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Diagnosing Covid-19 Disease from Computed Tomography Images with Deep Learning and Machine Learning

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Abstract

The new virus disease (COVID-19) first came to China towards the end of December 2019 and became a pandemic all over the world. The disease caused a large number of people to be infected and die. Rapid diagnosis of the disease is of great importance in controlling transmission. A computed Tomography device provides successful results in the diagnosis of COVID-19 disease. In this study, two-class (COVID-19 and normal) data sets were created from 7200 lung Computed Tomography images diagnosed between March 2020 and November 2020 in a private hospital with the help of specialist physicians. Verification and testing processes were carried out on Artificial Neural Network (ANN), Support Vector Machine (SVM), K-Nearest Neighbour (KNN) algorithms from Machine Learning algorithms, and ResNet-50, DenseNet-201, InceptionResNetV2, Inceptionv3, VGG-16, Xception architectures from Deep Learning models. As a result of the studies, the DenseNet-201 architecture obtained the highest result from deep learning models with %99,35 training and test %98,75 accuracy rates, respectively. ANN %97,6, KNN %97,4 and SVM %96,9 accuracy rates were obtained from machine learning.

Key Words

"Cnn, Covid-19, Deep learning, Knn, Svm"

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1. Introduction

COVID-19 first appeared in the seafood and animal market in Wuhan Province, China, towards the end of December 2019. As a result of research on a group of patients, symptoms such as fever, cough, and shortness of breath were observed, and it was named COVID-19 on January 13, 2020. The disease has turned into a pandemic by spreading from Wuhan to Hubei province and from there to all other provinces of the People's Republic of China and all countries of the world. COVID-19 disease is caused by severe acute respiratory syndrome coronavirus two (SAR-CoV-2) viruses. The main symptoms of COVID-19 disease include shortness of breath, cough and fever. As the disease worsens, pneumonia, severe respiratory failure, kidney failure, and death can occur. Some patients may not show any symptoms. The disease can usually be transmitted by inhaling the infected droplets spread by the person carrying the virus to the environment during coughing or sneezing by another person. Even if a healthy person touches the surfaces contaminated by respiratory particles of this carrier patient and touches their face, nose and eyes with their unclean hands, the disease can be transmitted (Yang et al.,2020; Brunese et al.,2020; Wang et al.,2020; Demirbilek, 2021).

According to the World Health Organization (WHO) 's updated data on 10 july 2023, 767,726,861 confirmed cases were detected and 6,948,764 deaths occurred (URL, 2023). As can be seen from the increasing number of cases and deaths, it is of great importance that people carrying the virus be diagnosed and isolated as soon as possible to reduce transmission. For the diagnosis of COVID-19 disease, WHO recommends and uses the Real-Time PCR (Polymerase Chain Reaction) test, which detects the presence of antigen from respiratory samples. PCR test results can vary according to hospital protocols, usually between a few hours and a day or two (Boeckmans. J & et al,2021). In addition, Numerous studies have been conducted to control the spread rate of the disease. Deep learning models trained on datasets containing computed tomography images can also assist in the diagnosis of the disease (Gupta et all., 2023). Successful results have been achieved in diagnosing COVID-19 using machine learning models such as SVM, KNN, DT, and Naive Bayes (Albataineh et all., 2022). In order to diagnose COVID-19, a two-dimensional (2D) tunable Q-wavelet transform (TQWT) based on a memristive crossbar array (MCA) has been employed for the decomposition of chest X-ray images from two distinct datasets (Jyoti et all., 2023). In another study, computed tomography devices and X-ray imaging methods of the lungs were utilized (Li and Xia, 2019).

In the article, there are 4 main sections after the introduction. In the second part, there is a short literature review on the diagnosis of COVID-19 disease with Artificial Intelligence. In the third section, general information about the methods presented in the article is given. Chapter 4 contains the experimental results of the study. Chapter 5 contains conclusions and recommendations.

2. Related Works

It can be stated that the use of Artificial Intelligence studies for medical diagnoses has many advantages such as saving time, more accurate diagnoses and helping specialist physicians to work efficiently. With the COVID-19 epidemic, many studies have been carried out using artificial intelligence and lung images around the world. In these studies, disease diagnoses were conducted by using Convolutional Neural Networks **(**CNN), Deep Neural Networks (DNN), and Machine learning. The results of these studies show that imaging lungs with Computed Tomography provide high success in diagnosing the disease more quickly.

Govardhan Jain Et Al. has implemented a four-stage deep network model design for rapid diagnosis of COVID-19 disease, using existing resources and advanced deep learning techniques by classifying 1832 X-ray images as healthy, bacterial, and other viral origins. Obtained results of this study show %97,77 classification accuracy and %97,14 accuracies for COVID-19 disease diagnosis (Jain. G & et all, 2020). Shuo Wang and Wang's colleagues created a dataset containing 5372 images from seven different cities for the diagnosis of COVID-19 disease from lung computed tomography images. Performed operations on four external validation sets, yielding %86 AUC from viral pneumonia %87 AUC from other pneumonia. The systems succeeded in dividing patients into high and low risk groups (Wang et all., 2020).

Y.Pathak et al. obtained %96,22 training and %93,1 test accuracy rate by using the CNN architectural model for the diagnosis of COVID-19 infected patients (Pathak et al., 2020). Ghulam Gilanie and Gilanie's colleagues proposed an automated detection system for COVID-19 disease using CNN networks. The average accuracy of the proposed method was %98,68 (Gilanie et al., 2021).

Zhua Tao et al. created a dataset by combining aggregated datasets from previous studies and new images from the healthcare institution and conducted training and testing on different deep CNN networks (Zhou. T & et al, 2021). M.Turkoglu proposed the ELM-based Deep Neural Network (ELM-DNN) method for lung CT images for the diagnosis of disease and performed deep feature extraction from CNN and CT images. The proposed model for the diagnosis of the disease achieved a success rate of %98,28 (Turkoglu, 2021). Lu Huang et al. classified lung Computed Tomography images for the diagnosis of COVID-19 disease as mild, moderate, severe and critical according to the laboratory and clinical picture of the patients. The study was compared with commercial software and follow-up CT images (Huang et al., 2020).

Ophir Gozes et al. created a dataset from a large number of international CT images for the diagnosis of COVID-19 disease. Using 2D and 3D Deep Learning models, they presented a system that modifies and adapts existing AI models and combines them with clinical understanding. They analyzed the performance of the system by detecting the COVID-19 thoracic Computed Tomography features and used 3D skin examination. Ophir Gozes et al. performed a retrospective experiment to create a "Corona score" by evaluating the evolution of the disease over time in each patient. The dataset included a test set of 157 international patients. As a result of their study, classification results for coronavirus and non-coronavirus cases per thoracic Computed Tomography studies achieved an accuracy of %99,6 AUC (%95 CI: 0,989-1,00). The probable study point of COVID-19 cases in China obtained %98,2 sensitivity and %92,2 specificity (Gozes, 2020).

