Covid-19 detection on x-ray images using a deep learning architecture

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ABSTRACT

Recently, coronavirus disease (Covid-19) has become a serious public health threat, spreading worldwide in a very short time and threatening the lives of millions. With the increasing number of cases and mutations, medical resources are being drained day by day due to the rapid transmission of the disease, and the health systems of many countries are negatively affected. For this reason, it is very important to use available resources appropriately and timely for the detection and treatment of the disease. In this study, VGG16 and ResNet50 deep learning models were used to quickly evaluate x-ray images and to make the pre-diagnosis of Covid-19, and an alternative model (IsVoNet) was proposed. As a result of the training of the models, success accuracy of 99.92% in the VGG16 model, 99.65% in the ResNet50 model and 99.76% in the proposed model were obtained. According to the results, it was observed that the models classified Covid-19 and normal lung x-ray images with high accuracy and the proposed model showed a high success rate at lower time complexity than other models.

Keywords: deep learning, coronavirus, chest x-ray, classification.

INTRODUCTION

Recently, the coronavirus disease (Covid-19) epidemic has become a major health problem that has spread all over the world in a very short time and has a cause for concern in the society. According to the World Health Organization (WHO), the increase in the number of affected people by the epidemic increases the spread and mortality rates every day (Hemdan et al., 2020; Soundariya et al., 2020). The important reason for the increase in the rate of spread of coronavirus is due to its transmission from one human to another through contact. In addition, the virus spreads in the air and affects people nearby, resulting in a wider area of transmission (Ni et al., 2020; Kandil et al., 2021). Furthermore, many patients infected with coronavirus can transmit the disease without showing any symptoms (Brunese et al., 2020). Therefore, a large part of the world population has taken protective measures to reduce the impact of the epidemic (M. M. Islam et al., 2020). Covid-19 causes upper respiratory and lung infections in many patients, which results in the gradual depletion of medical resources and negatively affects the health systems of many countries (Apostolopoulos et al., 2020; Ismael & Şengür, 2021).

It is becoming increasingly important that medical resources are used appropriately to prevent the further spread of Covid-19 (Oh et al., 2020). Recently, new precautions and measures have been implemented against the pandemic (Altmann et al., 2020; Jamshidi et al., 2020; Li et al., 2020; Ginting & Luckyardi, 2021). The appropriate and timely use of available resources has become very important for the detection and treatment of the disease (Ribeiro et al., 2020; Zeroual et al., 2020). Currently, x-ray devices are available everywhere in the world and are used by specialist healthcare personnel to detect Covid-19 without the need for special test devices (Ouchicha et al., 2020). However, the need for specialist doctors to analyze x-ray images increases the workload of healthcare professionals. Thus, it is seen that there is a need for a support system that quickly evaluates x-ray images and makes a pre-diagnosis in order to save time for healthcare personnel and reduce their workload.

Recently, many deep learning algorithms have been used to help detect the Covid-19 epidemic quickly (Shorten et al., 2021). With deep learning algorithms, Covid-19 was detected from x-ray images and the workload of physicians was reduced (Nayak et al., 2021). The convolutional neural network, especially used in deep learning methods, has provided important results in feature extraction and learning from medical images (Wang et al., 2021). Therefore, deep learning approaches have also been an important reason for choosing to detect Covid-19 disease (Bhattacharya et al., 2021).

In this study, unlike those in the literature, a new dataset consisting of the data of 12,739 lung x-ray images confirmed by a specialist physician was used and this dataset has been trained with VGG16 and ResNet50 models. However, a new convolutional neural network model was proposed to detect Covid-19 with high accuracy at lower time complexity.

The remainder of the study is structured as follows: Related literature studies are presented in Section 2, materials and methods based on deep learning are explained in Section 3, experimental results are discussed in Section 4 to evaluate the performance of the model, and Section 5 concludes the paper in light of the results of the study.

LITERATURE STUDIES

In a study based on Covid -19 radiographic changes in CT images, a method that changes the inception transfer learning pattern has been proposed. In the proposed method, 0.88 specificity, 0.87 sensitivity and 89.5% accuracy were obtained in the validation data set participating in the training. In addition, 0.83 specificity, 0.67 sensitivity and 79.3% accuracy were obtained in the test data set that did not participate in the training (Wang et al., 2021).

