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Research Article

Analysis of Deep Transfer Learning Methods for Early Diagnosis of the Covid-19 Disease with Chest X-ray Images

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ABSTRACT

This study aimed to present an analysis of deep transfer learning models to support the early diagnosis of Covid-19 disease using X-ray images. For this purpose, the deep transfer learning models VGG-16, VGG-19, Inception V3 and Xception, which were successful in the ImageNet competition, were used to detect Covid-19 disease. Also, 280 chest x-ray images were used for the training data, and 140 chest x-ray images were used for the test data. As a result of the statistical analysis, the most successful model was Inception V3 (%92), the next successful model was Xception (%91), and the VGG-16 and VGG-19 models gave the same result (%88). The proposed deep learning model offers significant advantages in diagnosing covid-19 disease issues such as test costs, test accuracy rate, staff workload, and waiting time for test results.

Keywords: Biomedical informatics, Deep learning, Covid-19 diagnosis, Image classification

Göğüs Röntgeni Görüntüleri ile Covid-19 Hastalığının Erken Teşisine Yönelik Derin Transfer Öğrenme Yöntemlerinin Analizi

ÖZ

Bu çalışmada, X-ray görüntüleri kullanılarak Covid-19 hastalığının erken teşhisini belirlemek için derin transfer öğrenme modellerinin analizinin sunulması amaçlanmıştır. Bu amaçla ImageNet yarışmasında başarılı olan VGG-16, VGG-19, Inception V3 ve Xception derin transfer öğrenme modelleri Covid-19 hastalığının tespiti için kullanılmıştır. Ayrıca eğitim verileri için 280 göğüs röntgeni görüntüsü ve test verileri için 140 göğüs röntgeni görüntüsü kullanılmıştır. İstatistiksel analiz sonucunda en başarılı modelin Inception V3 (%92), sonraki başarılı modelin Xception (%91) olduğu ve VGG-16 ve VGG-19 modellerinin de aynı sonucu verdiği görülmüştür (%88). Covid-19 hastalığı teşhisi için önerilen derin öğrenme modelleri, test maliyetleri, test doğruluk oranı, personel iş yükü ve test sonuçları bekleme süresi gibi covid-19 hastalığı sorunlarının teşhisinde önemli avantajlar sunmaktadır.

Anahtar Kelimeler: Biyomedikal bilişim, Derin öğrenme, Covid-19 teşhisi, Görüntü sınıflandırma

I. INTRODUCTION

One of the biggest global public health problems in humanity's history is Covid-19. In December 2019, many patients were admitted to hospitals with pre-diagnosed pneumonia of unknown origin in Wuhan, China. Covid-19 is one of humanity's most significant worldwide public health issues. The difference between this virus from other coronaviruses is that it can be disseminated and spread from person to person and infection factors are very high. In February 2020, World Health Organization (WHO) reported that a new type of coronavirus caused the disease and named this disease "2019 coronavirus disease"/Covid-19 [1]. Globally, as of 28 July 2021, there have been 194.608.040 confirmed cases of Covid-19, including 4.170.155 deaths, reported to WHO. Although the symptoms vary from person to person, in general, Fever (not all), cough, sore throat, fatigue, headache, myalgia, and breathlessness are common clinical characteristics [2].

MERS-CoV and SARS-CoV are expressed as types of other coronaviruses. The diagnosis for MERS-CoV and SARS-CoV included X-ray chest images and CT scans [3]. CT scan is an advanced x-ray machine that gives a clearer image of internal tissue and organs [4]. However, X-ray use is quicker, faster, more cost-effective, and less hazardous than CT. Therefore, it is appropriate to use X-Ray images in the diagnosis of Covid-19. Death and transmission can increase if Covid-19 pneumonia is not diagnosed and treated early [5]. Considering the economic, social, and public health effects of COVID-19, the pandemic should be prevented, and early diagnosis is vital in this regard.

