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

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ABSTRACT

Coronavirus disease (Covid-19) has recently emerged as a serious public health threat, spreading rapidly worldwide and threatening millions of lives. With an increasing number of cases and mutations, medical resources are being drained daily owing to the rapid transmission of the disease, and the health systems of many countries are negatively affected. Therefore, it is important to use the available resources appropriately and in a timely manner to detect and treat the disease. In this study, VGG16 and ResNet50 deep learning models were used to quickly evaluate x-ray images and perform a prediagnosis of Covid-19, and an alternative model (IsVoNet) was proposed. Following model training, success accuracies of 99.92%, 99.65%, and 99.76% were achieved in the VGG16 model, ResNet50 model, and proposed model, respectively. According to the results, the models classified the Covid-19 and normal lung x-ray images with high accuracy, and the proposed model showed a high success rate at a lower time complexity than the other models.

Keywords: Deep Learning; Coronavirus; Chest X-Ray; Classification.

INTRODUCTION

The coronavirus disease (Covid-19) pandemic has become a major health problem that has rapidly spread worldwide, causing concern in society. According to the World Health Organization, an increase in the number of people affected by the pandemic increases the daily spread and mortality rates every day (Hemdan et al., 2020; Soundariya et al., 2020). An important reason for the increase in the rate of spread of the coronavirus is its transmission from one human to another through contact. In addition, the virus spreads into the air and affects nearby people, 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 exhibiting any symptoms (Brunese et al., 2020). Therefore, a large proportion of the world population has adopted protective measures to reduce the impact of the pandemic (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 and 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 to combat the pandemic (Altmann et al., 2020; Jamshidi et al., 2020; Li et al., 2020; Ginting and Luckyardi, 2021). The appropriate and timely use of available resources has become important for the detection and treatment of this disease (Ribeiro et al., 2020; Zeroual et al., 2020). Currently, x-ray devices are available worldwide and are used by specialists to detect Covid-19 without the need for special testing devices (Ouchicha et al., 2020). However, the need for specialist doctors to analyze x-ray images increases the workload of healthcare professionals. Therefore, a support system is required, which quickly evaluates x-ray images and prediagnose to save time for healthcare personnel and reduce their workload.

Recently, many deep learning algorithms have been used to quickly detect the Covid-19 pandemic (Shorten et al., 2021). Using deep learning algorithms, Covid-19 has been detected in x-ray images, and the workload of physicians has been reduced (Nayak et al., 2021). The convolutional neural network (CNN), particularly those used in deep learning methods, have provided good results in feature extraction and learning from medical images (Wang et al., 2021). Therefore, deep learning approaches were selected to detect Covid-19 disease (Bhattacharya et al., 2021).

In contrast to previous studies, this study used a new dataset consisting of 12,739 lung x-ray images confirmed by a specialist physician, and this dataset was trained with the VGG16 and ResNet50 models. However, a new CNN model was proposed to detect Covid-19 with high accuracy and low 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, Section 4 presents the experimental results 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 computed tomography (CT) images, a method that changed the inception transfer learning pattern was proposed. In the proposed method, specificity, sensitivity, and accuracy of 0.88%, 0.87%, and 89.5%, respectively, were obtained in the validation dataset used in the training. In addition, specificity, sensitivity, and accuracy of 0.83%, 0.67%, and 79.3%, respectively, were obtained in the test dataset that did not participate in training (Wang et al., 2021).

In another study, a CNN-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 another study using deep learning-based CNN models, the Inception V3, Xception, and ResNeXt models were compared to detect Covid-19. Consequently, the highest accuracy was achieved with the Xception model with 97.97% compared to other models (Jain et al., 2021).

A hybrid model was developed 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 with 99.69% accuracy (Altan and 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 the model, an accuracy of 93.01% was achieved in distinguishing between healthy individuals, those with bacteria-induced pneumonia, and those with viral-induced pneumonia. In the second stage, Covid-19 was detected with an accuracy of 97.22% by training the datasets separately to identify the x-ray images indicative of viral pneumonia (Jain et al., 2020).

