Volume 14, Issue 1, Page 156-166, 2025 https://doi.org/10.46810/tdfd.1472034 Research Article

BİNGÖL UNIVERSITY

Türk Doğa ve Fen Dergisi
Turkish Journal of Nature and Science
www.dergipark.gov.tr/tdfd

Development of an Effective Deep Learning Model for COVID-19 Detection from CT Images

Tanju CEYLAN[*], **Özkan İNİK**[2]

[1] Tokat Gaziosmanpaşa University, Department of Computer Engineering, Tokat, Türkiye
[2] Tokat Gaziosmanpaşa University, Department of Computer Engineering, Tokat, Türkiye
Tanju CEYLAN ORCID No: 0009-0001-3843-5785
Özkan İNİK ORCID No: 0000-0003-4728-8438

**Corresponding author: tanju.ceylan@gop.edu.tr*

(Received: 26.04.2024, Accepted: 17.02.2025, Online Publication: 26.03.2025)

Keywords
Deep learning,
Image classification,
COVID-19 ,
Computed tomography

Abstract: Coronavirus Disease (COVID-19) is an RNA-type virus that is spreading worldwide. COVID-19, which was first seen in Wuhan, China, in December 2019, quickly began to be seen in all countries of the world.Symptoms such as respiratory tract infections, fever, cough and shortness of breath are common in the diagnosis of the disease. The diagnosis of the disease is made in the first stage by applying the Polymerase Chain Reaction (PCR) test. The long duration of laboratory research has led researchers to different methods. In this study, a model was designed that can help radiologists detect the disease through Computed Tomography (CT) images. This system, based on deep learning, aims to detect the disease by classification method through COVID-19 positive and negative chest tomography images. The data set used in the study consists of a total of 5000 images. Experimental studies have been conducted on Convolutional Neural Network (CNN) models such as AlexNet, Densenet201, GoogleNet, ResNet-50, Vgg-16, EfficientNet and the proposed CNN model. COVID-19 prediction was made with the designed CNN model with a success rate of 99.20%. An effective and successful model is proposed for COVID-19 detection from CT images.

BT Görüntülerinden COVID-19 Tespiti İçin Etkili Bir Derin Öğrenme Modeli Geliştirilmesi

Anahtar Kelimeler
Derin öğrenme,
Görüntü sınıflandırma,
COVID-19,
Bilgisayarlı tomografi

Öz: Coronavirüs Hastalığı (COVID-19), dünya çapında yayılan RNA tipi bir virüstür. İlk olarak Aralık 2019'da Çin'in Wuhan kentinde görülen COVID-19, hızla dünyanın tüm ülkelerinde görülmeye başlandı. Hastalığın tanısında solunum yolu enfeksiyonları, ateş, öksürük ve nefes darlığı gibi belirtiler sık görülüyor. Hastalığın tanısı ilk aşamada Polimeraz Zincir Reaksiyonu (PCR) testi uygulanarak konmaktadır. Laboratuvar araştırmalarının uzun sürmesi araştırmacıları farklı yöntemlere yöneltmiştir. Bu çalışmada Bilgisayarlı Tomografi (BT) görüntüleri aracılığıyla radyologların hastalığı tespit etmesine yardımcı olabilecek bir model tasarlandı. Derin öğrenmeye dayanan bu sistem, COVID-19 pozitif ve negatif göğüs tomografisi görüntüleri üzerinden hastalığın sınıflandırma yöntemiyle tespit edilmesini hedefliyor. Çalışmada kullanılan veri seti toplam 5.000 adet görselden oluşmaktadır. AlexNet, Densenet201, GoogleNet, ResNet-50, Vgg-16, EfficientNet gibi Evrişimsel Sinir Ağı (CNN) modelleri ve önerilen CNN modeli üzerinde deneysel çalışmalar yapılmıştır. Tasarlanan CNN modeliyle %99.20 başarı oranıyla COVID-19 tahmini yapıldı. BT görüntülerinden COVID-19 tespiti için etkili ve başarılı bir model önerilmiştir.

1. INTRODUCTION

Coronavirus group diseases were first seen in world history in 1960 [1]. Considering the last 25 years, there have been virus epidemics with high lethal effects. “Severe Acute Respiratory Syndrome (SARS-CoV) respiratory disease was seen in Asia, Europe and North America in 2003 [2]. The Middle East Respiratory Syndrome-coronavirus (MERS-CoVS) virus, which occurs with serious respiratory failure problems, affected humanity in the Arabian Peninsula in 2012 [3]. Finally, in December 2019, pneumonia cases began to be seen in Wuhan, China's Hubei Province, with symptoms such as high fever, cough, weakness and shortness of breath. The symptoms were first seen in animal markets and areas where seafood is sold. The World Health Organization (WHO) has defined this new virus as "COVID-19". This name consists of the initials of "co" corona, "vi" virus and "d" English word "dease". WHO has named this virus that causes COVID-19 disease as Severe Acute Respiratory Syndrome-Coronavirus-2 (SARS-COV-2). WHO announced COVID-19 to the world as a pandemic, that is, a global epidemic, on March 11, 2020. The first case in our country was officially recorded on this date.

The most used method for detecting COVID-19 is the PCR method [4]. It is known that PCR test results take an average of 6 hours. While the main goal in combating the disease is to use time in the most effective way, using kits sometimes delays the result and may cause high economic costs. Even if the PCR test result is negative in the early stages of the disease, the advantage of radiology imaging methods such as X-ray or CT is that the disease can be detected from images at every stage. In the later stages of the disease, comments can be made about the patient's condition and necessary precautions can be taken thanks to these detailed imaging techniques. CT images provide the opportunity to obtain detailed information about many vital structures such as the status of organs, lesions, developing pneumonia, soft tissues, and the status of vessels. Although the CT imaging method has such advantages, the patient's condition must be reported by a physician. After reporting, appropriate treatment must be administered to the patient as quickly as possible. It is vital that the sooner the reporting process ends, the isolation of the patient and the initiation of treatment will reduce the risk of transmission. Reporting the diagnoses made significantly increases the workload of radiologists. The exponential increase in the number of patients during the pandemic has led the scientific world to seek various solutions to reduce this burden on physicians. One of these solutions is work done with artificial intelligence. Artificial intelligence-based systems are used to detect many diseases [5-8]. Various deep learning models are used to mark disease-related parts on X-Ray imaging and CT images and to process the generated data. When looking at these studies, it can be seen that deep learning models are generally used. Because deep learning models have been shown to provide results with high accuracy in many areas [9-15]. In addition, many artificial intelligence models and experimental studies developed for COVID-19 detection are also included in the literature. Some of the studies in the literature are mentioned below.

