I. Covid-19 Detection using Deep Learning Models

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***Abstract*— The outbreak of Corona disease, or the so-called Covid-19, has affected the course of human life. Detecting this disease early reduces the risk of spreading the disease. Thus, get rid of this epidemic sooner. In this paper, a system is created that helps to identify and detect Covid-19 disease through X-ray radiation. GoogLeNet, ResNet-101, Inception v3 network, and DAG3Net that are used for comparison purposes. Good results have been obtained in detecting Covid-19 disease, where the DAG3Net produces diagnostic (validation, training, testing and overall) accuracies of (96.15%, 94.34%, 96.75% and 96.58%) respectively, while the GoogLeNet, ResNet-101, and Inception v3 network are produced (98.08%, 100%, 99.59% and 99.72%) respectively.**

***Keywords*——: Corona, Covid-19, X-ray, GoogLeNet, ResNet-101, Inception v3, DAG3Net**

II. Introduction

At the present, the world is going through the Corona pandemic, which stopped the world in various fields [1]. Because the epidemic is spreading rapidly in narrow places, many places have been closed to prevent the spread of the epidemic.

The discovery of Corona disease in its early stages makes the disease's recovery rate higher, therefore many studies have been conducted regarding the discovery of the covid-19 disease[2], [3]. The deep learning model achieved high performance in disease diagnosis and detection [4],[7]. Deep learning models have achieved good results in recognition and discovery processes [7], [9].

During the diagnosis of Covid-19 disease. Many studies have researched the properties of radiography in aid in diagnosis and treatment [10],[12].

In this paper, the GoogLeNet model has 22 layers, ResNet-101 has 101 layers, the DAG3Net has three layers, and finally, the Inception net has 316 layers were used. These four models were compared in terms of time spent during training and the accuracy of diagnosing and detecting the Corona disease. The training was conducted on the Covid-19 dataset [13].

GoogLeNet, ResNet-101, and Inception net achieved equally and high detection and diagnosis of Covid-19.

In [14], a CNN was proposed in which FC-DenseNet103 and ResNet-18 were both worked on. The model is working to diagnose Covid-19 disease and good results have been obtained in the diagnostic process.

In [15], a deep learning strategy for diagnosing the covid-19 disease is proposed. The moderated strategy relies on diagnosing disease from CT images. The proposed model achieves high AUC, precision, and accuracy for the classification.

In [16], a 3D deep learning model (3D-ResNet-10) has been developed to diagnose covid-19. The model is based on the diagnosis of disease from CT images. AUC was used to evaluate the performance of the model, and its value was 0.909.

In the next section, the proposed models will be explained, where the structure for each model is explained, including the image dimensions required by the model in addition to the model layers. In the third section, the data set that was used in training these models is described in addition to the results obtained during this paper, where the results of the four proposed models are compared to make the diagnosis of Covid-19 disease, or the so-called Corona.

III. Utilized Models

In this section, four models are proposed to detect the emerging disease Covid-19 from chest X-ray images. As the early diagnosis of the disease greatly contributes to treating this disease and preventing its spread. Below is a description of the architecture of each model:

A. DAG3Net

This Model is a CNN that is four layers deep. The network has an image input size of 224-by-224. The structure of the DAG3Net model is shown in Fig.1.

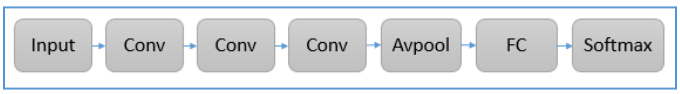


Fig. 1. The architecture of the DAG3Net model

In this paper, the DAG3Net model was trained in which the X-ray images were standardized within a certain size and dimensions to make the classification levels equal between the two categories (Covid-19 and Non-Covid-19) and to meet the requirements of the classification model. The fully connected layer ranks in two categories. The parameters during the model training process are the batch size of 10 and the initial learning rate of 0.0001. Stochastic Gradient

Descent with momentum was also used to improve the model's performance during the training process.

B. GoogLeNet

GoogLeNet model is a convolutional neural network, and also called Inception V1 [17]. It was named GoogLeNet after the team that presented it in the ILSVRC14 competition, where this model won the ILSVRC 2014 image classification challenge. It achieved a much lower error rate than the ZF-Net, VGG, and AlexNet models [17].

All convolutional layers contain the ReLU activation function. This model requires converting the dimensions of the input images to 224x224x3 and it contains 22 layers. This model is based on making average pooling after fully connected layers as it is found that the accuracy of the model increases by 0.6% [17].

Inception modules are models that allow the network to choose between several sizes of convolutional filters within each block. Then it stackes these models one on top of the other followed by max-pooling layers with stride 2 [17].