In a different study, a convolutional neural network-based ResNet50 model from deep learning methods was used to detect real-time Covid-19 disease in chest X-ray images and 98% accuracy was obtained (Rehman et al., 2021). In a different study using deep learning-based convolutional neural network models, Inception V3, Xception, and ResNeXt models were compared to detect Covid-19. As a result of the comparison, the highest accuracy was achieved with the Xception model with 97.97% compared to other models (Jain et al., 2021).

A hybrid model was constructed to identify Covid-19 patients from x-ray images. In the model, 2D curvelet transformation, feature matrix and chaotic salp algorithm were applied to chest x-rays, and Covid-19 was diagnosed at a rate of 99.69% accuracy (Altan & Karasu, 2020). In another study, a two-stage network model was proposed to detect Covid-19 cases using deep learning techniques. In the first stage of that model, an accuracy of 93.01% was achieved in distinguishing healthy individuals, those with bacterial-induced pneumonia, and patients with viral-induced pneumonia. In the second stage, Covid-19 was detected at an accuracy of 97.22% by training the datasets separately to identify x-ray images indicating viral pneumonia (Jain et al., 2020).

In another study using deep learning, the combination of the long short-term memory (LSTM) and convolutional neural network (CNN) was used to detect Covid-19 cases. In that study, a dataset, compiled from different sites, consisted of a total of 4,575 x-ray images containing was reported to have an accuracy of 99.4% in identifying the disease (M. Z. Islam et al., 2020). In a different study, a new model was created to differentiate coronavirus from healthy controls with pulmonary computed tomography images and influenza-A viral pneumonia (influenza-A viral pneumonia), and the classification was made with an accuracy rate of 86.7% (Xu et al., 2020). In another study detecting lung disease and coronavirus on x-ray images, a three-stage approach was used to distinguish between pneumonia and Covid-19 and to localize areas in the x-rays in symptomatic Covid-19 cases. Using the proposed approach, the experimental results showed that Covid-19 was successfully detected in approximately 2.5 seconds at an accuracy rate of 97% (Brunese et al., 2020).

In a different study, chest x-ray images of InstaCovNet-19, a deep convolution network, were used to detect Covid-19. With the proposed model, Covid-19, normal findings, and pneumonia were identified with a 99.08% accuracy rate using models, such as MobileNet, InceptionV3, Xception, and ResNet101 (Gupta et al., 2020). In another study, a deep transfer learning that detected Covid-19 cases using CT and chest x-ray was proposed. It was observed that the proposed algorithm was faster than the reverse transcription polymerase chain reaction test used in the identification of Covid-19 cases. A Grad-CAM-based color visualization approach was used in the experiments to accurately interpret radiology images (Panwar et al., 2020).

In a study aiming to detect Covid-19 from on chest radiology images, a new approach was proposed based on deep learning using Densenet-121. In this approach, training were carried out using the COVIDx dataset, and double and triple classifications were undertaken to determine the accuracy of the model. The result of the classifications was reported as 96.49% and 93.71%, respectively. In addition, Grad-CAM was used to indicate the areas where Covid-19 was found, and a website emphasizing the potentially infected areas (Sarker et al., 2020). In a different study, using the Xception model, a model based on automatic deep transfer learning on chest x-rays was proposed. Performance criteria such as accuracy, f-score, sensitivity, specificity, and kappa statistics were used in the proposed model. An extensive analysis was performed to evaluate the model, and an accuracy of 99.52% was achieved (Das et al., 2020).

A different study proposed a model using InceptionV3 and Inception-ResNetV2 models with ResNet models such as ResNet50, ResNet101, ResNet152, which were first trained on the chest x-rays of infected with coronavirus pneumonia. According to the performance results, the highest accuracy in process of classification was obtained with in ResNet50 model (Narin et al., 2020). Lastly, convolutional CapsNet was proposed to detect Covid-19 on x-ray images using capsule networks. In the proposed approach, binary and multi-class classifications were used to accurately diagnose Covid-19, and the accurate rates were reported as 97.24% and 84.22%, respectively (Toraman et al., 2020). Comparison of the proposed model with existing methods in detecting Covid-19 is given in Table 1.

Table 1 Comparison of the proposed model with existing methods in detecting Covid-19.

