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Automatic prediction of covid-19 from chest- computed tomography (CT) images using deep learning architectures

Derin öğrenme mimarilerini kullanarak göğüs BT görüntülerinden otomatik Covid-19 tahmini

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Abstract

Machine learning has been actively used in disease detection and segmentation in recent years. For the last few years, the world has been coping with the Coronavirus disease 2019 (COVID-19) pandemic. Chest-computerized tomography (CT) is often a meaningful way to detect and detect patients with possible COVID-19. This study aims to classify COVID-19 and non-COVID-19 chest-CT images using deep learning (DL) algorithms and investigate whether we can achieve successful results in different parameters using four architectures. The study was performed on proved positive COVID-19 CT images, and the datasets were obtained from the GitHub public platform. The study evaluated four different deep learning architectures of VGG16, VGG19, LeNet-5, and MobileNet. The performance evaluations were used with ROC curve, recall, accuracy, F1-score, precision, and Root Mean Square Error (RMSE). MobileNet model showed the best result; F1 score of 95%, the accuracy of 95%, the precision of 100%, recall of 90%, AUC of 95%, and RMSE of 0.23. On the other hand, VGG 19 model gave the lowest performance; F1 score of 90%, the accuracy of 89%, the precision of 90%, recall of 90%, AUC of 89%, and RMSE of 0.32. When the algorithms' performances were compared, the highest accuracy was obtained from MobileNet, LeNet-5, VGG16, and VGG19, respectively.
This study has proven the usefulness of deep learning models to detect COVID-19 in chest-CT images based on the proposed model framework. Therefore, it can contribute to the literature in Medical and Engineering in COVID-19 detection research.

Keywords: *COVID-19, Deep learning, LeNet-5, MobileNet, VGG16, VGG19*

Öz

Makine öğrenmesi, son yıllarda hastalık tespiti ve segmentasyon araştırmalarında aktif olarak kullanılmaktadır. Son yıllarda insanlık, Koronavirus hastalığı 2019 (Covid-19) ile mücadele etmektedir. Göğüs-bilgisayarlı tomografi (BT) görüntüsü, olası Covid-19 hastalarını tespit etme de önemli bir araçtır. Bu çalışma, Derin Öğrenme (DÖ) algoritmaları kullanarak Covid-19 ve Covid-19 olmayan göğüs BT görüntülerini, sınıflandırmayı ve dört mimari kullanarak farklı parametrelerde başarılı sonuçlar elde edip edemeyeceğimizi araştırmayı amaçlamaktadır. Çalışma, kanıtlanmış pozitif Covid-19 CT görüntüleri üzerinde gerçekleştirildi ve görüntüler GitHub kamu platformundan elde edilmiştir. VGG16, VGG19, LeNet-5 ve MobileNet gibi dört farklı derin öğrenme mimarisi değerlendirildi. Performans değerlendirmelerinde ROC eğrisi, duyarlılık, doğruluk, F1-ölçütü, kesinlik ve RMSE kullanılmıştır. MobileNet modeli en iyi sonucu vermiştir sırasıyla; F1-ölçütü %95, doğruluk %95, kesinlik %100, duyarlılık %90, AUC %95 ve RMSE 0.23'tür. En düşük performansı ise; F1-ölçütü %90, doğruluk %89, kesinlik %90, duyarlılık%90, AUC %89 ve RMSE 0.32 ile VGG19 modeli vermiştir. Algoritmaların performansları karşılaştırıldığında en yüksek doğruluk sırasıyla MobileNet, LeNet-5, VGG16 ve VGG19'dan elde edilmiştir. Bu çalışma önerilen modeller çerçevesinde, Covid-19'u tespit etmek için derin öğrenme modellerinin kullanışlılığını göstermiştir. Bu nedenle araştırma, Covid-19 tespit çalışmalarında Tıp ve Mühendislik literatürüne katkı sağlayabilir.

***Anahtar kelimeler**: Covid-19, Derin öğrenme, LeNet-5, MobileNet, VGG16, VGG19*

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1. Introduction

1. Giriş

The Coronavirus disease (COVID-19) is a new strain that occurred in Wuhan, China, in December 2019 and it has not been previously identified in the world (Huang et al., 2020). The World Health Organization (WHO) officially declared the Covid-19 outbreak as a pandemic on 11 March 2020. The disease has shown a very rapid and serious global spread. According to the latest data, there have been more than 232.636.622 confirmed cases and 4.762.089 confirmed deaths of COVID-19 in the 216 countries in the world, as of September 29, 2021 (WHO, 2021). Due to the COVID-19 pandemic, countries apply various limitations to their citizens. This situation caused restrictions in many fields such as social, economic, education, health, and industry. Some countries have provided an economic support package for their citizens (Açikgöz & Günay, 2020). However, this pandemic has affected not only developed countries but also developing and poor countries. The important thing here is the development of cost-effective, fast, and accurate detection methods that all countries can benefit from. Chest computed tomography (CT) images are a method for clinical diagnosis of COVID-19 detection (Shi et al., 2020; Nasir et al., 2020; Zheng et al., 2020; Caruso et al., 2020). Chest CT scans play a vital role in the diagnosis of this pandemic (Shi et al., 2020; Akçay et al., 2020; Chung et al., 2020; Lei et al., 2020; Bao et al., 2020). Early detection, diagnosis, isolation, and treatment are critical to prevent further extension (Güner et al., 2020). In this study, we have proposed an automatic prediction of COVID-19 using deep learning-based using on chest CT images. Deep learning is one of the sub-topics of machine learning (Deng, 2014; Çatal Reis, 2022). Recently, deep learning techniques have been used to show effective performance in the medical image processing field.

