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Detection of COVID-19 Cases Using Deep Learning

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ABSTRACT: COVID-19, which emerged in late 2019 with symptoms of respiratory infection, has significantly affected human life, disrupting daily social activities such as health, education and economy. Although the pandemic is now under control, it is of great importance to quickly identify cases with chronic diseases. In this context, Deep learning, which is obtained by the development of artificial neural networks, one of the Artificial Intelligence technologies actively used today, is a method that uses large volumes of data to analyze and learn information from them. Medical imaging techniques such as X-rays, MRIs and CT scans are known to be analyzed using various deep learning architectures. This study aims to detect COVID-19 cases using deep learning models. The models used include CNN, Xception, VGG19, AlexNet and ResNet50. The dataset consists of 6,432 chest X-ray images, of which 576 are positive for COVID-19, 1,583 are normal cases, and 4,273 are diagnosed with pneumonia. Of this dataset, 80% was used for training and 20% for testing. The performance of the deep learning models was evaluated and compared based on certainty, precision, sensitivity and F1 score. The best result obtained was 93.71% for the VGG19 model. The results showed that deep learning models can significantly contribute to the detection of COVID-19 and similar diseases in healthcare systems and help physicians in diagnosis and treatment.

Keywords – *COVID-19, Artificial Intelligence, Artificial Neural Networks, Deep Learning, Convolutional Neural Networks.*

1. Introduction

Today, artificial intelligence is a technology used in many fields. Deep learning, a sub-branch of artificial intelligence, has been used in areas such as pneumonia detection, skin cancer detection, breast cancer detection, classification of pathogenic bacteria and detection of brain abnormalities from chest X-ray images using medical data sets. In this study, X-ray images will be analysed using deep learning techniques. The COVID-19 pandemic, where the disease can be detected with X-ray images, has increased the need for specialists in the field of radiology, but due to the limited number of specialists in this field, artificial intelligence models can be of great benefit in detecting COVID-19 cases. When the studies in the literature are analysed, instead of developing a new system, the DarkCovidNet model is presented in the study of Ozturk et al. ,(2020) inspired by the DarkNet architecture, which has a state-of-the-art architecture designed for object detection. In this new model, fewer layers and filters are used compared to the DarkNet architecture. DarkCovidNet model was trained with 100 epoch values. In this model, 17 layers were applied and certainty, precision, sensitivity and F1 score results were analysed. The DarkCovidNet model was used in two classification studies with 2 classes to distinguish between COVID-19 and normal cases, and with 3 classes to distinguish between COVID-19, pneumonia and normal cases.

DarkCovidNet model achieved an certainty rate of 98.09% in binary classification and 87.02% in triple classification. In another study, Ouchicha et al. , (2020) presented CVDNet, a convolutional neural network model to classify COVID-19 infection from normal and pneumonia cases using chest X-ray images. The CVDNet architecture is built using two parallel layers with different core sizes. The model is trained on a publicly available dataset containing 219 COVID-19, 1341 normal and 1345 pneumonia diagnosed chest X-ray images obtained from Kaggle's COVID-19 Radiography database. Of this dataset, 70% was used for training, 10% for validation and 20% for testing. The training was completed with 20 epochs and the certainty, precision, sensitivity and F1 score results of the model were analysed. It was observed that CVDNet achieved an average certainty of 97.20% for detecting COVID-19 and an average certainty of 96.69% for three-class classification. In another study, Ismael and Sengür. , (2021) presented the CVDNet model. A total of 180 COVID-19 and 200 normal chest X-ray images were collected from three different publicly available sources. 75% of the dataset was used for training and the remaining 25% was used to test the proposed method. Five pre-trained convolutional neural network models, namely VGG16, VGG19, ResNet18, ResNet50 and ResNet101, were used in the experiments of the study. Deep learning was performed with MATLAB software. It was observed that ResNet50 model obtained 92.6%, VGG16 model 89.8%, ResNet101 model 89.5%, VGG19 model 88.1% and ResNet18 model 87.4% average certainty scores. It was observed that CVDNet achieved an average certainty of 97.20% for detecting COVID-19 and an average certainty rate of 96.69% for three-class classification (COVID-19, normal and pneumonia), showing a promising performance in classifying COVID-19 cases. In another study, Hemdan et al. ,(2020) presented the COVIDX-Net model. The COVIDX-Net model includes pre-trained Xception, VGG19, MobileNetV2, ResNet201, DenseNet201, ResnetV2, InceptionV3, InceptionResNetV2 models. The dataset they used includes 25 COVID-19 diagnosed and 50 normal chest x-ray images. The training was completed with 50 epochs and the certainty, precision, sensitivity and F1 score results of the model were analysed. Among all the models tested, VGG19 and DenseNet201 models achieved the best certainty values with 91%, while the certainty of the InceptionV3 model was the worst with 50%. In another study, Ucar and Korkmaz (2020) presented the COVIDiagnosis-Net model based on the Bayesian optimised SqueezeNet deep learning model. The dataset contains 4290 pneumonia, 1583 normal, 76 COVID-19 cases. 80% of this dataset was used for training, 10% for validation and 10% for testing. The model was designed with 3 classes giving COVID-19, normal and pneumonia results. Deep learning was programmed on MATLAB. The results of the tests were evaluated by confusion matrix analysis and the certainty, precision, sensitivity and F1 score results of the model were analysed. While the average certainty rate was 76.37% in the first test results, the average certainty rate reached 98.26% after Bayesian optimisation was applied, showing how useful Bayesian optimisation is. It was stated that this model showed very successful results in COVID-19 diagnosis. In another study, Panwar et al. , (2020) proposed the nCOVnet model to detect COVID-19 cases using X-ray images. Detailed information about the architecture of the convolutional neural network-based nCOVnet model is given. The dataset used in the study contains 142 COVID-19 diagnosed and 142 normal chest X-ray images. Since the images in the dataset have different sizes, all of them were converted to 240x240 pixels. 70% of the dataset was used for training and 30% for testing. Confusion matrix and Iteration/Certainty analyses of the obtained results were performed. The training was completed with 80 epochs and the certainty, precision, sensitivity and F1 score results of the model were analysed. nCOVnet model's COVID-19 case prediction rate was 97.97%. In another study, Pandit et al. , (2020) used the VGG-16 deep learning model for the diagnosis of COVID-19 cases. The dataset in the study includes 224 COVID-19, 504 normal and 700 pneumonia diagnosed chest X-ray images. 70% of this dataset was trained as training and 30% as test. The model was trained in two different ways: COVID-19 and healthy and COVID-19, healthy and diagnosed with pneumonia. The training was completed with 25 epochs and the certainty, precision, sensitivity and F1 score results of the model were analysed. It was observed that the model achieved 96% success rate in binary (COVID-19 and normal) classification and 92.5% success rate in triple (COVID-19, normal and pneumonia) classification. The results of the study were compared with the results of other studies. In order to provide detailed understanding of the comparison and to determine the originality and adequacy of our study, the studies in the literature are presented in Table 1.