Hemdan et al. (2020) designed a CNN model called COVIDDX-Net. They carried out their studies with the aim of early diagnosis of COVID-19 disease with this design. COVIDX-Net includes 7 CNN methods such as VGG19 and GooglleNet. They used 50 chest X-ray images as the data set. They reached a success rate of 89% with VGG-19 and 91% with DenseNet [16]. Bozkurt (2021) conducted a study using deep learning techniques to prevent the spread of COVID-19 disease and make a rapid diagnosis. With the applied methods, He aimed to examine lung X-Ray images in 3 classes: COVID-19, normal and viral pneumonia patients. In the study conducted with 11 different methods, he achieved the highest success rate of 97.17% using the DenseNet121 method [17]. Seyyed Mohammad et al. (2021) aimed to detect COVID-19 with the help of artificial intelligence through CT images and used data from 2 separate public hospitals for this study. The data set consists of 3 categories. The number of images used in the categories consists of 5.705 pneumonia cases, 4.001 COVID-19 patients and 9.979 normal people. In the study, they compared different DNN models. They achieved the best result with their proposed model called Wavelet CNN-4 with a success rate of 99.03% [18]. Oğuz (2021) worked on a COVID-19 diagnostic model to support radiologists. 1.345 CT images taken from Siirt Training and Research Hospital were used as a data set. He used 80% of the data for training and 20% for testing. Feature extraction was performed using ResNet-50, ResNet-101, AlexNet, Vgg-16, Vgg-19, GoogLeNet, SqueezeNet, Xception models. The most successful results were achieved with a success rate of 96.29% through the ResNet-50 model [19]. Panahi et al. (2021) believed that the interpretation of PCR test kits and CT methods by physicians in detecting COVID-19 disease delayed the process and aimed to make a faster diagnosis with the help of artificial intelligence. For this purpose, they used X-Ray images of 940 people as the data set for their study. They developed a classification method called Fast COVID-19 Detector (FCOD) and achieved a 96% accuracy rate with the developed method [20]. Urut and Özdağ (2022) aimed to detect COVID-19 with the recurrent neural network method Recurrent Neural Network (RNN) using a deep learning algorithm on chest x-ray images. They aimed to reduce the burden of diagnosis on physicians. The data set used in the study consists of 576 positive cases and 1.583 normal person images. They worked on models such as Resnet, VGG and DenseNet for the system that will perform the classification process. They achieved the highest success rate with the Resnet method with a prediction accuracy of 97% [21]. Ceylan and İnik (2022) developed an original deep learning model aiming to detect COVID-19. The data set used in the study was obtained from the open access Kaggle platform. In the data set they created from a total of 6.000 images, they used 3.600 images for training, 1.800 images for testing, and 600 images for verification. During the experimental studies, they reached the highest success rate of 99.7%. They reported that conditions such as the clarity, size, and learning frequency of the visuals affected the success rate [22]. Çelik and İnik (2023) used artificial intelligence-based computer vision systems to diagnose monkeypox disease in their study. Monkeypox disease is similar to other chickenpox diseases. They aimed to reduce the workload of experts with the study. The dataset was trained on VGG-19, VGG-16, MobileNet V2, GoogLeNet, and EfficientNet-B0 models. It has been observed that the success rate increases as the number of images in the data set increases. They achieved the highest success rate of 99.25% with the increased data set [23]. Pacal (2023) used the data set named COVID-QU-Ex in his study. In his study, he trained with the ViT-L16 model. 11.956 COVID-19 images, 11.263 non-COVID pneumonia cases and 10.701 Normal case images were used in the dataset. As a result of the study, they reached a 96% accuracy rate with the ViT-L16 model [24]. Doğan (2023) used the widely used COVID-19 data set in his study and performed a cross-data set evaluation. ResNet50 model was used in the research and the highest success rate (71.47%) was achieved with this model [25]. In their study, Tüfekçi and Gezici (2023) aimed to distinguish between COVID_19 and Pneumonia diseases. Cross-validation was performed 10 times on the data set used and the highest success rate (99.90%) was obtained with the Alexnet model. [26].

The contributions made to the literature in this study are given below:

• The data set used in the study consists of CT images of people treated at Tokat Gaziosmanpaşa University Hospital. This data set was created originally.

• An novel CNN model was designed and a high success rate was achieved with the original data set.

• The success of the proposed original CNN model was compared with state-of-the-art models.

In the second part of the article, information will be given about the methods and materials used, in the third part, information will be given about the experimental studies, and in the fourth part, information will be given about the obtained results and inferences.

2. MATERIAL AND METHOD

2.1. Deeep Learning

In this section, information about artificial intelligence and deep learning concepts will be given. Under the title of deep learning, information about Convolutional Neural Networks (CNN) architecture will be given. Information is given about layers such as Input Layer, Convolution Layer, Pooling Layer, Fully Connected Layer, Dropout and Classification Layer in the CNN architecture. With its ability to think and interpret, the human brain can decide in a very short time what its next move will be or easily solve a numerical operation. A person can interpret what may happen to him and what consequences his actions will have based on his previous experiences. Although computers can solve very complex operations instantly, they do not have direct abilities such as interpretation and decision-making[27]. The development process of artificial intelligence started with studies using these skills that the human brain can do as a model. Artificial intelligence can be defined as a machine performing tasks such as solving a problem, extracting meaning, and producing a solution by imitating human characteristics. Although the history of deep learning does not date back to ancient times, it is a very popular subject in terms of application areas and experimental studies. The concept of deep learning attracted attention for the first time thanks to the large-scale visual recognition competition (ImageNet. Large-Scale Visual Recognition Challenge / ILSVRC) held in the object recognition category in 2012 [28]. While there are scientists who see deep learning as a sub-branch of machine learning, there are also scientists who argue the opposite and argue that it is a completely different field of study. With deep learning, tasks that may take a long time for humans to do, as well as tasks in daily life, can be done easily, and humanoid disadvantages such as mental state or fatigue are not encountered [29]. Deep learning consists of multi-layer artificial neural networks and can process large amounts of data simultaneously. The increase in Big Data day by day and the continuous development of graphics card (GPU) features have improved the capabilities of deep learning and it has become increasingly popular after 2000.

Deep learning is used in many areas such as image processing, facial recognition systems, natural language processing, voice recognition, fingerprint readers, robotics, gene analysis, and driverless cars. The most commonly used features of deep learning are classification, recognition and detection [30].

2.2. Convolutional Neural Network (CNN)

Convolutional Neural Network (CNN) architecture is frequently used in computer vision applications. CNN architecture consists of various layers such as input layer, convolution layer, pooling layer, fully connected layer, relu layer, scaling layer, classification layer. A classical CNN architecture is given in Figure 1.

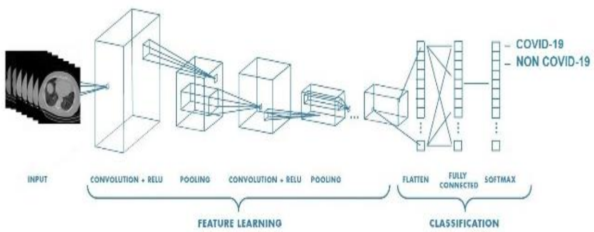


Figure 1. Classic CNN architecture

Input Layer: The input layer is the first layer of the CNN architecture. The data enters the system as it is from this layer. The size of the data transferred to the system is important. If the size is chosen small, the memory requirement will decrease, the training time will decrease, but the success rate may decrease. If it is chosen larger, the training time increases, the memory requirement increases and the success rate may increase. Finding the perfect input size for our system is important for training time and performance.