The real-time polymerase chain reaction technique used to detect the Covid-19 virus is the most basic and standard method around the world [5]. PCR test is costly and gives results in 6-9 hours. Also, since it has less sensitivity, it has a high false-negative rate. Therefore, since the patients who are infected but not diagnosed cannot be identified, the transmission rate of the disease increases. However, the workload that falls on radiologists during the diagnosis of COVID-19 is generally high and moderate [6]. Therefore, to assist and enhance the efficiency of the radiologist, further technology-supported investigations are required. Furthermore, patient congestion and the heavy workloads of radiologists, which can increase exhaustion, affect diagnostic results [7].

Carulla et al. stated that due to the rapid increase in Covid-19 cases, the health ecosystem is insufficient for rapid response and effective treatment. This gap will be overcome with digital technologies [8]. In this study, X-Ray images are used for Covid-19 detection due to advantages such as Accessibility, Common Usage, Portability, and Rapid triage. Due to the reasons given above, images obtained from X-Ray devices are widely used to detect Covid-19 disease. For this reason, it is crucial to increase the accuracy of the diagnoses to be made by this method. Covid-19 CT images include indicators such as Ground-glass opacity (GGO), consolidation and crazy-paving pattern [9]. In the literature, crucial criteria and signs indicating COVID-19 disease from the images of X-ray devices are presented in Figure-1.

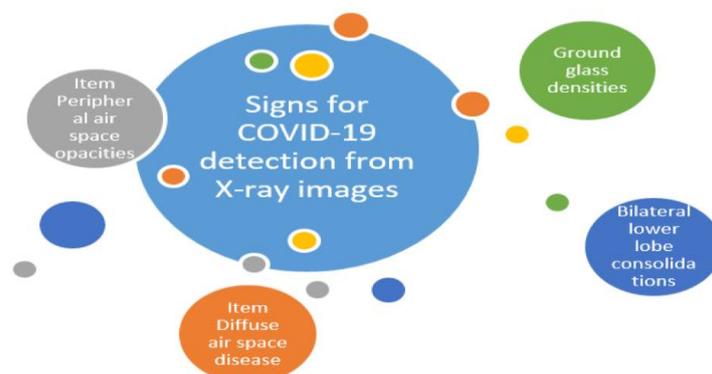


Figure 1. General Signs of Covid-19

Below in Figure 2 is a chest X-ray image of a 56-year-old patient who presented to the emergency room in Toronto, Canada, containing the above (Figure-1) signs.



Figure 2. Covid-19 Patient Chest x-ray image [10]

Health systems' resources are typically limited and thus require technological improved precaution and policies that ensure optimal use of beds and cost of use [11]. Accordingly, the rapid spread of the pandemic has led researchers to develop fast and reliable computer or software aided methods [12]. Since the examination of chest X-ray images by radiologists takes time, it can be done with deep learning-based approaches that can speed up the analysis time [12]. The Artificial Intelligence academic area aims to pair grasp and construct intelligent assets and comprises both Machine Learning (ML) and its Deep Learning (DL) subfield [13]. DL is performed in a Deep Neural Network by algorithms architecturally constructed of artificial neurons and several data processing layers [14]. In the field of medical imaging, DL models held the best results in classifying and identifying objects. A few artificial intelligence systems focused on deep learning have been proposed for public health, especially convolutionary neural networks. The findings were very encouraging in terms of effectiveness in identifying COVID-19 contaminated clinicians using chest X-ray images [9,15].