D. Javor et al. developed a simplified Deep Learning-derived machine learning classifier for the diagnosis of COVID-19 disease. They divided the dataset consisting of 6868 CT lung images of 418 open-source patients into training and validation subsets. They obtained %95,6 Area Under The Curve (AUC) overall accuracy in the independent test dataset of 90 patients (Javor et al., 2020). Song Ying et al. created a data set from CT images of 88 patients diagnosed with COVID-19, 101 patients with bacterial pneumonia, and 86 healthy people from hospitals in two cities in China for diagnosis of COVID-19 disease. They developed a Computed Tomography diagnostic system with Deep Learning methods for the diagnosis of the disease. As a result of their studies, they obtained %95 AUC, %96 recall (sensitivity) and %79 precesion (Y, Song et al., 2021).

3. Background

A total of 9 different studies from Deep learning and Machine learning models were carried out with the classification method for the diagnosis of covid-19 disease. It aims to determine the model that gives the highest accuracy among these methods used in diagnosing the disease.

3.1. Convolutional neural network (CNN)

Artificial Neural Networks are models of computational systems developed by taking the learning ability of the human brain as an example. The human brain has a large number of nerve cells (neurons) connected by synapses. Artificial neural networks emerged as a result of the artificial creation of human synapse and neuron connections (Song et al., 2021). Each artificial neuron is connected to another artificial neuron. Each of these links has its value. Link values contain learned information. The network obtained by connecting artificial nerve cells is called an artificial neural network. Artificial neural networks consist of three layers, the input layer, the hidden layer and the output layer. The input data is included in the network in the input layer, where every input data is transferred to the hidden layer. The hidden layer is the layer where the new data coming from the input is processed, the number of hidden layers may vary according to the structure of the network. A new output value is generated for each input value in the output layer. There are studies in many different fields with Artificial Neural Networks (Abiodun et al., 2018; Sivari et al., 2020). Artificial neural networks determine an output value for each input value (Etyemez, 2019; Dongare et al., 2018). Epochs 30 was preferred in the ANN model in the study, and cv 5 was chosen using the Cross-Validation method for validation.

Convolutional Neural Network (CNN) is a class of neural networks that are organized form of multilayer perceptrons. It was first proposed by Hubel and Wisel in 1960 (Hubel. D & H.Wiesel, 1962). CNN's have reduced the complexity of traditional neural networks in various manners. CNN networks are advantageous because they require less preprocessing. It has applications in many different fields such as image recognition, image classification and natural language processing (Orman et al. ,2021; Türk et al., 2020; Küçük, 2021).By extracting the properties of the data given to the architecture, correlations within the data are made and classified. CNN networks consist of three main parts; the Convolutional Layer, Pooling Layer and Fully Connected layer.

The input layer is the part of the CNN networks where the raw pixel values of the new image coming from the input are located. The data from the input is transferred to the Convolution Layer of the CNN. The Convolution layer is the most basic layer where the convolution operation is applied (Liu et al., 2021). The images from the input are detected and mapped by extracting the features of the images. A certain number of filters are used for the image to extract the features of the images. It performs matrix multiplications by moving filters over images. The convolution operation applied to the image reveals a form of activation. The activation process allows the linear variables of some input data to be changed (Qian et al., 2018). In CNN networks, the input layer is the input part of CNN networks where the raw pixel values of the image newly introduced to the network are included. The data from the input is transferred to the Convolution Layer of the CNN.

The Convolution layer is the most basic layer where the convolution operation is applied (Wei et al., 2020). The main purpose of the convolution layer is to detect the images coming from the input by removing their attributes. Each image comes from the input consisting of pixels with certain values. Matrices with dimensions smaller than the input data try to extract definite features by scanning the images. Matrix multiplications are performed by moving filters over the images while the images are indefinite matrices. A certain number of filters are applied to the images to extract the features of the images. Convolution operations in CNN networks update parameter values by performing multiplication operations continuously. Since CNN networks are deep networks, they can contain very loaded parameters. The convolution process applied to the image reveals a form of activation. The activation process allows changing the linear variables of some input data.

In this study, the sigmoid activation function was used for all architectures. The sigmoid activation function interprets the preceding values and obtains values between 1 and 0. The sigmoid activation function achieves successful results in classification problems. The image is transferred to the pooling layer after the convolution layer. The main purpose of this layer is to reduce the number of parameters in the network. Reducing the parameters allows concentrating on more definite features while ignoring insignificant features. Data in matrix form passing through the convolution and pooling layer in a certain cycle is converted fully connected layer, neurons from the preceding layer are completely interconnected in the flattened part. They are then correlated with the selected density function. The output layer of the network is the part where the result values are labeled. In this study, lung images diagnosed with COVID-19 were labeled '1' and healthy lung images were labeled '0'. Epochs for training 30, batch size 20. Rotation rate in the data augmentation section, rotation range width and height shifts were specified. The basic CNN architectural layers are given in figure 1.

