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Evaluation of Poor Prognosis in rRT-PCR Positive Covid-19 Cases with Using Deep Transfer Learning Network

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ABSTRACT

The infection called Covid-19 caused by the new type of coronavirus (SARS-CoV-2) is an epidemic and deadly disease that spreads rapidly worldwide. Early detection of Covid-19 will enable the patient to receive appropriate treatment and increase the chance of survival. This study aims to investigate the detection of poor prognosis from chest CT images in Covid-19 patients who died and healed using deep learning. In this retrospective study which was carried out in collaboration with a specialist radiologist, a dataset was created by evaluating a total of 5997 CT images by the expert. Images belonging to two classes in the dataset were classified using the Inception-v3 deep learning model. In order to evaluate the classifier, ROC curves were drawn, AUC and accuracy values were used as performance metrics. Inception-v3 model was run 10 times, and a maximum classification performance of 97.55% and an average of 97.01% was achieved. The classification results prove that Inception-v3 can classify CT images with a high accuracy rate for evaluating the Covid-19 prognosis.

Derin Transfer Öğrenme Ağı Kullanılarak rRT-PCR Pozitif Covid-19 Olgularında Kötü Prognozun Değerlendirilmesi

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ÖZ

Yeni tip koronavirüsün (SARS-CoV-2) neden olduğu Covid-19 olarak isimlendirilen enfeksiyon, tüm dünyada hızla yayılan salgın ve ölümcül bir hastalıktır. Covid-19'un erken teşhisi, hastanın uygun tedavi almasını sağlayacak ve hayatta kalma şansını artıracaktır. Bu çalışmada derin öğrenme kullanılarak ölen ve iyileşen Covid-19 hastalarında göğüs BT görüntülerinden kötü prognoz tespitinin araştırılması amaçlanmıştır. Yapılan retrospektif çalışma bir uzman radyolog ile işbirliği gerçekleştirilmiş ve toplam 5997 CT görüntüsü uzman tarafından değerlendirilerek veriseti oluşturulmuştur. Verisetindeki iki sınıfa ait görüntüler Inception-v3 derin öğrenme modeli kullanılarak sınıflandırılmıştır. Sınıflandırıcıyı değerlendirmek için ROC eğrileri çizilmiştir, performans ölçütleri olarak AUC ve doğruluk değerleri kullanılmıştır. Inception-v3 modeli 10 kez çalıştırılmış ve maksimum %97,55 ve ortalama %97,01 sınıflandırma performansı elde edilmiştir. Sınıflandırma sonuçları, Inception-v3'ün CT görüntülerini Covid-19 prognozunun değerlendirilmesi için yüksek doğrulukla sınıflandırabildiğini kanıtlamaktadır.

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1. Introduction

Coronaviruses (CoV) usually cause mild or moderate respiratory tract infections. However, two new coronaviruses called SARS and MERS, which cause more severe clinical pictures, have emerged in recent years. After these two epidemics due to coronaviruses, in December 2019, an increase in the number of patients who presented with pneumonia in Wuhan, China, was noted, and it was understood that a newly emerging coronavirus caused these cases. This new coronavirus, which causes a worldwide pandemic, is named SARS-CoV2, and the disease caused by this virus is called Covid-19. The disease negatively affects many organs, especially the lungs, and gives symptoms such as high fever, cough, and shortness of breath.

Some laboratory features have been associated with worse outcomes. Blood absolute lymphocyte count <800/microL, serum CRP level >40 mg/L, ferritin level >500 mcg/L, and D-Dimer level >1000 ng/mL were indicated as poor prognostic factors for Covid-19 disease (Del Valle et al., 2020; Liao et al., 2020; Shi et al., 2020; Wu et al., 2020; Zhou et al., 2020). These criteria were also used in this study to determine patients who were projected to have a severe course of the disease and those who were expected to have a mild course. In other words, it was used to predict whether the disease would be severe or mild.

Computed tomography (CT) is widely used to diagnose Covid-19 and supports the diagnosis. Pneumonia may develop significantly in patients with a severe course. So, rRT-PCR, blood tests, and chest CT are performed together to diagnose patients with suspected Covid-19 (Simpson et al., 2020). In SARS-CoV-2 rRT-PCR positive patients, chest CT; sensitivity is reported as 97% (Ai et al., 2020).

The interpretation of lesions in CT may differ depending on the workload or experience of the radiologist. For example, visual evaluation of images may not allow fine details to be detected by humans. Automated measurement methods can obtain objective, detailed and reproducible measurements of the extent and severity of lesions. In addition, various automated measurement methods are developed based on the structure of the lung tissue. These methods have helped evaluate disease severity and prognosis (Park et al., 2016). Quantitative evaluation is obtained by evaluating the pathological and normal areas in the lung tissue with computer software.

Machine learning methods are systems that include different algorithms and allow classification, clustering, or prediction over CT images (Kirienko et al., 2020). In addition, there are studies suggesting that deep learning algorithms contribute to increasing the diagnostic efficiency of radiologists for Covid-19 pneumonia (Wu et al., 2020). Zhang et al. (2020) reported that deep learning could help determine the correct diagnosis and prognosis of Covid-19 pneumonia with computed tomography.

