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DEEP LEARNING BASED METHOD FOR THE ACTIVITY OF NOBEL CORONAVIRUS DISEASE PREDICTION FROM THE MEDICAL RADIOGRAPH CHEST X-RAY IMAGES

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ABSTRACT

Nearly 2 years ago, a new virus called Severe Acute Respiratory Syndrome CoronaVirus 2 (SARS-CoV-2) which is often referred to as Covid-19 was declared to be a pandemic by “World Health Organization” (WHO). The virus is among the most deadly virus diseases in the world, which has a high percentage of mortality and widespread rates. The standard procedure used for diagnosing suspected Coronavirus patients is through the use of kits called Real-time Reverse Transcriptase-Polymerase Chain Reaction (RT-PCR) kits that are usually available in small scale quantities and in addition to their high demand to spend a significant amount of time in the laboratory in the process of determining whether the suspected patients are Coronavirus positive or negative, which might result in increasing the chances to spread the virus. Radiologists discovered the presence of changes in radiograph Chest X-Ray medical images and Computer Tomography images whose ability is to detect the presence of the Coronavirus disease with higher sensitivity than using the RT-PCR, where the X-Ray images happened to be the most affordable among the duo. Therefore, there is a need to provide a kind of rapid diagnostic alternative that can be used to detect the presence of Coronavirus, “Covid-19”, that will control its spreading. Several radiological Chest X-Ray radiograph images have been used to propose a model that is capable of diagnosing Covid-19 patients through applying Convolutional neural networks (CNN). Two fine-tuned pre-trained models are compared to determine the model with the best performance. The experimental results show that the model using fine_tuned pre-trained VGG16 has achieved 92.50% of classification accuracy with 93.89% of sensitivity, 91.11% of specificity, 91.35% of precision, and 92.60% of F1_Score; while the results of the proposed model using fine-tuned pre-trained MobileNet has achieved 98.82% of classification accuracy with 100% of sensitivity, 97.64% of Specificity, 97.69% of Precision, and 98.83% of F1-Score. This revealed that MobileNet outperformed the VGG16 in the classification of the Chest X-Ray radiograph images for Coronavirus detection. It further indicates that even without applying many pre-processing techniques as did in creating existing models, our proposed model can perform better than many of them. This system can also be used in a situation where experts and clinical test kits are insufficient. The proposed model can also be used to fast track the time required to detect the Coronavirus disease by applying Chest X-Ray radiograph images of the suspected patients.

Keywords: *CNN, Covid-19, Fine_tuned, MobileNet, VGG16*

1. INTRODUCTION

Covid-19 popularly known as coronavirus is a virus that started in the month of December 2019 in the province of Chinese [1], [2]. The cause of the disease is due to a SARS-Cov-2, an acronym for “Severe Acute Respiratory Syndrome Coronavirus-2”, which can have more complications in patients with other comorbidities [3]. As of 25th June 2021, it was recorded to have been 179,686,071 numbers of confirmed cases of the Coronavirus, comprising 3,899,172 cases of the death, while as of 24th June 2021, the total number of 2,624,733,776 Covid-19 vaccine doses has been administered globally [4]. This coronavirus disease pandemic is still spreading to many countries throughout the four continents of this world despite initial development of vaccines that are now available but in limited quantities which is alarming to the global health sector since the only limited number of the world population are the ones that have secured the vaccines, and the major symptoms of the coronavirus happened to be sore throat, difficulty in breath, headache, cough, muscles pain, fatigue, headache, and fever [5], [6]. Research shows that this virus has no cure currently available [7], and the best method of preventing the outbreak of this deadly disease is by isolating any person that exhibits coronavirus symptoms by quarantining him at home [8]. Another research indicated that the novel coronavirus pandemic has a mortality rate of 2% [3]. The use of Real-time Reverse Transcriptase-Polymerase Chain Reaction termed as an “RRT-PCR” kit is considered to be a standard procedure for the detection and diagnosis of coronavirus from the patients. This procedure usually takes a very long time to obtain the result of diagnosis which may result in further spread of the disease [9], and moreover, the research also shows that this procedure is associated with low sensitivity of between 60% - 70% [10].

Various research have been conducted by many researchers to apply different type of artificial intelligence techniques to human X-ray images, CT scan images, etc. in trying to solve different disease classification problems in the concept of the healthcare system unit. The use of the X-Ray radiographs are the cheapest type of chest radiograph images as compared to any other kind of chest radiography [11], and it was also considered to be one of the most popular and commonly used clinical chest radiographs for the diagnosis of Pneumonia disease [12], [13]. However, it is difficult, error-prone, and time-consuming to detect the presence of coronavirus cases manually from the radiograph X-Rays even among the few available numbers of expert radiologists. Consequently, it has been reported that a deep learning technique serves as a complex tool that can be used for learning complicated and intellectual or cognitive problems [14], [15]. In our proposed study, we employed the use of the Deep learning concept through applying convolutional neural networks that can use the images of human X-Ray to detect the Coronavirus cases automatically.