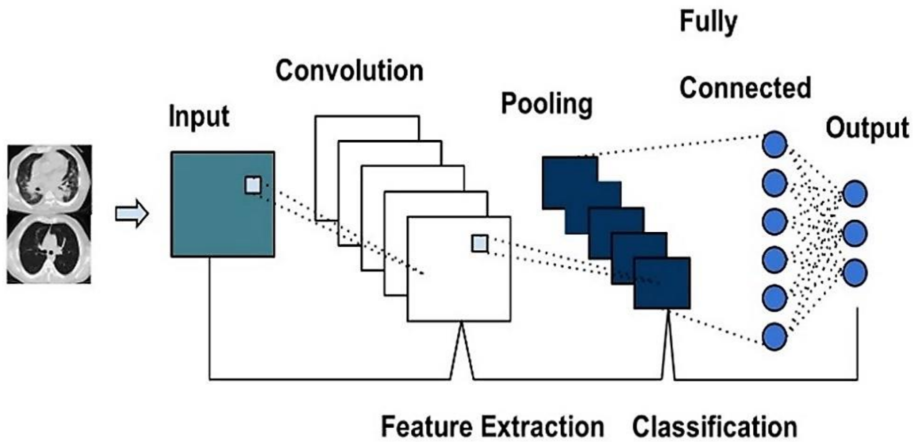


Figure 1. The Basic CNN Architectural Layers

3.2. K nearest neighbours (KNN)

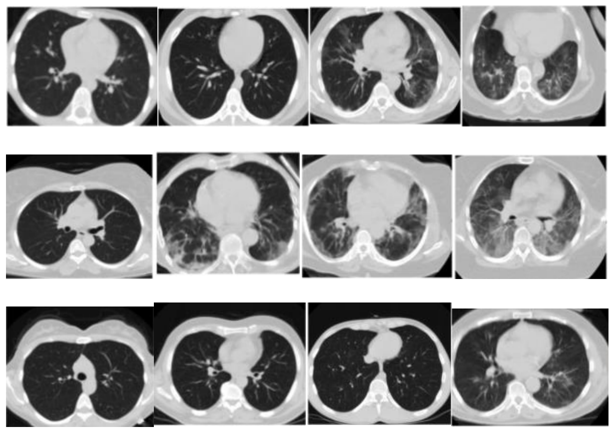
K is the nearest neighbor classification algorithm. It was first proposed by T.M. Civer and P. E. Hart in 1967. It is preferred in solving classification and regression problems (Shaban et al., 2020; Kaya et al., 2018). In the KNN algorithm, a K value is determined first. This K value represents the number of nearest neighbors found according to the given point. This K value represents the number of nearest neighbors found according to the given point. In this case, for the determined K value, the classification is performed according to the distance from the neighbor as much as the nearest K value. The distance of the new data to be included in the data set is calculated one by one according to the existing data. Euclid, Manhattan, and Minkowski distances are used to calculate the distance between them. In this study, K values were 1,3,5,10 and 20, respectively, and the Euclidean function was used for distance calculation.

3.3. Support vector machine (SVM)

Support Vector Machine is a supervised learning algorithm based on statistical learning theory, which is generally used in classification problems. It was first founded in 1963 by Vladimir Vapnik and Alexey Chervonenkis. The main purpose of classification problems is to predict which class the new data will belong to (Dixit et al., 2021). To make the classification, a line is drawn between the two classes. The region between the two lines (1,-1) is called the margin.

3.4. Dataset

In this study, a data set consisting of 7200 images was created together with specialist doctors from the lung Computer Tomography device images of adult patients from the radiology department of a private hospital, which has not been used in



any study before March 2020 and November 2020. The images selected for the datasets were created from definitively diagnosed cases. The total image data in the dataset were used for training, validation and testing. Two different classes were used in the study. The first of these classes consists of images with a definite diagnosis of COVID-19, and the second consists of images of healthy lungs. Test image data was generated by randomly selecting positive and negative images.In Figure 2, images from our own dataset are displayed.

Figure 2. Sample Images from The Dataset

4. Experimental Results

Python language and Keras library were used in classifications for the diagnosis of COVID-19 disease. The results of the models used in the study should be interpreted statistically, and the accuracy and errors of the estimated values should be evaluated crosswise. For this, the results of Precision, recall, F-measure, accuracy and Receiver Operating Characteristics Curve criteria, sensitivity, and specificity were evaluated.

True Positives (TP) = Accurate estimation of the data diagnosed positives as positives.

True Negatives (TN) = Accurate estimation of negatives data.

False Positives (FP) = Inaccurate estimation of the negatives data as positives.

False Negatives (FN) = Inaccurate estimation of the data diagnosed positives as negatives.

Accuracy = The sum of all correctly predicted True Positives (TP) True Negatives (TN) values in the model to the total number of data, to the sum of True Positives (TP), True Negatives (TN), False Positives (FP), False Negatives (FN) values is the rate.

Accuracy = $(TP + TN)/(TP + FP + FN + TN)$ (I)

Precision = It is expressed as the ratio of the correct prediction positives diagnosed data (TP) to the sum of incorrectly estimated positives data (FP) and correctly estimated positives data (TP).

Precision = $(TP)/(TP + FP)$ (II)

Recall = The ratio of the correctly estimated positive diagnosed data (TP) to the total of the correctly estimated positives data (TP) by incorrectly estimating the negative diagnosed data as positives diagnosed data (FN).

Recall = $(TP)/(TP + FN)$ (III)

F-Score = It is the harmonic mean of Recall and Precision values. Indicates the accuracy of the classification performance.

F-Score =$2 \times (Precesion \times Recall) \times (Precesion + Recall)$ (IV)

Receiver Operating Characteristics Curve (ROC) = Roc is a probability curve. X coordinate of the curve represents False Positives (FP), Y coordinate represents True Positives (TP).

The area under the curve is called the Area Under the Curve (AUC). AUC shows the disaggregated measure and value of the parameters. AUC is the part where the performance of the model is summarized, the size of the area covered improves in direct proportion to the class distinctions of the models used.

Sensitivity = It is obtained by dividing the correctly predicted positive (TP) data by the percentage sums of the correctly predicted positive data (TP) and the positive data that was predicted as negative (FN).

Sensitivity = $(TP)/\ float\ (TP + FN)$ (V)

Specificity = It is obtained by dividing the correctly predicted negative data (TN) by the sum of the correctly predicted negative data (TN) and the negative data that was predicted as positive (FP).

Specificity = $(TN)/\ (TN + FP)$ (VI)

The confusion matrix has been utilized to test the accuracy rates of the models. It compares the real and predicted classes of the data divided into two sets. By using the confusion matrix, classification results have been obtained, and the correct or incorrect values of the predictions have been presented in a table format.

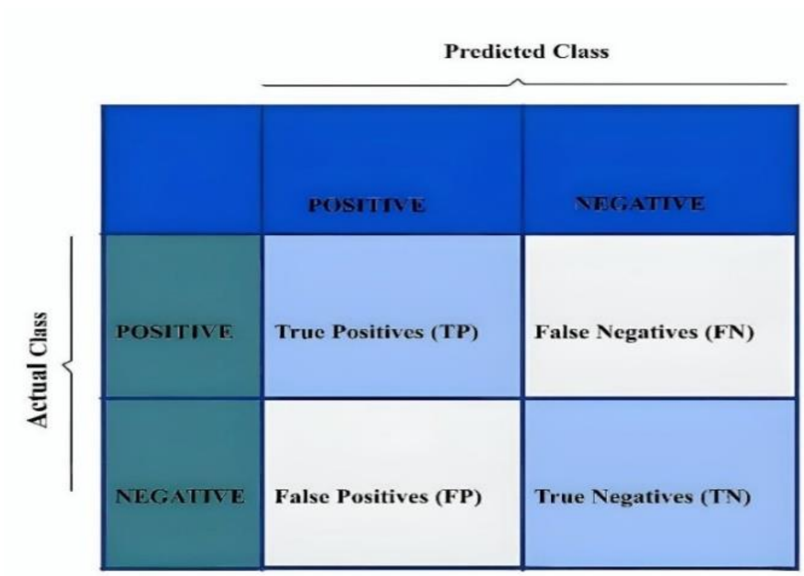


Figure 3. Confusion Matrix Basic Notation

4.1. Results from the CNN models

Training and testing processes were carried out on CNN models. AUC, train accuracy and test accuracy values obtained from 6 different CNN models are given in table 1. Precision, recall and f-score values obtained from 6 different CNN models are given in table 2. Based on table 1 and table 2, when we take the accuracy value as a reference, it could be stated that Densenet architecture is slightly more successful than other models in the test results.