The diagnosis of Covid-19 disease is confirmed by RT-PCR test. However, since this test is costly and does not provide fast results, researchers have started to investigate computer-assisted diagnostic methods for detecting Covid-19. There are many studies in the literature for the detection of Covid-19. Most used thorax CT or chest X-ray images obtained from imaging techniques as data. Bargshady et al. (2022) made a study to detect Covid-19 from chest X-ray images. They used a novel data augmentation method by applying a Generator Adversary Network (GAN) combined with a trained, semi-supervised CycleGAN. They detected Covid-19 with 94,2% accuracy with the modified Inception-v3 architecture. In another study (Manokaran et al., 2021), 9573 X-ray images labeled as normal, pneumonia, and Covid-19 were used, and a three-class problem was tried to be solved. In the study in which DenseNet201, one of the transfer learning models, was used as a method, 92,19% classification performance was achieved.

In the literature, studies using CT images to detect Covid-19 are more common than studies using X-ray images. Kart and Başçiftçi (2021) tested classical machine learning algorithms on a dataset consisting of 750 normal and 750 Covid-19 CT images. The best results were obtained from the Support Vector Machine (SVM) algorithm with 96,7% accuracy. In another study, Erdem and Aydın (2021) created a hybrid model by combining CNN and SVM. They trained and tested this model on a dataset consisting of 2482 CT images, and as a result, they managed to classify Covid-19 with 85,56% accuracy. Using DenseNet169, one of the proven transfer learning models, Ala and Polat (2021) reached a performance of 98,6% on a dataset consisting of a total of 2482 CT images, 1252 of which were with Covid-19 and 1230 without.

In recent studies on the detection of Covid-19, some studies use laboratory findings instead of CT or X-ray images and classify them with machine learning techniques. For example, Alakus and Turkoglu (2020) examined 18 laboratory findings from 600 patients to detect Covid-19 infection. They achieved 92,30% success with the hybrid deep learning model, in which they used CNN and Long Short-Term Memory (LSTM) together. Göreke et al. (2021) created a new set of features based on 18 laboratory findings that take into account ethnic and genetic differences to interpret blood data. Then, using this feature set, they designed a new hybrid classifier model based on deep learning that achieved 94,95% accuracy in classification performance. Covid-19 is detected from audio recordings of cough, breath, and speech in a different study. Pahar et al. (2022) evaluated the existence of Covid-19 using deep transfer learning and bottleneck features on a dataset, including cough, breath, and speech sounds. Among them, they determined that the most significant sound recording in recognition of Covid-19 belonged to cough.

In the future, it will be possible to diagnose poor prognosis in Covid-19 patients with software that analyzes images in computed tomography devices. This study aims to investigate the detection of poor prognosis with chest CT texture analysis in Covid-19 patients who died and healed using deep learning. The contributions of this paper can be summarized as follows: With this study, the worsening course of the disease and poor prognosis in patients with Covid-19 disease can be determined without wasting time. By detecting patients who will get worse beforehand, more careful monitoring and treatment of patients will affect the course of the disease. In addition, knowing that the disease will have a bad prognosis will constitute an advantage in predicting the hospital capacities and the burden on the health system. Even if some patients' clinical follow-up and laboratory findings are reasonable, warnings about the poor prognosis can be received thanks to the advance warning of these software, which will be integrated to the tomography devices; and in this case, the mortality and morbidity of the disease could be reduced.

This study aimed to understand the success of estimating the distinction of dead patients by analyzing chest CT images of patients with rRT-PCR positive Covid-19 who died and healed with a deep learning algorithm. For this purpose, we applied the Inception-v3 transfer learning model on chest CT images to investigate the poor prognoses of Covid-19. As a result of the experiments, we have demonstrated the effectiveness of the proposed method in distinguishing between died and healed cases.

2. Materials and Methods

Dataset

Approval for this study was obtained from the Turkish Ministry of Health Scientific Research Platform (No:2020-2020-05-12T16_41_53) and Sivas Cumhuriyet University Non-Interventional Clinical Research Ethics Committee (Decision No:2020-05/11) for retrospective imaging and laboratory data analysis. In the study, thorax CT images and laboratory findings of the patients were used. A dataset was created with the images of the patients who applied to the pandemic clinic and were treated as inpatients who had positive RT-PCR tests and Covid-19 findings on CT. Thorax CT images were obtained from tomography examinations. This study was performed using the 16 section multidetector CT device (Alexion, Toshiba Medical Systems, Tokyo, Japan) and the standard thorax CT protocol. Chest CT examination was obtained in the supine position and was used with the parameters of kV: 80-120, mAs: 50-100, pitch: 1-1.5. After the CT scan, reconstruction was performed on the images at a thickness of 3 mm. The dataset contains 5997 CT images of a total of 140 patients who died (2889 images) and healed (3108 images). CT image samples of died and healed patients are shown in Figure 1.