With the development of deep learning methods, it has been used in many areas such as image, gene and sound analysis, cancer diagnostics, virtual reality and image transformation robotics, classification, object detection, image segmentation autonomous systems, and disease diagnoses in medicine (Doğan & Türkoğlu, 2019; Yan et al., 2017; İnik & Ülker, 2017; Bahdanau et al., 2016; Docevski et al., 2018; Patnaik et al., 2018; Swapna et, 2018; Wanga et al., 2018; Anthimopoulos et al., 2016; Shin et al., 2016; Acharya et al., 2013; Kim et al., 2019). In the COVID-19 detection study from CT images, DenseNet121, InceptionV3, ResNet50 V1&V2, MobileNet V1&V2 architectures from deep neural networks, and hybrid method with SVM from machine learning algorithms were used. In the proposed study with the DenseNet-SVM model, an Accuracy value of 90.61% was obtained (Saeedi et al., 2020). Murugan et al. (2021) proposed the ResNet-50 deep neural network architecture optimized with Whale Optimization Algorithm (WOA). The proposed WOANet architecture produced a successful result with 98.78% accuracy. Song et al. (2021) proposed that DRE-Net deep neural network architecture developed with pre-trained ResNet and multi-layer perception (MLP) architectures was used in the COVID-19 disease detection study consisting of CT images. They obtained a value accuracy of 86% in the proposed study with the DRE-Net model. A normal, pneumonia non-COVID-19, COVID-19 detection application was developed with the pre-trained EfficientNet architecture using 13.800 X-ray images. A 93.90% Accuracy value was obtained in the proposed study with the EfficientNet model (Luz et al., 2022).
According to Kogilavani et al. (2022) DeseNet121, VGG16, NASNet, Xception, MobileNet, and EfficientNet architectures from deep neural networks were used in the COVID-19 detection study from 3873 CT images. The proposed research with the VGG16 model was successful, with an accuracy value of 97.68%. On the other hand, by Khan et al. (2022) for the classification of Normal, Pneumonia, Lung Opacity, and COVID-19 diseases, the previously trained deep neural network architectures NasNetMobile, EfficientNetB1, and MobileNetV2 were used. Despite all these studies, there is still a gap in the literature on the diagnosis of COVID-19 using deep learning. A deep learning algorithm helps to develop a new useful diagnosis and management system for the COVID-19 cases.

We have used four models to obtain an automatic prediction of COVID-19 with high accuracy using chest CT datasets. These are LeNet-5, VGG16, VGG19, and MobileNet. We used Receiver Operating Characteristic Curve (ROC) for the accuracy of the study. The use of computer technology with medical technology can make it simpler to detect COVID-19 just from the images of the infected chest CT image and could assist the medical staff's ability to analyze complex information. With this study, it is also aimed to present a second perspective to those working in medical fields.
This study is organized into the following sections:

Dataset is expressed in detail in section 2. Material and methods (Deep learning models, proposed models are presented, LeNet-5, VGG16, VGG19, MobileNet and data processing are described). Performance metrics are given in detail in Section 2. Obtained results from the proposed models are presented in section 3 and finally, the discussion and the future works are summarized.

2. Material and methods

2. Materyal ve yöntemler

The data were downloaded and used from the public database. No human and animal rights have been violated. The research was performed according to the Declaration of Helsinki principles. We don't need to inform consent from patients who participated in clinical investigations. Because we used a public database of various researchers sharing to assist new approaches in the COVID-19 pandemic. Deep learning (DL) is a subclass of artificial intelligence and machine learning and is the most popular approach in artificial intelligence applications (LeCun et al., 2015). Inspired by the learning process of the human brain, DL is a method that targets new approaches to automatic knowledge discovery and analysis of complex structured information (Çatal Reis, 2022). The most important feature that distinguishes deep neural networks from traditional artificial neural networks is that they have more than one hidden layer (Sejnowski & Tesauro, 1989). General convolution neural network architecture consists of input-output, convolution, pooling, fully connected (fcc), and prediction. In this study, a data set was created by combining randomly selected chest CT images. We used approximately 90% of all data for training and 50% of the remaining data for validation (Val) and the other 50% for testing. Keras, an open-source deep learning library, was used to carry out the training. Used four effective algorithms of deep learning-based models for Covid-19 problems are described below in Fig 1. In this step, we first described the dataset used in the study, secondly followed by the proposed MobileNet LeNet-5, VGG16, and VGG19. The flowchart of the study is given in Figure 1.

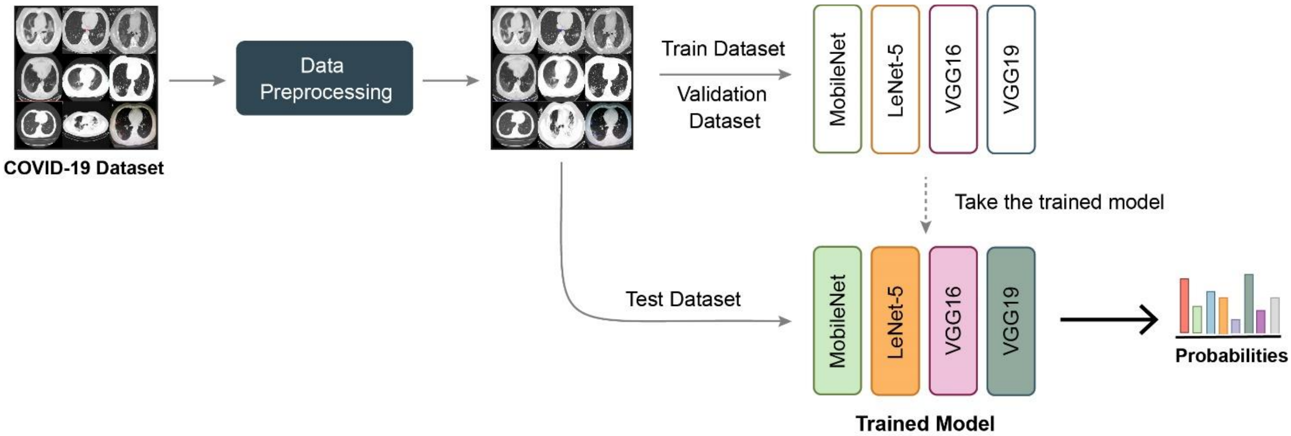

Figure 1. Flowchart of the study
***Şekil 1**. İş akış şeması*

In 1998, LeNet was published and also gave the first successful result as a convolution neural network model (LeCun et al., 1998). The structure of the network was expanded with complex questions and updated according to the questions with the help of hyper-parameters. The structure of the network is an important architecture in pattern recognition with its resistance to noise and its invariable invariance (Sarraf & Tofighi, 2016) (Figure 2).