This situation draws attention as a result of the densely connected layer structure of the Densenet architecture and its success in classification. Figure 4 shows the accuracy, sensitivity and specificity values of six different CNN models. Considering these values, it could be claimed that Resnet-50 and inception-v3 models are more successful than other models for our data set. As a result of the hyperparameters mentioned in figure 5, although it gives parallel results in ROC analysis, it confirms that the Densenet architecture is one step ahead with a slight difference.

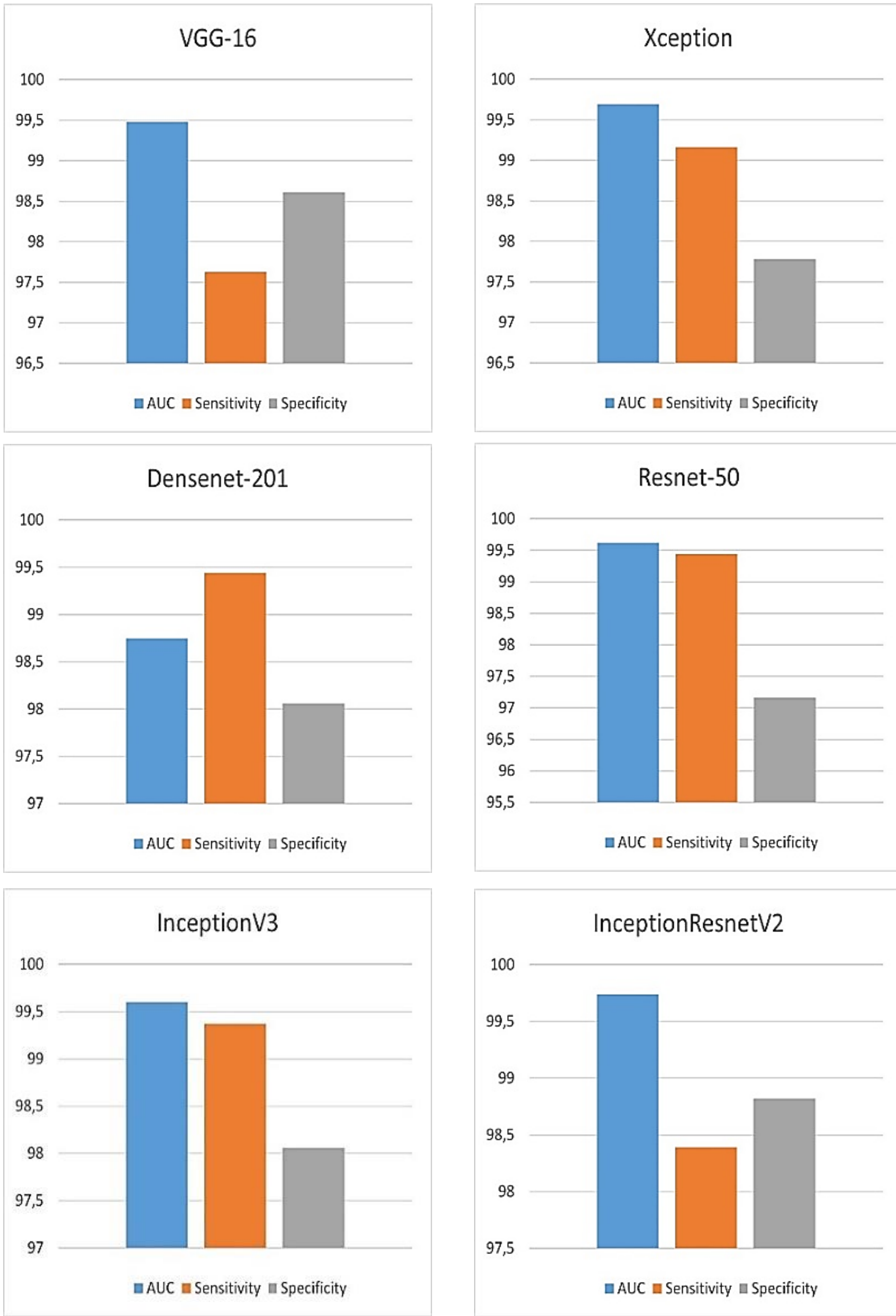


Figure 4. Graphs of AUC, Sensitivity, Specificity Values of All CNN Models

The graphs in Figure 4 display the AUC, sensitivity, and specificity values for each model. The AUC value ranges between 0 and 1. The closer the value is to 1, the better the performance of the selected model. The sensitivity values indicate how accurately the COVID-19 diagnosed data is predicted, while the specificity values indicate how accurately the healthy image diagnosed data is diagnosed.

Table 1 Train Accuracy, Test Accuracy and AUC Values for All CNN Models

Model (%)	Train Accuracy (%)	Test Accuracy (%)	AUC (%)
VGG-16	98,61	98,13	99,48
InceptionResNetv2	99,05	98,61	99,74
ResNet-50	99,44	98,3	99,62
Inception-v3	99,51	98,72	99,6
Xception	99,68	98,47	99,69
DenseNet-201	99,35	98,75	98,75

Table 2 Precision, Recall and F-score Values for All CNN Models

Model	Precision (%)	Recall (%)	F-score (%)
VGG-16	98,59	97,63	98,11
InceptionResNet	98,87	98,39	98,6
ResNet-50	97,21	99,44	98,31
Inception-v3	98,07	99,37	98,72
Xception	98,8	99,16	98,47
DenseNet-201	98,07	99,44	98,75

The precision values in Table 2 represent the ratio of correctly predicted COVID-19 diagnosed data to the total COVID-19 data. On the other hand, recall indicates the ratio of truly predicted COVID-19 data to the total actual COVID-19 data. F-score measures the true performance of the classification model by combining precision and recall values.