References	Model	Dataset Images			Accuracy
		Covid-19	Normal	Others	
(Rehman et al., 2021)	ResNet50	912	912	-	98.00%
(Jain et al., 2021)	Inception V3, Xception, and ResNeXt	576	1583	4273	97.97%
(Altan & Karasu, 2020)	hybrid 2D curvelet transform-CSSA-EfficientNet-B0	2660	2660	2660	99,69%
(M. Z. Islam et al., 2020)	CNN-LSTM	1525	1525	1525	99.4%
(Brunese et al., 2020)	VGG-16	250	3520	2753	97%
(Gupta et al., 2020)	InstaCovNet-19	361	1341	1345	99.08%
(Sarker et al., 2020)	COVID-DenseNet	11416	8851	6045	93.71%
(Das et al., 2020)	Xception	125	500	500	99.52%
(Narin et al., 2020)	ResNet50, ResNet101, ResNet152, InceptionV3 and Inception-ResNetV2	341	2800	-	96.1%
		341	-	1493	99.5%
		341	-	2772	99.7%
(Toraman ve ark., 2020)	CapsNet	1050	1050	-	97.24%
		1050	1050	1050	84.22%
The proposed method	**IsVoNet**	**9121**	**3618**	**-**	**99.76**%

MATERIAL AND METHOD

Dataset

The dataset was obtained using lung x-ray images examined by Erzincan Binali Yıldırım University Mengücek Gazi Education and Research Hospital specialist physicians to detect Covid-19 (Clinical Research Ethics Committee Decision: E-21142744-804.01-59450). This dataset consisted of a total of 13,339 RGB lung x-ray images belonging to 6,157 patients. Of the 13,339 images, 9,666 had Covid-19 indications and 3,673 had normal findings.

Each image was pre-processed separately, and after excluding 600 lung x-ray images that were considered to be inappropriate for an evaluation, a total of 12,739 lung x-ray images (9,121 with Covid-19 findings and 3,618 with normal findings) were included in the final version of the dataset. Since the lung x-ray images in the original dataset were 3,200x3,200 pixels in size, they were converted to the 224x224 pixel dimension in gray format during the pre-processing stage. Then, the images in the dataset were tagged under classes named Covid-19 and normal (Figure 1).

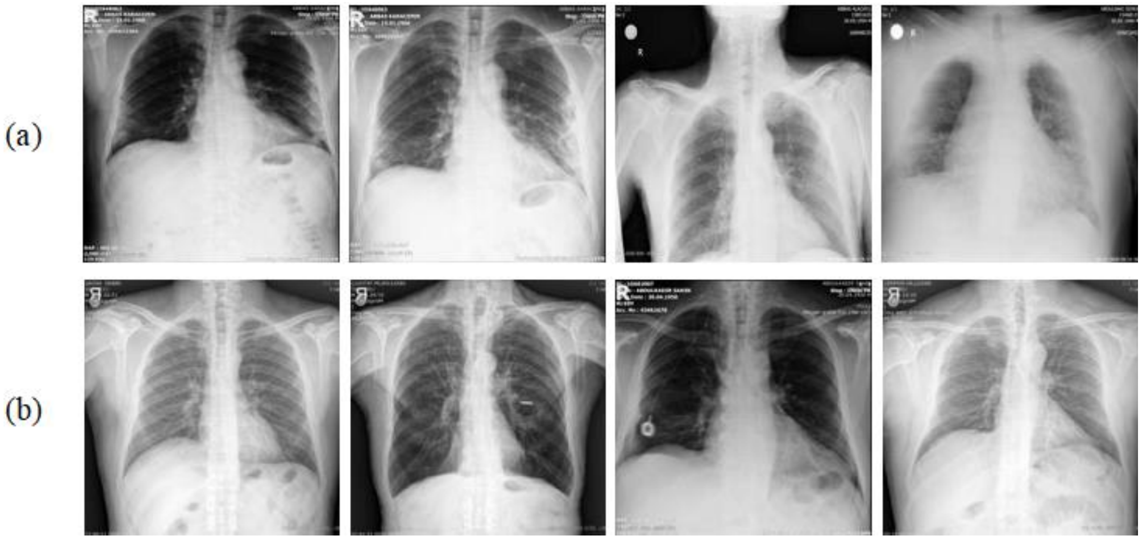


Figure 1 Image examples from the dataset: (a) Covid-19, (b) Normal.

CNN Model

CNN is the most widely used deep learning model of computer vision applications. CNN has achieved outstanding success and become popular in recent studies. In this study, VGG16 and ResNet50 models accepted in the literature were used. However, a new model whose diagram is given in Figure 2 is proposed. The proposed model (IsVoNet) was developed using deep learning architecture (Figure 3). In this model, convolution, pooling, dropout, ReLu, flattening, fully connected and classification layers were used. Using a total of 18 layers, 5,926,018 parameters were obtained.