In another study using deep learning, a combination of long short-term memory (LSTM) and a CNN was used to detect Covid-19 cases. In that study, a dataset compiled from different sites consisting of 4,575 x-ray images was reported to have an accuracy of 99.4% for identifying the disease (M. Z. Islam et al., 2020).

In another study, a new model was developed to differentiate coronaviruses from healthy controls using pulmonary CT images and influenza-A viral pneumonia, and the classification was performed with an accuracy rate of 86.7% (Xu et al., 2020). In another study on 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 that approach, experimental results showed that Covid-19 was successfully detected in approximately 2.5 s with an accuracy rate of 97% (Brunese et al., 2020).

In another study, chest x-ray images from InstaCovNet-19, a deep convolutional network, were used to detect Covid-19. 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, deep transfer learning algorithm to detect Covid-19 cases using CT and chest radiography was proposed. The 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 the radiology images (Panwar et al., 2020).

In a study aimed at detect Covid-19 from chest radiology images, a new approach based on deep learning using Densenet-121 was proposed. In this approach, training were performed using the COVIDx dataset, and double and triple classifications were performed to determine the accuracy of the model. The double and triple classification results with 96.49% and 93.71% of accuracy, respectively, were reported. In addition, Grad-CAM was used to indicate the areas where Covid-19 was found, and a website emphasizing potentially infected areas (Sarker et al., 2020). In another study, using the Xception model, a model based on the automatic deep transfer learning of 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).

Another study proposed a model using InceptionV3 and Inception-ResNetV2 models with ResNet models, such as ResNet50, ResNet101, and ResNet152, which were first trained on chest X-rays of patients infected with coronavirus pneumonia. Based on the performance results, the highest accuracy of the classification process was obtained using the ResNet50 model (Narin et al., 2020). Finally, a convolutional CapsNet was proposed to detect Covid-19 in x-ray images using capsule networks. In the proposed approach, binary and multiclass classifications were used to accurately diagnose Covid-19, and the accuracy rates were reported as 97.24% and 84.22%, respectively (Toraman et al., 2020). A comparison of the proposed model with existing methods for detecting Covid-19 is listed 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)	VGG16	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%
Proposed method	**IsVoNet**	**9121**	**3618**	**-**	**99.76%**

MATERIALS AND METHODS

Dataset

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

Each image was preprocessed separately, and after excluding 600 lung x-ray images that were considered inappropriate for evaluation, 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. Because the lung x-ray images in the original dataset were 3,200 × 3,200 pixels in size, they were converted to 224 × 224 pixel dimension in gray format during the preprocessing stage. The images in the dataset were then tagged under classes named Covid-19 and normal (Figure 1).

(a)

(b)

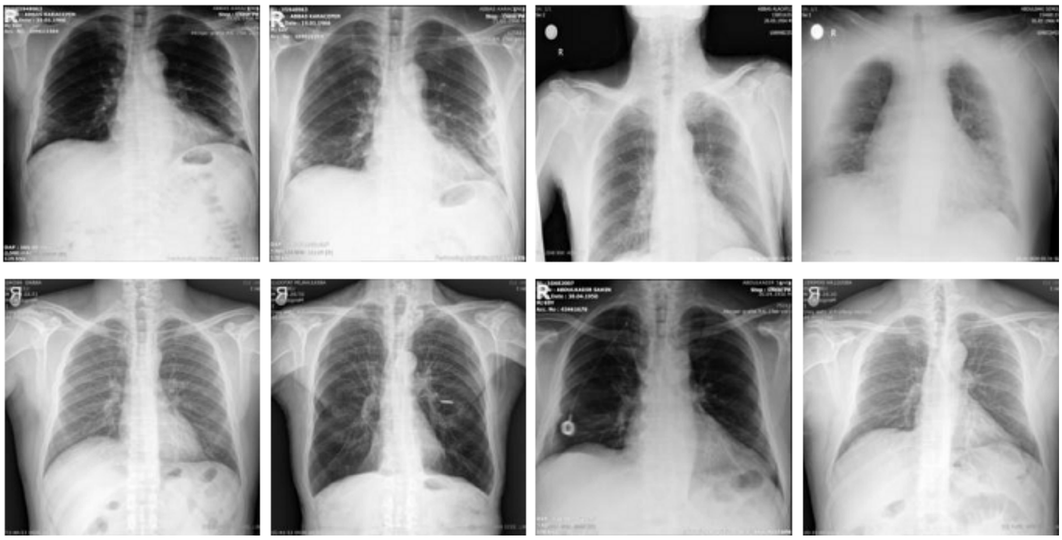


Figure 1 Image examples from the dataset: (a) Covid-19, (b) Normal.