The proposed deep learning of the CNN method was developed based on the above in order to conduct a binary class classification as either the case is a Coronavirus case or a Normal case. A total number of 13,808 X-Ray images comprising Covid 19 and Normal X-ray images have been retrieved from the largest Covid_19 online public database repositories that are updating constantly, out of which a sum of 7,200 X-Ray images was randomly selected and used in this research in order to have balanced datasets. The proposed approach has two distinct stages: The first stage involves pre-processing the medical radiograph images and the process of data selection; while the second stage involves using two (2) pre-trained models of CNN model comprising VGG16 as well as MobileNet, and applying the fine-tuning concept in designing the proposed approach, which was later compared in order to determine the best among the duo models.

The major contributions of our proposed technique include:

1. The activity of classifying COVID_19 and normal X-Ray through applying a deep learning of the CNN.
2. Providing an automatic, rapid, low cost, as well as diagnosis of the Coronavirus patients from the medical radiograph images.
3. Making comparisons between the results of our proposed approach and that of the existing system.

The summary of the remaining components of this paper manuscript is outlined as follows, section two (2) discusses about some of the related existing literature, section three (3) discusses the methodology that has been used in the research, section four (4) of this study describes the results that were obtained from experiments, and finally, section five (5) concludes the study.

2. RELATED EXISTING LITERATURES

Various studies have been conducted by many authors worldwide in order to create a Covid-19 model that can be used to determine whether suspected patients are covid-19 positive or not, and sometimes they can be used to determine the presence of diseases that are related to the lung like viral pneumonia, bacterial pneumonia, and many other diseases through the use of medical Chest X-Ray or Computer Tomography images so as to avoid the further outbreak of Coronavirus pandemic [12], [13]. It also helps reduce the cost and time taken by radiologists and other medical practitioners to detect and determine the presence of Coronavirus with the help of RRT-PCR kits.

In a similar study, Alhudhaif et al [16] proposed to use the concept of CNN to classify the Coronavirus cases from medical radiograph X-ray views. A dataset that contained 1218 medical X-ray radiograph images comprising of 368 Coronavirus images and 850 images for pneumonia was used to design the CNN model which was believed to be based on the concept of transfer learning through applying pre-trained architectures comprising DenseNet201, SqueezeNet and ResNet18. The authors considered using 90% of the dataset as a training dataset while 10% of the dataset have been used as a testing dataset of 5-fold cross-validation, while 20% out of the 90% training dataset was used to validate the model in order to prevent overfitting. 80 epochs were considered to train the proposed CNN model approach. The results indicate that the architecture developed on DenseNet-201 has performed better than the other architectures with a high classification recall, precision, F1-scores, and accuracy of 94.59%, 89.74%, 92.11% and 94.96%, respectively. The authors concluded that the proposed system is useful in minimizing the workload of the experts, the time taken for diagnosing the patients, and controlling the risk of spreading the pandemic.

Horry et al. [17] proposed to demonstrate how a pretrained deep learning method of the CNN be applied to detect a Coronavirus disease through the help of using chest X-Ray images. Five (5) common off-the-shelf pre-trained CNNs comprising VGG16, Resnet50, VGG19, Inception V3, and Xception were tested to determine the most effective CNN implementation from limited public COVID-19 X-Ray image samples that were available for use. The datasets are obtained from various multiple sources with inconsistent quality, and a pre-processing pipeline technique was implemented in order to reduce any unwanted noise like non-lung area on the X-Rays images, which helps in reducing of sampling bias impact based on this comparison. After the applying the pre-processing pipeline, only 400 images from two public image data were considered for the experiment; 200 of which contained images of normal X-Ray while another 100 contained images of Pneumonia radiograph chest X-Ray, where both have been extracted from the same NIH datasets, and the remaining 100 images containing Coronavirus X-Ray which have been extracted from Coronavirus image dataset. The performance of the five pretrained CNNs was compared and found that the results show the model's suitability for the available dataset, and it also indicates that the models possess simpler networks like that of VGG19 and it performs better with nearly 83% of precision.

In a similar study, Dhaya [18] proposed an automatic detection system that was claimed to be vital for preventing the spread of COVID-19. A sum of 100 images of medical X-Ray radiographs was applied to train and detect a Coronavirus from X-Ray radiograph images through applying three (3) pre-trained CNNs models which include ResNet50, Inception_ResNet_V2, and Inception_V 3. After conducting experiments, the performance accuracy of the three pretrained CNN models has been compared, and it found that the ResNet50 outperformed better than both the Inception-ResNetV2 and InceptionV3 with the highest performance accuracy of 98%. However, there are a lot of overfitting problems associated with the model as a result of using a limited number of datasets in designing the model.