Examining the studies conducted to diagnose COVID-19 disease, the patient's chest CT and X-ray images were used as a dataset, and generally, deep learning methods were used. Pathak et al. Used a deep transfer learning technique (ResNet-50) to classify patients diagnosed with COVID-19 using chest CT images in the research. They stated that the method suggested efficient results relative to other supervised learning models [16]. Brunese et al. used the VGG-16 deep learning model in their research to provide a completely automated and quick diagnostic when detecting COVID-19. They published their research from numerous institutions on 6,523 chest X-rays. The detection time for COVID-19 was found to be nearly 2.5 seconds and the accuracy rate to be 0.97 with the solution they suggested [17]. Ozturk et al., a model is proposed using the DarkNet-19 model-based real-time object classification system (YOLO) using raw chest X-ray images. In the study, 17 convolutional layers were applied to detect COVID-19, and different filtering was applied to each layer. The suggested approach was provided accurate tests for dual determination (COVID and No Evidence) and multi-class classification (No Evidence with COVID and Pneumonia) [5].

Panwar et al. obtained an accuracy rate of 97.62% for diagnosing the disease from the chest X-ray images of the patients with their CNN-based method, which they called nCOVnet [18]. Alakus and Turkoglu [19], Laboratory findings (Hematocrit, haemoglobin, platelets, etc.) from 600 patients were analyzed by deep learning methods, and an alternative COVID-19 prediction study was conducted to X-ray and CT images. In the study of [20], disease detection accuracy rates were compared with ResNet18, ResNet50, SqueezeNet, and DenseNet-121 deep learning models using a dataset consisting of chest X-ray images of COVID-19 patients. Khan et al. indicated that on their dataset, CoroNet was trained and evaluated. The experimental findings reveal that the suggested framework obtained an accuracy rate of 89.6 per cent. More specifically, 93 per cent and 98.2 per cent for 4-class cases are the accuracy and recall rate for COVID-19 cases (COVID vs Pneumonia bacterial vs pneumonia viral vs normal). The suggested model provided a categorization accuracy of 95 per cent for three-class grouping (COVID / Pneumonia / normal) [21].

When the studies in the literature are analyzed, the diagnosis of Covid-19 disease is usually made using a single CNN model or approach. Also, since the deep transfer learning method is not used in the studies, the number of data sets used and the time spent for training is higher. Therefore, the top four best performing CNN deep learning models that have proved themselves have been developed. Fine-tuning has been performed to provide comparative results to find Covid-19 disease with fast and high accuracy in our research. For this purpose, the accuracy rates for the detection of Covid-19 disease were determined by developed with fine-tuning VGG-16, VGG-19, Inception V3, and Xception from the deep learning models that were successful in the ImageNet competition. Also, this research used relatively fewer images for training compared to other studies in the literature, but despite this, successful results were obtained.

In this study, this analysis adjusted four separate pre-trained deep transfer learning models (VGG16, VGG19, InceptionV3, Xception) with fine-tuning. Using effective transfer learning and fine-tuning techniques, they retrained on publicly accessible 420 x-ray images with two classes (Covid-19, Normal). This paper proposes that deep learning be implemented such that it is possible to detect whether COVID-19 is present in X-ray images via transfer learning. This may be a suggestion or help to the radiologists that the X-ray areas of concern are localizing immediately.

This study is organized as follows: Section 2 information about the data set, deep learning models used, fine-tuning processes, and technical procedures are presented. Suggested Models and their processes are discussed in section 3. Experimental analysis and results are given in section 4. Finally, concluding comments and recommendations are presented in section 5.

II. METHODOLOGY AND TECHNICAL BACKGROUNDS

A. DATASET

The dataset features and source used in our research are as follows. The database, including chest X-ray images, consists of 2 classes labelled COVID-19 and Normal. 210 images of the COVID-19 labelled class were taken from the public repository shared by Dr Joseph Cohen [22]. 210 images belonging to the standard labelled class were taken from the Kaggle database, which is also available to the public [23]. 280 images are reserved for training and 140 images for testing. In Figure 3, representative chest X-ray images of normal (healthy) COVID-19 patients are given, respectively.