Table 1. Researchers and Their Results

1	Ozturk et al.	DarkCovidNet	87.02%
2	Ouchicha et al.	CVDNet	96.69%
3	Ismael and Şengür	ResNet50	92.6%,
4	Hemdan et al.	VGG19	91%
5	Uçar and Korkmaz	SqueezeNet	76.37%
6	Panwar et al.	nCOVnet	97.97%
7	Pandit et al	VGG-16	92.5%

When reviewing the literature, it can be seen that many researchers have obtained results in various models, as shown in Table 1. When these results are examined, although Ouchicha and colleagues achieved an certainty rate of 96.69% in their study and Panwar and colleagues achieved an certainty rate of 97.97% with a small data set in their study, the use of a small data set reduced generalisability. In addition, it has been observed in the literature that single or double validation is performed, and triple validation is rare. Within the scope of this study, it was considered that triple validation would be more efficient in helping doctors make more effective and faster decisions and that a larger data set was needed. In this direction, open-access data sets were meaningfully combined. Bayesian optimisation was applied to increase certainty rates, and it was observed that this increased certainty to a certain extent. Considering all these factors, efforts were made to plan for faster and more effective results to assist doctors in their decision-making in the model to be developed.

Within the scope of this study, in the light of the information obtained from the literature, it is aimed to develop a useful model that can help doctors in decision-making situations for COVID-19 diagnosis. In this context, by reviewing the literature, datasets, deep learning models and the results obtained from them, a useful model development study was carried out to guide future studies by using a large dataset with triple validation. In this context, in the **materials and methods** section, we provide detailed information about the datasets we obtained from open source databases, deep learning structure and deep learning models, and try to create a roadmap for future studies. In addition, the section describes the procedures on how the results are evaluated. In the results section, the results obtained with the training cases of all models are given and analyzed graphically. The results obtained from all models are tabulated and discussed in the **discussion** section. These cases are explained in detail below.

2. Material and Methods

Within the scope of this study, this section aims to provide a roadmap for those who want to develop in this field by providing detailed information about the environment in which we work, our triple data set obtained from open source databases and the models we have developed applications. In line with this purpose, we have worked on improving the working environments, models and results by proceeding with the information obtained from the literature.

2.1. Application Environment

When the literature was examined, it was understood that the environments studied were MATLAB, which was a limitation for the generalization of the data obtained. In order to eliminate this limitation, it was decided to use the Python programming language and the CPU Google Colaboratory environment with high processing power that can perform operations on visuals faster, considering that the use of open source environments and programming languages can be useful for future development work and operations. It was envisaged that the model and weight information of the model obtained from here could be transformed and transferred to other environments. Detailed information about the dataset and models are given in this section respectively.

2.2 Dataset

In this study, X-ray images used were collected from various publicly available sources and worked with the COVID-19 radiography dataset obtained from Kaggle. A total of 6432 chest X-ray images with 576 COVID-19 positive, 1583 normal and 4273 pneumonia diagnoses were used in the study. Table 2 shows a summary of the dataset and Table 3 shows sample images from the dataset.

Table 2. Dataset.

Dataset	COVID-19	Normal	Pneumonia	Total
Test	116	317	855	1288
Training	460	1266	3418	5144
Total	576	1583	4273	6432

Table 3. Sample Images From The Dataset.

COVID-19	Normal	Pneumonia
		
		

The purpose of creating and using this dataset was based on the information obtained from the literature. The reason for this is that triple validation is considered more accurate in case detection. This triple validation includes Covid-19, Normal and Pneumonia. Another situation is that the dataset is larger than the literature. It is thought that a larger dataset will increase generalization and certainty.