Wang et al. [19] claimed that an intensive screening of those patients that have been infected with Covid-19 appeared to be the most effective step to avoid the spread of the Coronavirus pandemic, where a Chest radiography examination happens to be one of those key screening approaches. However, the need for radiological experts that can have the ability to interpret the radiograph X-Ray images happened to be among the major problems being faced in the radiography field, since the visual indicators can be difficult to analyze even for the experts. Therefore, the authors proposed to design a deep CNN COVID-Net designed for the activity of Coronavirus detection from COVIDx, and CXR images containing 13,975 images obtained from various open-source sources. These images comprise 358 Coronavirus cases, 8,066 normal person cases, and finally, 5,538 patient cases have no COVID19 pneumonia. The architecture of the proposed COVID-Net network make use of a heavy lightweight residual projection expansion projection extension pattern to produce the final features, which allows enhanced representational capacity while trying to maintain a reduced computational complexity. The results indicate that the proposed system architecture achieved the sensitivity and accuracy of 91% and 93.3% respectively. The performance of the Covid-net architecture has been compared to that of both VGG-19 and ResNet50 architectures that have been referenced in the literature and it found that the COVID-NET architecture had achieved the highest sensitivity and accuracy.

In another study, a model has been proposed by Kamel et al. [20] to help radiologists in diagnosing a Covid-19 patient through chest radiograph images, which assists in saving efforts and time. For the experimental purpose, 591 CT image Dataset were obtained from two sources, comprising 206 COVID19 CT images retrieved from the Italian Society of Medical Radiology (ISMR) for Coronavirus CT scan, and 385 Normal CT scan images were retrieved from VIAG, an acronym for Vision and Image Analysis Group. Some pre-processing techniques were applied in three different stages. It started by converting the CT images into the binary scale using an algorithm called, global threshold. Then it applied a particular algorithm called median filter for the purpose of noise removal. In the end, it included only the region of Interest (ROI), while the rest of the images have been discarded. Conclusively, VGGNet 19 which happened to be a popular architecture of CNN previously trained on ImageNet has been used for the purpose of feature extraction from already pre-processed CT images. The results indicated that this system has achieved 98.31%, 98.19%, 100%, along with 98.64% of classification accuracy, precision, recall, and F1-score, respectively. It concluded that the proposed system achieved a high performance as compared to other existing CNNs architectures.

In the research of Das et al. [21], it has been claimed that even though many of the existing researchers proposed Coronavirus cases detection systems from the images of medical chest X_Ray radiographs, however, they were characterized by a low accuracy rate, and the difficulties associated with the overfitting problem increases for the model to learn based on the recent Covid-19 datasets. A transfer learning concept of the CNN model was proposed to solve the problem through the use of medical radiograph X_Ray images to detect the presence of coronavirus cases. Covid_19 Database consisting 219 images of positive Coronavirus patients, 1345 medical images of viral pneumonia patients, as well as 1341 images of Non-infection cases that have been obtained from Kaggle's public data website were used in this study. The model performs the image classification in three categories that include positive Coronavirus class, other Pneumonia infections class, and No-infection class cases. Three (3) different learning schemes comprising VGG-16, CNN along with ResNet-50 have been used independently for the model learning purposes. The performance result of three learning schemes was compared and it found that the VGG16 outperformed better than both the CNN and ResNet-50. The result achieved by the model with VGG-16 was 97.67% of accuracy, 96.59% of F1-score, and 96.65% of recall.

Considering these reviewed literatures, it is observed that the X-ray images can be used to accurately recognize and predict whether a given individual patient has been infected with Covid_19 or not by using deep Convolutional Neural Networks. Similarly important, it is also observed that most of the literatures have suffered from using relatively a limited number of X-Ray images for constructing their models. In contrary, in this study, we have employed the use of 3600 different Coronavirus medical X-Ray radiographs which are quite a huge number than the ones used in most of the aforementioned studies. Additionally, the best model developed in this study, MobileNet, happened to be one of the lightest models in term of size as when compared to most of the other Coronavirus models that have been designed, where here the model has a size of 17MB.

3. METHODOLOGY

The experiments on the model as shown in Figure 1 were conducted on a Jupiter notebook, which is a scientific notebook for python using Keras Neural Network API that is configured to use a TensorFlow as its backend engine. Each of the experiments involved the use of 30 epochs as well as the minimum number of 10 batch sizes for both the training and validation of our model. Additionally, 0.0001 was set to be our initial learning rate for binary classification for each of the epochs. The most popularly used activation function called Rectified Linear Units (commonly shorten as Relu) was used to be our activation function, because of its ability to return 0 whenever it receives a negative input. These activation functions of the neuron are what defines the type of outputs of that neuron given a set of inputs. An ADAM optimizer technique was selected and used in the experiments because it employed the best of AdaGrad and RMSProp techniques to yield an optimal technique that has the capability of handling noisy problems associated with sparse gradients. Two CNN models including VGG16 and MobileNet were chosen as our base models which were later compared to determine which configuration is the best among the two configurations. During the application of transfer learning process which improves the performance of a model and shorten the time required to train a model, we freeze certain numbers of layers while the rest are to be trained on the new dataset.