CNN Model

CNN models are the most widely used deep learning models in computer vision applications. CNN models have achieved outstanding success and have become popular in recent years. In this study, the accepted VGG16 and ResNet50 models in the literature were used. In addition, a new model is proposed, as shown in Figure 2. The proposed model (IsVoNet) was developed using a deep learning architecture (Figure 3). In this model, the convolution, pooling, dropout, ReLU, flattening, fully connected, and classification layers were used. Using 18 layers, 5,926,018 parameters were obtained.

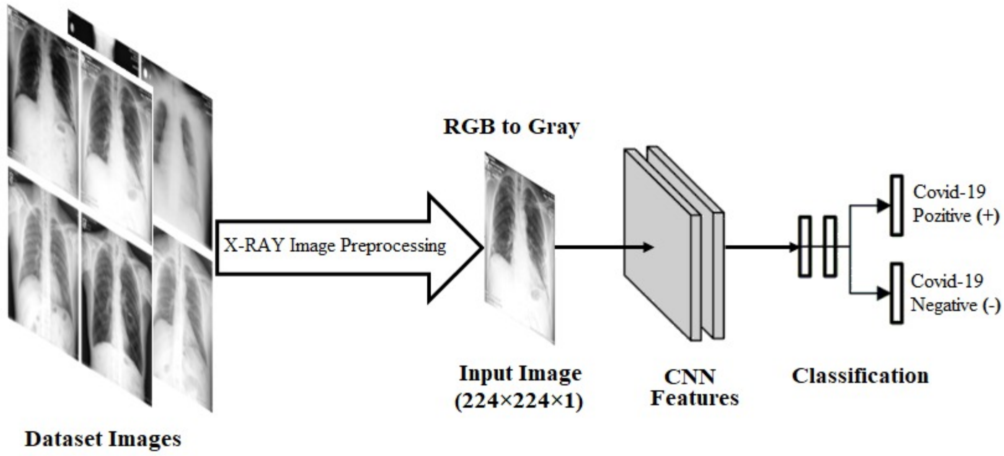


Figure 2 Schematic of the proposed method.

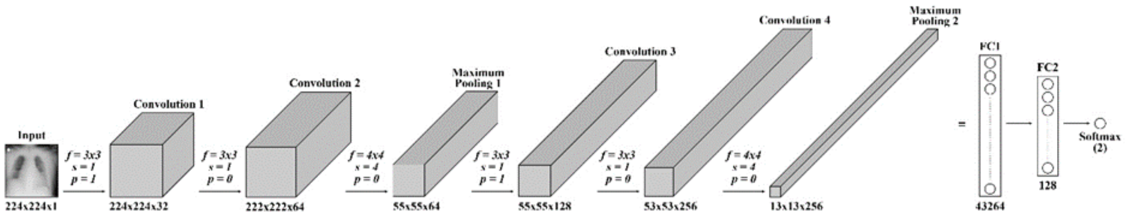


Figure 3 Convolutional neural network model used in the current study (f: filter size, s: stride, p: padding, FC: fully connected).

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

EXPERIMENTAL RESULTS

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

According to the experimental results, the number of parameters calculated in VGG16, ResNet50, and the proposed model were approximately 134 M, 25 M, and 5 M, respectively. The number of calculated parameters is a factor that significantly affects the system performance and time complexity. Therefore, the number of parameters calculated in the proposed model was reduced by at least five times compared with the other models. Therefore, the proposed model showed a high success rate at a lower time complexity than the 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 for the criteria of precision, recall, F1-score, and accuracy used in the study are provided in Equations 1–4.