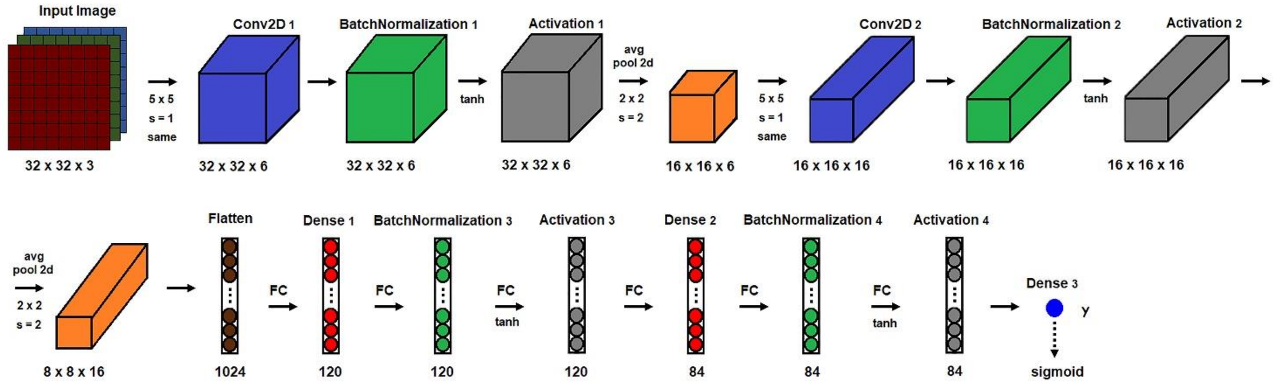

Figure 2. The architecture of the proposed LeNet-5
Şekil 2. *Önerilen LeNet-5 mimarisi*

VGG16 was proposed in 2014 by the Visual Geometry Group (VGG) and it is a CNN architecture. The name VGG16 is given because it consists of 16 layers (Simonyan & Zisserman, 2014). Although it does not have many hyperparameters, its focus is on the 3 × 3 kernels size and 2 × 2 max pooling in the convolution layer (El Asnaoui et al., 2021) (Figure 3).

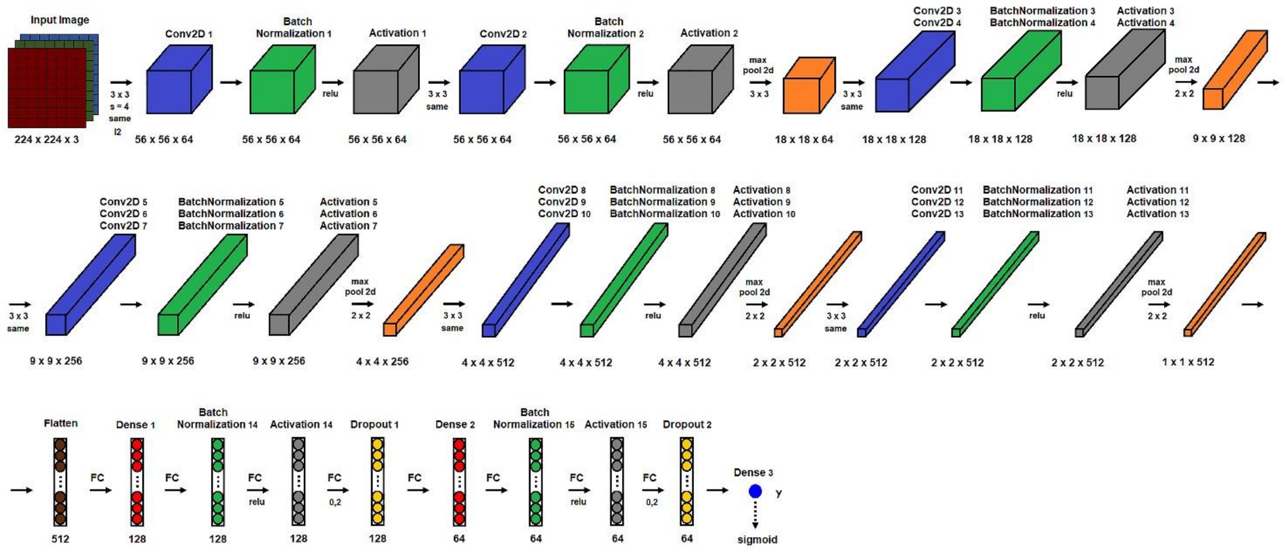

Figure 3. The architecture of the proposed VGG16
Şekil 3. *Önerilen VGG16 mimarisi*

VGG 19 is VGGNET deep network architecture and has 19 convolution layers (Hemdan et al., 2020). VGG 16 consists of 13 convolution layers and 3 fully connected layers, while VGG 19 consists of 16 convolution layers and 3 fully connected layers. In VGG 16 and VGG 19, data enters as 224 × 224 × 3. They consist of a total of 41 layers, including max pooling, ReLu, dropout, softmax, and fully connected (Özyurt, 2020) (Figure 4).

