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Prediction of Covid-19 Disease with Resnet-101 Deep Learning Architecture Using Computerized Tomography Images

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Abstract: Many pandemics have caused the deaths of millions of people in world history from past to present. Therefore, the measures to be taken in the prevention of pandemics are of great importance. In addition to the precautions, it is very important to be able to diagnose the disease early. The most recent pandemic occurred in the world is the COVID-19 outbreak that emerged in China in late 2019. In this study, Computerized Tomography images of 746 patients taken from an open source (GitHub) website were used. The data set was made ready for training by performing sizing and normalization operations on the data set. Images were analyzed using the Resnet-101 model, which is one of the deep learning architectures. Classification process was carried out with the created Resnet-101 model. With the Resnet-101 model, individuals with Covid-19 disease were tried to be identified. The Resnet-101 model detected individuals with Covid-19 disease with an accuracy rate of 94.29%.

Resnet-101 Derin Öğrenme Mimarisi ile Bilgisayarlı Tomografi Görüntüleri Kullanılarak Covid-19 Hastalığının Tahminlenmesi

Anahtar Kelimeler
Covid-19,
Derin Öğrenme,
ResNet-101,
Bilgisayarlı Tomografi Görüntüleri

Öz: Geçmişten günümüze dünya tarihinde birçok salgın milyonlarca insanın ölümüne neden olmuştur. Bu nedenle salgınlardan korunmada alınacak önlemler büyük önem taşımaktadır. Önlemlere ek olarak, hastalığın erken teşhis edilebilmesi çok önemlidir. Dünyada en son yaşanan salgın 2019 yılının sonlarında Çin'de ortaya çıkan COVID-19 salgınıdır. Bu çalışmada 746 hastanın açık kaynaklı (GitHub) bir web sitesinden alınan Bilgisayarlı Tomografi görüntüleri kullanılmıştır. Görüntüler, derin öğrenme mimarilerinden Resnet-101 modeli kullanılarak analiz edilmiştir. Oluşturulan Resnet-101 modeli ile sınıflandırma işlemi gerçekleştirilmiştir. Resnet-101 modeli ile Covid-19 hastalığı olan bireyler tespit edilmeye çalışılmıştır. Resnet-101 modeli, Covid-19 hastalığı olan bireyleri %94,29 doğruluk oranıyla tespit ettiği belirlenmiştir

1. INTRODUCTION

Health is one of the most important factors affecting societies today. Undoubtedly, pandemics are one of the factors that significantly affect human health. The first known pandemic in history is the Plague of Justinian that emerged in 541 [1]. Many pandemics, such as the black death [2], the modern plague [3], which occurred between 1346 and 1353 in world history after the Plague of Justinian, killed thousands of people. The last pandemic in the world is the COVID-19 pandemic. The COVID-19 pandemic first appeared in Wuhan, China in late December, and it has influenced the whole world and has been declared a pandemic by the world health organization [4,5]. In order to prevent the spread of the SARS-CoV-2 virus, a serious isolation was attempted around the world. Another important point to prevent the spread of the SARS-CoV-2 virus is the early detection of the virus. The COVID-19 test kit is often used to detect the virus. The fact that Covid-19 test kits are low in number and the results obtained from those test kits took time caused people to look for different alternatives. One of the alternative ways explored recently is Computerized Tomography (CT) images. CT images consist of data obtained by solid state detectors using a fan-shaped x-ray that rotates around the patient [6].

Doctors, virologists, epidemiologists, other public health officials and policy developers observed the spread of the SARS-CoV-2 virus together on CT imaging models. Many medical professionals, healthcare authorities, and policy makers have used CT images to monitor Covid-19 spread [7- 18]. When CT images of Covid-19 patients were examined, it was found that the posterior and peripheral parts of the patients were affected and these regions appeared as frosted glass on the CT images [13, 19]. However, it is not always possible to detect Covid-19 using CT images. For this reason, as in many fields, artificial intelligence methods are used in analyzing the CT images. For example, deep learning methods have been used on CT images to differentiate SARS-CoV-2 virus from viral pneumonia [20].