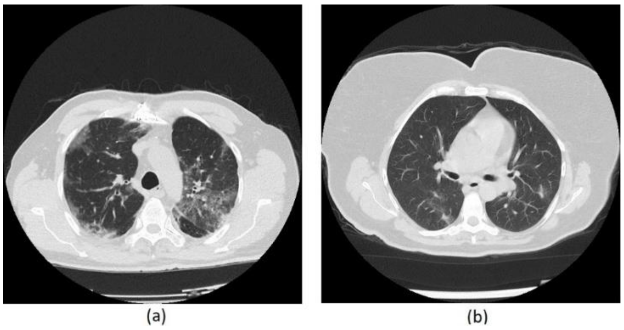


Figure 1. Original chest CT images of two different patients who died and healed with Covid-19 disease

a) Died b) Healed

The images were collected as 512×512 DICOM and then converted into JPEG with 224×224 dimensions for the deep learning model. In order to train and test the model, the dataset was divided into two at the rate of 70% and 30%; 70% was used for training, while the rest was used for the test.

This study consisted of 65 females (24 died and 41 healed) and 75 male Covid-19 positive patients (34 died and 41 healed). The mean age of the whole group was 63.1±16.1 years. In died group, 47 patients (81%) were aged ≥65, and 11 patients (19%) were aged <65. In the healed group 27 patients (32.9%) were aged ≥65, and 55 patients (67.1%) were aged <65.

Laboratory Findings

Laboratory data were included lymphocyte count, serum CRP level, ferritin level, D-Dimer level. The patients who died and healed were grouped from the laboratory findings defined as poor prognostic factors (Zhou et al., 2020; Wu et al., 2020; Shi et al., 2020; Liao et al., 2020; Del Valle et al., 2020): Blood absolute lymphocyte count <800/microL and >800/microL, serum CRP level <40mg/L and >40mg/L, ferritin level <500 mcg/L and >500 mcg/L, D-Dimer level <1000 ng/mL and >1000 ng/mL. Of the 38 patients with blood absolute lymphocyte count <800/microL, 29 died, and 9 healed. The difference between the counts of died and healed patients in terms of the blood absolute lymphocyte count <800/microL was found to be statistically significant (X^2=26,16, p<0,005). Of the 78 patients with serum CRP levels>40mg/L, 53 patients died, and 25 patients healed. The difference between the counts of died and healed patients in terms of the serum CRP level >40mg/L was found to be statistically significant (X^2=51,05, p<0,005). Of the 41 patients with serum ferritin level >500 mcg/L, 31 died, and 10 healed. The difference between the level of died and healed patients in terms of the serum ferritin level >500 mcg/L was found to be statistically significant (X^2=27,92, p<0,005). Of the 21 patients with serum D-Dimer level >1000 ng/mL, 17 patients died, and 4 healed. The difference between the counts of died and healed patients in terms of the serum D-Dimer level >1000 ng/mL was found to be statistically significant (X^2=15,90, p<0,005). Laboratory findings are shown in Table 1.

Table 1. Laboratory findings of dead and healed RT-PCR positive Covid-19 patients

		Died	**Healed**	**Statistical significance**
Age	<65 years	11	55	X^2=31.55 p=0.0001
	≥65 years	47	27	
Gender	Female	24	41	X^2=1.01 p>0.05
	Male	34	41	
Blood absolute lymphocyte count	<800/microL	29	9	X^2=26.16 p=0.0001
	≥800/microL	29	73	
Serum CRP level	<40mg/L	5	57	X^2=51.05 p=0.0001
	≥40mg/L	53	25	
Serum ferritin level	<500mcg/L	27	72	X^2=27.92 p=0.0001
	≥500mcg/L	31	10	
Serum D-Dimer level	<1000ng/mL	41	78	X^2=15.90 p=0.0001
	≥1000ng/mL	17	4	

Convolutional Neural Networks (CNN) based Inception-v3

Convolutional neural networks are a special type of neural networks used to process data with a grid-like topology. Time series data that can be considered as a 1-D grid that takes samples at various time intervals and image data that can be thought of as a 2-D pixel grid can be given as examples (Goodfellow et al., 2016). Convolutional networks (LeCun et al., 1989) use a mathematical operation called convolution. The convolution operation in 2-D space means that the reciprocal elements of two matrices are multiplied and then added together to obtain a value, and this process continues by shifting one of the matrices over the other. As a result of these operations, a new matrix called feature map emerges.

CNNs have different layer types and different parameters used in these layers. The first is the convolution layer, where the convolution operation takes place. Image and filter are given as input to this layer, and the feature map appears as output. The feature map is obtained by shifting the filter on the image, multiplying the reciprocal values, and summing these multiplication results. An example of a 2-D convolution process can be seen in Figure 2.