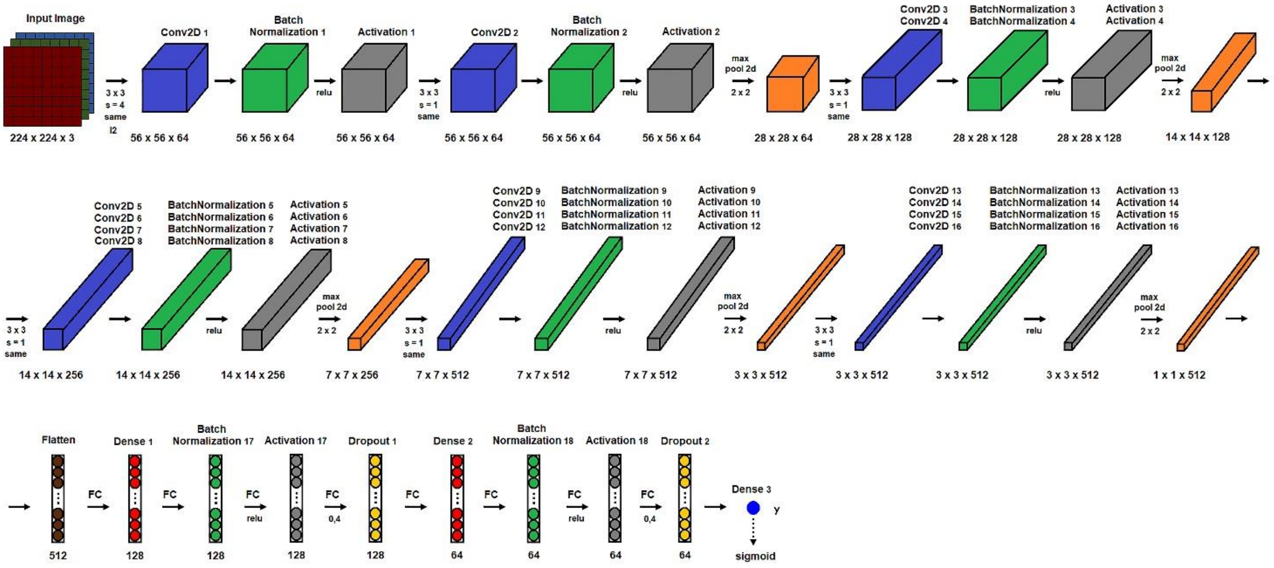

Figure 4. The architecture of the proposed VGG19
Şekil 4. *Önerilen VGG19 mimarisi*

MobileNet was proposed in 2017 (Howard et al., 2017). MobileNet consists of layers that can be deeply separated from two layers of kernels (Sae-Lim et al., 2019). They have fewer parameters than the convolution layer and have less tendency to overfitting. It requires less processing with few parameters, which makes the system fast. It is one of the algorithms used effectively in applications to reduce size and delay and for high accuracy (Xu et al., 2018) (Figure 5). In this study, we detect, evaluate, and analyze COVID-19 with four deep learning algorithms.

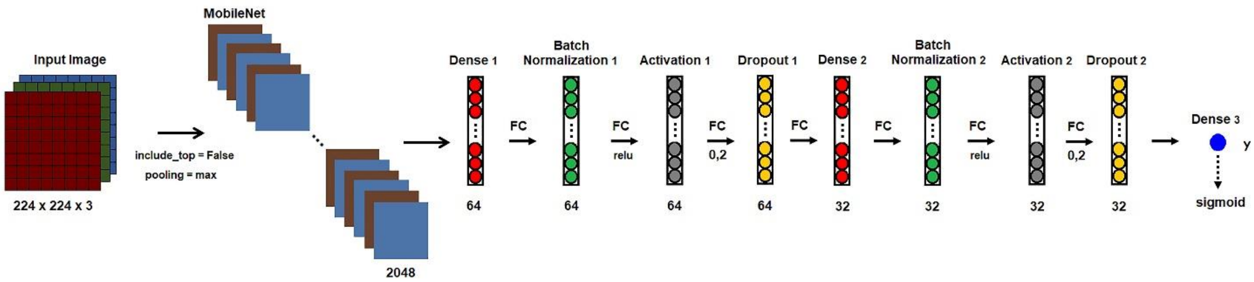

Figure 5. The architecture of the proposed MobileNet
Şekil 5. *Önerilen MobileNet mimarisi*

2.1. Data processing (retrospective collection of datasets)
2.1. Veri ön işleme (Anonim veriseti toplama)

This research study presents a methodology for the classification/detection of COVID-19 chest CT and normal chest CT images using deep learning architectures. We used the Python programming language and Tensorflow-Keras deep learning library to implement our models. This study was done on a laptop equipped with an Intel i5 processor, 6GB of RAM, and a GTX 940MX NVidia GPU with 2GB of VRAM. We use the publicly available dataset from "GitHub". The used data is accessible at https://github.com/UCSD-AI4H/COVID-CT. 397 normal chest-CT scans and 360 patients' COVID-19 chest-CT scans were used in Table 1. These images were from 216 patient cases (Yang et al., 2020). Different sizes and resolutions and low-quality CT-image data were studied (Figure 6). Each CT image has been pre-processed. We applied LeNet-5, VGG16, VGG19, and MobileNet for the diagnostic and classification of COVID-19 diseases.

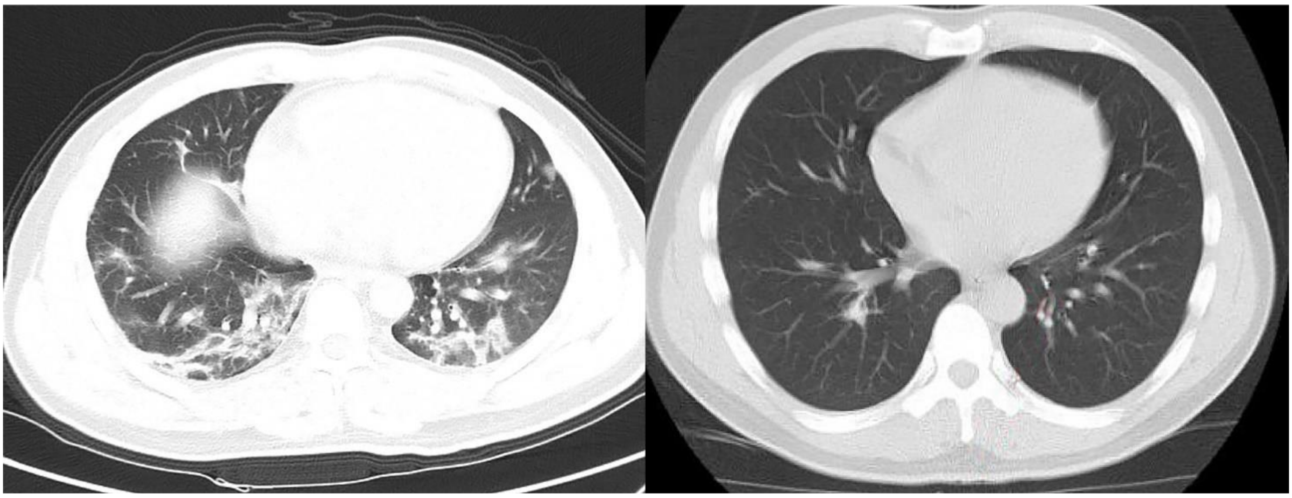

Figure 6. Samples of raw low- resolution CT images
Şekil 6. *Düşük çözünürlüklü örnek CT görüntüleri*