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

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

$$F1 - score = \frac{2*Precision*Recall}{Precision+Recall} \tag{3}$$

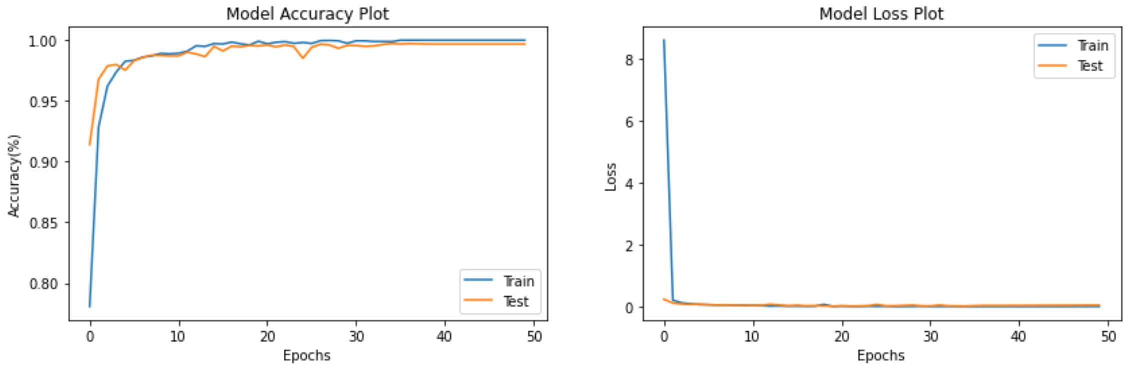
$$Accuracy = \frac{TP+TN}{TP+FP+FN+TN} \tag{4}$$

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

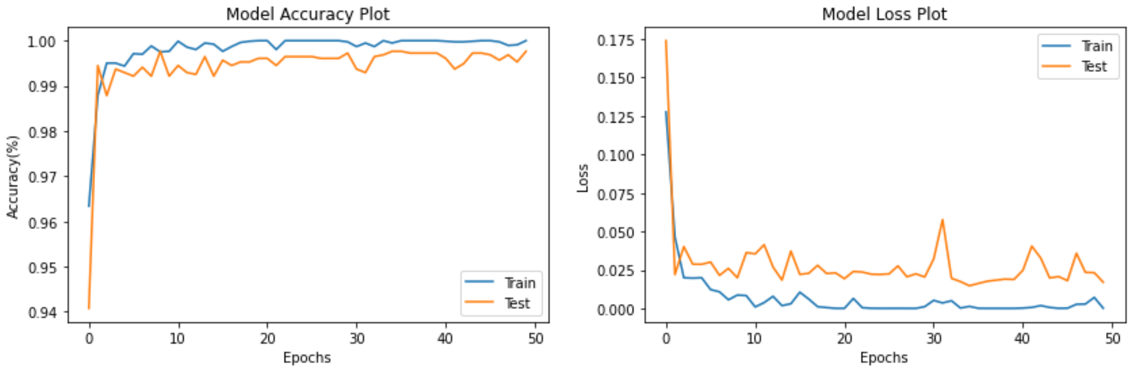
Table 4 lists the precision, recall, F1-score, and accuracy performance results measured by the training process of the models, and Figure 4 presents the accuracy and loss plots of the models. When the graphics are examined, we observed that the network started to learn at a high rate from the first iterations, and the network continued to learn in the following iterations; at the end of 50 iterations, it achieved a success rate of approximately 99% in the three models.

Table 4 Performance measures of the models.

