SAKARYA ÜNİVERSİTESİ
FEN BİLİMLERİ ENSTİTÜSÜ DERGİSİ

Sakarya University Journal of Science
SAUJS

e-ISSN 2147-835X | Period Bimonthly | Founded: 1997 | Publisher Sakarya University | http://www.saujs.sakarya.edu.tr/en/

Title: Detection of Covid-19 from Chest CT Images Using Xception Architecture: A Deep Transfer Learning Based Approach

Authors: Özlem POLAT

Recieved: 2021-04-01 14:11:06

Accepted: 2021-05-05 13:21:05

Article Type: Research Article

Volume: 25
Issue: 3
Month: June
Year: 2021
Pages: 800-810

How to cite
Özlem POLAT; (2021), Detection of Covid-19 from Chest CT Images Using Xception Architecture: A Deep Transfer Learning Based Approach. Sakarya University Journal of Science, 25(3), 800-810, DOI: https://doi.org/10.16984/saufenbilder.903886
Access link
http://www.saujs.sakarya.edu.tr/en/pub/issue/62736/903886

New submission to SAUJS
http://dergipark.org.tr/en/journal/1115/submission/step/manuscript/new

Sakarya University Journal of Science 25(3), 800-810, 2021

SAKARYA ÜNİVERSİTESİ

Detection of Covid-19 from Chest CT Images Using Xception Architecture: A Deep Transfer Learning Based Approach

Özlem POLAT*[1]

Abstract

Covid-19 infection, which first appeared in Wuhan, China in December 2019, affected the whole world in a short time like three months. The disease caused by the virus called SARS-CoV-2 affects many organs, especially the lungs, brain, liver and kidney, and causes a large number of deaths. Early detection of Covid-19 using computer-aided methods will ensure that the patient reaches the right treatment without wasting time, and the spread of the disease will be controlled. This study proposes a solution for detecting Covid-19 using chest computed tomography (CT) scan images. Firstly, features are extracted by Xception network, convolutional neural network (CNN) based transfer learning method, then classification process is performed with a fully connected neural network (FCNN) added at the end of this architecture. The classification model was tested ten times on the accessible SARS-CoV-2-CT-scan dataset containing 2482 CT images labelled as covid and non-covid. The precision, recall, f1-score and accuracy metrics were used as performance measures; and ROC curve related to the model was drawn. While obtaining an average of 98.89% accuracy, in the best case, 99.59% classification performance was achieved. Xception outperforms other methods in the literature. The results promise that the proposed method can be evaluated as a clinical option helping experts in the detection of Covid-19 from CT images.

Keywords: Covid-19, Classification, Deep learning, Xception

1. INTRODUCTION

The infection epidemic caused by the SARS-CoV-2 virus was named Coronavirus Disease 2019, shortly Covid-19, by the World Health Organization (WHO). Covid-19 spread rapidly to many countries and was officially announced as a pandemic by WHO on March 11, 2020, with the death of more than 4000 people [1]. Covid-19 is a respiratory disease, and adversely affects many organs, especially the lungs. The disease is highly contagious and has many different symptoms, mainly fever, dry cough and tiredness. Since the first Covid-19 case was detected in China, the disease spread first to other provinces of China and then to all over the world [2]. Due to the sudden emergence of Covid-19 and its spread all over the world, different research centers immediately started working for the detection, prevention and treatment of the disease [3]. Studies are not only conducted in the field of medicine and biotechnology; In addition, researchers from different fields are working on

*Corresponding author: ozlem.polat@cumhuriyet.edu.tr
[1] Sivas Cumhuriyet University, Faculty of Technology, Department of Mechatronics Engineering, Sivas, Turkey.
ORCID: https://orcid.org/0000-0002-9395-4465

the diagnosis and prevention of the disease with the help of computer-aided systems.