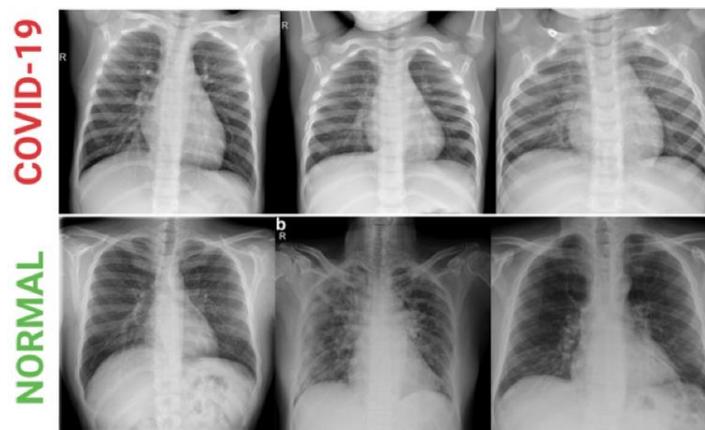


Figure 3. Example of X-ray images dataset of first-line Normal, second-line COVID-19 patients

B. DEEP LEARNING

Deep Learning (DL), which is the most common application area of Artificial Intelligence (AI) and known as one of its sub-branches, is vital with the opportunities it offers [24], [25]. Classical machine learning methods had some drawbacks, primarily being based on handmade features, restricting itself to the accuracy of the human level. However, handmade feature engineering is not mandatory in the case of DL, but features are extracted from the data during training instead [26]. Furthermore, with the innovative algorithms, the computational power of modern computers, and the availability of Big Data Clusters, DL can make more precise classifications and predictions. Based on Artificial Neural Networks (ANN), DL is examined under the concept of AI as a learning algorithm according to some sources and as a learning model according to others. There are various DL algorithms such as; CNN, Long Short Term Memory (LSTM), Recurrent Neural Networks (RNN), GAN, etc. After the success of a CNN-based model called AlexNet, many DL models are used, especially for computer vision tasks such as ZFNet, VGGNet, GoogLeNet, ResNet, DenseNet, etc. thrived [26]. The literature makes it possible to examine the similarities and differences of deep learning and artificial neural networks under three main headings: definition, structure, and architecture [27]. Neural Networks; It is a construct of Machine Learning (ML) algorithms in which artificial neurons form the core computational unit focused on uncovering key patterns or connections in a dataset, just as the human brain does when making decisions. Deep Learning, on the other hand, is a branch of ML that leverages a set of nonlinear processing units with multiple layers for Feature conversion and extraction. It has several different artificial neural network layers that perform the ML process [28]. The first layer of the neural network processes the raw data input and transmits the information to the second layer. The latter then processes this information further by adding additional information and transmits it to the next layer. This process continues in all layers of the Deep Learning network until the desired result is achieved. Neural networks are composed of Neurons, Connection and weights, Propagation function and Learning rate structures in terms of structure. Deep learning has a structure in which powerful hardware components come to the fore. Neural networks architecturally include Feed Forward Neural Networks, Recurrent Neural Networks, and Symmetrically Connected Neural Networks. The architecture of a Deep Learning model includes respectively Unsupervised Pre-trained Networks, Convolutional Neural Networks, Recurrent Neural Networks, and Recursive Neural Networks [29].

C. MODELS AND FINE-TUNING PROCESS

The transfer learning method in this study is used to train the dataset with a CNN [30]. Transfer learning is used to train a dataset containing new data with the information obtained based on the data extracted from CNN's data. Compared to conventional machine learning models, the DTL (Deep Transfer Learning) model is the solution because DL requires a large amount of training data. By choosing a fixed feature extractor or a pre-trained model for more fine-tuning, DTL significantly decreases training data and training time for a target area-specific mission [31].

Transfer learning helps retrain a model for classifying rare or emerging disease images. This is particularly true for models with a wide range of parameters for training based on deep neural networks [20]. Recently, major networks participating in the ImageNet Large-Scale Visual Recognition Challenge (ILSVRC) in medical fields have been used in image classification with transfer learning [32]. Determining the necessary fine-tuning techniques is the crucial point to mention in transfer learning. In this paper, the fine-tuning process, pre-trained networks, and the number of classes in the training dataset are presented in Section-3.