2.3. Deep Learning

Deep learning aims to simulate the learning process of the human brain by imitating the human learning process and artificially creating the learning connection between nerve cells and cells. During the deep learning process, which is a sub-branch of the field of machine learning, data is processed in successive layers. In recent years, deep learning techniques continue to show impressive performance in many areas, including medical image processing. Deep learning is widely used in working with medical datasets. Image and signal data from medical imaging methods such as X-Ray, MRI and CT can be analysed using various deep learning architectures. Thanks to these analyses, it has become possible to detect and diagnose diseases such as skin cancer, breast cancer and brain tumours. Deep learning methods have become an important field in medical image processing. One of the most important reasons for choosing deep learning methods in this study is the information obtained from the literature. This information is that it is vital to make urgent decisions in cases such as skin cancer, brain tumors and breast cancer as well as covid-19 detection. In this context, the most important feature of the model to be developed is to give the process that a human would analyze for long hours quickly and accurately. For this reason, in order to optimize the model or models to be developed, the deep learning models and structure obtained from the literature are examined and model information is given in order to create a road map for those who will develop.

2.4. Deep Learning Layers

Deep learning models consist of layers. The layers receive information from the previous layers in the architecture of the model and transfer it to the next layers. The input layer is the layer where preprocessing is performed through filters. It is also called the image processing layer. The convolution layer is the layer where a set of images, called feature maps, are created to generate new images. Feature maps are designed to emphasise the unique features of the original image. It consists of filters that transform the images. These filters are called convolution filters and perform scaling operations on the image. Figure 1 shows the convolution layer.

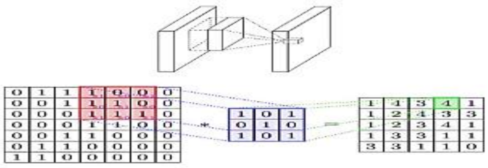


Figure 1. Convolution Layer. (medium,2025)

The activation layer is the layer where the layers in the image are rectified, negative image values are equalised to zero and positive image values are equalised to their values. Figure 2 shows the mathematical equation and graph of the activation layer.

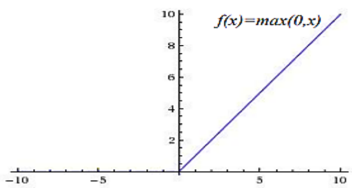


Figure 2. Activation Layer. (medium,2025)

The pooling layer is used to determine how to reduce the size of the image, which pixels to select from the image and how to set the representative value. The average or maximum value of the pixels is used as the representative value. Figure 3 shows the pooling layer.

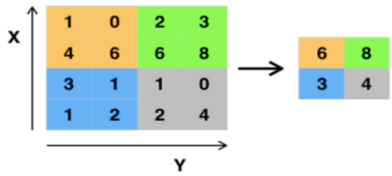


Figure 3. Pooling Layer. (medium,2025)

The normalisation layer is used to organize the data from the other layers and allows the network to make the data more regular, thus improving the performance of the neural network. The fully connected layer is the layer where the data from the previous layers are converted into a one-dimensional matrix to optimise the results. The dropout layer is the layer that prevents the artificial neural network from memorising. This layer works by eliminating the memorising neurons of the network at a certain rate. Softmax layer deep learning models perform probabilistic value generation between classes. The probabilities assigned to each class are decimal values and their sum should always be 1. The classification layer is usually located after the softmax layer in deep learning models and its output value matches the number of classes. The output value of this layer is the same as the number of classes.

2.5. Deep Learning Models

In this study, deep learning methods were used with multiple classifications including COVID-19, normal and pneumonia classes. Deep learning methods were used to identify features extracted from X-Ray images and make accurate classifications based on these features. Pre-trained CNN, VGG19, Resnet50, Alexnet and Xception models were used. These models were chosen because they are widely used in the field of deep learning and have given successful results.

2.5.1. CNN

Convolutional Neural Networks are a class of deep neural networks used for image classification. Images given as input are converted into a suitable format to be recognised and processed by the computer. In this conversion process, images are converted into matrix format. The system analyses the differences in the matrices and classifies the images. In the training phase, it learns the effect of the differences on the label and makes predictions for new images using this information. CNN has achieved successful results in image processing applications. CNN is frequently used in image processing studies in the biomedical field. Figure 4 shows the CNN model architecture.

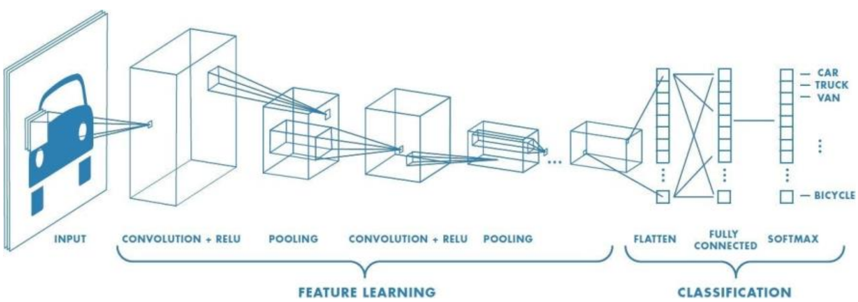


Figure 4. CNN Model Architecture.(medium,2025)

2.5.2. Alexnet

It was developed by Alex Krizhevsky. It consists of 25 layers including input layer, 5 convolution, 7 ReLU, 3 pooling, 2 dilution, 3 fully connected, 2 normalisation, softmax layer and output layer. It achieved an certainty rate of 83.6% in the ILSVRC (ImageNet Large Scale Visual Recognition Challenge) competition and increased the interest in deep learning. Alexnet model architecture is shown in Figure 5.