Deep learning is a sub-branch of machine learning and consists of data model layers for feature extraction and pattern recognition [21]. Deep learning is structurally a combination of high and low level hierarchy [20]. In deep learning, models such as Convolutional Neural Networks (CNN), Generative Adversarial Networks / GAN, Recurrent Neural Networks / RNN, CapsNet, Auto Encoder, HitNet are frequently used. These deep learning models are frequently used in many areas such as education [22, 23], facial recognition [24, 25] voice and emotion recognition [26, 27], cyber security [28] and health [29, 30].

In this study, a dataset containing 746 Covid-19 CT images created and shared on open source websites [31] by Zhao et al. (2020) was used. The data set was made ready for training by performing sizing and normalization operations on the data set. 349 Covid-19 positive CT images and 397 Covid-19 negative CT images were taken from this data set. Using the Resnet-101 deep learning method on the data set, Covid-19 patients were identified with an accuracy of 94.29%.

2. RELATED WORKS

When the academic studies that reviewed Covid-19 using CT images and Deep learning methods were examined; Li et al. (2020b) used CNN model for Covid-19 detection on lung CT images. The model created has been determined as 96% accurate according to AUC (Area Under Curve) performance evaluation criteria [20]. In another study, a model that helps radiologists to control the Covid-19 pandemic was created using the data set created by using CT images of MERS, SARS and ARDS from github, Open-i and Kaggle, and the CNN model [32]. In their study, Apostolopoulos et al. (2020) used X-ray images for the CNN network, which automatically detects features for the diagnosis of Covid-19 [33].

They obtained the best result in the study with MobilNet v2. In another study, they detected 90% accurate according to AUC performance evaluation criteria by using deep learning methods on CT images of patients diagnosed with viral pneumonia [34]. In another study, deep learning methods were used on the CT images of patients diagnosed with viral pneumonia, and they found 90% accurate according to the AUC performance evaluation criteria [35]. In their study, Wang and Wong (2020) proposed the Covid-NET model for Covid-19 detection on Chest CT images. Three results were obtained with the proposed model: normal 91.3%, covid-19 93.8% and non-Covid-19 88.9%. In another study, they created a diagnostic system based on CNN model for the diagnosis of COVID-19. The established diagnostic model has been determined as 97% accurate according to AUC performance evaluation criteria. In their study, Shan et al. (2020) developed a deep learning model to automatically measure the amount of infection occurring in the lungs of patients carrying the SARS-CoV-2 virus [36]. In Narin et al.'s (2020) study, 98% accuracy was achieved with the CNN-based ResNet50 model using CT images of Covid-19 patients using the transfer learning technique [37].

3. MATERYAL VE METOT

3.1. Materyal

In this study, Covid-CT-dataset created by [38], which includes a total of 746 CT images, 397 Non-Covid and 349 Covid-19, shared on an open-source site [31] has been used. This data set was modeled using the Resnet-101 deep learning method with a software prepared in Python programming language. Information about the data set used in the study is given in Section 3.1.1 and the structure of Resnet-101 architecture is given in section 3.1.2.

3.1.1. Dataset

The properties of the data set used in this study are given in Table 1. When the table is examined, it is seen that a total of 746 images are selected from the Covid-CT-dataset in a way that the number of Covid and Non Covid is balanced. The Covid-19 dataset consists of 349 images and this dataset is divided into two datasets as 279 training and 70 test. The Non- Covid-19 dataset consists of 397 images and this dataset is divided into two datasets as 327 training and 70 tests.

Table 1. Covid-19 CT dataset distribution used in this study

Dataset	Non-Covid-19	Covid-19	Total
Test	70	70	140
Train	327	279	606
Total	397	349	746

3.1.2. ResNet-101 network architecture

The Resnet-101 structure consists of 101 layers. Based on the Residual neural network learning method, this architecture is one of the deepest proposed architectures for ImageNet [39]. The biggest feature of Resnet-101 that differs from other architectures is that it optimizes the residues between input and desired convolution properties. Desired features are obtained more easily and efficiently compared to other architectures. Thus, residual optimization can be applied to reduce the number of parameters in a deeper network. By reducing the number of parameters, the number of layers can be reduced to an effective number [40].