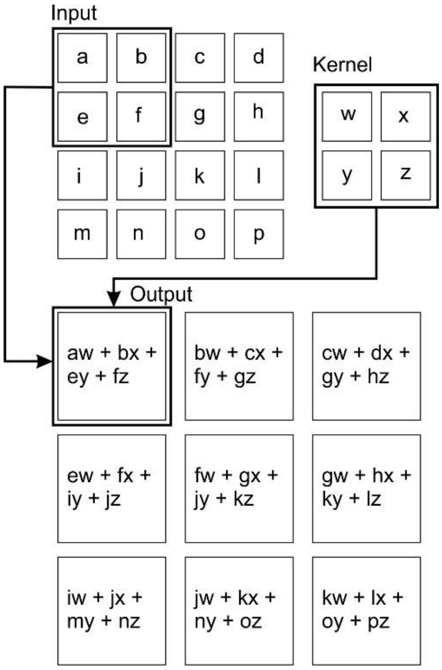


Figure 2. An example of 2-D convolution process

In Figure 2, the image size is 4×4, the filter size is 2×2, and the stride is 1. The stride is one of the parameters used in CNN layers and informs that the convolution process will shift the filter on the image in steps of one pixel or larger steps. In case the image size is $n\times n$, the filter size is $f\times f$, and the stride is s, the size of the output matrix is $[(n-f)/s+1]\times[(n-f)/s+1]$. Thus, the output of the convolution process shown in Figure 2 is 3×3. After convolution, it is up to us to manage the input and output size difference. This process is provided by extra pixels to be added to the input matrix. Let the padding value be p, in this case the size of output matrix is $[(n+2p-f)/s+1]\times[(n+2p-f)/s+1]$.

A non-linearity layer, sometimes called the activation layer, in a CNN consists of an activation function that takes the feature map generated by the convolutional layer and gives the activation map as its output. The dimensions of the input and the output in this layer are identical, and this layer returns the same number of filters. There are various types of activation functions, the most common of which is ReLU (Nair and Hinton, 2010):

$$g(x) = \max(0, z)$$

The pooling layer is often used after the activation layer to reduce the network's number of parameters and dimensions. The reduction in size leads to loss of information, and for the network, these losses are beneficial for two reasons. First, the decrease in the number of parameters and dimensions reduces the computational load of the subsequent network layers, and the second is that the overfitting of the network is prevented. Pooling operation is done in two different ways: max pooling and average pooling. Max pooling selects the maximum value in the filter as the output value, while average pooling takes the average of the values in the filter. Examples of pooling operations are shown in Figure 3.

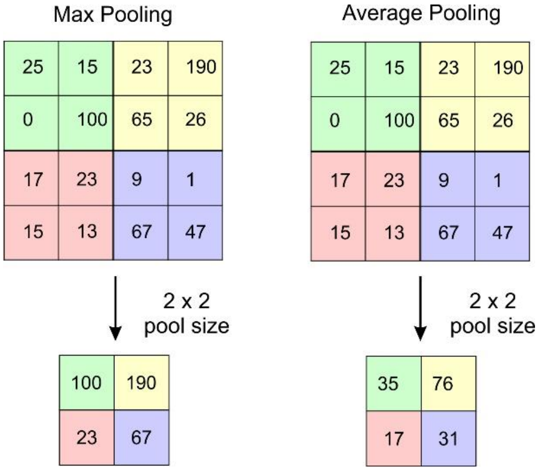


Figure 3. An example of max pooling and average pooling operations

The dropout layer is used to prevent overfitting problems in CNN by randomly removing some network nodes. Overfitting in classification problems is that the network can only classify the samples in training set with high accuracy. Dropout provides a better generalization ability for the network to classify new data.

The flattening layer converts the output from previous layers to one-dimensional data. That is, it converts the feature maps expressed in matrix form into vectors by adding each row one after the other.

The fully connected layer is the last layer and classifies the images. Fully connected layers are feed-forward neural networks that connect every neuron in one layer to every neuron in another layer. The final pooling or convolution layer output is given as input to the fully connected neural network (FCNN) layer after it has been flattened.

CNNs have the ability to automatically extract features from images with the filters they use. In this way, images can be classified accurately and efficiently without the need for more feature selection (Guo et al., 2016). Transfer learning is the use of the weights of a model that has been created before for classification and has a good performance for another classification problem. Transfer learning benefits from different aspects: (1) Learning is faster, and therefore, less time is spent on training. (2) High accuracy rates can be obtained with less data. (3) Better performances are obtained by adding the desired classifier to the end of the transfer learning model.

There are several transfer learning models in the literature. In this study, Inception-v3 model was preferred for the classification of images with Covid-19 of died and healed patients. The Inception architecture was first introduced by Szegedy et al. (2015a), and is also referred to as GoogLeNet in the literature. In order to improve the performance of the Inception architecture, different versions were developed as follows: Inception-v1 (Szegedy et al., 2015a), Inception-v2, Inception-v3 (Szegedy et al., 2015b), Inception-v4 and Inception-ResNet (Szegedy et al., 2016); each version is enhanced with changes made to the previous version.

