers adapted to the X-ray data set. The training options were specified and the modified SqueezeNet was trained with training X-ray images.

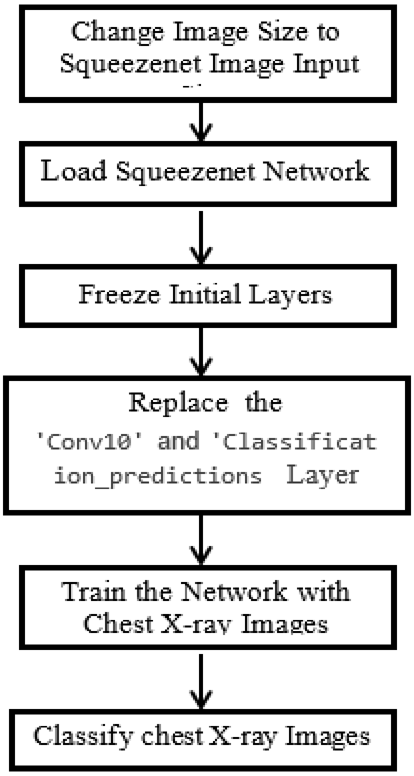


Figure 4: Block Diagram for the Classification of Chest X-ray Images using modified SqueezeNet

### 3.4 Performance Evaluation of the Models

Accuracy, True Positive Rate (Sensitivity) and True Negative Rate (Specificity) of the models were determined in order to evaluate the performance of the models [27]. Accuracy refers to the ratio of number of correct predictions to the total number of input X-ray images sample. Accuracy

$$= \frac{\text{True Positive} + \text{True Negative}}{\text{Total Number of Samples}}$$

.

Sensitivity is the ratio of positive data points that are correctly considered as positive, to all positive data points.

$$\text{True Positive Rate} = \frac{\text{True Positive}}{\text{False Negative} + \text{True Positive}}$$

Specificity is the proportion of correct negative predictions divided by the total number of negatives

$$\text{True Negative Rate} = \frac{\text{True Negative}}{\text{True Negative} + \text{False Positive}}$$

In order to obtain the overall classification performance of the developed detection system, the overall accuracy, average sensitivity and average specificity of the results were determined as follows [28] :

$$Overall\ accuracy = \frac{1}{N}\sum_{i=1}^{c} TP_i$$

$$Average\ Sesitivity = \frac{1}{N}\sum_{i=1}^{c} \frac{TP_i}{TP_i + FN_i}$$

$$Average\ Specificity\ \ \frac{1}{N}\sum_{i=1}^{c} \frac{TNi}{TN_i + FP_i}$$

where TPi, TFi, FNi, FNi, C and N are the true positives, true negatives, false positives, false negatives, total number of classes and number of instances respectively

## IV. RESULTS AND DISCUSSIONS

The experiment was implemented in Matlab 2020 installed on a laptop computer system with an intel core processor i5, 2.8 central processing unit (CPU) processor speed, 8 GB of RAM. The networks were trained at a learning rate of 0.0001 and for 6 epoch. The CNNs were compiled using Adam optimization method. The CNNs training graphs for Dataset 1 is as shown in Figure 5.1a, b and c. It can be observed that the highest validation accuracy was obtained by Alexnet . Alexnet model increases validation accuracy faster than either Googlenet or Squeezenet and approaches 100% .Similarly, The CNNs training graphs for Dataset 2 is as shown in Fig. 6.1a, b and c. Validation accuracy and Training Time For binary classes classification and three classes classification are as shown in Table1 and Table 2 respectively. Alexnet gives the highest validation accuracy while Squeezenet gives lowest validation accuracy. Alexnet takes shortest time to train why Googlenet take longest time to train for dataset 1 and dataset 2 . The training time depends on the number of convolutional layers and learnable parameters. Alexnet also uses ReLU as an activation function which makes it faster than equivalent network that use Tanh or Sigmoid.