Table 1. Statistics of the dataset
Tablo 1. *Veri seti istatistikleri*

Classifier/Models	Target Images	Train	Val	Test	Total Images
	COVID-19	319	21	20	360
MobileNet	nonCOVID-19	362	17	18	397
	Total Images	681	38	38	757
	COVID-19	331	13	16	360
LeNet-5	nonCOVID-19	350	25	22	397
	Total Images	681	38	38	757
	COVID-19	327	18	15	360
VGG16	nonCOVID-19	354	20	23	397
	Total Images	681	38	38	757
	COVID-19	321	18	21	360
VGG19	nonCOVID-19	360	20	17	397
	Total Images	681	38	38	757

2.2. Statistical and performances analysis
2.2. İstatistik ve performans analizi

In this section, we evaluate and compare the performances of four models. We examine the performance with receiver operating characteristics (ROC) curves and the corresponding area-under-curve (AUC) values and Root Mean Square Error. The confusion matrix is summarized in Tables 2 (Figure 7). F1-Score, Precision, Recall, and Accuracy, which are defined as follows (Hajian-Tilaki, 2013).

Table 2. Confusion matrix
Tablo 2. *Karmaşıklık matrisi*

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

$$\text{Precision} = \frac{(TP)}{(TP + FP)} \quad (1)$$

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

$$\text{F1} - \text{Score} = \frac{2 * (\text{Recall} * \text{Precision})}{(Recall + Precision)} \tag{3}$$

$$\text{Accuracy} = \frac{(\text{TP} + \text{TN})}{(\text{TP} + \text{TN} + \text{FP} + \text{FN})} \tag{4}$$

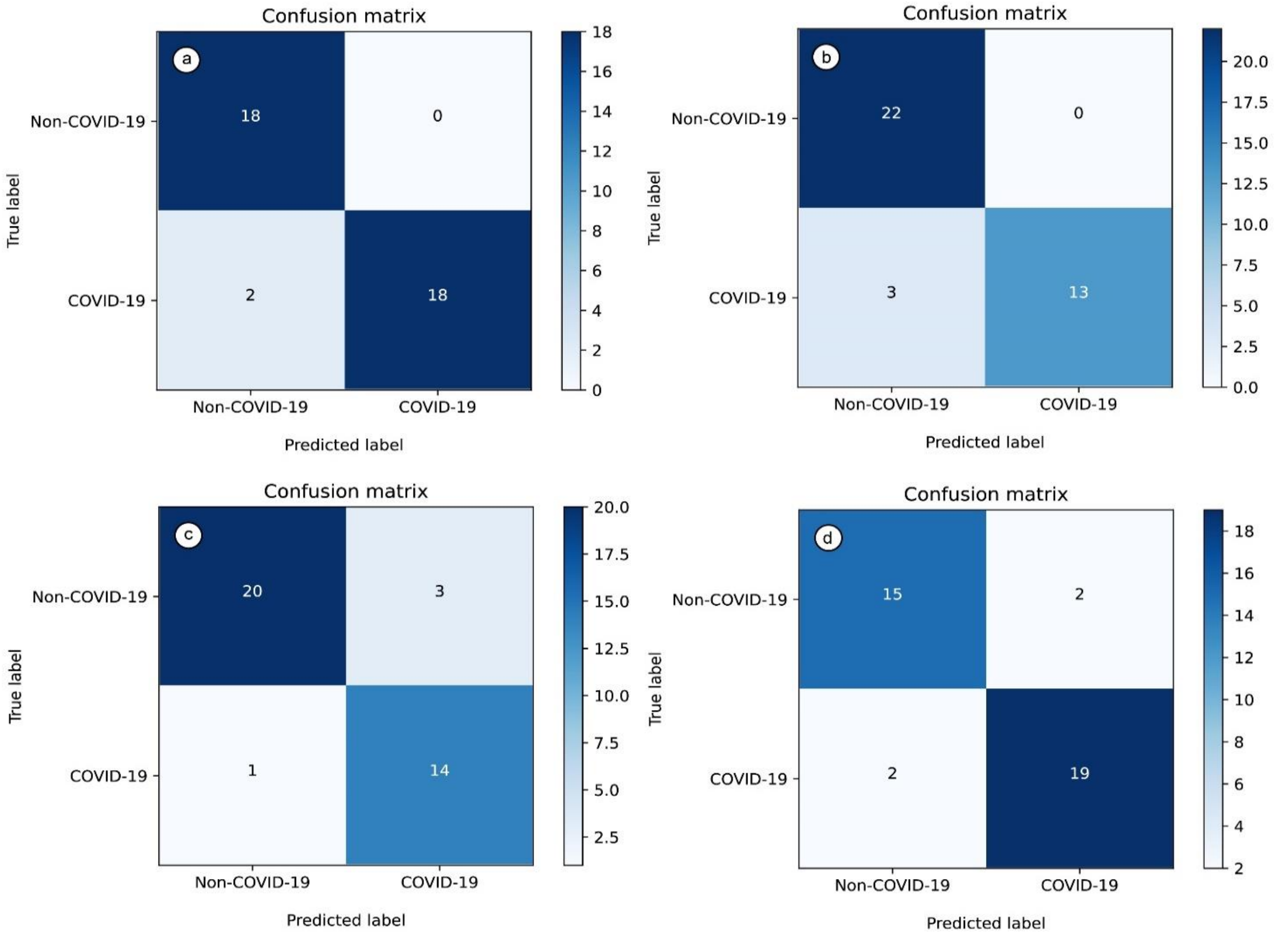

Figure 7. The confusion matrix visualization (a) MobileNet model produced FN=2 and FP=0 (b) LeNet-5 model produced FN=3 and FP=0 c) VGG16 model produced FN=1 and FP=3 (d) VGG19 model produced FN=2 and FP=2
Şekil 7. *Derin öğrenme mimarilerinin karışıklık matrisleri (a) MobileNet modeli FN=2 ve FP=0 (b) LeNet-5 modeli FN=3 ve FP=0 c) VGG16 modeli FN=1 ve FP=3 (d) VGG19 modeli FN=2 ve FP=2 metrik değerlerini üretmiştir*