The advantage of Inception over other models is that it enables the use of filters of different sizes. Thus, objects of different sizes in the images can be easily detected with filters of different sizes. For example, figure 4 shows the schematic of the naive Inception module. Accordingly, the convolution process is performed using filters of different sizes, 1×1, 3×3 and 5×5 at the input, and maximum pooling is applied to reduce the size. The filter outputs are then combined and sent as input to the next Inception module.

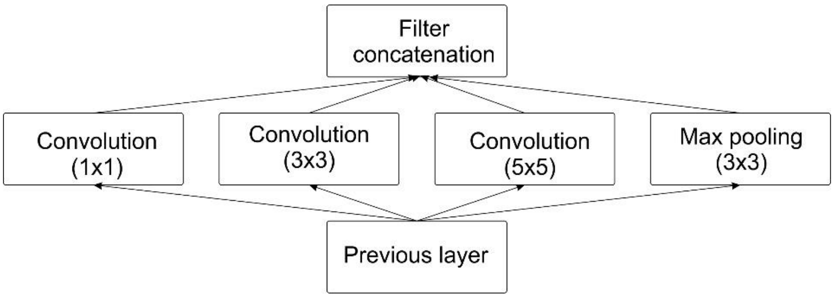


Figure 4. Schematic representation of naive Inception module (Szegedy et al., 2015a)

Figure 5 shows the model classifying CT images of died and healed Covid-19 cases. The Inception-v3 architecture used in this study differs from the literature in terms of two fully connected layers added to the end. For classification purposes, 2048 and 16 nodes were used in these layers, respectively. In the last layer, softmax, the number of nodes represents the number of classes in the problem we are focusing on and is 2.

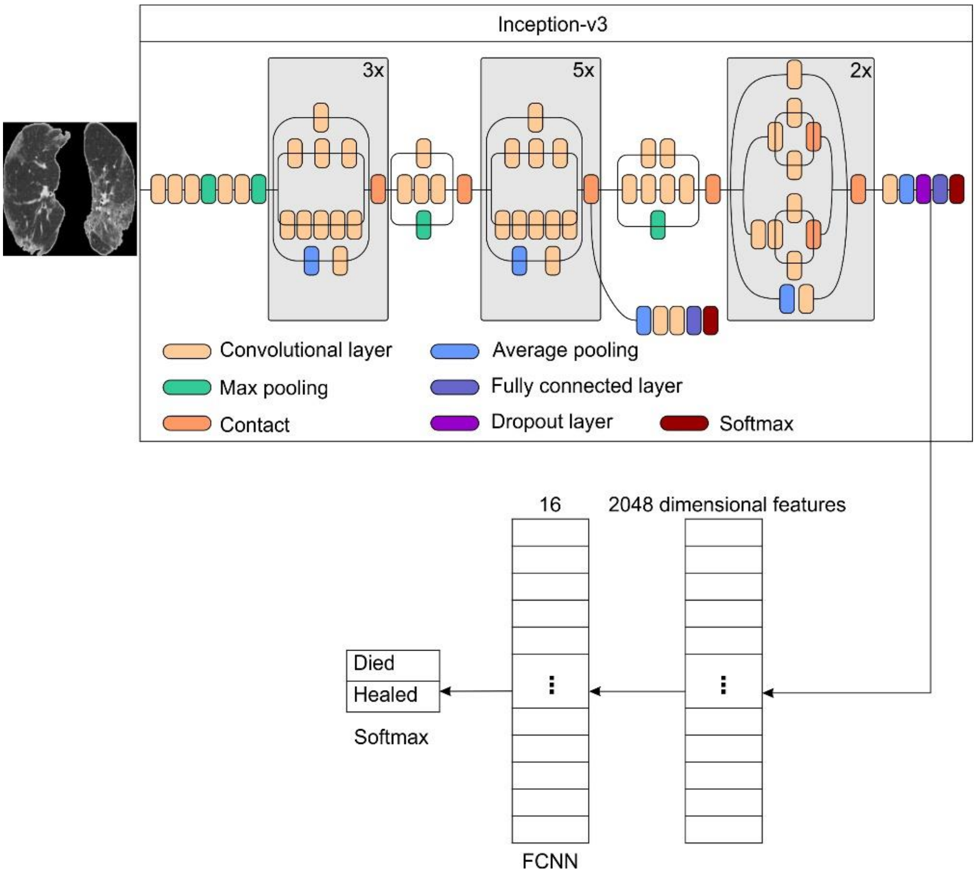
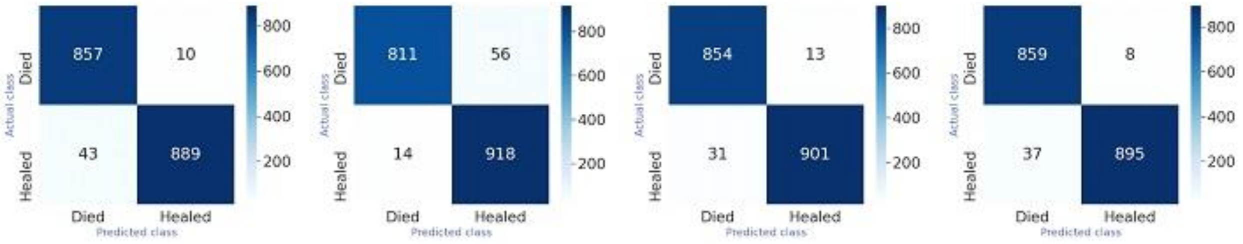