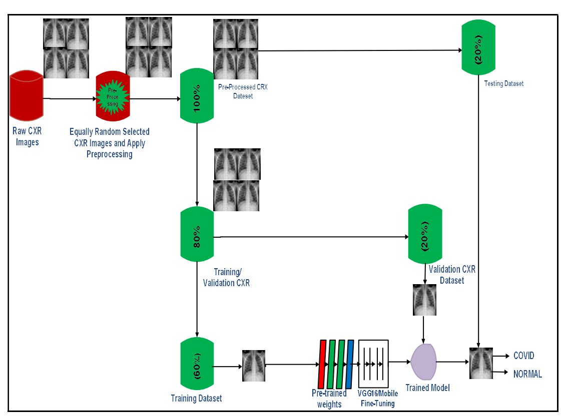

Figure 1: A Proposed Model Architecture

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Where for the MobileNet architecture of the CNN model that initially has a total of 3,230,915 parameters, a global_average_pooling2d _1 layer was added to the architecture in order to minimize an overfitting issue through minimizing the total available parameters that were present in the architecture of the model. Moreover, a dense layer with RELU activation functions and a dropout layer were added to the existing architecture of the model. We have randomly chosen to add the sum of a 30% dropout rate to avoid the overfitting problem. Finally, a single output dense layer containing two (2) output units for our binary classification, along with the activation function called a softmax, were also added in developing the proposed covid-19 prediction system. After the fine-tuning process, the architecture of the MobileNet model comprises 1,865,730 trainable parameters and 1,365,184 non-trainable parameters. On the other hand, the VGG16 architecture of the CNN model which initially has a 16-layers deep with a total of 134,268,738 parameters. It is a pre-trained network that has the capability of classifying images into about 1000 different categories. Consequently, it learned many representation features for a variety of images. And after the fine-tuning process has been applied, it comprises 8,194 trainable parameters and 134,260,544 non-trainable parameters.

Samples containing images of human X-Ray radiographs used in this study have been retrieved from a public online dataset source, called Kaggle [22], which contains data from various countries and various sources that the research communities are continuously updating them. This public data website hosts many other datasets including Covid_19 Radiography Database, which happens to be the largest Covid-19 positive public dataset that is currently available. This Covid_19 Radiography Database contains four (4) dataset folders namely Covid, Lung-Opacity, Normal as well Viral Pneumonia, where only the Covid_19 and Normal dataset folders have been considered and later been combined into a single dataset Folder. From these two folders (i.e., Covid and Normal) that we have considered for this study, we have randomly selected the same amount of Coronavirus images and Normal images in both the training and testing dataset images so as to have a balanced dataset that is desirable in designing better models. A sum of 7200 radiograph X-Ray images comprising 3600 X-Ray radiograph images of Coronavirus cases and another 3600 X-Ray radiograph of Normal cases have been randomly selected and used in designing this model. The breakdown summary of the dataset used in this study has been illustrated in Table 1 of this section. Figure 2 illustrates examples of typical radiograph X-Ray samples; where the first row is used to represent the examples of radiograph images of X-Ray for human Coronavirus patients, while the second row represent examples of the X-Ray radiograph images for Normal persons.

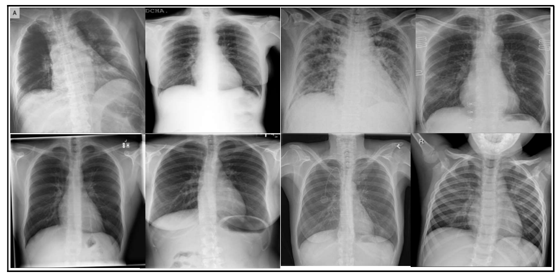

Figure 2: Typical Examples of Medical Radiograph of Human Chest X_Ray

Table 1: Dataset used in our Experiments

Class	Sum of X-Rays used for Model Training	Sum of X-Rays used for Model Testing	Sum of X-Rays used for Model Validation
Covid-19 [22]	2160	720	720
Normal [22]	2160	720	720
Total	4320	1440	1440