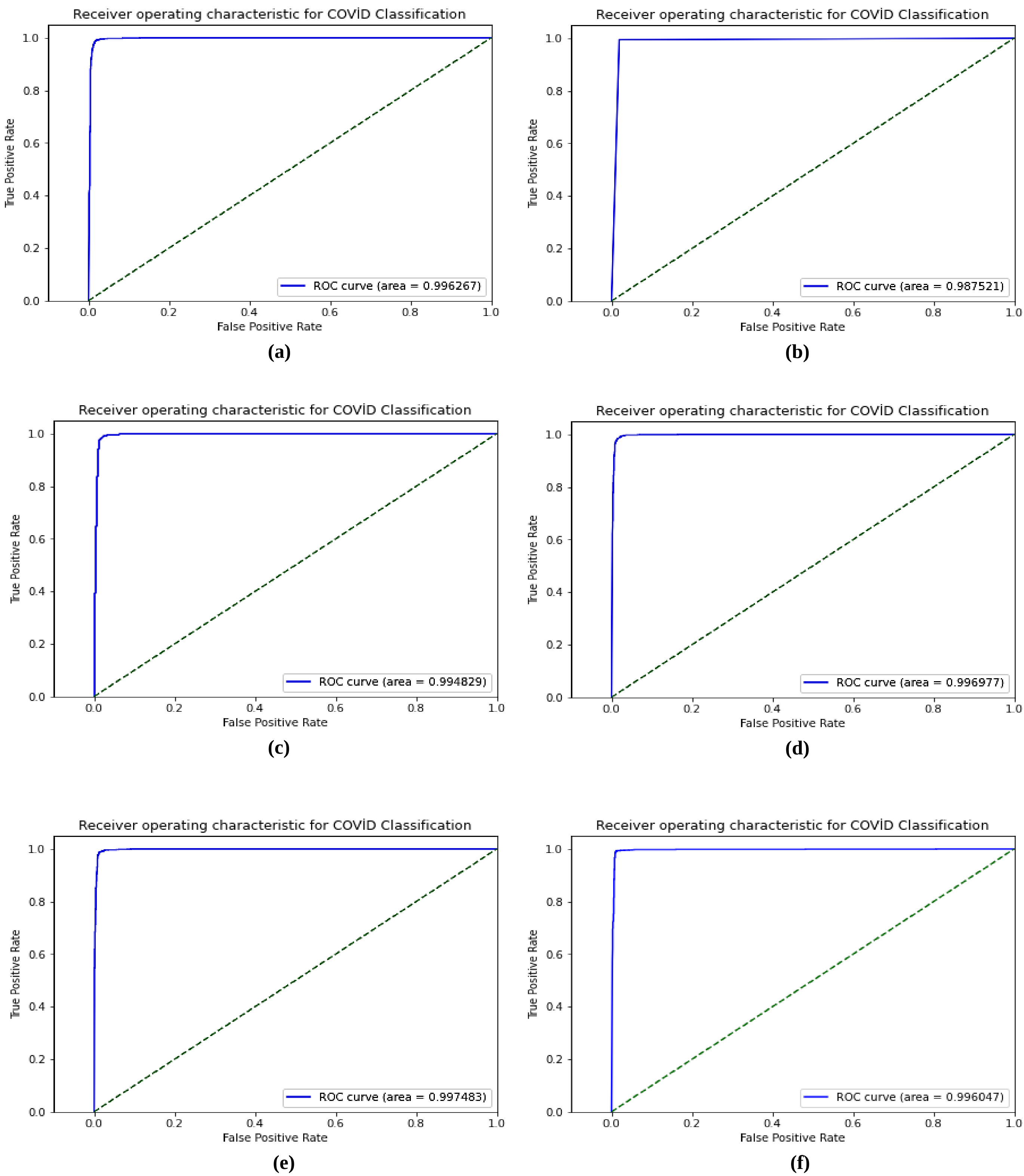


Figure 5. ROC graph of a-) Resnet-50, b-) Densenet-201, c-) VGG16, d-) Xception e-) InceptionResnetv2, f-) Inceptionv3 model

The ROC graph in Figure 5 visualizes the relationship between precision and specificity of the model. The AUC value represents the area under the ROC curve and measures the overall classification performance of the model. A higher AUC value indicates better diagnostic performance of the model.

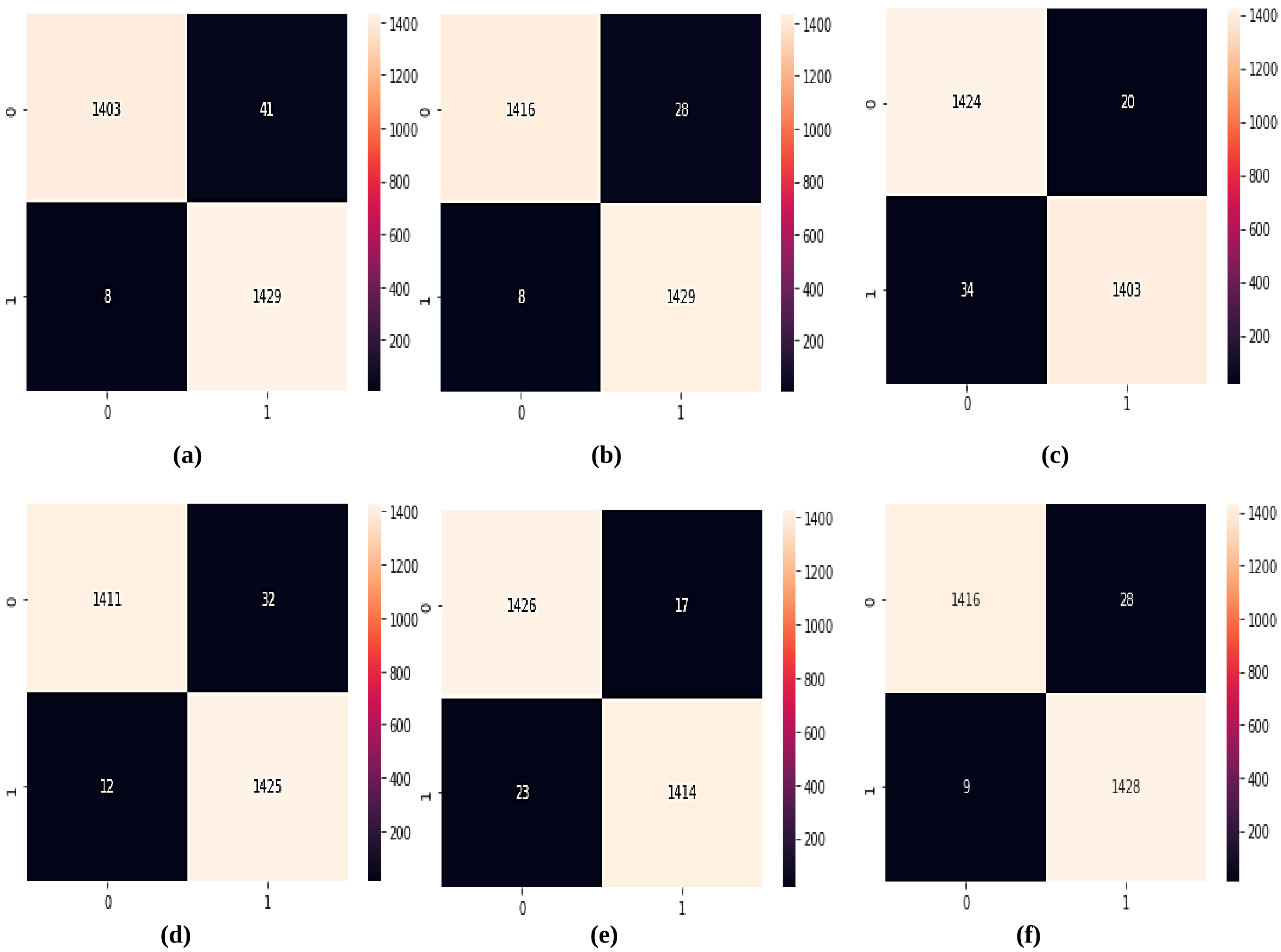


Figure 6. 0 Normal Data 1 Label Represents COVID-19 Data Confusion Matrix of a-) Resnet-50, b-) Densenet-201, c-) VGG16, d-) Xception, e-) InceptionResnetv2, f-) Inceptionv3 Model