3. Results
3. Sonuçlar

This study deep learning methods that use chest CT images to predict COVID-19. We have employed LeNet-5, VGG16, VGG19, and MobileNet as deep learning algorithms for the detection of COVID-19 for training and testing purposes. Visual performance plots are given and the evaluation results of the methods are shown in Table 3 and test results of deep learning models are given in Table 3.

Table 3. Performance results of deep learning models
Tablo 3. *Derin öğrenme modellerinin deneysel sonuçları*

Models	Accuracy	Precision	Recall	F1-score	ROC	TP	TN	FP	FN
MobileNet	0.9474	1.0000	0.9000	0.9474	0.9500	18	18	0	2
LeNet-5	0.9211	1.0000	0.8125	0.8966	0.9062	13	22	0	3
VGG16	0.8947	0.8235	0.9333	0.8750	0.9014	14	20	3	1
VGG19	0.8947	0.9048	0.9048	0.9048	0.8936	19	15	2	2

The maximum accuracy value of 94.74% was obtained from MobileNet. We have obtained a performance accuracy of 92.11%, 89.47%, and 89.47% in LeNet-5, VGG16, and VGG19 architecture respectively. In Figure 8, the accuracy graphs obtained during the training processes of the models are given.

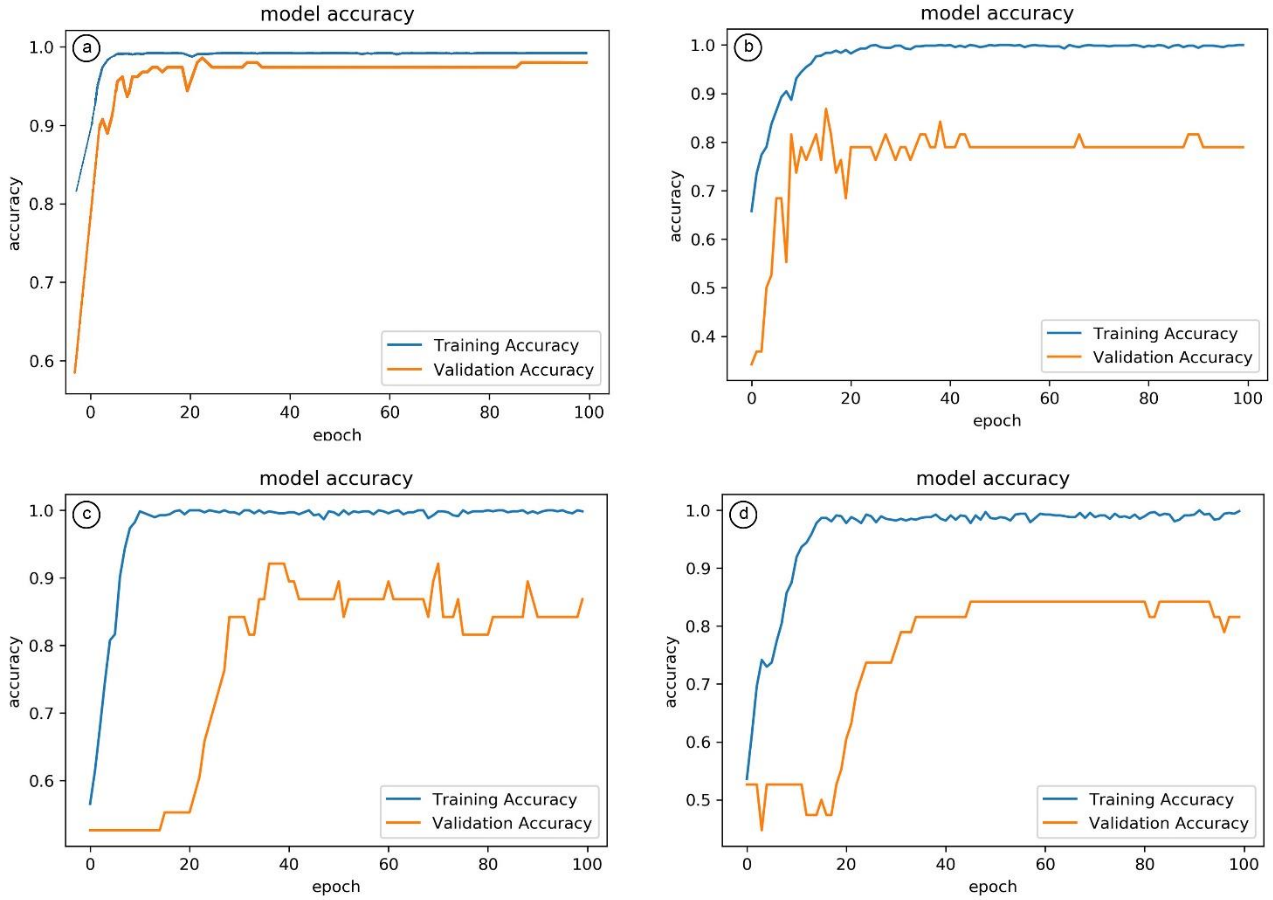

Figure 8. Training and validation accuracy graph for models (a) MobileNet (b) LeNet-5 (c) VGG16 (d) VGG19
Şekil 8. *(a)* MobileNet *(b) LeNet-5 (c) VGG16 (d) VGG19 modellerin eğitim ve doğrulama doğruluk grafiği*

We obtained the best ROC curve value of 95% from the MobileNet model. We obtained the second-best value of 90 % from LeNet-5 and VGG16 models for ROC. We obtained the lowest AUC value of 89% from the VGG 19 model (Figure 9).