Convolution Layer: This layer, which is the most basic component in the CNN architecture, is also known as the convolution layer or transformation layer. The most basic operation of this transformation occurs by creating new matrices by moving a certain filter of 3x3, 5x5, 7x7, 9x9 size over the entire image.

Pooling Layer: Pooling layer usually comes after the relu layer. The input data studied may be large in size, which causes complexity and prolongation of training time. The pooling layer aims to gradually reduce this large size of data, preventing memorization while preserving important parts of the feature map. This reduction affects length and width but not depth. These reductions in the number of parameters also prevent system confusion.

Fully Connected Layer: In the CNN architecture, the fully connected layer comes after the convolution layer, relu layer and pooling layer. The neurons in this layer connect to all the neurons of the previous layer and work by transferring their outputs to the next layer [31]. It is used in studies such as fully connected layer classification processes, natural language processing and image processing. The feature in the layer is obtained by connecting the matrices on this layer.

Dropout Layer: It is a method developed to prevent multilayer neural networks from memorizing. After a determined threshold value, information that may be considered unimportant is forgotten. The system prevents excessive loss of time and prevents memorization. Dropout process is accomplished by deleting some random links.

Classification Layer: In this layer, results are produced as many as the number of items to be classified. For example, if 4 different types of objects are to be classified, the classification layer output value should be 4. Different classification types are used for the classifier layer applied as the last layer. Softmax can be said to be the most well-known classifier [30].

2.3. Data Set

The data set used in the study consists of CT images of people receiving treatment at Tokat Gaziosmanpaşa University Hospital, as a result of the permissions obtained in accordance with the ethics committee decision no. 26. 23-KAEK-033 and 83116987-092. The data set was created from CT images of patients and healthy people diagnosed as COVID-19 positive, who were examined at the relevant polyclinic between 2019 and 2023. The data set consists of 5.000 images in total, including 2.500 images of 250 Covid-19 patients and 2.500 images of 250 healthy individuals. Images representing CT image classes of COVID-19 Positive and COVID-19 Negative people in the data set are given in Figure 2.

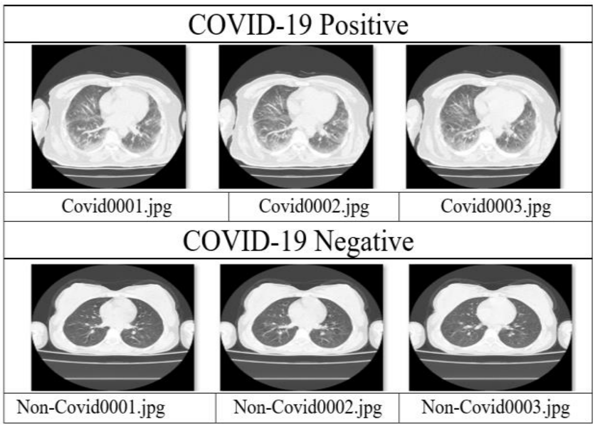


Figure 2. CT images of COVID-19 Positive and COVID-19 Negative people

As a result of dozens of experimental studies conducted on the data set, the highest accuracy rate was achieved with the figures in Table 1.

Looking at Table 1, we see that 70% are used for training, 15% for validation, and 15 for testing. In total, 3,500 training, 750 validation and 750 test images were used.

Table 1. Number of images of the data set used in experimental studies

Data Set Class	**Training**	**Validation**	**Test**
	% 70	**% 15**	**% 15**
COVID-19 Positive	1.750	375	375
COVID-19 Negative	1.750	375	375
Total	**3.500**	**750**	**750**

2.4. Proposed Method

The processing steps applied for this study are given in Figure 3.In the first stage, the data set was created, and in the second stage, the dcm format of the data was converted to .jpg image format. Pre-processing steps such as classifying the data and changing the names to make them meaningful were carried out. In the third stage, the distribution of data to be used for training, validation and testing was determined. In the fourth stage, it was determined which deep learning network models would be used for training. In the final stage, performance metrics and accuracy rates were obtained, allowing the results to be compared.

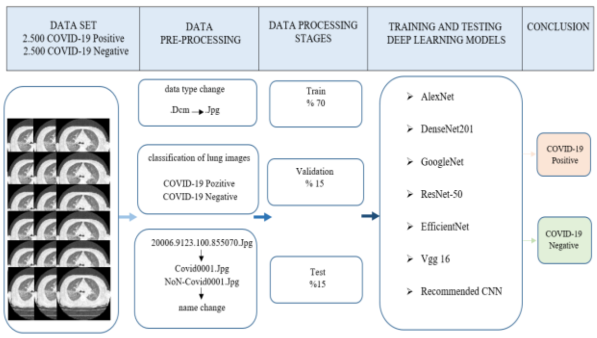


Figure 3. Methodology of the proposed method

The network design of the proposed model is given in Figure 4. The model has a two-class output and consists of a total of 50 layers.

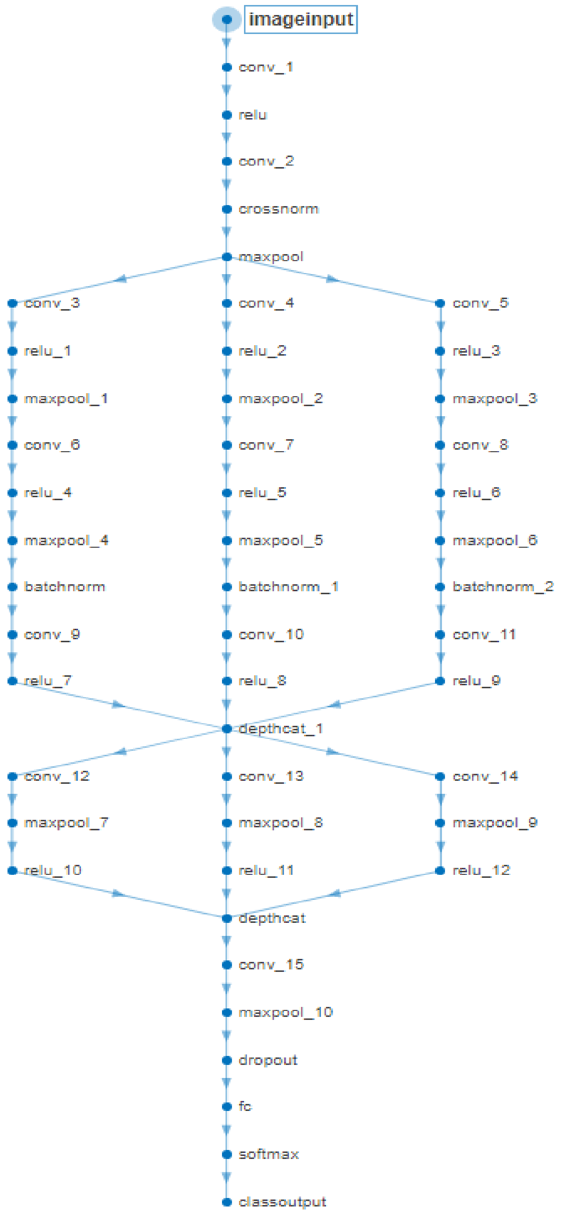


Figure 4. Network design of the proposed model

3. EXPERIMENTAL STUDIES

Information about the sources of hardware and software used in experimental studies is given in Table 2.