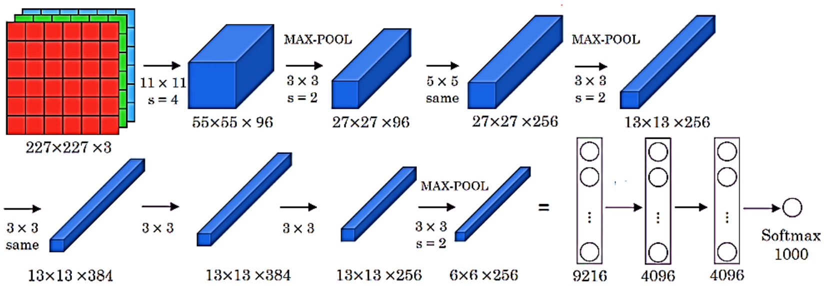


Figure 5. Alexnet Model Architecture. (medium,2025)

2.5.3. VGG19

It is a 19-layer model developed by the Visual Geometry Group to improve the classification result by increasing the CNN depth. It performed successfully in the ILSVRC competition with an certainty rate of 92.7%. Figure 6 shows the VGG19 model architecture.

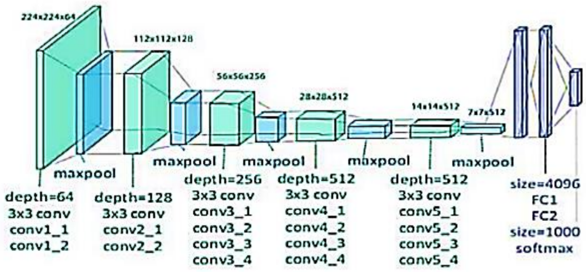


Figure 6. VGG19 Model Architecture.(Pashine et all,2021)

2.5.4. Resnet50

It is named Resnet50 because it has 50 layers. In its structure, there are 1x1, 3x3 and 1x1 convolution layers respectively. By reducing the number of parameters, the computational load is reduced and the error rate of the model is greatly reduced. Figure 7 shows the Resnet50 model architecture.

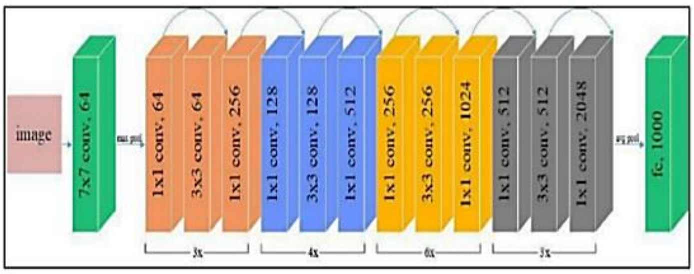


Figure 7. Resnet50 Model Architecture. (Talo, M.,2019)

2.5.5. Xception

Since it is based on the Inception architecture, it is called Xception, which means 'Extreme Inception'. There are 71 layers in its structure. In the Xception model, deeply separable convolution is implemented, which can significantly reduce the computational cost. Figure 8 shows the Xception model architecture.

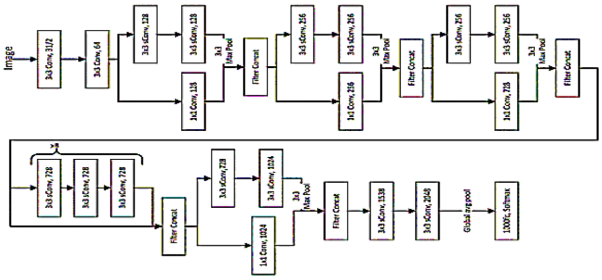


Figure 8. Xception Model Achitecture.(Eryılmaz F., et all,2021)

2.5.6. Model Evaluation Metrics

In this study, four criteria, namely certainty, precision, sensitivity and F1 Score, are used to determine the classification performance. The performance success of the model varies in direct proportion to the height of the results of these criteria. When analysing deep learning results, four different parameters are used: true positive (TP), true negative (TN), false positive (FP) and false negative (FN). TP is the amount of data that is actually positive and predicted as positive by the model. TN is the amount of data that is actually negative but the model predicts as negative. FP is the amount of data that is actually negative but the model predicts as positive. FN is the amount of data that is actually positive but the model predicts as negative. Certainty is the most important criterion for deep learning classifiers and refers to the number of correctly classified examples.

$$\text{Certainty} = \frac{\text{TP+TN}}{\text{TP+TN+FP+FN}} \tag{1}$$

Precision refers to the model's performance in correctly predicting true positives.

$$\text{Precision} = \frac{\text{TP}}{\text{TP+FP}} \tag{2}$$

Sensitivity is the proportion of correctly identified positives in the model that are true positives.

$$\text{Sensitivity} = \frac{\text{TP}}{\text{TP+FN}} \tag{3}$$

The F1 Score aims to find the delicate balance between sensitivity and certainty. It is obtained by taking the harmonic mean of precision and sensitivity results.

$$\text{F1 Score} = \frac{2*\text{Precision}*\text{Sensitivity}}{\text{Precision+Sensitivity}} \tag{4}$$

The confusion matrix is created using the information obtained from equations 1, 2, 3, and 4. The confusion matrix is a tool that summarises the prediction results obtained in a classification problem. Many deep learning classification systems use the confusion matrix to evaluate their performance. This matrix provides information about the errors made by the classifier and the types of errors in the system. Table 4 shows the confusion matrix.

Table 4. Confusion Matrix.