C. 1. VGGNet (VGG-16 and VGG-19)

The Visual Geometry Group Network (VGG), addressed by the Large Scale Visual Recognition Challenge (ILSVRC2014) in 2014, is a deep convolutional neural network developed by the Oxford Vision Geometry Group. The VGGNet has been trained in the ImageNet database from more than 14 million images and can divide images into 1000 different classes [33]. A mixture of five convolutional blocks (13 convolutionary layers) and completely connected layers of the structure is VGG-16. VGG-

19 uses 19 layers, plus five convolutional blocks (16 convolutional layers) and ultimately linked layers of the structure. In our research, both VGG-16 and VGG-19 models were used and compared with other models.

C. 2. Inception V3 Model

In 2014, the ImageNet large-scale object classification competition winner was the network architecture known as Inception or GoogleNet. It has 22 layers and consists of 9 inception modules. The different sizes of convolution and max pooling operations are included in each module [34]. In our research, due to the success of the InceptionV3 model in object classification competitions, the situation on Covid-19 X-ray images was analyzed and compared with other successful methods. A Covid-19 image size of 320 x 320 x 3 is required for the fine-tuned model input layer. After the average pooling layer, an aggregate average pooling layer is used. Two ultimately linked layers are applied to the model for the Covid-19 classification query, 512, 512 neurons, and an output layer based on the relevant Covid-19 dataset, respectively.

C. 3. Xception Model

The Xception model represents the Inception modules in coevolutionary neural networks as an intermediate phase between periodic convolution and the profoundly separable convolution method [35]. Studies are showing that the Xception model produces very efficient results in the literature. Xception slightly outperforms Inception V3 on the ImageNet dataset. The efficiency gains are not due to increased capability but rather to further productive model parameters because the Xception structure has the same number of parameters as Inception V3 [36]. The Xception structure contains 14 blocks with 36 levels. The input image size of the model is $320 \times 320 \times 3$. A global average pooling layer has been modified to include a 512-fully connected layer and an output layer after convolution layers, according to the Covid-19 classification task.

III. THE PROPOSED MODEL AND PROCESSES

In this study, The VGG-16, VGG-19, InceptionV3, and Xception deep learning models were improved by fine-tuning processes and compared to determine whether the patient had COVID-19 using chest X-ray images of the patients. Models were analyzed with the accuracy, f-measure, sensitivity, and specificity values. In order to classify Covid-19 images, the analysis was made on the Covid-19 datasets according to the distinguishing features in the literature. Firstly Image Pre-processing was done, such as Light Balance adjustment, Image Size adjustment. After the pictures made suitable for education were tagged with labelling software, the methods created the datasets. In our study, out of Covid-19 images that were enrolled in training for classification, the errors in the data sets of image sets with a low classification rate were corrected, reconstructed, and retrained.

For the classification system developed to work efficiently, the Covid-19 images that are put into training must reflect the distinctive features as clearly as possible. Otherwise, the training process will be repeated many times, since each image to be used in training will cause erroneous results. An improperly trained image will cause errors both in the classification of that Covid-19 patient group and in the classification of other groups. For this reason, it is of great importance that the images collected for the Covid-19 datasets belong to that disease, that the image reflects the characteristic feature of the Covid-19, and that it is images from as many angles as possible.

This study proposed to classify COVID-19 infectious diseases as a method for computer-assisted detection (CAD). We suggested that the profound learning approach would help radiologists diagnose COVID-19 infection. For this diagnosis, infections associated with COVID-19 were trained with four pre-trained neuronal coevolutionary networks (CNNs). The Python programming language was used to train proposed deep transfer learning models. Keras library was chosen for deep learning processes.