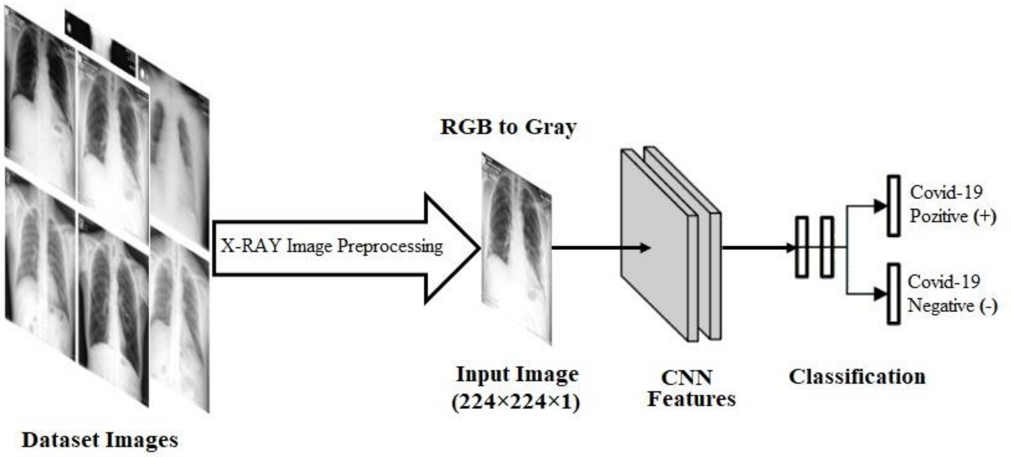


Figure 2 Diagram of the proposed method.

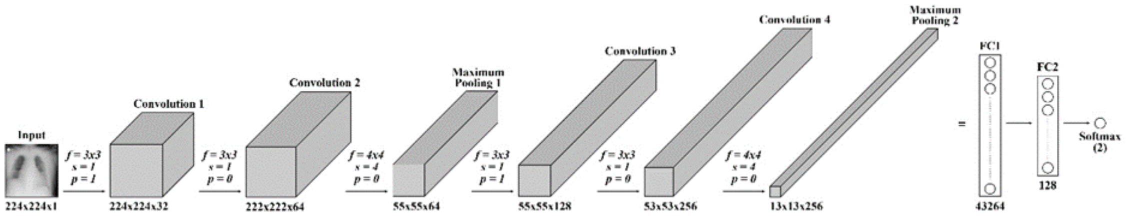


Figure 3 Convolutional neural network model used in the current study (f: filter size, s: stride, p: padding, FC: fully connected).

In the CNN model presented in Figure 3, two convolution layers and a maximum pooling layer were applied to the lung x-ray input images of 224x224 pixel size in gray color format. ReLu was used as the activation function during the convolution processes. A new matrix value was obtained using a four-step 4x4 filter matrix in the pooling layer. A 50% dropout layer was used to prevent the network from memorizing after the pooling layers. After flattening, 50% dropout and fully connected layers were utilized. Subsequently, the 43,264 neurons formed as a result of the flattening process were reduced to 128 through a full connection, a class with two outputs was obtained.

EXPERIMENTAL RESULTS

The experimental results were obtained using a computer with Intel Core i7 processor, NVDIA Geforce GTX 1660 Ti video card, and 16 GB RAM using Python programming language. First, VGG16, ResNet50 and proposed model were trained using the dataset of Covid-19 and normal lung x-ray images of 6,157 patients. The dataset was divided into three sets as shown in Table 2. Table 3 shows the parameter values used during the training of the network. The models were trained according to these parameters using the training and test datasets, and the performance of the models were determined with a validation dataset of the network that had not been used in the training stage.

According to the experimental results, the number of parameters calculated in VGG16, ResNet50 and the proposed model were found to be approximately 134M, 25M and 5M, respectively. The number of calculated parameters is a factor that significantly affects system performance and time complexity. Therefore, the number of parameters calculated in the proposed model has been reduced by at least 5 times compared to other models. So, the proposed model showed a high success rate at lower time complexity compared to other models.

Table 2 Lung x-ray dataset.

	Training (60%)	Testing (20%)	Validation (20%)	Total (100%)
Number of Data	7,643	2,548	2,548	12,739

Table 3 Models training parameters.