In this paper, the GoogLeNet model was trained in which the X-ray images were standardized within a certain size and dimension to make the classification levels equal between the two categories (Covid-19 and Non-Covid-19) and also to meet the requirements of the classification model. Then the last fully connected layer was deleted and replaced with another. The new fully connected layer ranks two categories where the learning rate factor was for bias and weight is 10. The parameters during the model training process are the batch size of 10 and the initial learning rate of 0.0001. Stochastic Gradient Descent with momentum was also used to improve the model's performance during the training process.

C. ResNet-101

This Model is a CNN that is 101 layers deep. The pertained network on more than a million images from the ImageNet database [18] can classify images into 1000 object categories, such as a keyboard, mouse, pencil, and many animals. As a result, the network has learned rich feature representations for a wide range of images. The network has an image input size of 224-by-224 [19]. The structure of the ResNet-101 model is shown in Fig.2.

In this paper, the ResNet-101 model was trained in which the X-ray images were standardized within a certain size and dimension to make the classification levels equal between the two categories (Covid-19 and Non-Covid-19) and also to meet the requirements of the classification model. Then the last fully connected layer was deleted and replaced with another. The new fully connected layer ranks two categories where the learning rate factor was for bias and weight is 10. The parameters during the model training process are the batch size is 10 and the initial learning rate is 0.0001. Stochastic Gradient Descent with momentum was also used to improve the model's performance during the training process.

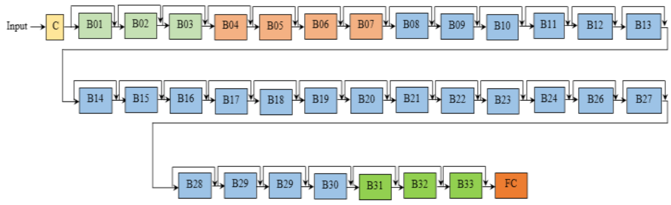


Fig. 2. The structure of ResNet-101 [20]

D. Inception V3

This Model is a CNN from the Inception family. It makes multiple improvements as it uses 7 x 7 Convolutions and Label Smoothing. It also uses an additional classifier for spreading label information down the grid [21]. The architecture of the Inception V3 model is shown in Fig.3. It is used on the coarsest (8 × 8) grids to promote high-dimensional representations.

In this paper, the Inception V3 model was trained in which the X-ray images were standardized within a certain size and dimension to make the classification levels equal between the two categories (Covid-19 and Non-Covid-19) and also to meet the requirements of the classification model. Then the last fully connected layer was deleted and replaced with another. The new fully connected layer ranks two categories where the learning rate factor was for bias and weight is 10. The parameters during the model training process are the batch size of 10 and the initial learning rate of 0.0001. Stochastic Gradient Descent with momentum was also used to improve the model's performance during the training process.

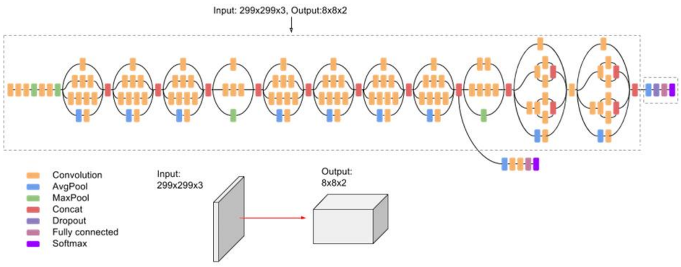


Fig. 3. The architecture of the Inception V3 model [21]

IV. EXPERIMENTAL RESULTS AND DISCUSSION

In this paper, covid-19 was diagnosed and detected using chest X-ray images with data set from [13] that includes two groups of Covid-19 and Non-Covid-19. Where 351 images were used (167 in a Covid-19 group and 184 in a Non-Covid-19 group). Four deep learning models were trained using this dataset. The first model is the DAG4Net which produces a diagnostic accuracy of 96.58% during a training time of 7 min and 43 sec and as shown in Table I. Fig.4 shows the curves of validation set and loss during the training process.