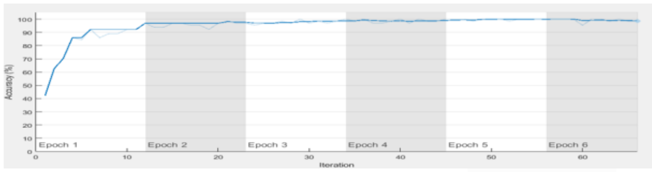

Figure. 5.1a. Training Graph for Detection of Covid-19 using Alexnet for Dataset 1

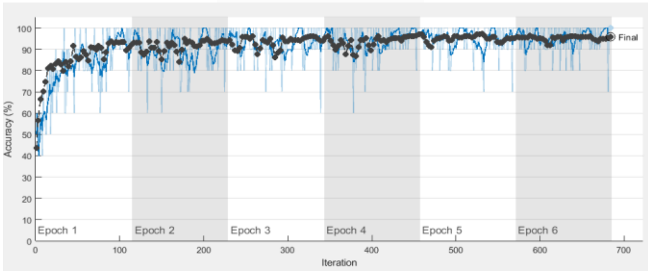


Figure 5.1b. Training Graph for Detection of Covid-19 using Googlenet for Dataset 1

 

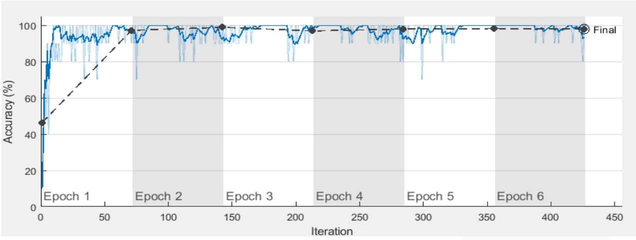


Figure 5.2c. Training Graph for Detection of Covid-19 using Squeezenet for Dataset 1

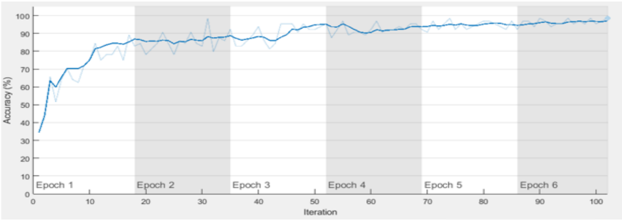


Figure 6.1a Training Graph for Detection of Covid-19 using Alexnet for Dataset 2

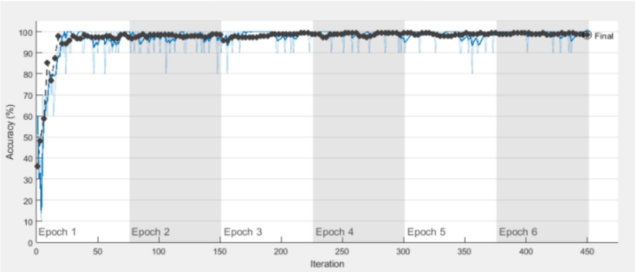


Fig. 6.1b. Training Graph for Detection of Covid-19 using Googlenet for Dataset 2

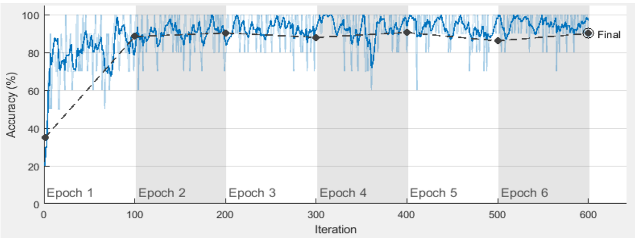


Fig. 6.1c. Training Graph for Detection of Covid-19 using Squeezenet for Dataset 2

Table 1: Validation and Training Time For binary classes classification

| CNN models | Validation Accuracy (%) | Training Time (mins:sec) |
|---|---|---|
| Alexnet | 99.49 | 8:27 |
| Googlenet | 98.41 | 96:12 |
| SqueezeNet | 98.03 | 14: 44 |

Table 2: Validation and Training Time for Three Classes Classification

| CNN models | Validation Accuracy (%) | Training Time (mins:sec) |
|---|---|---|
| Alexnet | 97.55 | 12 :59 |
| Googlenet | 96.04 | 1056:18 |
| SqueezeNet | 90.21 | 17:52 |

The confusion matrix of each model obtained by modified Alexnet, Googlenet and SqueezeNet for two classes are shown in Table 3.1a., 3.1b and 3.1c. True Positives (TP) are the correctly detected diseased cases, False Negatives (FN) are incorrectly identified diseased cases, True Negative (TN) are the correctly classified healthy cases, and False Positives (FP) are incorrectly detected healthy cases _In Table 3.1a, all tested COVID-19+VE and Normal X-ray images are correctly classified. In Table 3.1b, 1 COVID-19+VE image are misclassified as Normal. In Table 3.1c, 2 COVID-19+VE images were misclassified as normal while 2 normal images were misclassified as COVID-19+VE. The confusion matrix obtained by each model for three classes are shown in Table 4.1a, 4.1b and 4.1c. The confusion matrix shows the X-ray images that are correctly or incorrectly detected.