Table 2. Information about the hardware and software used

Hardware	Specification
Processor:	12th Gen Intel(R) Core(TM) i7-1255U 1.70 GHz
Ram:	16 GB
Graphics Card:	Intel(R) UHD Graphics
Display Memory:	8.129 MB

Within the scope of the study, an original data set was created to be used for the first time. The data set consists of lung CT images of people whose reporting results are COVID-19 Positive and COVID-19 negative. For the classification of these images, a study was conducted on the proposed CNN model and 6 models frequently used in the literature. Models were trained on a data set of 5.000 images. MATLAB R2023a software was used to train the models.

3.1. Performance Metrics

Convergence graphs, performance values obtained as a result of experimental studies and results obtained from the studied models were compared. The confusion matrix reflects the performance values of the trained network. The table of confusion matrix is given in Table 3.

Table 3. Confusion Matrix

Confusion Matrix		Predicted Values	
		Positive	Negative
Actuald Values	Positive	True Positive (TP)	False Positive (FP)
	Negative	False Negative (FN)	True Negative (TN)

TP: It is the process of correct classification of a positive sample.
TN: It is the process of correctly classifying the negative sample.
FP: It is the process of misclassifying the negative sample.
FN: It is the process of misclassifying a positive sample.
The ROC curve is created by plotting the true positive rate (Sensitivity) against the false positive rate at varying thresholds. The part below the ROC curve threshold constitutes the AUC value. AUC represents the degree of discriminability. It shows the model's ability to distinguish between classes. The higher the AUC rating, the better the model's ability to predict true negatives as negative and true positives as positive. The performance metrics used in the study are stated below.

$$\text{Accuracy} = \frac{TP + TN}{TP+TN+FP+FN} \times 100 \tag{1}$$

$$\text{Precision} = \frac{TP}{TP+FP} \times 100 \tag{2}$$

$$\text{Recall} = \frac{TP}{TP + FN} \times 100 \tag{3}$$

$$\text{F1-Score} = \frac{2 \times \text{Percision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{4}$$

Results Obtained with Deep Learning Models

The data set was trained on six different commonly used CNN models and the proposed network model, and different success rates were obtained. Experimental results obtained during the training phase are given under model headings.

Performance Evaluation of Alexnet Model

Looking at the confusion matrix in Figure 5, it can be seen that 330 of 369 COVID-19 positive patients were classified correctly and 39 were classified incorrectly. While 336 of 381 healthy samples were classified correctly, 45 were classified incorrectly.

The experimental results obtained during the training of the data set with the Alexnet model are 89.51% precision rate, 87.88% recall rate, 88.69% F1 score, as seen in Table 4. It can be seen that the model reached an accuracy rate of 88.79%.

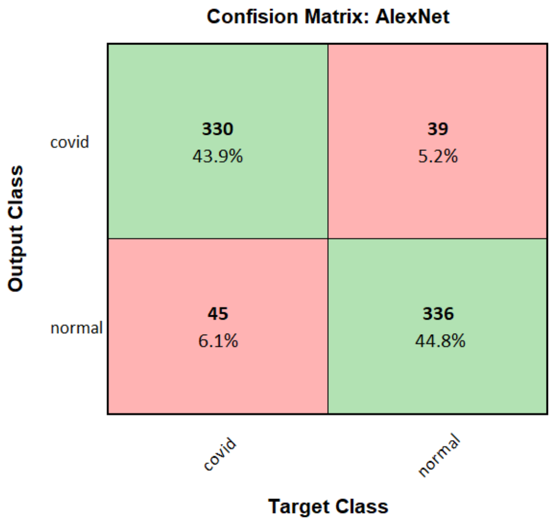


Figure 5. Confusion matrix obtained by the Alexnet model on test data

Table 4. Experimental results of the AlexNet model

Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
88.79	89.51	87.88	88.69

Performance Evaluation of DenseNet201 Model

Looking at the confusion matrix in Figure 6, it can be seen that 326 of 384 COVID-19 positive patients were classified correctly and 58 were classified incorrectly. While 320 of 366 healthy samples were classified correctly, 46 were classified incorrectly. The experimental results obtained during the training of the data set with the DenseNet201 model are 84.89% precision rate, 87.61% recall rate, 86.23% F1 score, as seen in Table 5. It can be seen that the model reached an accuracy rate of 86.14%.

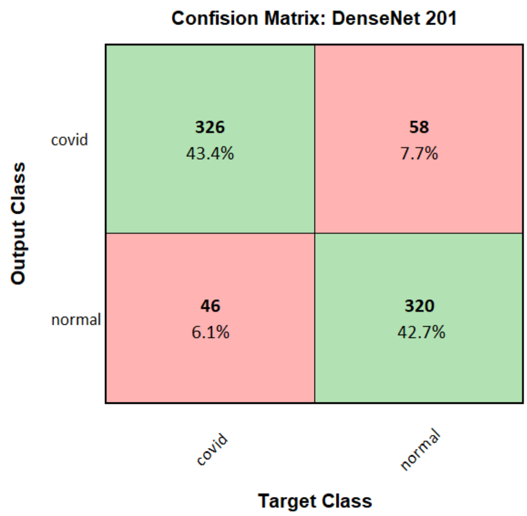


Figure 6. Confusion matrix obtained by DenseNet201 model on test data

Table 5. Experimental results of the DenseNet201 model

Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
86.14	84.89	87.61	86.23

Performance Evaluation of the EfficientNet Model

Looking at the confusion matrix in Figure 7, it can be seen that 357 of 362 COVID-19 positive patients were classified correctly and 5 were classified incorrectly. While 375 of 388 healthy samples were classified correctly, 13 were classified incorrectly. The experimental results obtained during the training of the data set with the EfficientNet model are 98.64% precision rate, 86.46% recall rate, 97.54% F1 score, as seen in Table 6. It can be seen that the model reached an accuracy rate of 97.60%.