TABLE I. DIAGNOSTIC ACCURACY EXTRACTED THROUGH THE DAG3NET MODEL

Accuracy of the validation set	**Accuracy of the testing set**	**Accuracy of overall data**	**Accuracy of the training set**
96.15%	94.34%	96.58%	96.75%

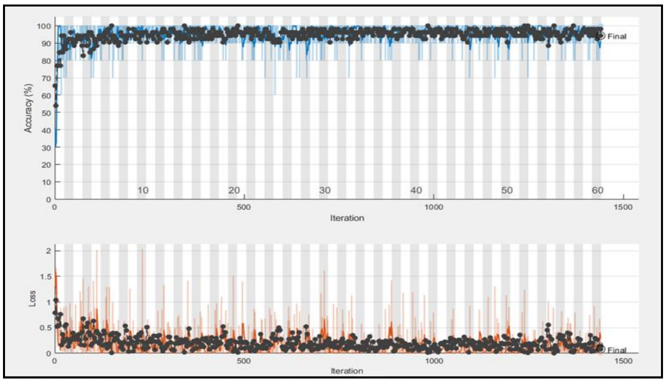


Fig.4. Curves of validation set and loss during the training DAG3Net model.

The second model is the ResNet-101 which produces a diagnostic accuracy of 99.72% during a training time of 7 min and 43 sec as shown in Table I. Fig.4 shows the curves of validation set and loss during the training process.

TABLE II. DIAGNOSTIC ACCURACY EXTRACTED THROUGH THE RESNET-101 MODEL

Accuracy of the validation set	**Accuracy of the testing set**	**Accuracy of overall data**	**Accuracy of the training set**
98.08%	100%	99.72%	99.59%

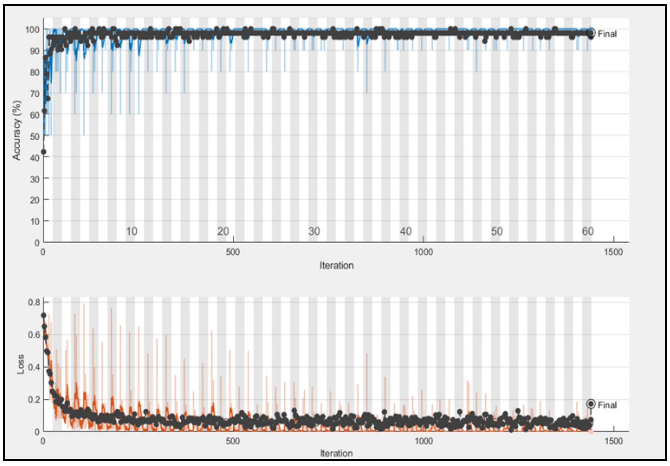


Fig. 5. Curves of validation set and loss during the training ResNet-101 model.

The third model is the Inception v3 that achieved a diagnostic accuracy of 99.72% during a training time of 85 min and 3 sec and as shown in Table III. Fig.6 shows the curves of validation set and loss during the training process.

TABLE III. DIAGNOSTIC ACCURACY EXTRACTED THROUGH THE INCEPTION V3 MODEL

Accuracy of the validation set	**Accuracy of the testing set**	**Accuracy of overall data**	**Accuracy of the training set**
98.08%	100%	99.72%	99.59%

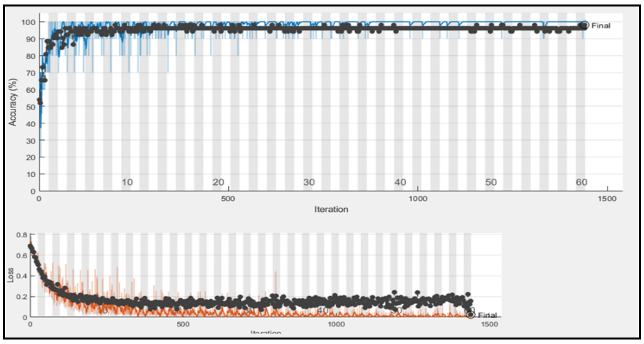


Fig. 6. Curves of validation set and loss during the training Inception v3 model.

The last model is the GoogLeNet, it introduces a diagnostic accuracy of 99.72% during a training time of 11 min and 2 sec and as shown in Table IV. Fig.7 shows the curves of validation set and loss during the training process.

TABLE IV. DIAGNOSTIC ACCURACY EXTRACTED THROUGH THE GOOGLENET MODEL

Accuracy of the validation set	**Accuracy of the testing set**	**Accuracy of overall data**	**Accuracy of the training set**
98.08%	100%	99.72%	99.59%