In ResNet architecture, information that cannot be learned in the previous layer is applied from the old layer to the new layer with the ResBlock layer. The Resblock layer is the blocks that feed residual values to the next layer in the Resnet architecture. This value added by this skip, which occurs between the weight layers and the Relu activation code at every two-layer activation, changes the system account [41].

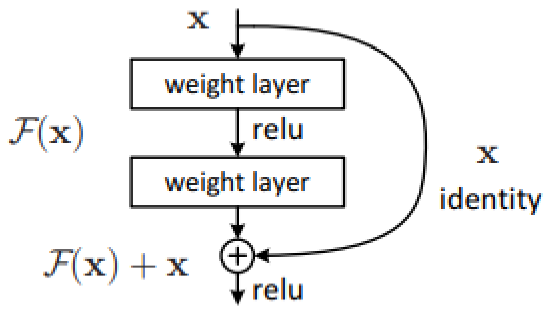

Figure 1. Residual Block [41]

The Residual Block structure has two layers and represents the nonlinear Relu function.

$$F = w_{2\sigma}(w_{1}x) \quad (1)$$

By adding the second Relu value to this result, y output is obtained.

$$y = F(x, \{w_i\}) + x \quad (2)$$

In Eq. 2, x represents the input vector and y represents the output vector.

3.1.3. Performance evaluation criteria

Different evaluation criteria such as Area Under the ROC Curve (AUC), Receiver Operating Characteristic Curve (ROC), sensitivity, specificity, accuracy and F1 score are used to detect diseases in medical images. AUC value and ROC curve are generally used in performance evaluation of classification processes in deep learning. These two performance evaluation criteria are often used when data sets are not balanced. The ROC curve is a probability curve created for classes. Normally, in an ideal ROC curve, the x-axis contains False Positive Rate (FPR) values, and the y-axis contains True Positive Rate (TPR) values. The AUC value is calculated by calculating the area under the ROC curve. The calculated field value is a value ranging from 0 to 1. If the calculated value is close to 1, the model created is so close to success. In Table 2, cross-classification table is given for sensitivity, F1 score, accuracy and specificity according to estimation and reference test results. In the table, True Positive is expressed as TP, False Negative as FN, False Positive as FP and True Negative as TN. TP represents the correctly predicted positive class, FN, the false predicted negative class, FP represents the false predicted positive class, and TN represents the correctly predicted negative class [42-46].

Table 2. Cross-classification table according to estimation and reference test results

		Predicted	
		Positive	Negative
Actual	Positive	TP	FN
	Negative	FP	TN

Using Table 2, the mathematical expressions of sensitivity, specificity, accuracy and F1 score are given between Eq. 3-6 [42-46].

$$Sensitivity = \frac{TP}{TP+FN} \quad (3)$$

$$\text{Specificity} = \frac{TN}{TN+FP} \quad (4)$$

$$\text{Accuracy} = \frac{TP+TN}{\text{TP+FN+}TN+FP} \quad (5)$$

$$\text{F1 Score} = \frac{2*TP}{2*\text{TP+FN+}FP} \quad (6)$$

3.2. Methods

The work block diagram of the study carried out is given in Fig.2. In the first stage of the study, a data set was created using a total of 746 Covid-CT-dataset data taken from open source websites [31]. This dataset contains a total of 349 CT images carrying SARS-CoV-2 virus and 397 CTS that do not carry SARS-CoV-2 virus. In the second stage, the images in Covid-CT-dataset were divided into two classes and labeled as Covid-19 and Non Covid-19. Images belonging to Covid-19 class are divided into three as 234 training, 45 validation and 70 test. Non-Covid-19 class data are divided into three as 282 training, 45 validation and 70 tests. After the data sets were categorized, all images were converted to 296x296 dimensions. All images were normalized after conversion was performed. In the third stage, the learning rate of the Resnet-101 model used in the study has been optimized by training. According to the learning rate determined in the optimization process, the training process was carried out using the Resnet-101 model with 30 epochs. As the number of epochs increases, the performance of the model increases, but overfitting may occur. Therefore, it is necessary to choose an appropriate number of epochs. In the study, the number of epochs was chosen in areas where it increased in very small units, based on the performance and loss of the model. Batch size 16 and adam optimization method was used in the training phase of the ResNet-101 model. The model obtained at the end of each epoch operation was validated with validation data. At the last stage, the final Resnet-101 model was tested with 140 CT images and the model accuracy was determined.