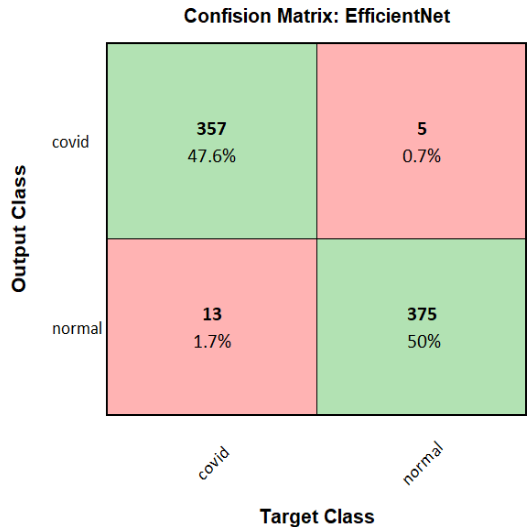


Figure 7. Confusion matrix obtained by the EfficientNet model on the test data

Table 6. Experimental results of the EfficientNet model

Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
97.60	98.64	96.46	97.54

Performance Evaluation of GoogleNet Model

Looking at the confusion matrix in Figure 8, it can be seen that 360 of 384 COVID-19 positive patients were classified correctly and 24 were classified incorrectly. While 353 of 365 healthy samples were classified correctly, 12 were classified incorrectly. The experimental results obtained during the training of the data set with the GoogleNet model are 93.71% precision rate, 96.75% recall rate, 95.21% F1 score, as seen in Table 7. It can be seen that the model reached an accuracy rate of 95.16%.

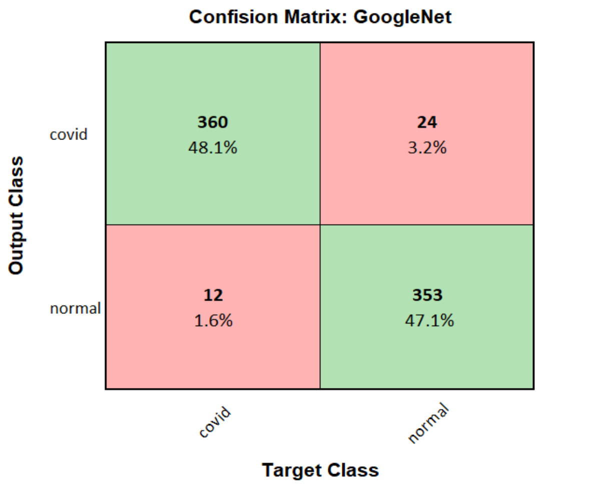


Figure 8. Confusion matrix obtained by the GoogleNet model on test data

Table 7. Experimental results of the GoogleNet model

Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
95.16	93.71	96.75	95.21

Performance Evaluation of ResNet-50 Model

Looking at the confusion matrix in Figure 9, it can be seen that 370 of 414 COVID-19 positive patients were classified correctly and 44 were classified incorrectly. While 331 of 336 healthy samples were classified correctly, 5 were classified incorrectly. The experimental results obtained during the training of the data set with the ResNet-50 model are 89.47% precision rate, 98.71% recall rate, 93.87% F1 score, as seen in Table 8. It can be seen that the model reached an accuracy rate of 93.55%.

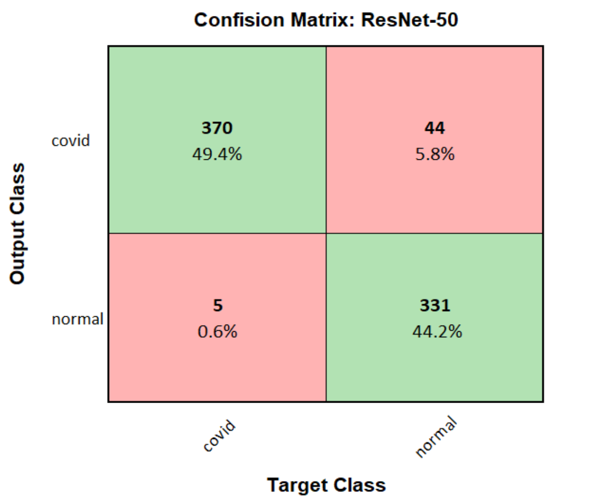


Figure 9. Confusion matrix obtained by ResNet-50 model on test data

Table 8. Experimental results of the ResNet-50 model

Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
93.55	89.47	98.71	93.87

Performance Evaluation of VGG-16 Model

Looking at the confusion matrix in Figure 10, it can be seen that 334 of 350 COVID-19 positive patients were classified correctly and 16 were classified incorrectly. While 354 of 400 healthy samples were classified correctly, 46 were classified incorrectly. The experimental results obtained during the training of the data set with the VGG-16 model are 95.39% precision rate, 87.88% recall rate, 91.48% F1 score, as seen in Table 9. It can be seen that the model reached an accuracy rate of 91.72%.

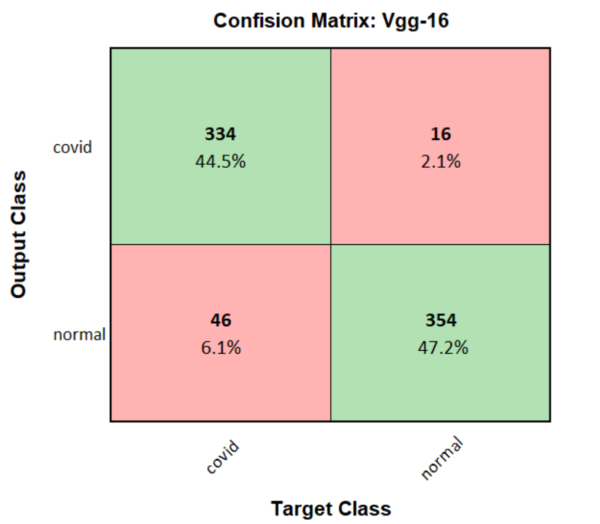


Figure 10. Confusion matrix obtained by the VGG-16 model on test data

Table 9. Experimental results of the VGG-16 model

Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
91.72	95.39	87.88	91.48

Performance Evaluation Of The Proposed Model

The convergence chart of the data set with the proposed model during the training phase is given in Figure 11. When the proposed model convergence graph is examined, a graph gradually increasing to 95% levels is seen until the 17th cycle. There is an increase, albeit low, from the 18th cycle to the 32nd cycle. Although the error rate increases between the 32nd and 35th cycles, it is seen that the accuracy rate after the 36th level converges to 99.20%.