3.1 Experiment Strategy

Five (5) performance metrics have been used in the study for measuring the effectiveness of this system. Accuracy is happened to be the first performance metric that we have considered which is simply referred to as the type of performance metric whose aim is to measure the entire effectiveness of the system. The remaining four (4) other performance metrics that we have applied include sensitivity, specificity, precision, and F1_Score. Where specificity on the other hand is simply be defined as the ratio of the correctly predicted negative patients by our proposed model to all other patients who are actually non-Coronavirus patients. Sensitivity can simply be refer to as the ratio of the correctly positive patients predicted by our proposed model to all actual Covid-19 patients when considering the COVID_19 class. Precision is referred to as the ratio of the correctly predicted positive by our proposed model to all actual positive Covid_19 patients. F1_Score

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makes use of both precision and sensitivity. These five (5) performance metrics which include Accuracy, specificity, sensitivity, precision, as well as F1_Score can be computed by applying Eqs. (1) - (5), respectively.

Accuracy = ((TP+TN) / (TP+FP+TN+FN)) (1)
Specificity = (TN / (TN+FP)) (2)
Sensitivity = (TP / (TP + FN)) (3)
Precision = (TP / (TP + FP)) (4)
F1_Score = (2(Precision × Sensitivity) / (Precision + Sensitivity)) (5)

Where,
'TP' denotes that the outcome is the actual Covid_19 cases that the model classified as Covid_19 cases,
'TN' is use to represent the outcome is actually normal cases that the model classified as normal,
'FP' represents that the outcome is actually normal cases that the model classified as Covid_19 cases,
'FN' represents that outcome is actually Covid_19 cases that the model classified as a normal person.

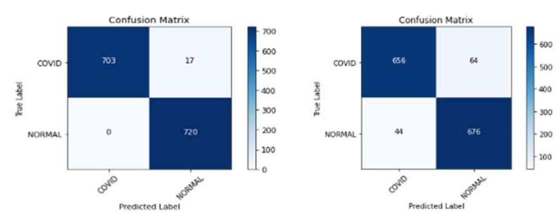
The overall performance metrics results of the two models are illustrated in Table 2.

Table 2: Overall Performance Metrics

Metrics	VGG16	MobileNet
Accuracy	92.500 %	98.82 %
Sensitivity	93.89 %	100 %
Specificity	91.11 %	97.64 %
Precision	91.35 %	97.69 %
F1_Score	92.60 %	98.82 %

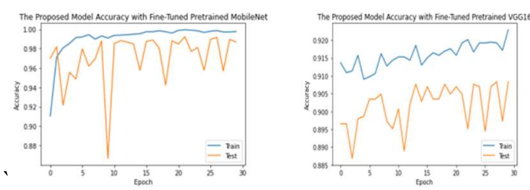
3.2 Results, Discussions and Evaluation

A Confusion matrix is simply an n by n matrix that provides us with a general overview of the performance of our models. Therefore, the 2 by 2 confusion matrix of the proposed MobileNet model as illustrated in Figure 3 (a) illustrates that the model was capable of predicting the Covid_19 patients 703 times while the patients are actually Covid_19 patients. This implies that our system has predicted 703 Covid_19 cases correctly. Similarly, the model predicted the Covid_19 patients 0 times, despite the fact that they are Normal. On the other hand, the model has predicted the Normal Patients 720 times despite the fact that they are Normal patients. Similarly, the model has predicted 17 Normal patients while there are actually 17 Covid_19 patients. The experimental result shows that our proposed MobileNet approach achieved a classification accuracy of 98.82%. This illustrates that the model can be applied in detecting Covid_19 cases.



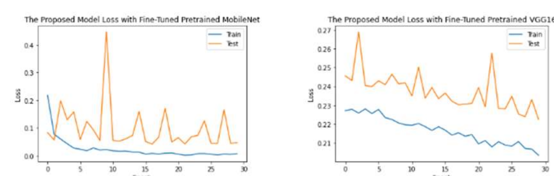
a- Fine-tuned with MobileNet *b- Fined-Tuned with VGG16*

Figure 3: Confusion Matrices



a - Fined Tuned with MobileNet *b - Fined-Tuned with VGG16*

Figure 4: Accuracy of the proposed MobileNet model Vs VGG16 Model



a - Fined Tuned with MobileNet *b - Fined-Tuned with VGG16*

Figure 5: Loss Function Graphs of MobileNet Vs VGG16 Model

Figure 3 (b) contains a confusion Matrix for the VGG16 model, which demonstrates that the model has correctly predicted the Covid-19 Patients 656 times while all the patients are actually Covid-19 patients. Similarly, the VGG16 model has predicted the Covid_19 patients 44 times, despite the fact that the patients are Normal. On the other hand, the VGG16 model has predicted the Normal

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patients 676 times despite the fact that they are Normal patients. Moreover, the VGG16 model has predicted the Normal patients 64 times despite the fact that the patients are actually Covid_19 patients.