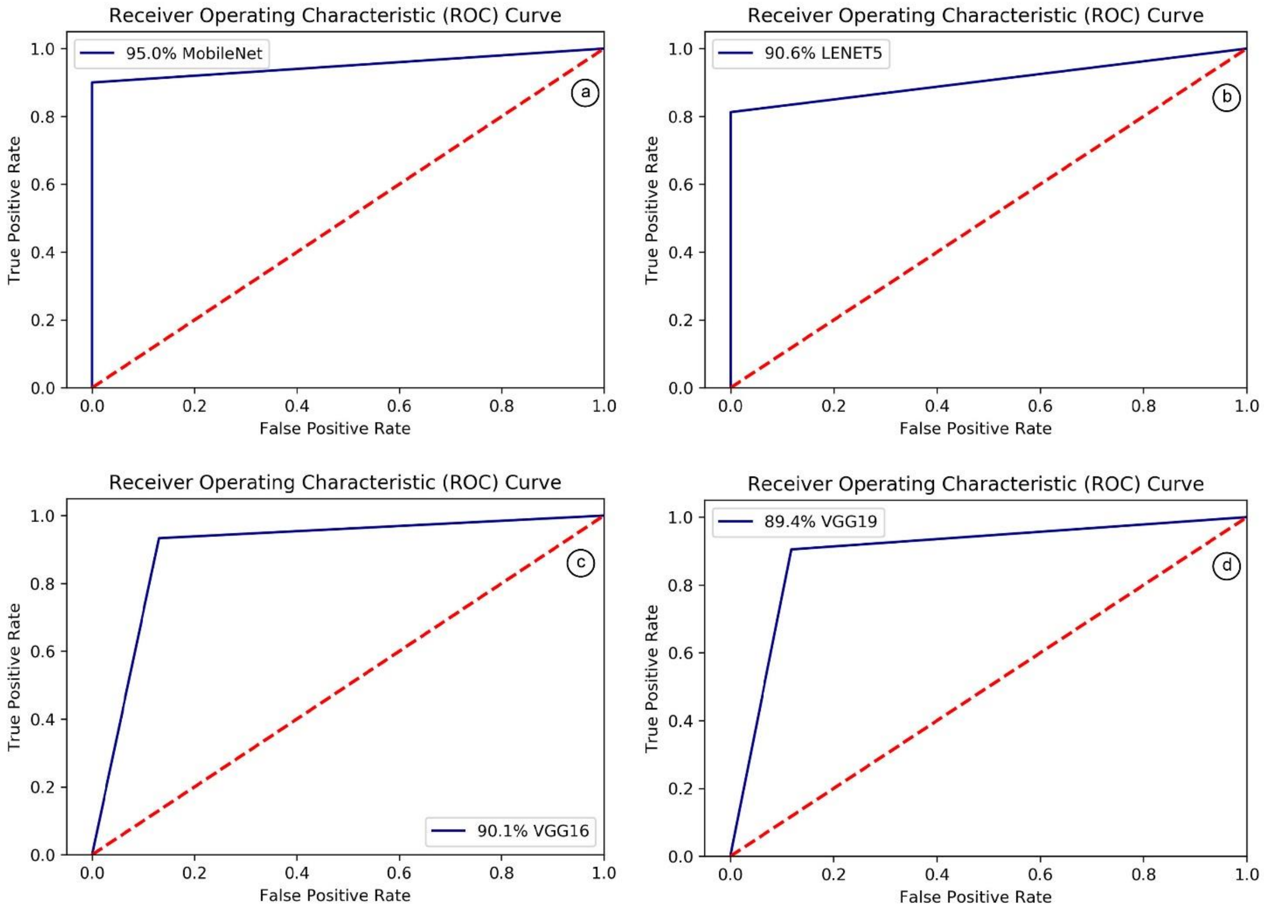

Figure 9. The ROC curves (a) MobileNet (b) LeNet-5 (c) VGG16 (d) VGG19
Şekil 9. *(a) MobileNet (b) LeNet-5 (c) VGG16 (d) VGG19 modellerin ROC grafiği*

The Loss function is to calculate how the model's prediction differs from the ground truth. If we have a good model, the loss value will be low. Our expectation from a good model is that it has a loss value close to zero (Figure10).