Parameter	Value
Epoch	50
Mini batch size	16
Dropout	0.5
Activation function	ReLu
Optimization algorithm	Adamax

The mathematical expressions of the criteria of precision, recall, f1-score and accuracy performance used in the study are given in Equations 1 to 4.

$$Precision = \frac{TP}{TP+FP} \tag{1}$$

$$Recall = \frac{TP}{TP+FN} \tag{2}$$

$$f1-score = \frac{2*Precision*Recall}{Precision+Recall} \tag{3}$$

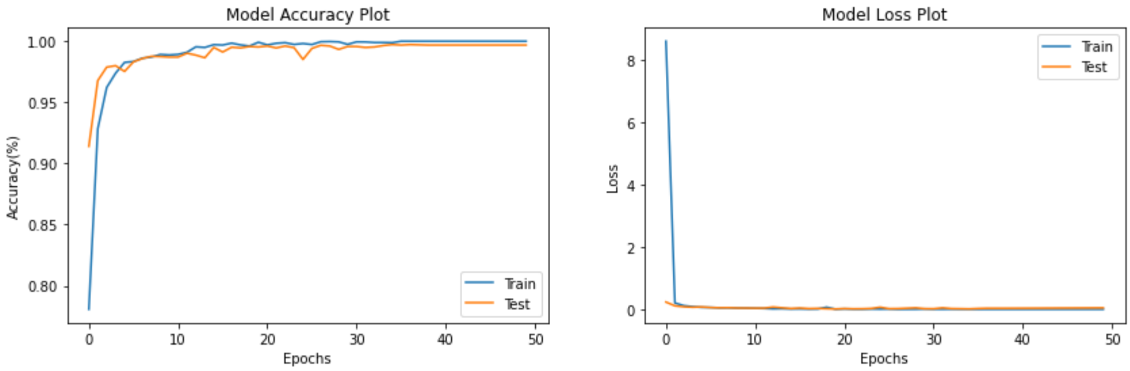
$$Accuracy = \frac{TP+TN}{TP+FP+FN+TN} \tag{4}$$

where TP represents true positive, TN represents true negative, FP represents false positive and FN represents false negative values.

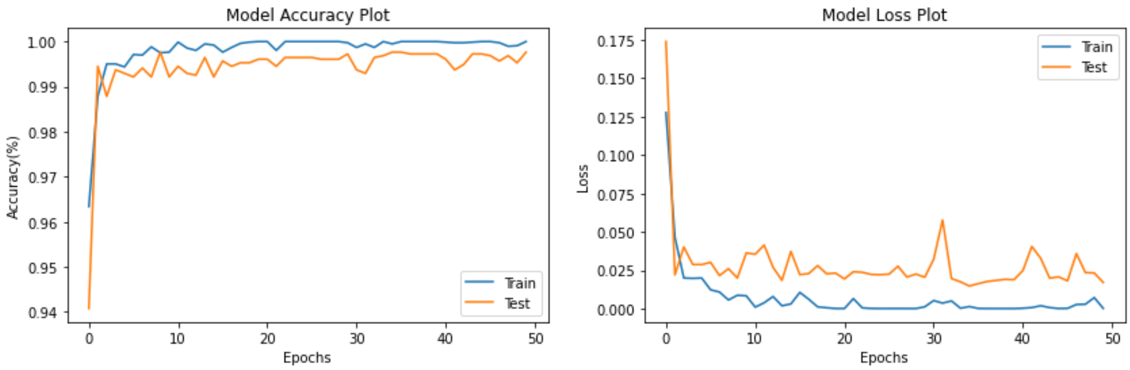
Table 4 shows the precision, recall, f1-score and accuracy performance results measured as a result of the training process of the models, and Figure 4 presents the accuracy and loss plots of the models. When the graphics are examined; It is seen that the network has started to learn at a high rate from the first iterations, and the network continues to learn in the following iterations, and at the end of 50 iterations, it has achieved a success rate of about 99% in its three models.

Table 4 Performance measures of the models.