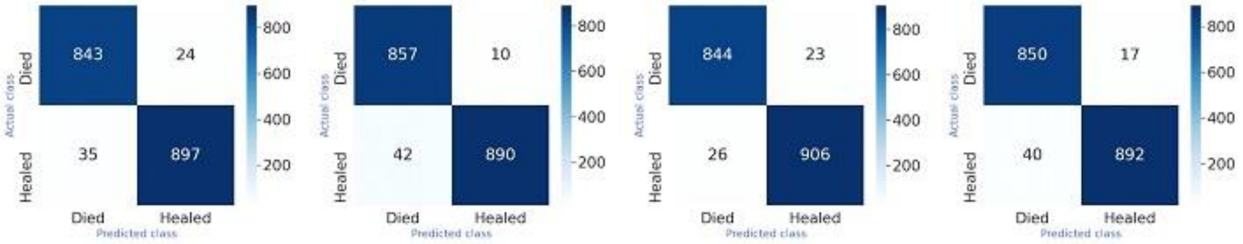
Figure 5. Schematic of the Inception-v3 model taken from Zhang et al. (2019) and modified for our study. The Inception-v3 model was trained on the ImageNet database, and the weights obtained were used to evaluate the poor prognosis of Covid-19.

Results and Discussion

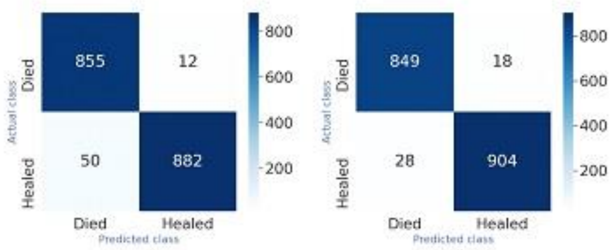
In this study, Inception-v3, one of the transfer learning methods, is used to evaluate poor prognosis in rRT-PCR positive Covid-19 patients. Inception-v3, which uses CNNs, extracts features for images of died and healed classes. For classification purposes, a two-layer FCNN has been added to the output of the Incetion-v3 model. In the first of these layers, 16 neurons are used. The second (last) layer is the softmax layer; the number of neurons in this layer equals the number of classes, that is, 2. Adadelta (Zeiler, 2012) is used as an optimizer with a learning rate of 1.0. ReLU is used as the activation function in fully connected layers. The method has been tested 10 times with 50 epochs and 16 batch sizes. Confusion matrices and results for each experiment are shown in Figure 6 and Table 2, respectively. According to Table 2, images with Covid-19 belonging to died and healed classes are classified with an average performance of 97,01% and a maximum of 97,55%. In addition, since all test results are over 96%, it can be said that the method is quite successful in evaluating poor prognosis in rRT-PCR positive Covid-19 patients.



a) Experiment 1 b) Experiment 2 c) Experiment 3 d) Experiment 4



e) Experiment 5 f) Experiment 6 g) Experiment 7 h) Experiment 8



i) Experiment 9 j) Experiment 10

Figure 6. Confusion matrix related to 10 experiments

Table 2. Accuracy and AUC values of 10 experiments on classifying dead or healed class CT images.

Experiment number	Accuracy (%)	AUC
1	97.05	0.971
2	96.11	0.960
3	97.55	0.976
4	97.50	0.976
5	96.72	0.967
6	97.11	0.972
7	97.28	0.973
8	96.83	0.969
9	96.55	0.966
10	97.44	0.975

Here, accuracy and AUC were used as performance metrics. The notations in the accuracy equation are:

- The images belonging to the dead class and correctly classified as died, called True Positives (TP); the number of TP is shown in the upper left of the confusion matrix.

- The images belonging to the healed class and correctly classified as healed are called True Negatives (TN); the number of TN is shown in the lower right of the confusion matrix.
- The images belonging to the dead class and incorrectly classified as healed are called False Negatives (FN); the number of FN is shown in the upper right of the confusion matrix.
- The images belonging to the healed class and incorrectly classified as dead, called False Positives (FP). The number of FP is shown in the lower left of the confusion matrix.