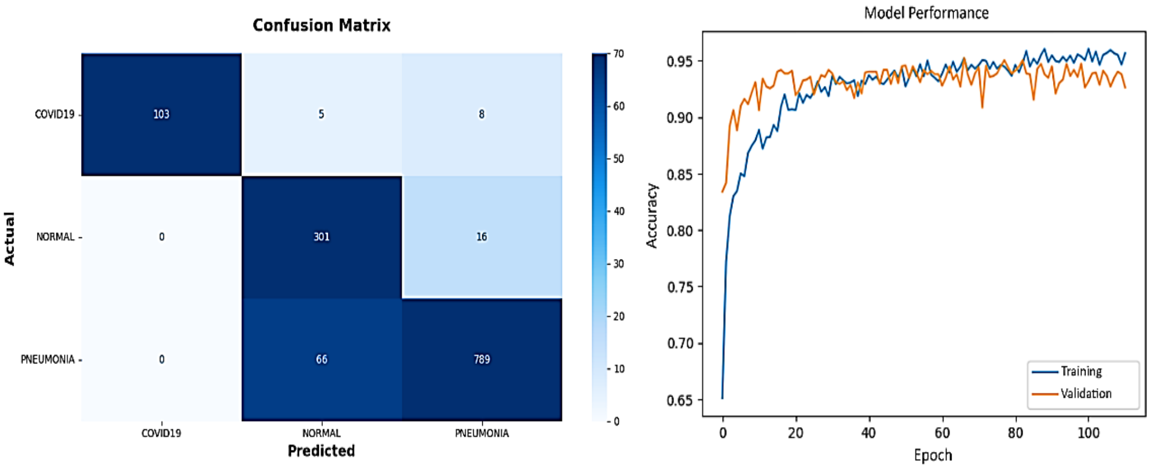
	Predicted Positive	**Predicted Negative**
True Positive	True Positive (TP)	False Negative (FN)
True Negative	False Positive (FP)	True Negative (TN)

3. Results and Discussion

Deep learning models were trained to give results with three classes (COVID-19, normal and pneumonia). In the study, 80% of the dataset consisting of a total of 6432 chest X-ray images of the lungs with 576 COVID-19 positive, 1583 normal and 4273 pneumonia diagnoses were used for training and 20% for testing. Certainty, precision, sensitivity and F1 Score ratios were evaluated together with the confusion matrix of the deep learning models created as a result of the study.

3.1. CNN Model Results

When mathematical calculations were made in the study, COVID-19 case detection rate was 88.79%, normal case detection rate was 94.95%, and pneumonia case detection rate was 92.28%. An certainty rate of 92.62% was obtained with the CNN model. Figure 9 shows the CNN model confusion matrix and Iteration/Certainty curve. Training was completed with epoch number 100 and batch size 16.According to the CNN model Iteration / Certainty curve graph shown in Figure 9, the training of the test images of the model was in the range of 85-90% in the first 10 cycles and stable in the range of 90-95% after the 20th cycle and gave successful results. According to the graph, it is seen that the area under the validation curve is similar to the average result of 92.62% as a result of the calculations in the confusion matrix.



Fiure 9. CNN Model Confusion Matrix And Iteration/Certainty Curve.

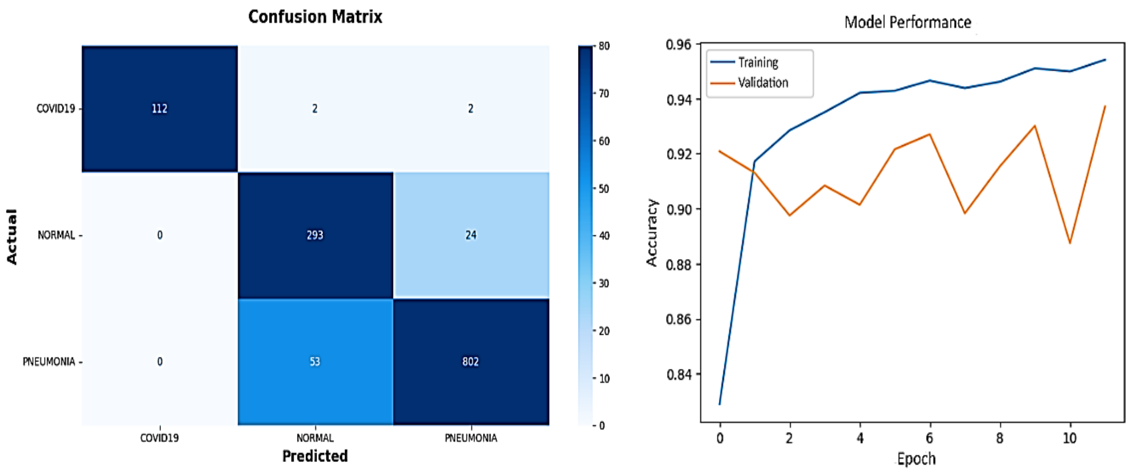
Table 5. CNN Model Performance Assessment.

Performance	**Epoch**	**Batch Size**	**Activation Function**	**Optimizer**	**Certainty**	**Sensitivity**	**F1 Score**
COVID-19	100	16	Relu Softmax	Adam	1.00	0.89	0.94
Normal					0.81	0.95	0.87
Pneumonia					0.97	0.92	0.95

When we interpret the performance evaluation of the CNN model as shown in Table 5, the average certainty of 92.62% shows that our model works efficiently. Epoch, Batch Size, Activation Function and Optimizer algorithms were tried separately until the best result was obtained. It should be noted that these algorithms require a powerful CPU for processing, so the hardware has an impact on this.