Keras R-CNN is a Python library that can process huge image datasets and perform automatic cell recognition for brighter fields and images.

A. IMAGE PRE-PROCESSING

Since the dataset consists of RGB images with 0-255 values, the images were scaled at the rate of 1-255 and values in the range of 0-1 were formed, making it easier to process the images. Images are resized to 320x320. Since the dataset consists of a limited number of images, the data was increased by flipping the images horizontally, shifting by 0.2 and zooming by 0.2.

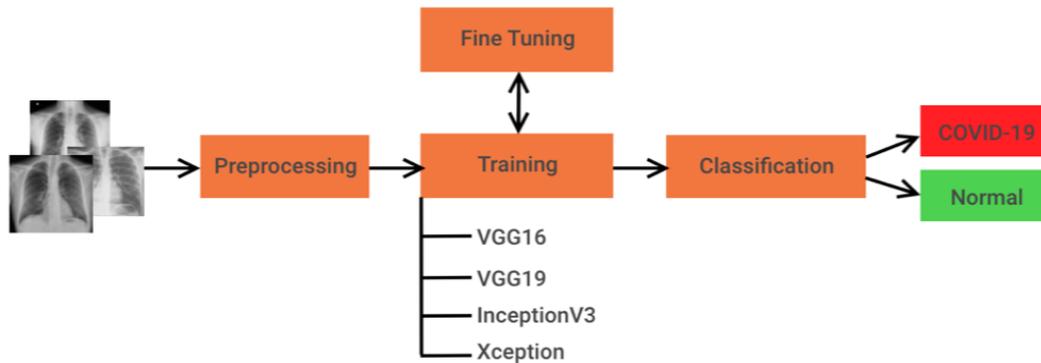


Figure 4. Workflow of the proposed framework for classifying X-ray images of COVID-19 and normal patients

B. PRETRAINED AND FINE-TUNING ON MODELS

Despite the limited number of chest X-ray images with COVID-19 disease, deep transfer learning methods succeed with many data. Therefore, it will be advantageous to use the transfer learning method. Transfer learning transfers the information gained from the data trained with the big dataset to the data to be trained. In this study, transfer learning was carried out using pre-trained VGG-16, VGG-19, InceptionV3 and Xception models successfully in the ImageNet competition. Fine-tuning was performed by creating a new fully-connected layer head consisting of AveragePooling2D, Flatten, Dense, Dropout, last Dense with Softmax layers for each model.

The operations performed in the fine-tuning stages are given as subtitles respectively:

AveragePooling2D: In the Average Pooling layer, the COVID-19 chest X-ray images were divided into 4x4 matrices, and down-scaling was performed by taking the average of each matrix. In this way, the pixel density was reduced, and the image was made ready for processing.

Flatten: At this stage, the feature matrix obtained in the previous stage was transformed into a vector, making it usable in a fully connected neural network classifier.

Dense1: In this layer, the ReLu (Rectified Linear Unit) activation function was used to add nonlinearity to the model after each convolution. The size of the output space for InceptionV3 and Xception models was determined as 256 units, and for VGG-16 and VGG-19, 64 units.

Dropout: In this layer, the process of ignoring (dropping) some neurons is provided to prevent excessive learning during training. Fine-tuning was performed with a rate of 0.3 for InceptionV3 and Xception and 0.5 for VGG-16 and VGG-19.

Dense2: In the study, the Softmax activation function was used to perform the classification process. In this way, the output was divided into two categories as COVID-19 and Normal.

Also, the training of these layers was frozen because the VGG-16, VGG-19, InceptionV3, and Xception models were trained with ImageNet data. In the convolutional neural network, the fully

connected layer obtained by fine-tuning was trained. Finally, the ADAM (Adaptive Moment Estimation) algorithm, which uses the Categorical cross-entropy function, has been adjusted. In this way, it is aimed to have the minor error between the output value produced by the modelled network and the actual value.