With regard to the accuracy graph plots of the models displayed in Figure 4 (a) and Figure 4 (b), it can be observed that the MobileNet applied on our combined X-Ray dataset images shown in Figure 4 (a) outperformed better than when the VGG16 was applied on the combined X-Ray dataset images shown in Figure 4 (b) in terms of performance.

Figure 5 (a) and Figure 5 (b) show the comparison of our proposed MobileNet model and VGG16 model on our combined X-Ray radiograph Dataset. It is observed that the plots illustrate the true randomness and the spreading of model losses in regard to epochs that are present in both our training and testing dataset on COVID_19 as well as the Normal dataset, respectively, and the results are shown after 30 epochs in Figure 6 for the MobileNet while shown in Figure 7 for the VGG16. Moreover, it can be observed that the training accuracy and loss graphs fluctuate due to the fact that all neural networks used to be trained with different distinct forms of gradient descent variants like that of SGD, Adams, and many among others, which might result in having oscillations while descent.

```
Epoch 1/30
432/432 - 554s - loss: 0.2181 - accuracy: 0.9104 - val_loss: 0.0836 - val_accuracy: 0.970
Epoch 2/30
432/432 - 1147s - loss: 0.0780 - accuracy: 0.9715 - val_loss: 0.0575 - val_accuracy: 0.98
Epoch 3/30
432/432 - 324s - loss: 0.0603 - accuracy: 0.9808 - val_loss: 0.1979 - val_accuracy: 0.921
Epoch 4/30
432/432 - 330s - loss: 0.0437 - accuracy: 0.9854 - val_loss: 0.1302 - val_accuracy: 0.955
Epoch 5/30
432/432 - 329s - loss: 0.0281 - accuracy: 0.9914 - val_loss: 0.1582 - val_accuracy: 0.948
Epoch 6/30
432/432 - 414s - loss: 0.0238 - accuracy: 0.9921 - val_loss: 0.0587 - val_accuracy: 0.979
Epoch 7/30
432/432 - 481s - loss: 0.0184 - accuracy: 0.9944 - val_loss: 0.1242 - val_accuracy: 0.961
Epoch 8/30
432/432 - 480s - loss: 0.0285 - accuracy: 0.9898 - val_loss: 0.0939 - val_accuracy: 0.969
Epoch 9/30
432/432 - 488s - loss: 0.0209 - accuracy: 0.9931 - val_loss: 0.0556 - val_accuracy: 0.988
Epoch 10/30
432/432 - 499s - loss: 0.0224 - accuracy: 0.9910 - val_loss: 0.4467 - val_accuracy: 0.866
Epoch 11/30
432/432 - 499s - loss: 0.0181 - accuracy: 0.9937 - val_loss: 0.0556 - val_accuracy: 0.985
Epoch 12/30
432/432 - 498s - loss: 0.0167 - accuracy: 0.9940 - val_loss: 0.0531 - val_accuracy: 0.988
Epoch 13/30
432/432 - 499s - loss: 0.0172 - accuracy: 0.9944 - val_loss: 0.0616 - val_accuracy: 0.986
Epoch 14/30
432/432 - 499s - loss: 0.0138 - accuracy: 0.9949 - val_loss: 0.0734 - val_accuracy: 0.984
Epoch 15/30
432/432 - 513s - loss: 0.0131 - accuracy: 0.9954 - val_loss: 0.1596 - val_accuracy: 0.957
Epoch 16/30
432/432 - 503s - loss: 0.0066 - accuracy: 0.9975 - val_loss: 0.0516 - val_accuracy: 0.987
Epoch 17/30
432/432 - 482s - loss: 0.0088 - accuracy: 0.9975 - val_loss: 0.0423 - val_accuracy: 0.988
Epoch 18/30
432/432 - 483s - loss: 0.0067 - accuracy: 0.9984 - val_loss: 0.0673 - val_accuracy: 0.980
Epoch 19/30
432/432 - 481s - loss: 0.0095 - accuracy: 0.9975 - val_loss: 0.1711 - val_accuracy: 0.942
Epoch 20/30
432/432 - 481s - loss: 0.0103 - accuracy: 0.9961 - val_loss: 0.0498 - val_accuracy: 0.988
Epoch 21/30
432/432 - 502s - loss: 0.0060 - accuracy: 0.9988 - val_loss: 0.0655 - val_accuracy: 0.984
Epoch 22/30
432/432 - 500s - loss: 0.0023 - accuracy: 0.9995 - val_loss: 0.0427 - val_accuracy: 0.992
Epoch 23/30
432/432 - 499s - loss: 0.0033 - accuracy: 0.9991 - val_loss: 0.0687 - val_accuracy: 0.977
Epoch 24/30
432/432 - 499s - loss: 0.0080 - accuracy: 0.9984 - val_loss: 0.0740 - val_accuracy: 0.981
Epoch 25/30
432/432 - 499s - loss: 0.0083 - accuracy: 0.9968 - val_loss: 0.1265 - val_accuracy: 0.957
Epoch 26/30
432/432 - 500s - loss: 0.0057 - accuracy: 0.9979 - val_loss: 0.0452 - val_accuracy: 0.989
Epoch 27/30
432/432 - 501s - loss: 0.0034 - accuracy: 0.9986 - val_loss: 0.0445 - val_accuracy: 0.991
Epoch 28/30
432/432 - 497s - loss: 0.0063 - accuracy: 0.9972 - val_loss: 0.1662 - val_accuracy: 0.956
Epoch 29/30
432/432 - 501s - loss: 0.0053 - accuracy: 0.9972 - val_loss: 0.0453 - val_accuracy: 0.98
Epoch 30/30
432/432 - 500s - loss: 0.0078 - accuracy: 0.9977 - val_loss: 0.0473 - val_accuracy: 0.98
```