3.2. VGG19 Model Results

When mathematical calculations were made in the study, COVID-19 case detection rate was 96.55%, normal case detection rate was 92.42%, and pneumonia case detection rate was 93.71%. An certainty rate of 93.71% was obtained with the VGG19 model. Figure 10 shows the confusion matrix and Iteration/Certainty curve of the VGG19 model. Training was completed with epoch number 10 and batch size 16. According to the Iteration / Certainty curve graph of the VGG19 model shown in Figure 10, the training of the test images of the model was stable in the range of 90-95% for 10 cycles from the beginning and gave successful results. According to the graph, it is seen that the area under the validation curve is similar to the average result of 93.71% as a result of the calculations in the confusion matrix.



Fiure 10. VGG19 Model Confusion Matrix and Iteration/Certainty Curve.

Table 6. VGG19 Model Performance Assessment.

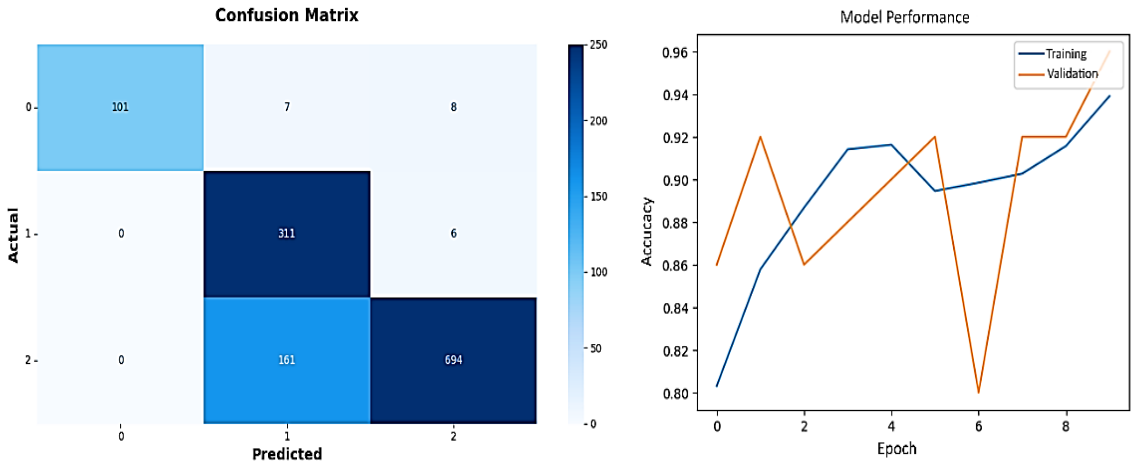
Performance	Epoch	Batch Size	Activation Function	Optimizer	Certainty	Sensitivity	F1 Score
COVID-19	10	16	Relu Softmax	Adam	1.00	0.97	0.98
Normal					0.84	0.92	0.88
Pneumonia					0.97	0.94	0.95

When we interpret the performance evaluation of the VCC19 model as shown in Table 6, the average certainty of 93.71% shows that our model works efficiently at 10 epochs and 16 batch sizes. This certainty was achieved by trying the Epoch, Batch Size, Activation Function and Optimizer algorithms separately until the best result was obtained. It should be noted that these algorithms require a powerful CPU to process, so the hardware affects this. The fact that Epoch and Batch Size are small and the average certainty is 93.71% clearly demonstrates the efficiency of the model.

3.3. Xception Model Results

When mathematical calculations were made in the study, COVID-19 case detection rate was 87.06%, normal case detection rate was 98.11%, and pneumonia case detection rate was

81.17%. An certainty rate of 85.86% was obtained with the Xception model. Figure 11 shows the Xception model confusion matrix and Iteration / Certainty curve. Training was completed with epoch number 8 and batch size 16.According to the Iteration/Certainty curve graph of the Xception model shown in Figure 11, the training of the test images of the model progressed successfully for the first 5 cycles, and although it weakened in the sixth cycle, it gave much more successful results in the remaining cycles. According to the graph, it is seen that the area under the validation curve is similar to the average result of 85.86% as a result of the calculations in the confusion matrix.



Fiure 11. Xception Model Confusion Matrix and Iteration/Certainty Curve.

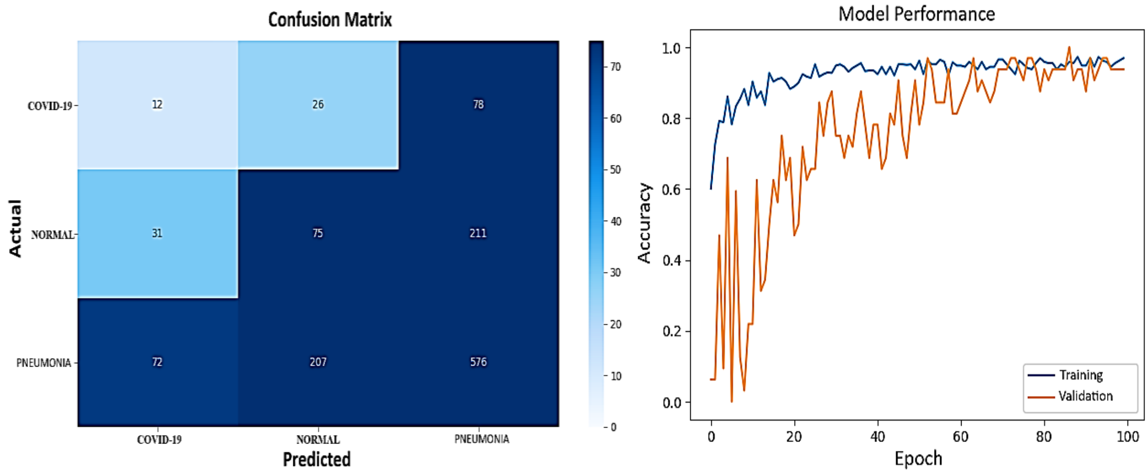
Table 7. Xception Model Performance Assessment.