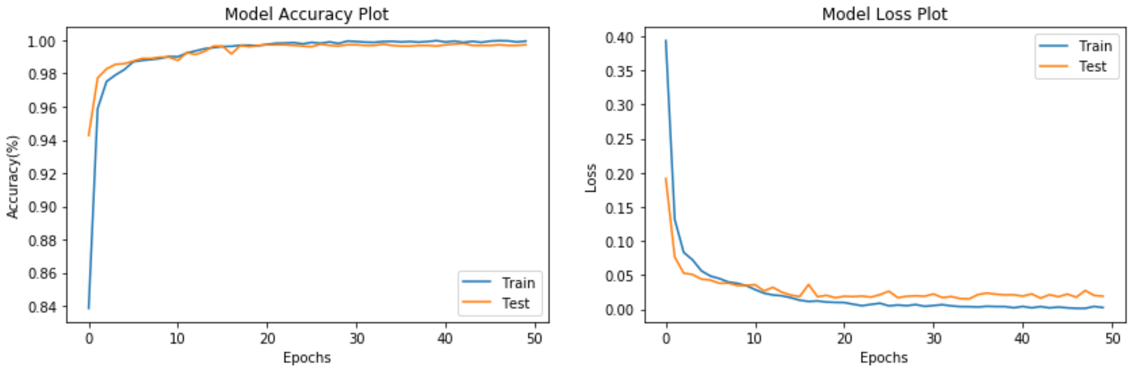
Model	Classification	Precision	Recall	F1-Score	Support
VGG16	Covid-19	1.00	1.00	1.00	1824
	Normal	1.00	1.00	1.00	724
	Accuracy	-	-	1.00	2548
	Macro Avg	1.00	1.00	1.00	2548
	Weighted Avg	1.00	1.00	1.00	2548
ResNet50	Covid-19	1.00	1.00	1.00	1824
	Normal	0.99	0.99	0.99	724
	Accuracy	-	-	1.00	2548
	Macro Avg	1.00	1.00	1.00	2548
	Weighted Avg	1.00	1.00	1.00	2548
Proposed	Covid-19	1.00	1.00	1.00	1824
	Normal	0.99	1.00	1.00	724
	Accuracy	-	-	1.00	2548
	Macro Avg	1.00	1.00	1.00	2548
	Weighted Avg	1.00	1.00	1.00	2548



(a)



(b)



(c)

Figure 4 Accuracy and loss plots of the the models: (a) VGG16, (b) ResNet50, (c) Proposed.

In all three models, after the completion of the training-testing process of the network, the efficiency of the models was analyzed with a validation dataset that had not been used in the training-testing process (Table 5), and the resulting confusion matrix is shown in Figure 5. When Table 5 is examined, it is seen that the success is 99.92% in VGG16, 99.65% in ResNet50 and 99.76% in the proposed model. In addition, it is seen that the loss ratio is 0.008 in VGG16, 0.022 in ResNet50 and 0.009 in the proposed model were obtained. Accordingly, it is seen that the highest success and lowest loss rate is achieved with the VGG16 model. According to the results of the confusion matrix obtained using the validation data set that the network has never seen in Figure 5, it is seen that Covid19 detected with 99.95% of VGG16, 99.73% of Resnet50 and 99.78% of the proposed model.

Table 5 Efficiency analysis of the models according to the validation dataset.

Model	**Accuracy**	**Loss**
VGG16	99.92%	0.008
ResNet50	99.65%	0.022
Proposed	99.76%	0.009

The validation data were evaluated in three model networks and the fitness values (validation losses) are given in Table 6. When Table 6 is examined, the fitness value is 0.0099 for VGG16, 0.0147 for ResNet50, and 0.0152 for the proposed model, which is the best value kept in memory.

Table 6 Fitness value for the VGG16, ResNet50 and proposed model.

Run	Fitness Value		
	VGG16	**ResNet50**	**Proposed Model**
1	0.2317	0.1739	0.1916
2	0.1113	0.0219	0.0764
3	0.0806	0.0401	0.0530
4	0.0667	0.0287	0.0509
5	0.0753	0.0286	0.0441
6	0.0564	0.0301	0.0427
7	0.0483	0.0215	0.0380
8	0.0512	0.0260	0.0384
9	0.0413	0.0199	0.0348
10	0.0398	0.0362	0.0348
11	0.0365	0.0354	0.0360
12	0.0383	0.0414	0.0268
13	0.0714	0.0268	0.0320
14	0.0477	0.0184	0.0250
15	0.0250	0.0372	0.0207
16	0.0403	0.0221	0.0185
17	0.0224	0.0228	0.0363
18	0.0273	0.0280	0.0183
19	0.0177	0.0226	0.0203
20	**0.0099**	0.0231	0.0168
21	0.0217	0.0193	0.0190
22	0.0148	0.0240	0.0185
23	0.0165	0.0236	0.0192
24	0.0258	0.0222	0.0177
25	0.0670	0.0221	0.0213
26	0.0190	0.0224	0.0264
27	0.0220	0.0276	0.0169
28	0.0345	0.0205	0.0189
29	0.0469	0.0224	0.0197
30	0.0189	0.0204	0.0190
31	0.0179	0.0321	0.0223
32	0.0475	0.0576	0.0170
33	0.0219	0.0195	0.0185
34	0.0179	0.0174	0.0155
35	0.0129	**0.0147**	**0.0152**
36	0.0250	0.0162	0.0215
37	0.0329	0.0176	0.0236
38	0.0329	0.0183	0.0220
39	0.0331	0.0190	0.0210
40	0.0340	0.0188	0.0211
41	0.0350	0.0248	0.0191
42	0.0361	0.0404	0.0225
43	0.0373	0.0327	0.0162
44	0.0387	0.0198	0.0212
45	0.0403	0.0207	0.0183
46	0.0413	0.0180	0.0222
47	0.0424	0.0358	0.0176
48	0.0436	0.0234	0.0274
49	0.0452	0.0232	0.0202
50	0.0464	0.0170	0.0192