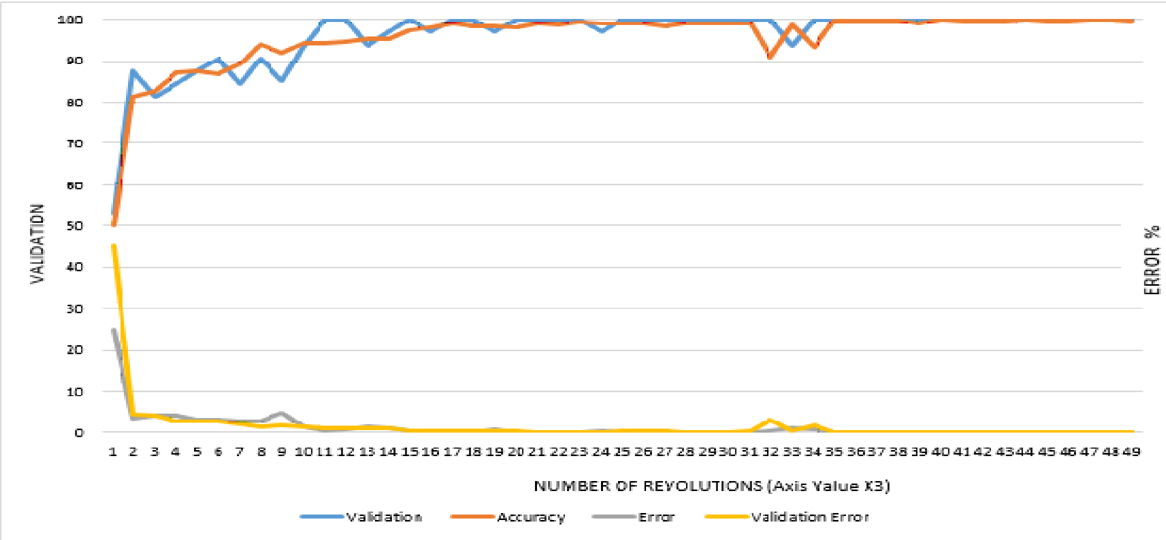


Figure 11. Convergence graph of the proposed model

The confusion matrix obtained on the test data with the proposed model is given in Figure 12. Looking at the confusion matrix, 372 of 375 COVID-19 positive patients were classified correctly and 3 were classified incorrectly. Of 375 healthy samples, 372 were correctly classified and 3 were misclassified as COVID-19 positive. When we look at the general accuracy of the model, it was seen that it achieved an accuracy rate of 99.20%.

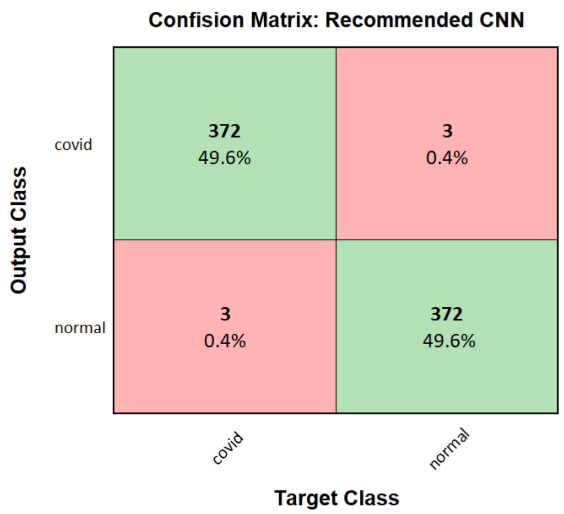


Figure 12. Confusion matrix obtained by the proposed model on the test data

The ROC Curve obtained during the training phase with the proposed model is given in Figure 13.

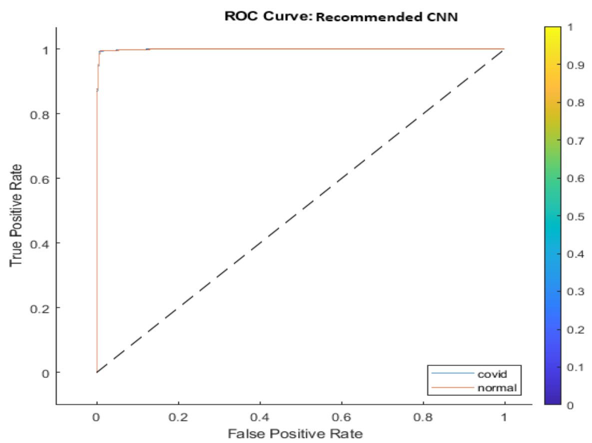


Figure 13. ROC Curve of the proposed model

The AUC diagram obtained during the training phase with the proposed model is given in Figure 14.

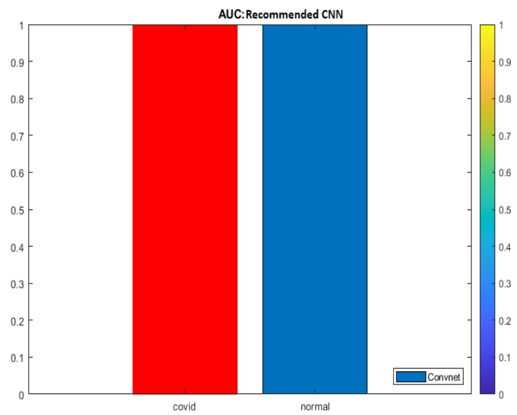


Figure 14. AUC Chart of the proposed model

The performance metrics obtained during the training phase with the proposed model are given in Table 10.

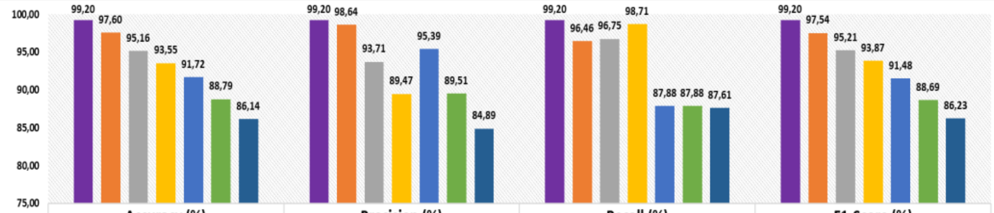
Table 10. Experimental results of the proposed model

Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
99.20	99.20	99.20	99.20

4. DISCUSSION AND CONCLUSION

COVID-19 disease has become a global problem and has caused serious problems.

Diagnosis of the disease, isolation of patients, application of the correct treatment and, as a result, minimizing the impact of the epidemic have been the common goal of all healthcare professionals and everyone who feels responsible. In this direction, image classification studies on COVID-19 have been carried out in the field of science and technology and experimental studies have been carried out that can predict the disease. This study was conducted to detect the disease and assist physicians. Experimental studies were conducted with 7 different CNN models on lung CT images of healthy people and people diagnosed with COVID-19. The data set used in experimental studies consists of 5.000 images. Comparison of performance metrics of the examined models is given in Figure 15. When parameters such as 99.20% accuracy, 99.20% precision, 99.20% sensitivity, 99.20% F1 score are examined, it is seen that the proposed model has the highest success rate. Considering these obtained values, we think that the proposed network model will be useful in detecting COVID-19.



	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Recommended Model	99,20	99,20	99,20	99,20
EfficientNet	97,60	98,64	96,46	97,54
GoogleNet	95,16	93,71	96,75	95,21
ResNet-50	93,55	89,47	98,71	93,87
VGG-16	91,72	95,39	87,88	91,48
AlexNet	88,79	89,51	87,88	88,69
DenseNet201	86,14	84,89	87,61	86,23

Figure 15. Comparison of experimental results of models

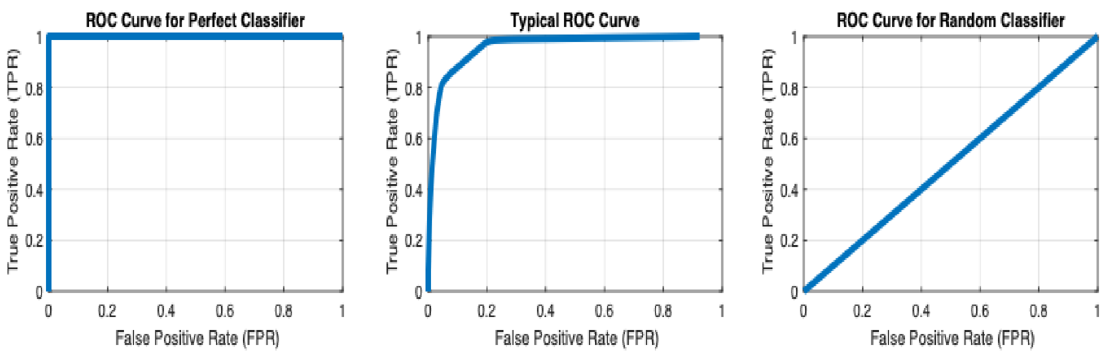
Looking at the performance metrics and accuracy rates given in Figure 15, the EfficientNet model is 97.60%, the GoogleNet model is 95.16%, the ResNet-50 model is 93.55%, the Vgg-16 model is 91.72%, the AlexNet model is 88.79%, DenseNet201 model is calculated as 86.14%.