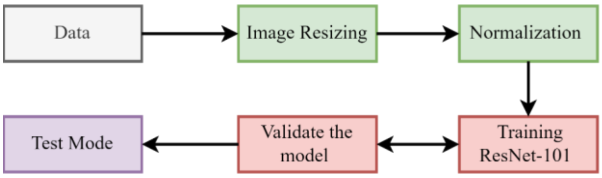

Figure 2. Work Block Diagram

4. RESEARCH FINDINGS

In this study, 746 Covid-CT-dataset images were modeled with one of the deep learning models Resnet-101. In Figure 3, the learning rate graph of the Resnet-101 model is given. When the graphic is analyzed, the learning rate for the Resnet-101 model was taken as 0.002 and the training process was carried out.

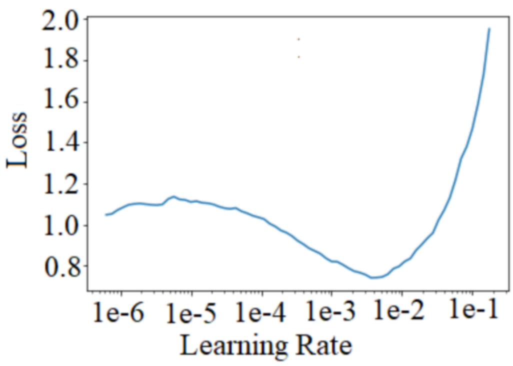

Figure 3. Learning rate effect graphic of Resnet-101 architecture

Choose an appropriate number of epochs and learning rate to avoid over fitting during the training phase. In order to check that there is no over fitting in the trained model, it was verified with the validation dataset during the training phase and tested using different data at the end of the training.

The confusion matrix of the model is given in Fig. 4 to determine the accuracy of the trained Resnet-101 architecture. It can be seen from the confusion matrix that 70 of 140 CT images used in the testing phase of the model are Covid-19 positive and the remaining 70 images are Covid-19 negative. As seen in the confusion matrix, the model created with Resnet-101 has classified 65 of 70 Covid-19 positive patients accurately and 5 patients inaccurately. In addition, the created model has classified 67 of 70 Covid-19 negative patients accurately and 3 patients inaccurately. The results obtained from the Confusion matrix show that the created model gives successful results in Covid-19 detection.

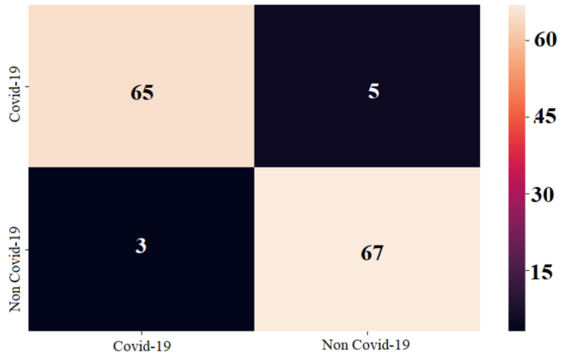

Figure 4. Confusion matrix

Following the successful results obtained from the confusion matrix, the sensitivity, specificity, accuracy and F1 score values for the Covid-CT data that the Resnet-101 model predicted correctly and incorrectly were calculated according to the values in the cross-classification table given in table 3. Sensitivity, specificity, accuracy, and F1 score values are showed in table 4 by using equations given between Eq. 3-6.