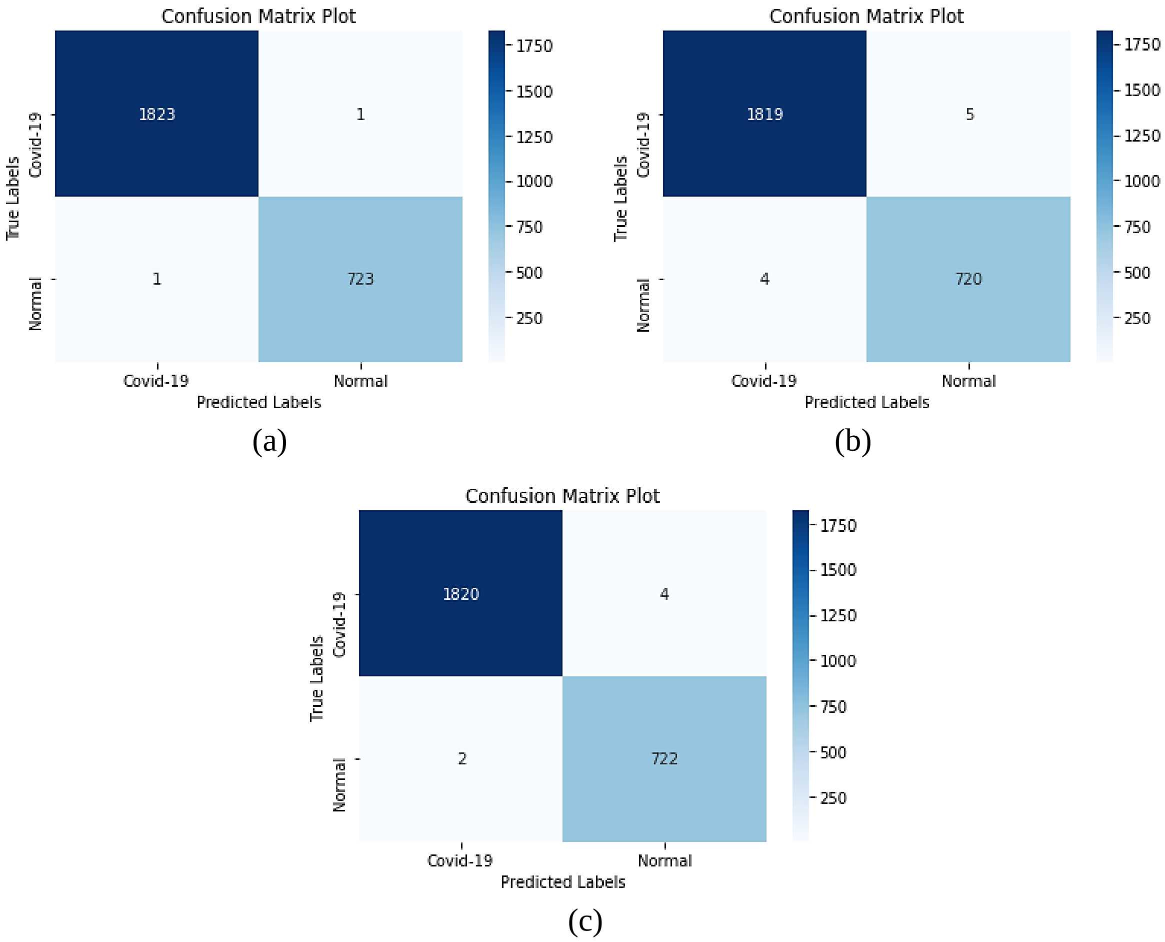


Figure 5 Confusion matrix of the models according to the validation dataset: (a) VGG16, (b) ResNet50, (c) proposed model.