Performance	Epoch	Batch Size	Activation Function	Optimizer	Certainty	Sensitivity	F1 Score
COVID-19	8	16	Relu Softmax	Adam	1.00	0.87	0.93
Normal					0.65	0.98	0.78
Pneumonia					0.98	0.81	0.89

When we interpret the performance evaluation of the Xception model as shown in Table 7, the average certainty of 85.86% shows that our model works efficiently at 8 epochs and 16 batch sizes. Epoch, Batch Size, Activation Function and Optimizer algorithms were tried separately until the best result was obtained. Although 8 epochs and 16 batch sizes were the most efficient, it was observed that the model memorized as the epoch was increased. It should be noted that these algorithms require a powerful CPU for processing, so it should not be forgotten that the hardware affects this. The fact that Epoch and Batch Size are low and the average certainty is 85.86% clearly shows that the efficiency of the model is low.

3.4. Alexnet Model Results

When mathematical calculations were made in the study, COVID-19 case detection rate was 10.34%, normal case detection rate was 23.66%, and pneumonia case detection rate was 67.37%. An certainty rate of 51.48% was obtained with the Alexnet model. Figure 12 shows the confusion matrix and Iteration/Certainty curve of the Alexnet model. Training was completed with epoch number 100 and batch size 32.According to the Alexnet model Iteration / Certainty curve graph shown in Figure 12, it is understood that the test images of the model fail during the first 20 cycles, and reach the ideal values after the 50th cycle of training. According to the graph, it is seen that the area under the validation curve is similar to the average result of 51.58% as a result of the calculations in the confusion matrix.



Fiure 12. Alexnet Model Confusion Matrix and Iteration/Certainty Curve.

Table 8. Alexnet Model Performance Assessment.

Performance	**Epoch**	**Batch Size**	**Activation Function**	**Optimizer**	**Certainty**	**Sensitivity**	**F1 Score**
COVID-19	100	32	Relu Softmax	Adam	0.10	0.10	0.10
Normal					0.24	0.24	0.24
Pneumonia					0.67	0.67	0.67

When we interpret the performance evaluation of the Alexnet model as shown in Table 8, the average certainty of 51.58% shows that our model is not efficient enough at 100 epochs and 32 batch sizes. This certainty was found by trying Epoch, Batch Size, Activation Function and Optimizer algorithms separately until the best result was obtained. Although 100% epoch and 32 batch size were the most efficient, it was observed that the model memorized as the epoch was increased. It should be noted that these algorithms require a powerful CPU for processing and therefore the hardware affects this. Although Epoch and Batch Size are high, the fact that the average certainty is 51.58% clearly shows that the efficiency of the model is low.

3.5. Resnet50 Model Results

When mathematical calculations were made in the study, COVID-19 case detection rate was 11.20%, normal case detection rate was 25.23%, and pneumonia case detection rate was 67.60%. An certainty rate of 52.10% was obtained with the Resnet50 model. Figure 13 shows the Resnet50 model confusion matrix and Iteration/Certainty curve. Training was completed with epoch number 100 and batch size 32 . According to the Iteration/Certainty curve graph of the Resnet50 model shown in Figure 13, although the training of the test images of the model started similar to the performance of the model, it was negatively differentiated from the model until the 80th cycle, and after the 80th cycle, the test images started to give successful results. According to the graph, it is seen that the area under the validation curve is similar to the result obtained as a result of the calculations in the confusion matrix with an average certainty rate of 52.10%.

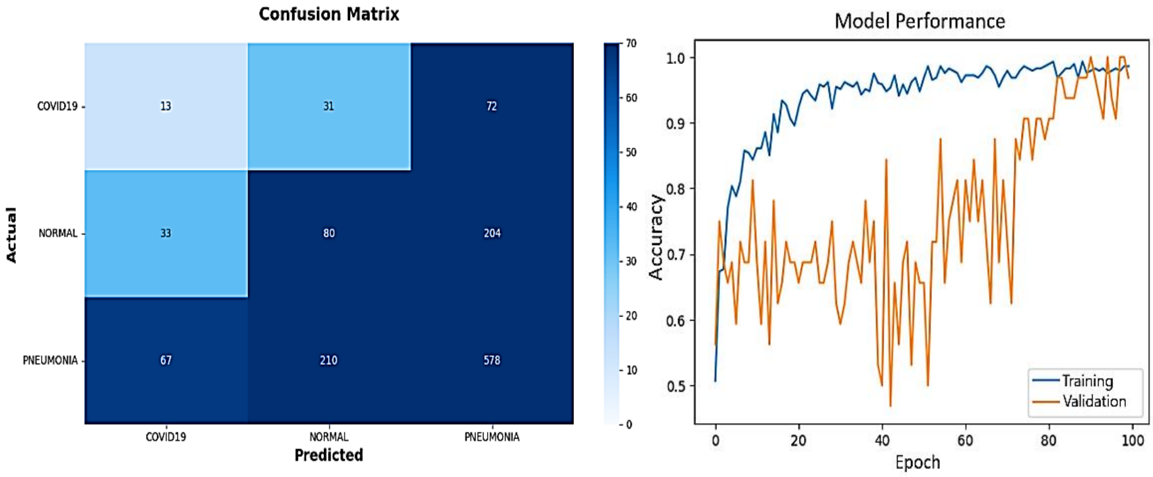


Figure 13. Resnet50 Model Confusion Matrix and Iteration/Certainty Curve.