Table 3.1a. **Confusion Matrix** for Detection of Covid-19 using Alexnet for Dataset 1

| | | **Predicted Class** | |
|---|---|---|---|
| | | COVID 19+VE | Normal |
| **Actual Class** | COVID-19+VE | 80 | 0 |
| | Normal | 0 | 79 |

Table 3.1b. **Confusion Matrix** for Detection of Covid-19 using Googlenet for Dataset 1

| | | **Predicted Class** | |
|---|---|---|---|
| | | COVID 19+VE | Normal |
| **Actual Class** | COVID-19+VE | 79 | 1 |
| | Normal | 0 | 79 |

Table 3.1c. Confusion **Matrix** for Detection of Covid-19 using SqueezeNet for Dataset 1

| | | **Predicted Class** | |
|---|---|---|---|
| | . | COVID 19+VE | Normal |
| **Actual Class** | COVID-19+VE | 78 | 2 |
| | Normal | 2 | 77 |

Table 4.1a. **Confusion Matrix** for Detection of Covid-19 using Alexnet for Dataset 2

| | | **Predicted Class** | | |
|---|---|---|---|---|
| | | COVID 19+VE | Normal | Pneumonia |
| | COVID-19+VE | 79 | 0 | 1 |
| **Actual Class** | Normal | 1 | 78 | 0 |
| | Pneumonia | 0 | 1 | 77 |

Table 4.2b Confusion **Matrix** for Detection of Covid-19 using Googlenet for Dataset 2

| | | **Predicted Class** | | |
|---|---|---|---|---|
| | | COVID 19+VE | Normal | Pneumonia |
| | COVID-19+VE | 79 | 1 | 0 |
| **Actual Class** | Normal | 2 | 76 | 1 |
| | Pneumonia | 1 | 1 | 76 |

 

Table 4.2c. **Confusion Matrix** for Detection of Covid-19 using SqueezeNet for Dataset 2

| | | **Predicted Class** | | |
|---|---|---|---|---|
| | | COVID 19+VE | Normal | Pneumonia |
| | COVID-19+VE | 77 | 2 | 1 |
| **Actual Class** | Normal | 2 | 75 | 2 |
| | Pneumonia | 2 | 2 | 74 |

The performance of each model in classification of abnormalities in chest X-ray into two classes are shown in Table 5.1a . Alexnet achieved an accuracy of 100%, sensitivity of 100% and specificity of 100%. Similarly, Googlenet achieved an accuracy of 98.75%, sensitivity of 98.7% and specificity of 100%. while SqueezeNet achieved an accuracy of 97.48%, sensitivity of 97.5% and specificity of 97.5%. The results show that Alexnet outperforms Googlenet and Squeezenet in the classification of abnormalities in chest X-ray into two classes. Furthermore, The performance of each model in the classification of abnormalities in chest X-ray into three classes are shown in Table 5.1b. It can be observed that Alexnet identified abnormalities at higher average accuracy, sensitivity and specificity than either Googlenet and Squeezenet. The comparison of the related detection results is as shown in Table 6. The results show that our modified Alexnet outperform other methods reported in the literatures for both binary classification and three classes classification In Alexnet network, a dropout placed after each fully connected layer reduces overfitting thereby improving the performance of the network.. However, squeezenet has the smallest size and can be considered to be used on Field Programmable Gate Arrays (FPGAs) and other hardware with limited memory.