According to the values given in Table 5, it is seen that the VGG16 model has the highest success accuracy and the ResNet50 model has the lowest success accuracy. It is seen that the success accuracy of the proposed model is higher than the ResNet50 model and proximate to the success accuracy of the VGG16 model. However, the high success accuracy and low loss rate in learning of networks seen in the graphs in Figure 4 and the low mistake rates seen in Figure 5 show that VGG16, ResNet50 and the proposed model have successfully classified.
Since the success accuracy of the proposed model is close to the success accuracy of the VGG16 and ResNet50 models, the performance results of the proposed model were tested using lung x-ray images from different patients, and the test results are given in Figure 6. Accordingly, the classification process was successfully carried out, and the proposed model was found to be highly accurate.

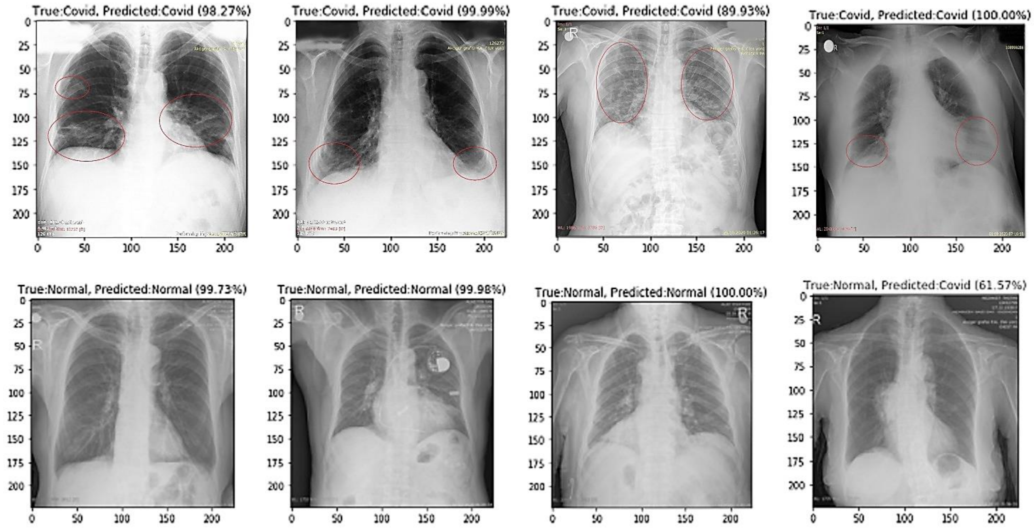


Figure 6 Examples of the performance test results made with the proposed model.

CONCLUSION

In this study, VGG16 and ResNet50 models used, and a decision support system based on the deep learning architecture was developed for Covid-19 detection on lung x-ray images. A new model was proposed and tested using CNN, one of the deep learning architectures. 9,121 Covid-19 and 3,618 normal lung x-ray images taken from 6,157 different patients were first examined in detail by specialist physicians and converted into a special data set. Then, using this data set, VGG16, ResNet50, and proposed model trainings were carried out.

VGG16, ResNet50, and proposed model as a result of training was tested using a validation dataset of 2,548 lung x-ray images that had not been used in the training stage. According to the test results, VGG16 99.92%, ResNet50 99.65%, and the proposed model 99.76% success was achieved. Although the number of layers used in the proposed model is less than the VGG16 and ResNet50 models, it has been observed that the proposed model is faster than the other models and provides a success accuracy proximate to other models. In addition, the proposed model was trained on computers with lower capacity than other models and showed a high success rate at lower time complexity. At the same time, high classification performance was obtained from the tests performed on Covid-19 and normal lung x-ray images taken from different patients with the proposed model.

Based on the results, it was observed that the VGG16, ResNet50 and proposed CNN model classified Covid-19 and normal lung x-ray images with a high accuracy rate and provided Covid-19 detection at lower time complexity using only lung x-ray images without the need for special test devices. As far as we know, there is no study that detects Covid-19 at a higher rate than this study. Thus, the fact that the proposed model can be directly applied in the health field increases the original value of the study, and it is considered that it will contribute to further studies on the detection of Covid-19.

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