If we explain the confusion matrix for the Densenet-201 model in Figure 6, based on the data presented in Figure 3, the true positives (TP) represent the cases where the true positive values are correctly predicted. The model correctly diagnosed 1416 examples as Covid-19 positive. False negatives (FN) represent the cases where true positive values are mistakenly predicted as negative. The model missed the presence of Covid-19 in 28 examples. False positives (FP) represent the cases where true negative values are mistakenly predicted as positive. The model incorrectly diagnosed 8 examples as Covid-19 positive. True negatives (TN) represent the cases where true negative values are correctly predicted. The model correctly classified 1429 examples as non-Covid-19.

4.2. Results from the ANN models

The training was carried out in 30 epoch iterations for the diagnosis of COVID-19 disease with the Multilayer Perceptron model. The Relu function is used in the Inner Layers and the sigmoid function is used in the output layer. As a result of the training, 98.98% accuracy, 97.68% test accuracy and 98.0% AUC were obtained as a result of the test. Precision, Recall and F-score values for the ANN model are given in table 3. In Figure 7, the ROC curve of the ANN model is presented.

Table 3 Precision, Recall and F-Score Values for The ANN Model

Class	Precision (%)	Recall (%)	F-score (%)
Negative	98	97	98
Positive	97	98	97

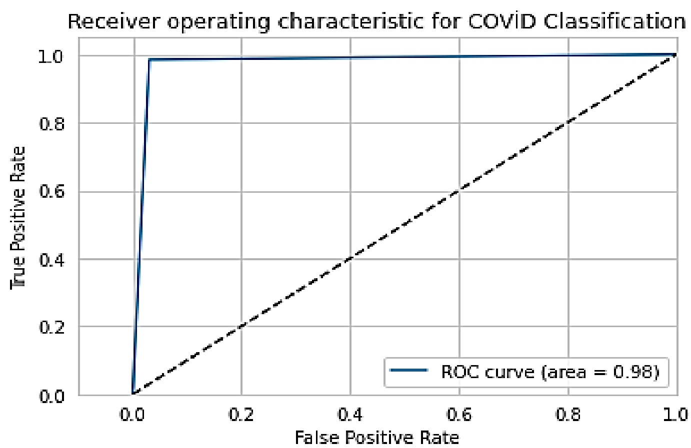


Figure 7. ROC Graph of The ANN Model

4.3. Results from KNN and SVM models

Different values are given for K in the KNN algorithm from Machine learning used for the diagnosis of COVID-19 disease. The accuracy was 97,44% for the K=1 value, %97,0 for the K = 3 value, %96,74 for the K=5 value, %96,56 for the K=10 value, and %96,36 for the K=20 value. As the K value increased, the accuracy decreased. K value and accuracy graph are given in figure 8.

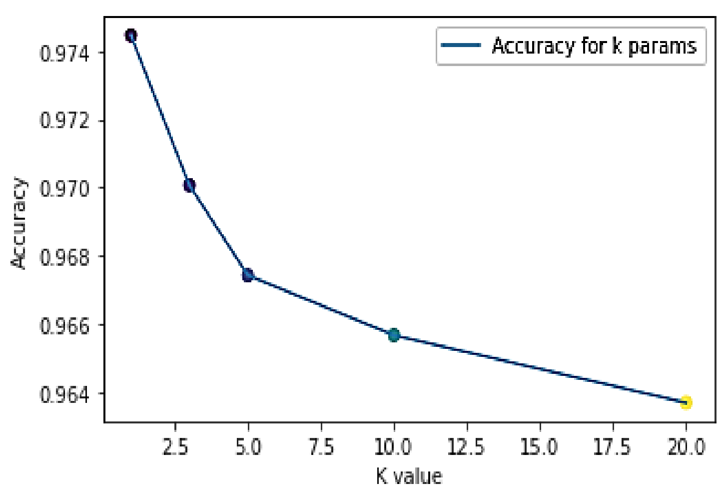


Figure 8. Accuracy Plot for All K values

The test process performed with the SVM model achieved %96,91 accuracies. Table 4 shows the Precision, Recall and F-score values for the SVM model.

Table 4 Precision, Recall and F-Score Values for SVM

Class	Precision (%)	Recall (%)	F-score (%)
Normal	97	98	98
COVID-19	96	95	95

5. Conclusion and Discussion

The rapid diagnosis of COVID-19 is highly important for human health due to the increasing number of cases and deaths rows caused by COVID-19. In this study, CNN architectural models and Machine Learning models KNN, SVM and ANN were used for the diagnosis of COVID-19 disease. It is aimed to detect the algorithm that provides the best results by attempting various algorithms. The highest test accuracy was obtained in the Densenet-201 model of CNN architecture compared to other models according to the results obtained in this study. Table 5 includes studies carried out for the diagnosis of COVID-19 disease. It is observed that the CNN architecture achieved higher success when the obtained results were compared with other algorithms.

Table 5 Some Studies Carried Out for The Diagnosis of COVID-19 Disease

Authors	Data Sources	Techniques	Performance (%)
D. Javor & et al. doi:10.1016/j.ejrad.2020.109402	6868 lung computed tomography images	Resnet-50	Test data set AUC %95,6 rule out (>0,0006) sensitivity 100, specificity 60, rule out (>0,4) AUC % 95,6 sensitivity 84,4 specificity 93,3 radiologist 1 (test dataset) 87,67 sensitivity 82,2 specificity 91,1 radiologist 2 (test dataset) 88, sensitivity 80, specifity 97,8
Aayush Jaiswal & et al. doi:10.1080/07391102.2020.1788642	2492 lung computed tomography images	Densenet-201, VGG-16, Resnet152V2, InceptionResnetV2	VGG-16 test accuracy %95,45, test specifity%95,67,InceptionResnetv2 test accuracy %90.90, test specificity %89,72, Resnet152V2 test accuracy %94,91, test specificity %92,43, Densenet-201 test accuracy %96,25, test specificity 96,21
Shervin Minaee & et al. doi:10.1016/j.media.2020.101794	5000 lung X-ray images	Resnet-18, Resnet-50, Squeezenet, Densenet-121	Resnet-18 AUC %98,9, Resnet-50 AUC %99, Squeezenet AUC %99,2, Densenet-121 AUC %97,6
Y.Pathak & et al. doi:10.1016/j.irbm.2020.05.003	852 lung computed tomography images	Resnet-50 ANN	Resnet-50 validation accuracy 87,35, validation specificity %86,97, validation sensitivity %87,73, ANN validation accuracy % 85,09