Table 9. Resnet50 Model Performance Assessment

Performance	Epoch	Batch Size	Activation Function	Optimizer	Certainty	Sensitivity	F1 Score
COVID-19	100	32	Softmax	RMSprop	0.12	0.11	0.11
Normal					0.25	0.25	0.25
Pneumonia					0.68	0.68	0.68

When we interpret the performance evaluation of the Resnet50 model as shown in Table 9, the average certainty of 52.10% shows that our model is not efficient enough at 100 epochs and 32 batch sizes. This certainty was found by trying Epoch, Batch Size, Activation Function and Optimizer algorithms separately until the best result was obtained. Although 100% epoch and 32 batch size were the most efficient, it was observed that the model memorized as the epoch was increased. It should be noted that these algorithms require a powerful CPU for processing and therefore the hardware affects this. Although Epoch and Batch Size are high, the fact that the average certainty is 52.10% clearly shows that the efficiency of the model is low.

4. Conclusion

Different results were obtained with the training processes performed in 5 different models of Convolutional Neural Networks, one of the deep learning architectures used in the detection of COVID-19 cases. As a result of the tests, CNN deep learning model has 100% certainty, 89% sensitivity, 94% F1 Score rate in COVID-19 cases, 81% certainty, 95% sensitivity, 87% F1 score rate in normal cases, 97% certainty, 92% sensitivity in pneumonia cases, 95% F1 Score, VGG19 deep learning model, 100% certainty, 84% sensitivity, 97% F1 score rate in COVID-19 cases, 84% certainty, 92% sensitivity, 88% F1 score rate in normal cases, 97% certainty, 94% sensitivity, 95% F1 score rate in pneumonia cases, Xception deep learning model, 100% certainty, 87% sensitivity, 93% F1 score rate in COVID-19 cases, 65% certainty, 98% sensitivity, 78% F1 score rate in normal cases, 98% certainty, 81% sensitivity, 87% F1 score rate in pneumonia cases, Alexnet deep learning model, 13% certainty, 13% sensitivity, 13% F1 score rate in COVID-19 cases, 23% certainty in normal cases, 22% sensitivity, 23% F1 score rate, 66% certainty, 68% sensitivity, 67% F1 score rate in pneumonia cases Resnet50 deep learning model achieved 12% certainty, 11% sensitivity, 11% F1 score rate in COVID-19 cases, 25% certainty, 25% sensitivity, 25% F1

Score rate in normal cases, 68% certainty, 68% sensitivity, 68% F1 score rate in pneumonia cases.

Table 10. Results

Model	Epoch	Batch size	Activation Functions	Optimizer	Class	Precision	Sensitivity	F1 Score	Certainty
CNN	100	16	Relu Softmax	Adam	COVID-19	1.0	0.89	0.94	%92,62
					Normal	0.81	0.95	0.87	
					Pneumonia	0.97	0.92	0.95	
VGG19	10	16	Relu Softmax	Adam	COVID-19	1.0	0.84	0.97	%93,71
					Normal	0.84	0.92	0.88	
					Pneumonia	0.97	0.94	0.95	
Xception	8	16	Relu Softmax	Adam	COVID-19	1.0	0.87	0.93	%85,86
					Normal	0.65	0.98	0.78	
					Pneumonia	0.98	0.81	0.89	
Alexnet	100	32	Relu Softmax	Adam	COVID-19	0.13	0.13	0.13	%51,48
					Normal	0.23	0.22	0.23	
					Pneumonia	0.66	0.68	0.67	
Resnet50	100	32	Softmax	RMSprop	COVID-19	0.12	0.11	0.11	%52,10
					Normal	0.25	0.25	0.25	
					Pneumonia	0.68	0.68	0.68	

When the results of all models are analysed, the VGG19 model obtained an certainty rate of 93.71%, CNN model 92.62%, Xception model 85.86%, Resnet50 model 52.10%, Alexnet model 51.48% in order of success. The number of Epochs, Batch size, Activation Functions and Optimizer Functions used in the models is one of the biggest factors in the formation of these results. It was found that the number of epochs and batch sizes directly affect the training and results of Activation Functions and Optimizer algorithms. These values were obtained by experimenting until the best presentation was obtained for each model and the best learning conditions of the models were provided. In obtaining successful results, care was taken to ensure that the models did not memorize. When the results are analysed, the rate of correct results of pneumonia cases was found to be more successful than COVID-19 and normal cases. The reason for this situation is that there are more X-Ray images containing pneumonia in the trained dataset than the others. It is understood that more successful results can be obtained for these parameters in trainings where the amount of chest X-Ray data with COVID-19 and normal diagnosis is increased. By using different deep learning models for disease diagnosis, higher performance can be achieved by increasing the amount of trained data. It is understood that deep learning applications will make great contributions to the diagnosis of COVID-19 and other diseases.

In this study, unlike the literature, triple verification was performed on a generalisable, broad data set. A model was developed and compared that could assist doctors in diagnosis and detection. As a result of this comparison, the VGG19 model achieved the best average accuracy of 93.71% within 10 epochs and 16 batches. It is believed that this development will form the basis for case detection throughout our country and for future studies. In the future, with the accessibility of quantum computing, it is thought that these algorithms can be obtained in a much shorter time and with more accurate values. It is believed that the development of these model applications in the healthcare sector in our country will have a positive effect on case analysis and public health, as the diagnosis period will be shortened and the treatment process will be accelerated.

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