Figure 6: Results of MobileNet Model after 30 Epochs

```
Epoch 1/30
432/432 - 3335s - loss: 0.2271 - accuracy: 0.9137 - val_loss: 0.2456 - val_accuracy: 0.89
Epoch 2/30
432/432 - 3252s - loss: 0.2278 - accuracy: 0.9109 - val_loss: 0.2431 - val_accuracy: 0.89
Epoch 3/30
432/432 - 3328s - loss: 0.2258 - accuracy: 0.9113 - val_loss: 0.2689 - val_accuracy: 0.88
Epoch 4/30
432/432 - 3321s - loss: 0.2280 - accuracy: 0.9157 - val_loss: 0.2404 - val_accuracy: 0.89
Epoch 5/30
432/432 - 3313s - loss: 0.2256 - accuracy: 0.9090 - val_loss: 0.2400 - val_accuracy: 0.89
Epoch 6/30
432/432 - 3616s - loss: 0.2277 - accuracy: 0.9097 - val_loss: 0.2430 - val_accuracy: 0.90
Epoch 7/30
432/432 - 3236s - loss: 0.2234 - accuracy: 0.9106 - val_loss: 0.2409 - val_accuracy: 0.90
Epoch 8/30
432/432 - 3245s - loss: 0.2224 - accuracy: 0.9162 - val_loss: 0.2465 - val_accuracy: 0.90
Epoch 9/30
432/432 - 3401s - loss: 0.2205 - accuracy: 0.9127 - val_loss: 0.2414 - val_accuracy: 0.89
Epoch 10/30
432/432 - 3795s - loss: 0.2196 - accuracy: 0.9144 - val_loss: 0.2418 - val_accuracy: 0.89
Epoch 11/30
432/432 - 3098s - loss: 0.2194 - accuracy: 0.9153 - val_loss: 0.2350 - val_accuracy: 0.90
Epoch 12/30
432/432 - 3534s - loss: 0.2203 - accuracy: 0.9153 - val_loss: 0.2502 - val_accuracy: 0.88
Epoch 13/30
432/432 - 3371s - loss: 0.2186 - accuracy: 0.9144 - val_loss: 0.2338 - val_accuracy: 0.90
Epoch 14/30
432/432 - 3161s - loss: 0.2166 - accuracy: 0.9185 - val_loss: 0.2394 - val_accuracy: 0.90
Epoch 15/30
432/432 - 3184s - loss: 0.2186 - accuracy: 0.9130 - val_loss: 0.2334 - val_accuracy: 0.90
Epoch 16/30
432/432 - 3144s - loss: 0.2167 - accuracy: 0.9150 - val_loss: 0.2365 - val_accuracy: 0.90
Epoch 17/30
432/432 - 3205s - loss: 0.2141 - accuracy: 0.9164 - val_loss: 0.2321 - val_accuracy: 0.90
Epoch 18/30
432/432 - 3137s - loss: 0.2153 - accuracy: 0.9157 - val_loss: 0.2302 - val_accuracy: 0.90
Epoch 19/30
432/432 - 3135s - loss: 0.2135 - accuracy: 0.9169 - val_loss: 0.2306 - val_accuracy: 0.90
Epoch 20/30
432/432 - 3109s - loss: 0.2144 - accuracy: 0.9176 - val_loss: 0.2310 - val_accuracy: 0.90
Epoch 21/30
432/432 - 3134s - loss: 0.2094 - accuracy: 0.9157 - val_loss: 0.2393 - val_accuracy: 0.90
Epoch 22/30
432/432 - 3118s - loss: 0.2112 - accuracy: 0.9192 - val_loss: 0.2292 - val_accuracy: 0.90
Epoch 23/30
432/432 - 3384s - loss: 0.2078 - accuracy: 0.9201 - val_loss: 0.2576 - val_accuracy: 0.89
Epoch 24/30
432/432 - 5081s - loss: 0.2106 - accuracy: 0.9167 - val_loss: 0.2282 - val_accuracy: 0.90
Epoch 25/30
432/432 - 3231s - loss: 0.2088 - accuracy: 0.9192 - val_loss: 0.2281 - val_accuracy: 0.90
Epoch 26/30
432/432 - 3201s - loss: 0.2083 - accuracy: 0.9192 - val_loss: 0.2348 - val_accuracy: 0.89
Epoch 27/30
432/432 - 4824s - loss: 0.2107 - accuracy: 0.9194 - val_loss: 0.2253 - val_accuracy: 0.90
Epoch 28/30
432/432 - 3782s - loss: 0.2070 - accuracy: 0.9192 - val_loss: 0.2239 - val_accuracy: 0.90
Epoch 29/30
432/432 - 3250s - loss: 0.2066 - accuracy: 0.9171 - val_loss: 0.2330 - val_accuracy: 0.89
Epoch 30/30
432/432 - 3289s - loss: 0.2034 - accuracy: 0.9229 - val_loss: 0.2225 - val_accuracy: 0.90
```