VI. EXPERIMENTAL ANALYSIS AND RESULTS

In this study, a binary classification labelled Normal, and COVID-19 was performed. Pre-trained deep learning models named VGG-16, VGG-19, InceptionV3 and Xception were used with fine-tuning. Through refining the cross-entropy function with the optimizer of adaptive moment estimation (ADAM), CNN models were pre-trained with random initialization parameters. For both tests, the batch size, learning rate, and steps per epoch were experimentally set at 10, 1E-04, and 28, respectively. Different hyperparameter combinations, for instance, the number of frozen convolution layers, completely connected layers, the drop ratio, the optimization algorithm, the speed of learning, and intervals, were calculated using the trial and error technique.

The hyperparameters of the active models were registered for testing after the training. The actual figure of linked layers was remained identical in both methods to help explain the efficiency of the models in extracting features. Performance metrics based on the confusion matrix are used to assess the significant convalescence of the suggested COVID-19 classification models over the efficient supervised COVID-19 classification models (see Figure 4). Specificity, sensitivity, precision, accuracy, and negative predictive value were included in these measures. TP (True Positive) refers to the positive (COVID-19) ratio correctly labelled as COVID-19 in the test result. TN (True Negative) is the negative (normal) rate that is correctly labelled. FP (False Positive) is the negative (normal) rate that is mislabeled as positive. FN (False Negative) is the positive (COVID-19) rate that is mislabeled as negative (normal) by the model. Using the TP, FP, TN and FN values, the accuracy, recall, specificity, precision, F1-score values are found respectively by the formulas in Equation (1), Equation (2), Equation (3), Equation (4) and Equation (5) given below.

$$Accuracy = \frac{TP+TN}{TP+FN+TN+FP} \quad (1)$$

$$Recall = \frac{TP}{TP+FN} \quad (2)$$

$$Specificity = \frac{TN}{TN+FP} \quad (3)$$

$$Precision = \frac{TP}{TP+FP} \quad (4)$$

$$F1\ Score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (5)$$

The matrix of confusion and related formulas are shown in Figure 5.

| | | | | |
|------------|----------|--|--|--|
| | | Precision $\frac{TP}{TP + FP}$ | Negative Prediction $\frac{TN}{TN + FN}$ | Accuracy $\frac{TP + TN}{TP + FN + TN + FP}$ |
| True Label | COVID-19 | True Positive (TP) | False Negative (FN) | Sensitivity $\frac{TP}{TP + FN}$ |
| | Normal | False Positive (FP) | True Negative (TN) | |
| | | COVID-19 | Normal | |
| | | Predicted Label | | |

Figure 5. Performance metrics

A total of 420 chest x-rays were used for 280 training and 140 tests. Confusion matrices obtained using VGG-16, VGG-19, InceptionV3, and Xception models are given in Figure 6, Figure 7, and Figure 8, respectively. For the VGG-16 and VGG-19 models, 67 of 70 images labelled COVID-19 were successful (TP), and three were unsuccessful (FN). Of the 70 images labelled with Normal, 14 failed (FP), and 56 were successful (TN) results.

| | | | |
|------------|----------|-----------------|-----------|
| | | COVID-19 | Normal |
| True Label | COVID-19 | 67 | 3 |
| | Normal | 14 | 56 |
| | | COVID-19 | Normal |
| | | Predicted Label | |

Figure 6. VGG-16 & VGG-19 Confusion Matrix (obtained same results)

| | | | |
|------------|----------|-----------------|-----------|
| | | COVID-19 | Normal |
| True Label | COVID-19 | 70 | 0 |
| | Normal | 11 | 59 |
| | | COVID-19 | Normal |
| | | Predicted Label | |