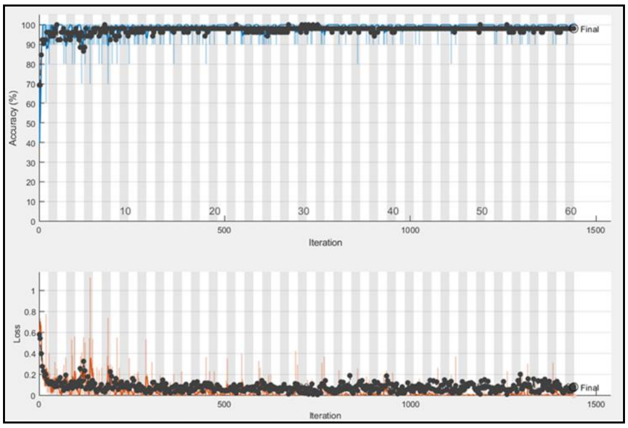
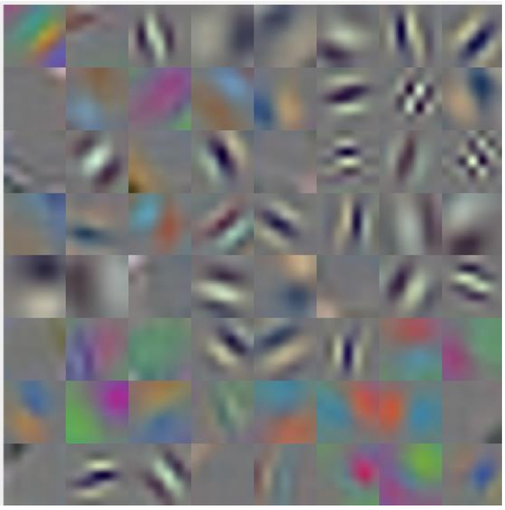
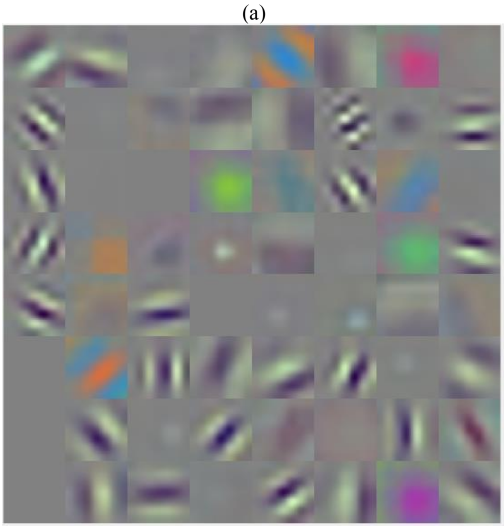


Fig. 7. Curves of validation set and loss during the training GoogLeNet model.

During the process of training the models on the training data, the result of the first convolutional layer was shown in Fig.8.



(a)



(b)

Fig. 8. First convolutional layer weights during training: (a) GoogLeNet and (b) ResNet-101 model

The results obtained from the training of the last three models of deep learning (ResNet-101, Inception v3, and GoogLeNet), which were very close or equal in terms of diagnostic accuracy, but that each model took a different time during the training process, as the ResNet-101 model got the highest training time of 135 min and 48 sec. While the GoogLeNet model got the least time Training amount 11 min and 2 sec. Therefore, according to the results obtained and taking the time to train the models into consideration, a GoogLeNet model is the best for diagnosing Covid-19 disease.

The presented models have different performances in terms of training (learning) and classification and they can be summarized in Table V.

Table V. COMPARISON BETWEEN THE PRESENTED MODELS

Models	**Training**	**Classification**
GoogLeNet	99.59%	99.72%
ResNet-101	99.59%	99.72%
Inception V3	99.59%	99.72%
DAG3NET	96.75%	96.58%

Our GoogLeNet model was compared with three recent references as shown in Table VI where our GoogLeNet model achieved heigher diagnostic accuracy compared to these researches.

TABLE VI. COMPARISON BETWEEN OUR GOOGLENET AND OTHER MODELS

Models	**Accuracy**	**Dataset**	
		Covid-19	Non-Covid-19
Our GoogLeNet	99.72%	167	184
[14]	88.9%	180	8851
[15]	89.2%	150	150
[16]	89.6%	199	122

V. CONCLUSIONS

In this paper, deep learning technology was used to detect the emerging disease Covid-19 via chest X-ray, four models were used for comparison. The models showed good performance in the diagnostic process, as the DAG3Net model achieved a diagnostic accuracy of 96.58% with a training time of 7 min and 43 Sec. The second GoogLeNet model achieved a diagnostic accuracy of 99.72% with a training time of 11 min and 2 sec, and the third ResNet-101 model achieved a diagnostic accuracy of 99.72% with a training time of 135 min and 48 sec. Finally, the fourth Inception model achieved a diagnostic accuracy of 99.72% with a training time of 86 min and 3 sec. Each of the GoogLeNet, ResNet-101, and Inception models achieved equal diagnostic accuracy, but the GoogLeNet model achieved high accuracy with less training time as a result of the fewer layers, this model was adopted to diagnose Covid-19 disease.

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