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

ROC curve is a graph showing the performance of the classification model and is frequently used in machine learning applications. It uses two values called true positive rate (TPR) and false-positive rate (FPR) as parameters:

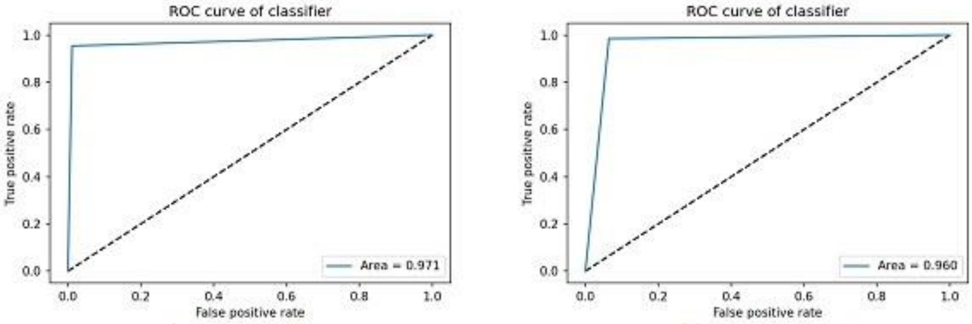
$$TPR = \frac{TP}{TP + FN}$$

$$FPR = \frac{FP}{FP + TN}$$

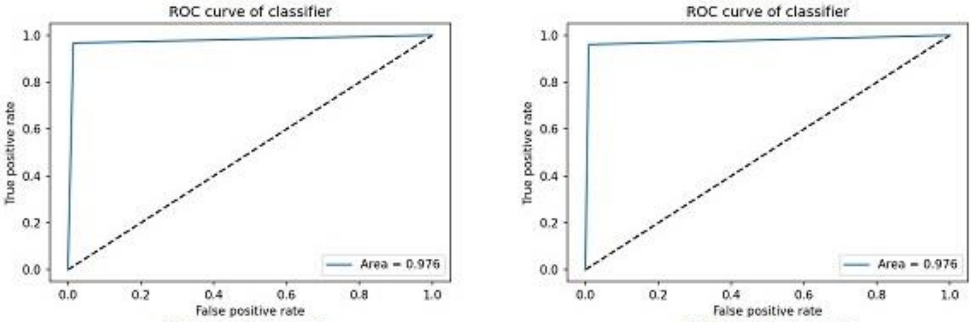
In the ROC graph, there is FPR on the x-axis and TPR on the y-axis. The ROC curve is a curve that starts at (0,0) and ends at (1.1). The area under the curve, in short, AUC, gives information about the classifier's performance and ranges between 0 and 1. The better the model's performance, the larger the area under the curve, that is, the higher the AUC value (Fawcett, 2006). The ROC curves obtained from the experiments are shown in Figure 7.

Looking at the ROC curves in Figure 7, it can be seen that the experiments for the best classification performance were Experiments 3 and 4 with an AUC of 0,976. However, considering the accuracy values, it is seen that the best classification performance is in Experiment 3.

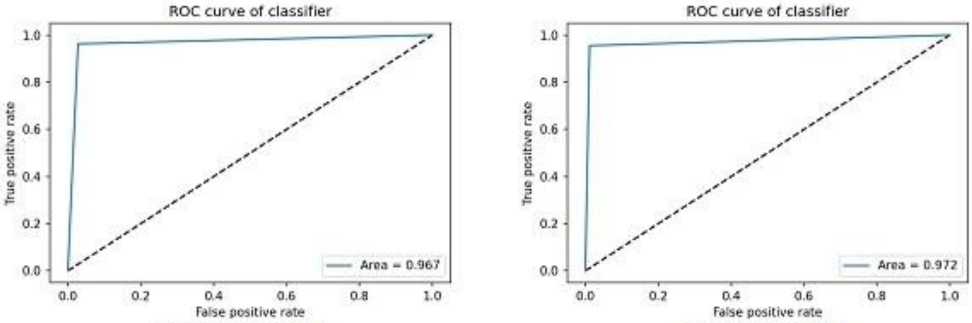
The proposed model was trained and tested on Google Colab using Keras (Chollet, 2015) and Tensorflow (Martin et al., 2015) libraries.