**Table 5.1a. Testing Result of the** Performance Evaluation of the CNN models in the classification of abnormalities in chest X-ray into two classes

| CNN models | Accuracy | Sensitivity | Specificity |
|---|---|---|---|
| Alexnet | 100 | 100 | 100 |
| Googlenet | 98.75 | 98.70 | 100 |
| Squeezenet | 97.48 | 97.50 | 97.50 |

**Table 5.1b.Testing Result of the** Performance Evaluation of the CNN models in the classification of abnormalities in chest X-ray into three classes

| CNN Models | Average Accuracy | Average Sensitivity | Average Specificity |
|---|---|---|---|
| Alexnet | 98.31 | 98.55 | 99.37 |
| Googlenet | 97.47 | 97.04 | 98.73 |
| Squeezenet | 95.34 | 95.72 | 97.49 |

**Table 6**. Comparison of COVID-19 Detection Results

| Authors | Classes | Detection Techniques | Performance (%) |
|---|---|---|---|
| [10] | COVID-19(+) and Normal<br>COVID-19(+), Normal and Pneumonia | Darknet | Accuracy 96.23<br>Accuracy 87.02 |
| [13] | COVID-19(+) and Normal | Inception Residual CNN | Accuracy 84.67 |
| [14] | COVID-19(+), Normal Pneumonia | COVIDNET | Accuracy 83.5 |
| [15] | COVID-19(+). Normal and Pneumonia | VGG 19 MobileNet | Accuracy 96.78, Specificity 96.46 |
| [16] | COVID-19(+) and Normal | SVM | Accuracy 98.77 |
| [17] | COVID-19(+) and Normal | ResNet50 | Accuracy 96.23 |
| [7] | COVID-19(+) and Normal | COVIDX-NET | Accuracy 90 |
| [18] | COVID-19(+) and Normal | ResNet50 | Accuracy 98 |
| [19] | COVID-19(+) and Normal | Deep Anamoly Detection | Accuracy 96 |
| [20] | COVID-19(+) and Normal | DCNN (COVID-NET) | Accuracy 83.5 |
| [21] | COVID-19(+) and Normal | ResNet 50+SVM | Accuracy 95.38 |
| **Proposed Method** | **COVID-19(+) and Normal**<br>**COVID-19(+) Normal and Pneumonia** | **Alexnet** | **Accuracy :100, sensitivity:100 Specificity: 100**<br>**Accuracy :98.31, sensitivity:98.55 Specificity: 99.37** |

## V. CONCLUSION

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In this paper, Alexnet, Googlenet and Squeezenet have been modified to detect COVID -19 from chest x-ray images and evaluated using accuracy, sensitivity and specificity. The modified Alexnet resulted in the highest accuracy, sensitivity and specificity. The classification performance also show that our modified Alexnet model yielded higher accuracy, sensitivity and specificity than those reported in the literature for both binary classification and multiple classification. Few COVID-19 dataset are available as at the time of the implementation of the developed models. Acquiring more dataset for training the CNN models in future could improve the performance of the developed models. The Detection of COVID-19 images obtained from other imaging modalities such as Computed Tomography (CT), Magnetic Resonance Imaging (MRI) may be considered in future. This research will help to improve detection of COVID-19 and thereby enhance medical decisions and COVID-19 treatment.

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Olatunde Michael ONI is a Professor of Radiation and Health Physics. He was born about 5 decades ago. He attended Ogun State University (Now Olabisi Onabanjo University), Ago-Iwoye, Nigeria, where he bagged B.Sc. (Hons) in 1992. He later bagged M.Sc. and Ph.D. from the University of Ibadan, Nigeria, respectively in 1995 and 2004. All his degrees are in Physics. Prof. Oni is a seasoned Administrator. He has served as the Acting Head of Department of Pure and Applied Physics, LAUTECH (2004 -2006), Director, Information and Communication Technology Centre, LAUTECH (2006-2010) Consultant on ICT matters to Lagos State University, Ojo Lagos (2011 – 2013) and Dean, Faculty of Pure and Applied Sciences, LAUTECH (2016 – 2018). Professor Oni is ubiquitously proficient, innovative and highly enterprising. He is skilled in scientific computation analysis, proficient in the use of MATLAB pand Python for data visualization, image processing and modelling with machine learning algorithms. Apart from being the Middle – East and Africa Region winner of the Google+ Social Media Marketing Challenge in 2015, Professor Oni recently led a team of scientists that Designed and constructed an automated walk-through disinfecting chamber, a 20 litre non-contact temperature controlled sanitiser Dispenser and a 20 litre basic automatic sanitiser dispenser The projects which are all approved and supported by LAUTECH, Ogbomoso, for preventing the spread of COVID-19 in tertiary institution in Nigeria. He has over forty publications in local and international scientific journals. Professor Olatunde Oni is a Member of Nigerian Institute of Physics (NIP) and International Union of Radio Science (URSI).

 