Figure 7. InceptionV3 Confusion Matrix

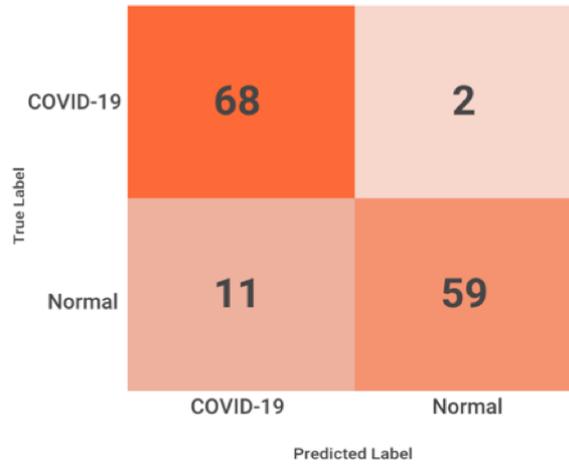


Figure 8. Xception Confusion Matrix

In the InceptionV3 model, 70 of 70 COVID-19 labelled images were successful (TP), 0 failed (FN), and 11 failed (FP), and 59 were successful (TN) results were obtained from 70 Normal labelled images. Also, in the Xception model, 68 of 70 COVID-19 labelled images were successful (TP), two unsuccessful (FN), and out of 70 Normal labelled images, 11 failed (FP), and 59 were successful (TN) results. Categorical cross-entropy is a loss function that is used in various classification tasks. These are tasks in which the only one in a variety of categories is an example, and the model has to decide which. Officially, the differences between two probability distributions are structured to be analyzed. The loss value of the training classification network consisted of a categorical cross-entropy loss function that calculates the loss of an instance by calculating the sum:

$$Loss = - \sum_{i=1}^{outputsize} y_i * \log y_i \tag{6}$$

Where y_i is the target value in the model output, and the output size is the number of scalar values in the model output.

Table 1. Comparative Performances of Fine Tuned Deep Learning Models

| Models | Accuracy (%) | Recall (%) | Specificity (%) | Precision (%) | F1-Score (%) |
|-------------|--------------|------------|-----------------|---------------|--------------|
| VGG-16 | 0.8786 | 0.9571 | 0.8 | 0.8272 | 0.8874 |
| VGG-19 | 0.8786 | 0.9571 | 0.8 | 0.8272 | 0.8874 |
| InceptionV3 | 0.9214 | 1.0 | 0.8429 | 0.8642 | 0.9272 |
| Xception | 0.9071 | 0.9714 | 0.8429 | 0.8608 | 0.9128 |

Table 1 shows the diagnostic performances of the four networks. According to Table 2, the highest accuracy rate (92%) was seen in the InceptionV3 model, and the lowest accuracy rates were seen in the VGG-16 and VGG-19 models (88%). On the other hand, The Xception model (91%) gives more successful results than the VGG-16 and VGG-19 models, but it has less accuracy than the InceptionV3 model.

V. CONCLUSION

The pre-trained CNN model was modified and retrained using various transfer learning and fine-tuning strategies to classify Covid-19 images during the experimental procedures. With the early diagnosis of COVID-19 disease, it is of great significance to prevent the shortening of the treatment

period of the patients and the contagion of other people. According to the results, it is expected that a positive contribution will be made to decision processes on the diagnosis of covid-19 disease. The proposed software offers significant advantages in issues such as test costs, test accuracy rate, staff workload, and waiting time for test results. In this study, a comparison was made by applying and improving the fine-tuning strategies to state-of-art deep transfer learning models to chest X-ray images of COVID-19 patients. As a result of the statistical analysis, it was seen that the most successful model was InceptionV3 (%92), the next successful model was Xception (%91), and the VGG-16 and VGG-19 models gave the same result (%88), giving the most unsuccessful result among the compared models. It has been concluded that deep transfer learning methods will be useful in the early diagnosis of COVID-19 disease in the decision-making stages of radiologists. In future studies, it is thought that the integration of recommended methods into computer-aided software systems used in hospitals will be beneficial. It can be developed methodically and technically using different datasets and deep learning models in future studies.

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