The accuracy rate of the proposed model was calculated as 99.20%, and the highest rate was obtained with this model among the models studied experimentally.

Roc curves are created by plotting the number of true positives as a function of false positives, looking at varying classification thresholds. ROC curves also provide information about the success rates of the results obtained. The Roc curve process, which is frequently used in clinical diagnosis, was created for each of the experimental studies conducted for the detection of COVID-19.

It is known that positives are completely separated from negatives when the ROC score reaches 1. The curve that the Roc curve will create in the coordinate system is the true positive value (sensitivity) and false positive value of the diagnostic test on the Y axis. (1-specificity) on the X-axis. At each loop point, the Roc curve is created by connecting the points where true positives and false positives intersect [32].

An image showing the distinction between a perfect classifier, a typical classifier, and a classifier that makes random predictions based on the performance of the Roc curves is shown in Figure 16.



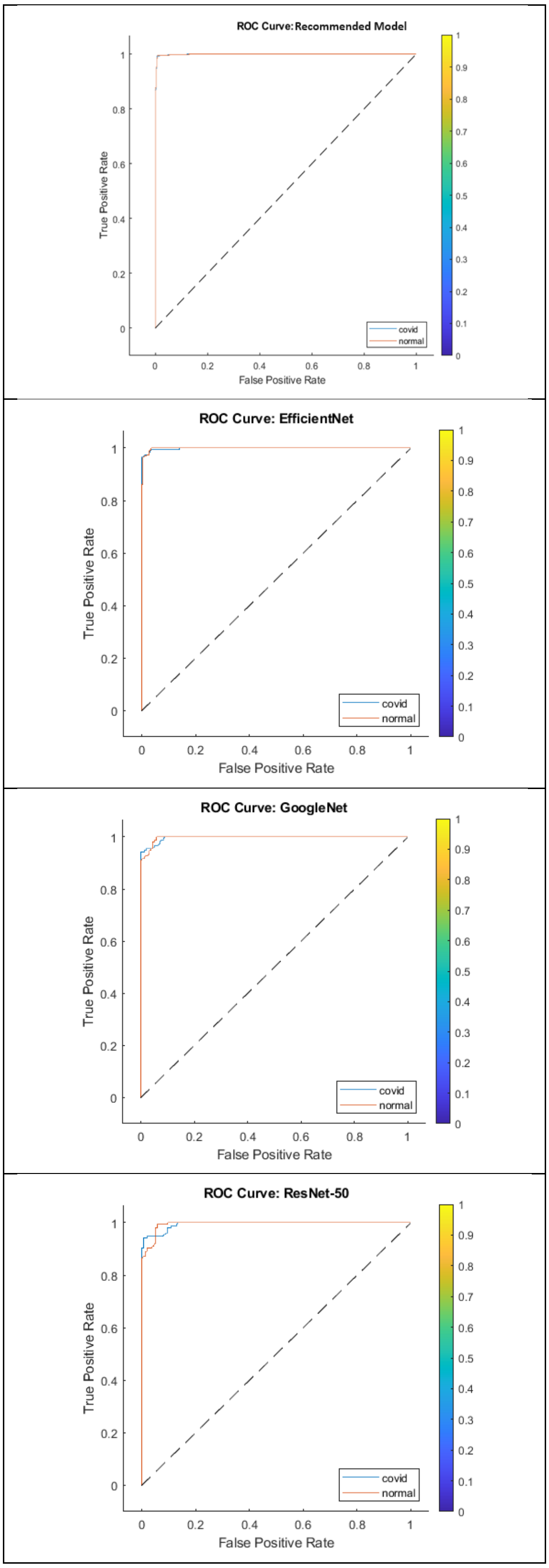
Perfect classifier

A typical classifier

Random classifier

Figure 16. Graphs based on classification levels [33]

Figure 17 shows the Roc curves of the models in which experimental studies were carried out. Looking at the performance values, it can be seen that the model that makes the best discrimination is the recommended model. In the study, model performances are listed from high to low as Recommended Model, EfficientNet, GoogleNet, ResNet-50, Vgg-16, AlexNet, DenseNet20.



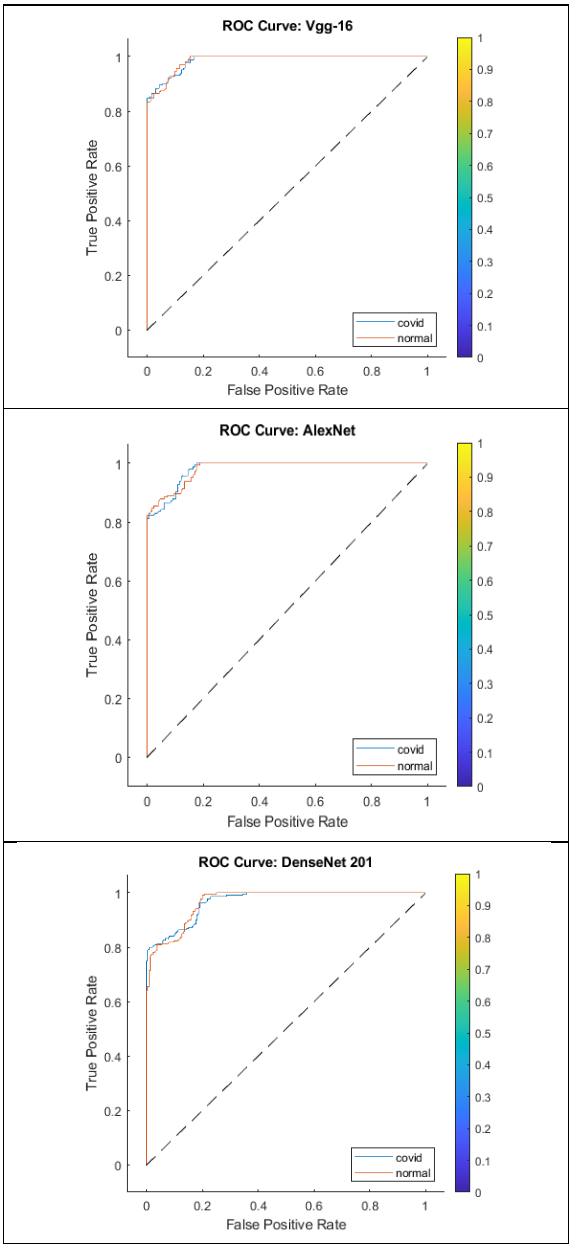


Figure 17. ROC curves of the models

As a result, when the studies were evaluated, it was understood that CNN models could be designed for image classification purposes. The trained data set has been used in a study for the first time, and it is aimed to further develop it by adding a pneumonia class and to conduct studies on pneumonia, COVID-19 positive and COVID-19 negative classes accordingly.