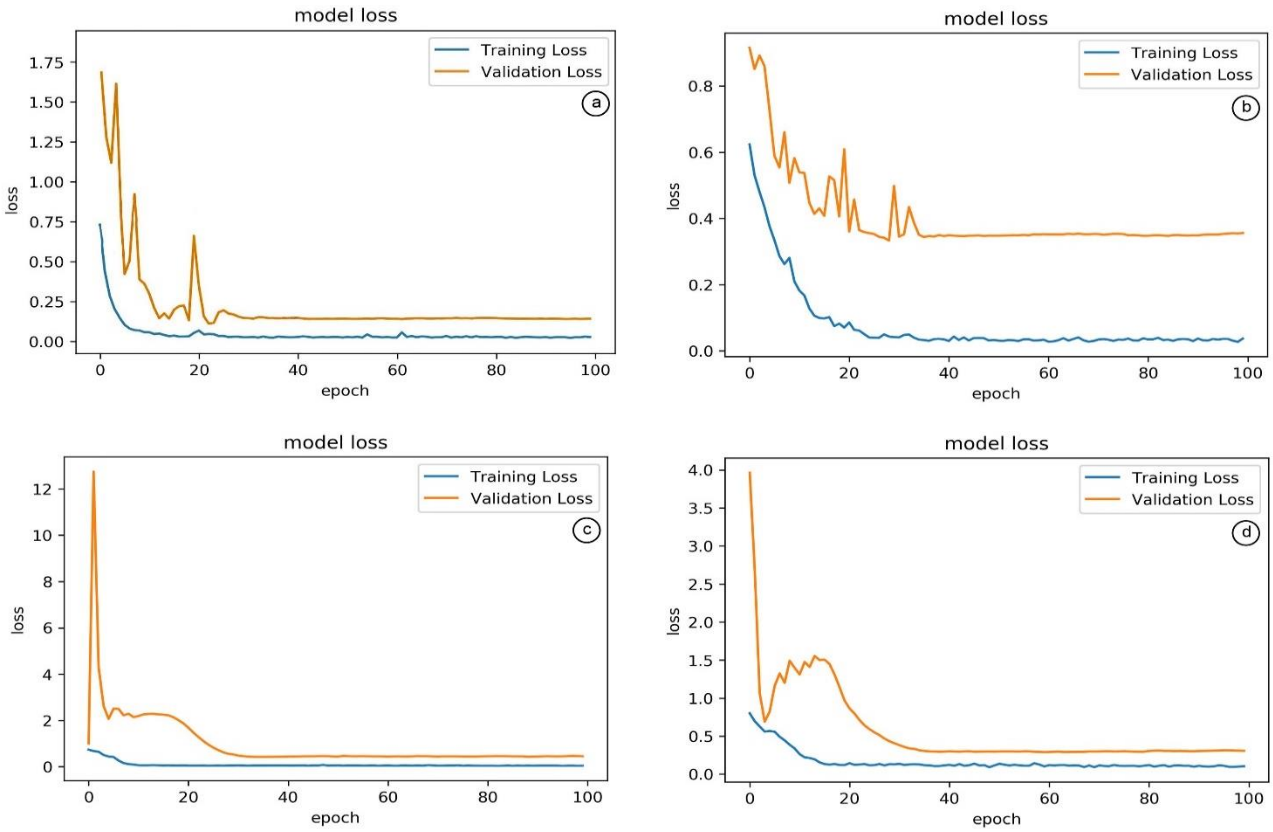

Figure 10. Training loss and validation loss values for models (a) MobileNet (b) LeNet-5 (c) VGG16 (d) VGG19
Şekil 10. *(a)* MobileNet *(b) LeNet-5 (c) VGG16 (d) VGG19 modellerin eğitim ve doğrulama kayıp grafiği*

In this study, a new approach to the prediction of COVID-19 diseases is done using deep learning algorithms. The lower the Root Mean Square Error (RMSE) value, the higher the predictive performance of the model. We obtained the lowest value of RMSE from MobileNet. We have obtained RMSE value of 0.23, 0.28, 0.32, and 0.32 in MobileNet, LeNet-5 VGG16, and VGG19 architecture respectively. The maximum precision value of 100 % was obtained for MobileNet with the LeNet-5 network. The second precision value of 90% was obtained for VGG19. We have obtained the lowest performance of 82% in VGG 16. We have obtained a recall of 93%, 90%, 90%, and 81% in VGG16, MobileNet, VGG19, and LeNet-5 architecture respectively. We have got a performance F1-Score of 94%, 90%, 89%, and 87% in MobileNet, VGG19, LeNet-5, and VGG16 architecture respectively. Compared to four deep learning models, we obtained the best result from the MobileNet algorithm. We have studied LeNet-5, VGG16, VGG19, and MobileNet kinds of deep learning algorithms for COVID-19 detection for training and testing purposes. Early prediction of COVID-19 is vital.

4. Discussion
4. Tartışma

In the proposed algorithms, CT data was analyzed to detect COVID-19 using LeNet-5, VGG16, VGG19, and MobileNet techniques.

Table 4. Comparison of the results with state-of-the-art deep neural networks with CT/X-ray images
Tablo 4. *CT/X-ray veri kümeleri ile son teknolojik derin sinir ağların sonuçlarının karşılaştırılması*

Reference	Deep Learning Model	No.of images	Accuracy (%)
Murugan et al. (2021)	WOANet	2700	98.78
Saeedi et al. (2020)	DenseNet-SVM	746	90.61
Luz et al. (2022)	EfficientNet	13.800	93.90
Kogilavani et al. (2022)	VGG16	3873	97.68
Song et al. (2021)	DRE-Net	274	86
Khan et al. (2022)	EfficientNetB1	21.165	96.13
Proposed	MobileNet	757	94.74

As seen in Table 4, the number of data shows that it is one of the main parameters affecting accuracy. This significant parameter influence is clearly visible in the DRE-Net and the DenseNet-SVM hybrid models. However, in the EfficientNet model, 93.90% accuracy was achieved with 13.800 images. Our proposed MobileNet model achieved an accuracy of 94.74% with 757 non-standard dataset. On the other hand, in the EfficientNetB1 model, with 21.165 images 96.13% accuracy has been reached.

A Deep Learning-based diagnosis model can accurately and cost-effective interpret a lot of images dataset where it is difficult for the human to interpret such big data and look into the details of the image inside. A second viewer was presented to radiologists who worked very hard during the pandemic process. Therefore, it is thought that the study will help radiologists. The study has been prepared entirely to assist the health sector and to provide a second perspective.

In conclusion, our study had some limitations. Firstly, this was a case series that included a limited number of COVID-19 patients. Secondly, CT images have got different sizes and resolution data. Due to the different reception standards and distortions in the images, the pre-process was added to the study, and time was lost. However, despite such low-resolution data, it has got a very high success. Further information on accuracy in COVID-19 can be get using a very large-sized input that has the same standard data. We anticipate that more comprehensive studies and high-accuracy studies will be produced if not the accessibility of medical images is obstructed. The study will continue to be developed with different deep learning and machine learning algorithms.

Author contribution
Yazar katkısı

The authors approved the last main version of the manuscript. Writing, algorithm development, software, editing, data preprocessing, image processing: Hatice Çatal Reis and Veysel Türk, Data collection and draft writing: Serhat Kaya.

Declaration of ethical code
Etik beyanı

The authors of this article declare that the material and the methods used in this study do not require ethical committee approval and special legal permission.

Conflicts of interest
Çıkar Çatışması

The authors declare that they have no conflict of interest.

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Kaynaklar

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