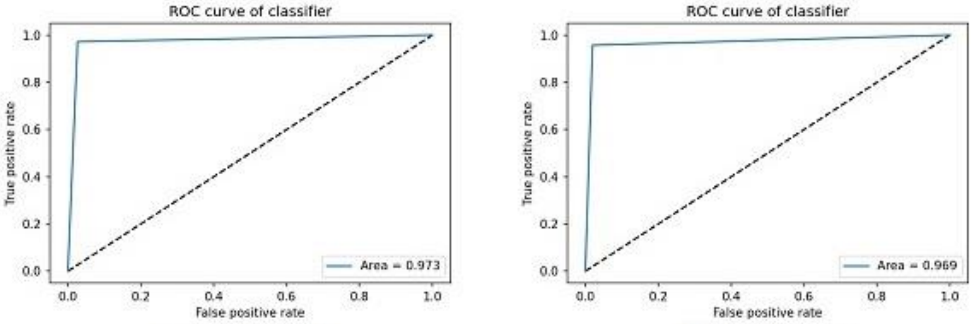
a) Experiment 1 b) Experiment 2



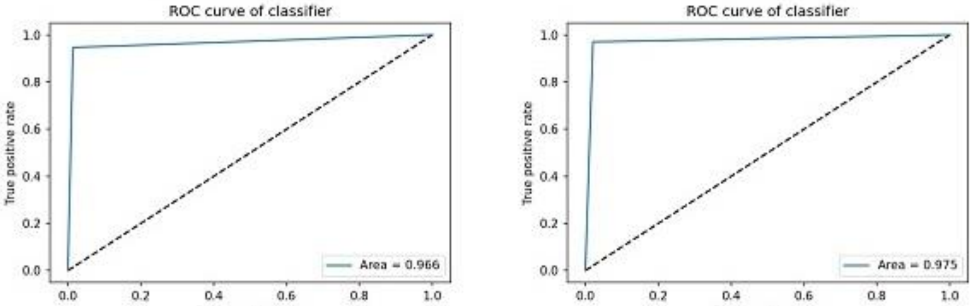
c) Experiment 1 d) Experiment 4



e) Experiment 5 f) Experiment 6



g) Experiment 7 h) Experiment 8



i) Experiment 9 j) Experiment 10

Figure 7. ROC curves for experiments showing classification performance of CT images belonging to died or healed class

Studies have been continuing rapidly since the emergence of Covid-19 and its threat to world health. Almost all of the existing studies in the literature are on detecting the presence of Covid-19. Studies primarily determine whether the data (CT image, X-ray image or laboratory findings) is Covid-19 or normal, making a binary classification. In this study, there is Covid-19 in all of the data, some of the cases have died, and some have recovered. Therefore, data in this study are classified as dead and recovered. This will help accurately determine the poor prognosis of a new case admitted to the hospital with suspected Covid-19. A comparison of recent studies on the detection of Covid-19 with the proposed study is shown in Table 3.

Table 3. Comparison with the recent studies in the literature

Method	Dataset	Classes	Accuracy (%)
CycleGAN+Inception (Bargshady et al., 2022)	9544 X-ray images	Normal Covid-19	94.20
DenseNet201 (Manokaran et al., 2021)	9573 X-ray images	Normal Pneumonia Covid-19	92.19
SVM (Kart and Başçiftçi, 2021)	1500 CT images	Normal Covid-19	96.70
CNN+SVM (Erdem and Aydın, 2021)	2482 CT images	Normal Covid-19	85.56
DenseNet169+FCNN (Ala and Polat, 2021)	2482 CT images	Normal Covid19	98.60
CNN+LSTM (Alakus and~~ve~~ Turkoglu,2020)	18 Laboratory findings from 600 patients	Normal Covid19	92.30
Hybrid deep learning model (Göreke et al., 2021)	18 Laboratory findings from 600 patient	Normal Covid-19	94.95
Inception-v3 (Proposed study)	5997 CT images (all with Covid-19)	Died Healed	97.55

Conclusion

Covid-19, which emerged in 2019, affected the whole world and caused the pandemic. This disease adversely affects daily life, public health, and the global economy. For this reason, it is essential to investigate the poor prognosis in rRT-PCR positive Covid-19 cases in order to increase the chance of patients' survival. Definitive diagnosis of Covid-19 is made by RT-PCR test; in addition, Covid-19 findings on CT images play an essential role in detecting the disease. However, diagnosis of the disease in this way is both time-consuming and expensive, so researchers have focused their work on the computer-assisted diagnosis. Almost all of the studies on Covid-19 in the literature are on the detection of Covid-19 from CT images, X-ray images, or, at least, from laboratory findings. In other words, recent studies mostly make a binary classification as Covid-19 or normal. In our study, all data (CT images) belong to Covid-19 cases. However, some of these cases have died due to Covid-19, and the rest have healed. Our study tried to determine whether the sample data belonged to the patient who died from Covid-19 or the patient who healed. So we classified the data in binary as dead or healed, not Covid-19 or normal. Our study is the first in the literature and is different from other studies.

This study focused on classifying CT images belonging to patients who died or healed from Covid-19. For this purpose, Inception-v3, one of the deep transfer learning models that have been preferred in recent years due to its superior performance, was used. In this retrospective study, collaboration was made with radiology and microbiology specialists. These experts evaluated the laboratory findings and CT images of the patients who applied to the pandemic clinic, and a dataset consisting of 5997 CT images was created. The proposed Inception-v3 model was trained and tested on this dataset. Test results showed that classes are separated with an average accuracy of 97,01% and a maximum of 97,55%. So, the proposed method can help radiologists evaluate the poor prognosis of the disease in cases with Covid-19. Consequently, patients whose conditions will worsen can be determined in advance, and the course of the disease can be changed with the measures to be taken. Thus, applied transfer learning is promising in medical sciences and can assist radiologists in making quick and accurate decisions.

The future plan for the development of the study is as follows: (1) Different deep learning models will be studied to achieve higher success. (2) The dataset will be expanded by adding images of new Covid-19 cases. (3) Studies will be conducted to evaluate the poor prognosis and detect Covid-19 from chest CT or X-ray images.

Conflict of Interest Statement

The authors declare that there is no conflict of interest regarding the publication of this paper.

Authorship Contribution Statement

The authors declare that they have contributed equally to the article.

Kaynakça

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