REFERENCES

[1] Selçuk EB. Pandemic Spread Process in the World and Turkey. Inonu University Faculty of Medicine Department of Family Medicine. 2020;12(3):87-91.

[2] Akyol, AD. Sars Severe Acute Respıratory Syndrome. Ege University Faculty of Nursing Journal.2005; 21(2):107-123.

[3] Nemli, SA. Middle East Respiratory Syndrome-Coronavirus (MERS-CoV). Kocatepe Medical Journal. 2016; 17:77-83.

[4] Ökçün S, Kurnaz M, Koçkaya G, Acar A. Overvıew Of Covıd-19 Dıagnosıs Methods: Rapid Review. Eurasian Journal Of Health Technology Assessment. 2020; 4(2):10-35.
[5] İnik Ö, Ceyhan A, Balcıoğlu E, Ülker E. A new method for automatic counting of ovarian follicles on whole slide histological images based on convolutional neural network. Computers in biology and medicine. 2019; 112:103350.
[6] Celik M, İnik Ö. Development of hybrid models based on deep learning and optimized machine learning algorithms for brain tumor Multi-Classification. Expert Systems with Applications. 2024;238: 122159.
[7] İnik Ö, Ülker E. Optimization of deep learning based segmentation method. Soft Computing. 2022; 26(7): 3329-3344.
[8] Çelik M, İnik Ö. Multiple Classification Of Brain Tumors For Early Detection Using A Novel Convolutional Neural Network Model. Eskişehir Osmangazi University Faculty of Engineering and Architecture Journal. 2023; 31(1) 491-500.
[9] İnik Ö, Balcıoğlu E, Ceyhan A, Ülker E. Using Convolution Neural Network for Classification of Different Tissue Images in Histological Sections. Annals of the Faculty of Engineering Hunedoara. 2019; 17.1: 101-104..
[10] İnik O, İnik Ö, Öztaş T, Demir Y, Yüksel A. Prediction of Soil Organic Matter with Deep Learning. Arabian Journal for Science and Engineering. 2023; 1-21.
[11] İnik Ö, Uyar K, Ülker E. Gender classification with a novel convolutional neural network (CNN) model and comparison with other machine learning and deep learning CNN models. Journal Of Industrial Engineering Research. 2018; 57-63.
[12] Nasip ÖF, Zengin K. Deep learning based bacteria classification. In. Tokat, Türkiye: 2nd International Symposium on Multidisciplinary Studies and Innovative Technologies (ISMSIT). 2018; 1-5.
[13] Singhal T. A Review of Coronavirus Disease-2019 (COVID-19). The Indian Journal of Pediatrics. 2020; 281–286.
[14] Kaya B, Önal M. Segmentation of Lung CT Images for COVID-19 Detection. European Journal of Science and Technology. 2021; 28:1296-1303.
[15] Çalışkan A. Detection Of Coronavirus Disease Using Wavelet Convolutional Neural Network Method. Kahramanmaraş Sütçü İmam University Journal of Engineering Sciences. 2023; 26(1):203-212.
[16] Hemdan EE, Shouman MA, Karar ME. COVIDX-Net: A Framework of Deep Learning Classifiers to Diagnose COVID-19 in X-Ray Images. 2020;2003.11055.
[17] Bozkurt F. COVID-19 Detection from Chest X-Ray Images Using Deep Learning Techniques. European Journal of Science and Technology. 2021;(24):149-156.
[18] JavadiMoghaddam S, Gholamalinejad H. A Novel Deep Learning Based Method For COVID-19 Detection From CT İmage. Biomedical Signal Processing and Control V70, (2021).
[19] Oğuz Ç. Determination Of COVİD 19 Possible Cases By Using Deep Learning Techniques. Master's Thesis, Ataturk University Institute of Science, Erzurum.2021.
[20] Panahi AH, Rafiei A, Rezaee A. FCOD: Fast COVID-19 Detector based on deep learning techniques. Informatics in Medicine Unlocked. 2020; (22):100506.
[21] Urut S, Özdağ R. COVID-19 Forecasting And Feature Detection Using Recurrent Neural Networks. Uluslararası Bilişim Kongresi. 2022; 523-530.
[22] Ceylan T, İnik Ö. COVID-19 Detection on Radiological Images with Deep Learning. 3rd International Conference on Applied Engineering and Natural Sciences. 2022;1807-1811.
[23] Çelik M, İnik Ö. Detection of Monkeypox Among Different Pox Diseases with Different Pre-Trained Deep Learning Models. Journal of the Institute of Science and Technology. 2023;13(1): 10-21.
[24] Pacal I. A Vision Transformer-based Approach for Automatic COVID-19 Diagnosis on Chest X-ray Images. Journal of the Institute of Science and Technology. 2023; 13(2):778-791.
[25] Doğan Y. COVID-19 Detection with Deep Learning Methods Under Cross-Dataset Evaluation. Gazi Universty Journal of Science Part C: Desıgn And Technology. 2023; 11(3) 813-823.
[26] Tüfekçi P, Gezici B. Detection of COVID-19 and Viral Pneumonia from Chest X-Ray Images with DeepLearning. Afyon Kocatepe University Journal of Science and Engineering. 2023; 23(1), 89-100.
[27] Yilmaz A. Artificial Intelligence, ISBN 978-605-9118-80-4, Irem Soylu, Istanbul. Kodlab; 2022.
[28] İnik Ö, Ülker E. Deep Learning and Deep Learning Models Used in Image Analysis. Gaziosmanpasa Journal of Scientific Research. 2017; 6(3): 85-104.
[29] Talan T, Aktürk C. Theoretical and Applied Research in Computer Science. Istanbul: Efe Academy Publications; 2021.
[30] Doğan F, Türkoğlu İ. The Comparison Of Leaf Classification Performance Of Deep Learning Algorithms. Sakarya University Journal Of Computer And Information Sciences. 2018; (1):10–21.
[31] Büyükarıkan B, Ülker E. Fruit Classification With Convolution Neural Network Models Using Illumination Attribute. Uludag University Faculty of Engineering Journal. 2020; (25), 81-100.
[32] Obuchowski NA. Receiver Operating Characteristic Curves And Their Use İn Radiology. Radiology. 2003; 229(1):3-8.
[33] mathworks.com [internet]. 2023 [cited 2023 november22].Available from:https://www.mathworks.com/products/new_products/release2023a.html/