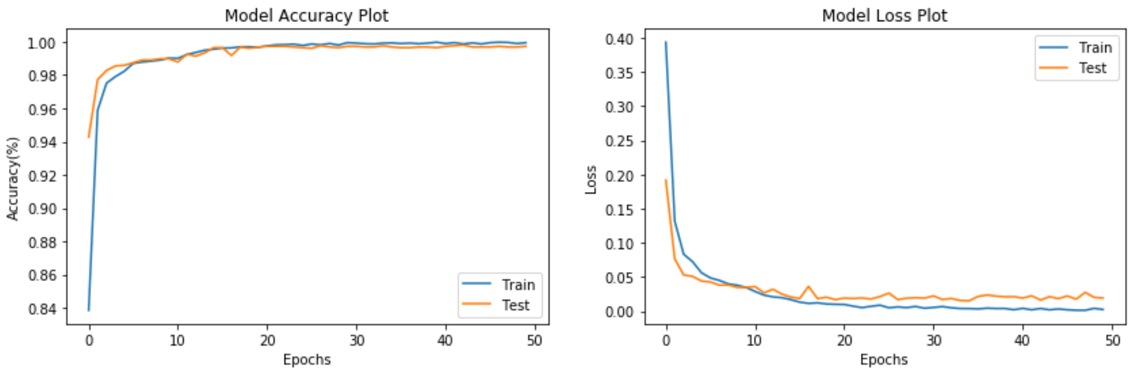
Model	Classification	Precision	Recall	F1-Score	Support
VGG16	Covid-19	1.00	1.00	1.00	1824
	Normal	1.00	1.00	1.00	724
	Accuracy	-	-	1.00	2548
	Macro Avg	1.00	1.00	1.00	2548
	Weighted Avg	1.00	1.00	1.00	2548
ResNet50	Covid-19	1.00	1.00	1.00	1824
	Normal	0.99	0.99	0.99	724
	Accuracy	-	-	1.00	2548
	Macro 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 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. Table 5 lists that the success rate is 99.92% for VGG16, 99.65% for ResNet50, and 99.76% for the proposed model. In addition, the loss ratios are 0.008 for VGG16, 0.022 for ResNet50, and 0.009 for the proposed model. Therefore, the highest success and lowest loss rates were achieved using the VGG16 model. According to the results of the confusion matrix obtained using the validation dataset that the network has never seen in Figure 5, we can observe that Covid-19 detected 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 for the three model networks. Table 6 lists the fitness values (validation losses). As shown in Table 6, the fitness values are 0.0099, 0.0147, and 0.0152 for VGG16, ResNet50, and the proposed model, respectively, which are the best values retained 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