Table 5 includes some studies with their results for the diagnosis of COVID-19 disease. D.javor et al. created a dataset consisting of 6668 lung computed tomography images. With the Resnet-50 model, they obtained %95,6 AUC, sensitivity 100, and specificity 60 for rule out (>0,0006), while they obtained %95.6 AUC, sensitivity 84.4, and specificity 93,3 for rule out (>0,4). In the Resnet-50 model in our study, %99.62 AUC, sensitivity %99.4, and specificity %97,16 results were obtained.

Aayush Jaiswala et al. created a dataset consisting of 2492 lung computed tomography images. They obtained %96,25 test accuracy and %99,21 test specificity from the Densenet-201 model. From the VGG-16 model, they obtained %95,45 test accuracy and %95,67 test specificity. They also obtained %90,90 test accuracy and %89.72 test specificity from the InceptionResnetV2 model and obtained %94,91 test accuracy and %92,43 test specificity from the Resnet152V2 model. These three model results were obtained in our study. Respectively, from the Densenet-201 model; %98,75 test accuracy and 98,06 test specificity, from the VGG-16 model; %98,13 test accuracy and %98,61 test specificity and lastly from the InceptionResnetV2 model; %98.61 test accuracy and %98,82 test specificity was obtained.

According to the results obtained by Shervin Minaee et al. from the Resnet18, Resnet-50, Squeezenet, and Densenet-121 architectures in datasets consisting of 5000 lung X-ray images, the obtained AUC %98,9 from Resnet-18, AUC %99 from Resnet-50, AUC %99,2 from Squeezenet, and AUC %97,6 from Densenet-121. %99,62 AUC was obtained from the common model, Resnet-50, in our study.

Y.Pathak et al. conducted studies on datasets consisting of 852 lung computed tomography images on models common with our study, Resnet-50 and ANN models.

They obtained %87,35 validation accuracy, %86,97 validation specificity, and %87,73 validation sensitivity in the Resnet-50 model while the ANN validation accuracy was %85,09. In our study, the Resnet-50 model had %98,30 test accuracy, %99,44 test specificity, %97,16 validation sensitivity. Moreover, the ANN model in our study had %97,68 test accuracy.

The success of CNN architectures in classification problems is also observed in those obtained results. With the classification method for disease diagnosis, better results can be obtained from the models by trying different methods and different models in CNN models. As the number of data increases and with a more efficient data set, higher test results can be obtained. To obtain higher results in machine learning algorithms, studies can be conducted with different values and different models.

The findings obtained in the study indicate that deep learning holds great potential for contributing to healthcare systems and humanity in the diagnosis of COVID-19 and other diseases. In this study, six different pretrained CNN architectures were employed for the diagnosis of COVID-19. The aim was to determine the network that achieves the highest accuracy by comparing their performance. The success rates of the classification can be observed by examining the confusion matrices presented in Figure 6. High accuracy rates were observed in all CNN models, which can be attributed to factors such as a larger dataset and data augmentation techniques that enable the networks to better learn from the data. The utilization of pretrained models has further improved the performance of the CNN architectures. Adjusting the networks at different layers and components has led to better results.

In addition to assisting healthcare professionals in disease diagnosis, artificial intelligence can perform the diagnostic process promptly upon data acquisition, thereby saving time and potentially protecting individuals from other risks. Generating a unique dataset for disease diagnosis studies can be challenging. By adding images from other lung-related diseases to the created dataset, multi-class classification can be performed, enabling the differentiation and diagnosis of multiple diseases simultaneously. Trained and tested networks can be integrated into a system and transformed into a ready-to-use program for utilization by experts. Disease diagnosis using artificial intelligence can reduce human error and increase the accuracy of diagnoses or validate existing ones, complementing human attention. As with many other fields, disease diagnosis with artificial intelligence is expected to become more actively utilized in the future.

References

Abiodun, O., I., Jantan, A., Omolara, A., E., Dada, K., V., Mohamed, N., A., E., Arshad, H. (2018). State-of-the-art in artificial neural network applications: A survey. Heliyon, 4(11), e00938.

A, Etyemez. Yapay Sinir Ağları Yöntemi ile Optimum Takım Seçimi. (2019). El-Cezeri Fen ve Mühendislik Derg.,no. 2, pp. 323–332, 2019, doi: 10.31202/ecjse.511882.

A, Jaiswal., N, Gianchandani., D, Singh and V, Kumar. (2020).Classification of the COVID-19 infected patients using DenseNet201 based deep transfer learning. J. Biomol. Struct. Dyn, vol. 0, no. 0, pp. 1–8.

A, Zaid., N, Aldrweesh., F, Alzubaidi., A., M (2023). COVID-19 CT-images diagnosis and severity assessment using machine learning algorithm J. Springer Nature 202. doi:10.1007/s10586-023-03972-5

A, Orman., U, Köse and T, Yiğit. (2021).Açıklanabilir Evrişimsel Sinir Ağları ile Beyin Tümörü Tespiti. El-Cezeri Fen ve Mühendislik Derg., no. 3, pp. 1323–1337, 2021, doi: 10.31202/ecjse.924446.

Boeckmans, J., Cartuyvels., R, Hilkens., P, Bruckers., L, Magerman., K, Waumans., L, Raymaekers., M.(2021). Follow-up testing of borderline SARS-CoV-2 patients by rRT-PCR allows early diagnosis of COVID-19. Diagnostic Microbiology Infectious Disease, Journal Pre-proof,100(2), 115350.

Brunese, L., Mercaldo, F., Reginelli, A., Santone, A. (2020). Explainable Deep Learning for Pulmonary Disease and Coronavirus COVID-19 Detection from X-rays. Computer Methods and Programs in Biomedicine, 196, 105608.

Dixit, A., Mani., A, Bansal., R. (2021). CoV2-Detect-Net: Design of COVID-19 prediction model based on hybrid DE-PSO with SVM using Chest X-ray images. Information Sciences, 676-692.

D, Kaya., M, Türk., and T, Kaya.(2018).Examining the Effect of Dimension Reduction on EEG Signals by K-Nearest Neighbors Algorithm. El-Cezeri Fen ve Mühendislik Derg., vol. 5, no. 2, pp. 591–595, doi: 10.31202/ecjse.385192

Dongare, A., D., Kharde, R., R., Kachare, A., D. (2012). Introduction to Artificial Neural Network (ANN) Methods. International Journal of Engineering and Innovative Technology (IJEIT), 2(1), 189–194.