Table 3. Cross classification table for Resnet-101 model

		Predicted	
		Covid-19 (Positive)	Non Covid-19 (Negative)
Actual	Covid-19 (Positive)	65(TP)	5(FN)
	Non Covid-19 (Negative)	3(FP)	67(TN)

Table 4. Performance Evaluation Results of the Model

Evaluation criteria	Sensitivity	Specificity	Accuracy	F1 score
Values	92.86	95.71	94.29	94.2

When the values obtained from the calculations are examined, the sensitivity value is 92.86%, the specificity is 95.71%, the accuracy is 94.29% and the F1 Score value is 94.20%. The Resnet-101 model used in the study was evaluated with the ROC curve. In Figure 5, the ROC curve was drawn using the reference test and prediction data of the Resnet-101 model. As seen in the figure, it is seen that the Resnet-101 model gives a high successful result in the detection of Covid-19 virus.

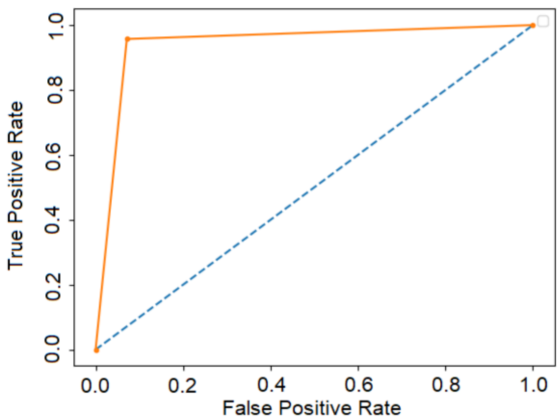

Figure 5. ROC Curve for Trained ResNet-19 model

The AUC value of the area under the ROC curve drawn according to the Resnet-101 model used in the study was determined as 0.943 using the ROC_AUC_score function of the scikit-learn library in the Python programming language. It was determined that the Resnet-101 model used to detect the SARS-CoV-2 virus by using the images in Covid-CT-Dataset detected the virus with an accuracy rate of 94.29%.

4. CONCLUSIONS

The SARS-CoV-2 virus, which appeared in China in December 2019, quickly spread and turned into a pandemic. Various measures have been taken in the world to prevent this pandemic. Many measures were taken, such as forbidding elderly people and children from going out, applying social distance rules, forbidding mass events. In addition to these precautions, isolating the individuals carrying the virus and personal cleaning are one of the most important measures to prevent the spread of the SARS-CoV-2 virus. Therefore, early diagnosis of patients with the SARS-CoV-2 virus is extremely important. Different methods are used to detect the SARS-CoV-2 virus. Among these methods, different methods such as Covid-19 blood test, chest x-ray are used.

In the study, 746 COVID-CT-dataset images taken from open access websites (GitHub) were used to determine COVID-19 disease. The reliability of the Resnet-101 model has been increased by taking an equal number of images with and without the SARS-CoV-2 virus in the data set. The Resnet-101 model used in the study was evaluated according to four different performance evaluation criteria. As a result of the evaluation;

- The Resnet-101 model was evaluated according to the Confusion matrix, the first performance evaluation criterion. As a result of the evaluation, 65 of 70 patients with SARS-CoV-2 virus and 67 of 70 patients without SARS-CoV-2 virus were determined correctly.
- Resnet-101 model was secondly evaluated according to sensitivity, specificity, accuracy and F1 score. As a result of the evaluation, it was found that the SARS-CoV-2 virus was detected with 92.86% sensitivity value, 95.71% specificity, 94.29% accuracy and 94.20% F1 Score value.
- When the Resnet-101 model is evaluated according to the ROC curve, it has been determined that it gives a highly successful result.
- In the last stage of the study, the Resnet-101 model was evaluated according to the AUC evaluation method. As a result of the evaluation, the AUC value was determined to be 0.943.

According to the four different evaluation criteria used in the study, the Resnet-101 model used to identify people with COVID-19 disease by using Covid-CT-dataset images detected the people with the disease with 94.3% accuracy. In future studies, it is thought that it would be appropriate to carry out different studies by using different deep learning methods or by enlarging the data set.

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