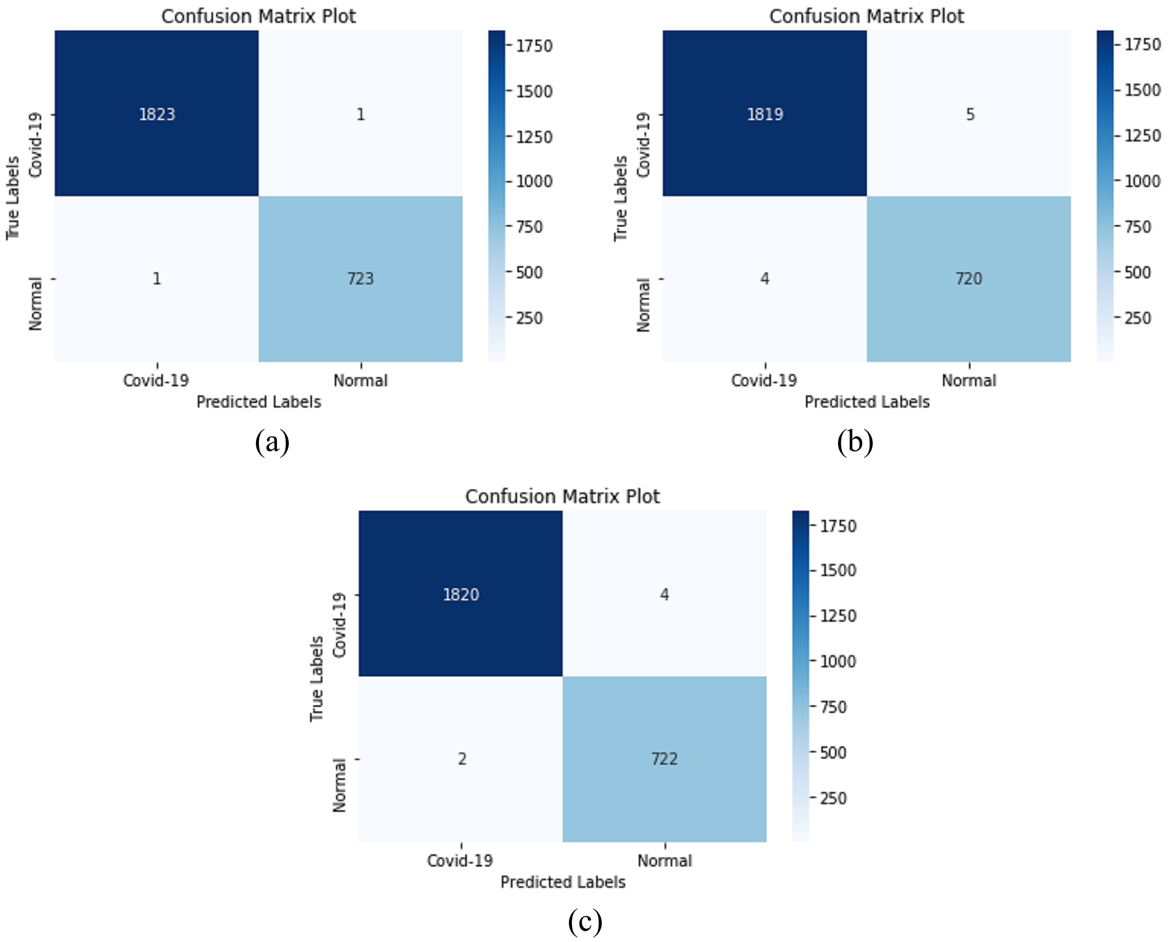


Figure 5 Confusion matrix of the models according to the validation dataset: (a) VGG16, (b) ResNet50, and (c) proposed model.

According to the values listed in Table 5, the VGG16 model achieved the highest accuracy, whereas the ResNet50 model achieved the lowest accuracy. We can observe that the success accuracy of the proposed model is higher than that of the ResNet50 model and close to that of the VGG16 model. However, the high success accuracy and low loss rate in the learning of networks shown in the graphs in Figure 4, and the low error rates observed in Figure 5 indicate that VGG16, ResNet50, and the proposed model are successfully classified.

Because the accuracy of the proposed model was close to that of the VGG16 and ResNet50 models, the performance of the proposed model was tested using lung x-ray images from different patients, and the test results are shown in Figure 6. Therefore, the classification process was successfully performed, and the proposed model was found to be highly accurate.

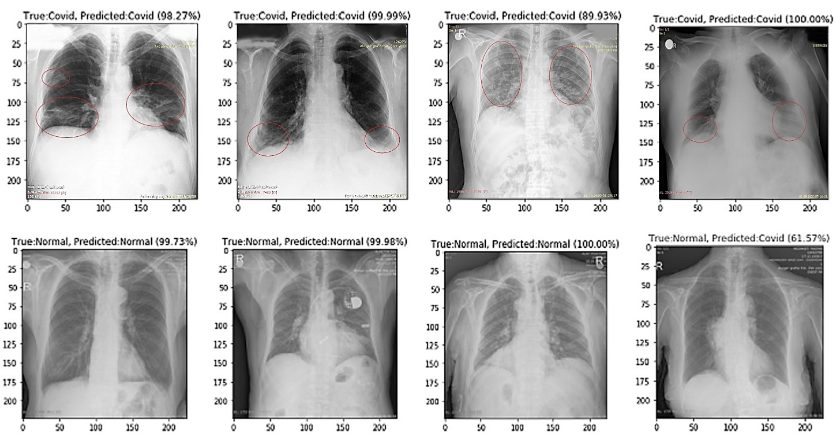


Figure 6 Examples of the performance test results obtained with the proposed model.

CONCLUSION

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

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

From the results, we can observe 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 a lower time complexity using only lung x-ray images, without the need for special test devices. To the best of our knowledge, no previous study has detects Covid-19 at a higher rate than that reported in this study. Therefore, the original value of the study increases because the proposed model can be directly applied to the health field, and it is expected to contribute to further studies on the detection of Covid-19.

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