Figure 7: Result of VGG16 Model after 30 Epochs

Transfer learning is a method that can be employed to help in improving the performance of model classification in addition to it is the reduction in time that is required to train the system.

The MobileNet model of the CNN model has appeared to provide higher classification accuracy as compared to the VGG16 model.

Albeit research shows that data augmentation could be applied in the event of having data scarcity to improve the accuracy and avoid the overfitting problem, we have not employed to use any of the data augmentation techniques since our Coronavirus dataset contained a large enough number of Coronavirus medical radiograph X-Ray image dataset than any of the Coronavirus medical radiograph X-Ray image datasets that have been applied in any of the referenced to in the literature.

Table 3: Comparison Between Our Proposed Approach And Some Of The Existing System

Technique Applied	Specificity (%)	Sensitivity (%)	Recall (%)	Precision (%)	F1-Score (%)	Accuracy (%)
MobileNetV2, Inception, Xception, & Inception ResNetV2 [23]	96.46	98.66	-	-	-	96.78
DenseNet-201, ResNet-18 & SqueezeNet [16]	-	-	94.59	89.74	92.11	94.96
VGGNet19 [19]	-	-	100	98.19	98.64	98.00
VGG-16 [20]	-	-	96.65	-	96.59	97.67
Our approach: MobileNet, VGG16	97.64	100	-	97.69	98.83	98.82

Table 3 of this section shows the performance comparisons between our proposed approach and that of the existing approaches. It is observed that our approach has obtained the highest accuracy of 98.82%, while the highest classification accuracy that has been achieved by the existing models is VGGNet19 [19]. This clearly indicated that our proposed classification approach had outperformed the existing systems based on classification accuracy. This might be as a result of the use of a large number of Covid-19 image dataset in addition to the use of the transfer learning concept.

4. CONCLUSION

The model which uses a pre-trained of the Convolutional Neural Network model that can be applied to detect a Coronavirus patient has been proposed, designed, and implemented using a number of radiological X-Ray radiograph images. Two fine-tuned pre-trained models were used in designing the proposed system, and their performance was compared to determine the model with the best performance. The experimental results indicated that the use of the fine_tuned pre-trained VGG16 entails 92.50% of classification accuracy with 93.89% of sensitivity, 91.11% of specificity, 91.35% of precision, and 92.60% of F1_Score; while the results of the proposed model using fine-tuned pre-trained MobileNet has achieved 98.82% of classification accuracy with 100% of sensitivity, 97.64% of Specificity, 97.69% of Precision, and 98.83% of F1-Score. This shows that our approach can be used to detect the Coronavirus from the medical radiograph X-Ray image dataset with higher classification accuracy than the results obtained from VGG16, as well as the results of most of the existing systems that has been referenced to in the literature.

The present study contributes to providing a rapid, low-cost, and a diagnosis of the Coronavirus disease from the medical radiograph image dataset automatically. Other IT researchers can consider our approach as a basis to develop a new method for coronavirus detection while considering different perspectives. However, this research has a lot of limitations like in many other researches. We have used only a dataset comprising Covid-19 and Normal radiograph X-Ray images, and incorporating other respiratory viral diseases can improve the specificity of the Convolutional Neural Network in predicting the Coronavirus cases. Additionally, we have not employed to use any data augmentation techniques as the datasets of the coronavirus images are available still in limited quantities, and employing this method might help improve the overall classification accuracy of the system. In a future study, a concept of reasoning will be explored to tell us precisely the number of days for which the patient got infected with the Covid-19 virus if found positive. Other concepts like an ensemble, a soft computing, and a hybrid method will also be explored.

5. DECLARATION

We declare no conflicts of interest.

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