E, Sivari., Z, Civelek and G, Kahraman.(2020). Artificial neural network model estimating the initial dose of propofol used in general anesthesia. El-Cezeri J. Sci. Eng., vol. 7, no. 3, pp. 1482–1495, 2020, doi: 10.31202/ecjse.764719

F,Türk., M, Lüy and B,Gökçen.(2020). International Journal of Engineering Research and Development. Multi Depth V-Net Model Ile 3 Boyutlu Böbrek ve Tümör Segmentasyonu 3D Kidney and Tumor Segmentation with Multi Depth V-Net Model.Vol.12.

Gilanie, G., Bajwa, U. I., Waraich, M. M., Asghar, M., Kousar, R., Kashif, A., Aslam, R. S., Qasim, M. M., Rafique, H. (2021). Coronavirus (COVID-19) Detection from Chest Radiology Images using Convolutional Neural Networks. Biomedical Signal Processing and Control, 66(February), 102490.

Gozes, O., Frid, M., Greenspan, H., Patrick, D. (2020). Rapid AI Development Cycle for the Coronavirus (COVID-19) Pandemic : Initial Results for Automated Detection Patient Monitoring using Deep Learning CT Image Analysis Article Type : Authors : Summary Statement : Key Results : List of abbreviate.

Gupta, K., Bajaj, V. (2023). Deep learning models-based CT-scan image classification for automated screening of COVID-19. Biomedical Signal Processing and Control, 80(February), 104268.

Huang. L, Han. R, Ai. T, Yu. P, Kang. H, Tao. Q, Xia. L.(2020). Serial Quantitative Chest CT Assessment of COVID-19 :A Deep Learning Apporach. Radiology: Cardiothoracic İmaging,(2) ,200075.

Hubel, D., H., Wiesel, T. (1962). AND FUNCTIONAL ARCHITECTURE IN THE CAT'S VISUAL CORTEX From the Neurophysiolojy Laboratory , Department of Pharmacology central nervous system is the great diversity of its cell types and inter- receptive fields of a more complex type (Part I) and to. Most, 106–154.

Jain, G., Mittal, D., Thakur., D, Mittal., M., K.(2020). A deep learning approach to detect Covid-19 coronavirus with X-Ray images. Science Direct,40(4), 1391–1405.

Javor, D., Kaplan, H., Kaplan., A, Puchner., S, B., Krestan., C, Baltzer., P.(2020). Deep learning analysis provides accurate COVID-19 diagnosis on chest computed tomography. European Journal of Radiology, 133, 109402.

Jyoti, K., Sushma, S., Yadav., S, Kumar., A, B., Pachori., B, R., Mukherjee., S (2023). Deep learning analysis provides accurate COVID-19 diagnosis on chest computed tomography. Computers in Biology and Medicine, 152, 106331.

Liu, T., Fang, S., Zhao, Y., Wang, P., Zhang., J. (2015). Implementation of Training Convolutional Neural Networks. Arxiv,1506, 01195.

Li,Y., Xia, L.Coronavirus disease.(2019). (COVID-19): Role of chest CT in diagnosis and management. American Journal of Roentgenology,214(6), 1280–1286.

M, Demirbilek.(2021). Tam ve Kısmi Kapanma Stratejilerinin COVID-19 Salgını Üzerinden Karşılaştırılması. No. 2, pp. 1024–1034, 2021.

Ö, Küçük., E, YAVŞAN and N, BARIŞCI.(2021). International Journal of Engineering Research and Development. An Autonomous-based, System Development, and Lane Recognition.Vol.13.

Qian, S., Liu., H, Liu., C, Wu., S, Wong., H, S.(2018). Adaptive activation functions in convolutional neural networks. Neurocomputing, 272, 204–212.

Shaban, W., M, Rabie., A, H., Saleh., A., I and Abo-Elsoud, M., A.(2020). A new COVID-19 Patients Detection Strategy (CPDS) based on hybrid feature selection and enhanced KNN classifier. Knowledge-Based Systems, 205, 106270.

S, Minaee., R, Kafieh., M, Sonka., S, Yazdani, and G, Jamalipour Soufi.(2020).Deep-COVID: Predicting COVID-19 from chest X-ray images using deep transfer learning.Med. Image Anal, vol. 65.

Turkoglu, M.(2021). COVID-19 Detection System Using Chest CT Images and Multiple Kernels-Extreme Learning Machine Based on Deep Neural Network.IRBM, pp. 1–8.

Wang, L., Lin., Z, Q., Wong., A.(2020). COVID-Net: a tailored deep convolutional neural network design for detection of COVID-19 cases from chest X-ray images. Scientific Reports, 10(1), 1–12.

Wang, S., Zha, Y., Li, W., Wu, Q., Li, X., Niu, M., Wang, M., Qiu., X, Li., H., Yu. H, Gong., W, Bai., Y, Li., L, Zhu., Y, Wang., L, Tian., J.(2020). A fully automatic deep learning system for COVID-19 diagnostic and prognostic analysis. European Respiratory Journal,56(2), 2000775.

Wei, L., Cai., J, Nguyen., V, Chu., J, Wen., K.(2020).P-SFA: Probability based Sigmoid Function Approximation for Low-complexity Hardware Implementation. Microprocessors and Microsystems,76, 103105.

Yang, X., Yu, Y., Xu, J., Shu, H., Xia., J, Liu., H, Wu., Y, Zhang., L, Yu., Z, Fang., M, Yu., T, Wang., Y, Pan., S, Zou., X, Yuan., S, Shang., Y.(2020). Clinical course and outcomes of critically ill patients with SARS-CoV-2 pneumonia in Wuhan, China: a single-centered, retrospective, observational study. The Lancet Respiratory Medicine, 8(5), 475–481.

Y, Pathak., P, K., Shukla., A, Tiwari., S, Stalinnand S, Singh.(2020). Deep Transfer Learning Based Classification Model for COVID-19 Disease," Irbm, vol. 1, pp. 1–6.

Y, Song et al.(2021). Deep learning Enables Accurate Diagnosis of Novel Coronavirus (COVID-19) with CT images. IEEE/ACM Trans. Comput. Biol. Bioinforma.,vol. 14, no. 8, 2021.

Zhou, T., Lu., H, Yang,. Z, Qiu., S, Huo., B, Dong., Y.(2021). The ensemble deep learning model for novel COVID-19 on CT images. Applied Soft Computing, 98, 106885.

URL. (2023). Novel coronavirus –2019. World health organization.https://covid19.who.int/accessed 10.07.2023.