In some cases, if there is no vaccine or drug for Covid-19, it is compulsory to detect the disease in a short time and isolate the infected person from healthy people for controlling the spread of the disease. With the onset of the Covid-19 pandemic, the reverse transcription polymerase chain reaction (RT-PCR) test developed by Corman et al. [4] has begun to be used for the definitive diagnosis of the disease. It is presented that the overall positive RT-PCR rate initially was in the range of approximately 30-60% for swab samples taken from the throat [5]. The sensitivity of the RT-PCR test in the first days of the Covid-19 is low. Therefore, the problem arises that people with Covid-19 cannot be diagnosed and cannot receive the appropriate treatment for them. In addition, patients who have not been diagnosed with Covid-19 infect more people because of the contagious nature of the virus. Lung CT is both easy to use and can give results in a short time for the determination the presence of Covid-19. According to the results of recent research, Covid-19 disease shows the same or very similar radiological features in almost all patients [6]. Radiological features of Covid-19 were seen in people with negative RT-PCR tests but with symptoms of the disease. Therefore, it is beneficial to use lung CT to determine whether the patient is infected with Covid-19 [7].

As soon as medical images were scanned and uploaded to a computer, researchers started processing it automatically. In recent years, computer technologies and machine learning techniques have begun to be preferred in medical sciences in order to diagnose some diseases or lesions in the body [8]. Panwar et al. [9] proposed a CNN-based model called nCOVnet for detecting Covid-19 from lung X-ray images. nCOVnet consists of 24 layers, and 18 of which are part of VGG16 model. They used a dataset of 337 chest X-ray images in total, including Covid-19 positive and negative; and revealed an accuracy of 88.10%. Apostolopoulos and Mpesiana [10] applied different transfer learning networks for solving Covid-19 detection problem; and used publicly available two datasets including 1427 and 1442 X-ray images. VGG19 provided the best classification results with 98.75%.

The study by Li et al. [11] offered COVNet using ResNet50 deep learning architecture as the backbone. They trained and tested the model on 4352 CT images of 3322 cases. As a result of the experiments, they obtained the values of 90%, 96% and 0.96 for sensitivity specificity and AUC, respectively. In the study explored by Jain et al. [12], ResNet101 deep learning model was attempted to distinguish Covid-19 and viral pneumonia from x-ray images. The dataset, originally containing 1215 X-ray images, was increased by data augmentation to 1832; and, as a result of the tests, 97.77% classification accuracy has been achieved. Harmon et al. [13] applied artificial intelligence based Grad-CAM method on CT images. They achieved up to 90.8% accuracy.

Rahimzadeh and Attar [14] solved the same problem using transfer learning methods on X-ray images. They extracted the features with the use of Xception and ResNet50V2 networks in parallel; and they concatenated the features and classified with FCNN with Softmax activation function. The dataset including normal, pneumoni and Covid-19 classes were augmented and the model tested on 11,302 images. 91.4% overall average accuracy was obtained for all classes. Ozturk et al. [15] used a network of 17 convolution layers in their study; and they applied different filters to each layer. They also preferred the DarkNet model as a classifier; and they achieved 98.08% and 87.02% success in the double and triple classification problem, respectively, in distinguishing Covid-19. In a study which set out to detection of Covid-19,

Wang et al. [16] proposed a deep learning model (Covid-Net), which achieved 92.4% classification performance. Sethy et al. [17] extracted the features related to X-ray images using deep CNN and classified them using Support Vector Machine (SVM) for detection of coronavirus infected patients. The methodology deals with three categories of images, i.e., Covid-19, pneumonia and normal. They achieved 95.33% success with ResNet50+SVM.

Hemdan et al. [18] reported 90% success rate using DenseNet201 and VGG16 in a study investigating Covid-19. Narin et al. [19] performed a series of experiments using five different transfer learning applications on X-ray images. They have implemented three binary classifiers. They had the best performance of 96.1% for covid-19 vs normal with ResNet50 and ResNet101. Ying et al. [20] developed a new deep learning model called DRE-Net built on the ResNet architecture; and detected Covid-19 from CT images with 86% accuracy.

Wang et al. [21] modified the Inception transfer learning network to build the Covid-19 detection algorithm from chest CT images; and they obtained 79.3% classification performance. Wang et al. [22] created a 3D deep neural network called DeCovNet, using 3D CT volumes. First, segmentation was applied using U-Net, and the segmented images were given as input to DeCovNet network. They managed to detect Covid-19 in CT images with 90.8% accuracy. Xu et al. [23] used two CNN 3D classification methods on CT images, and obtained 86.7% accuracy rate for three classes: Covid-19, viral pneumonia and normal. Yoo et al. [24] created deep learning based three binary decision trees and achieved 98%, 80% and 95% classification performance with ResNet18.

Another study was conducted by Albahli [25] using deep learning models. Albahli tried to classify other chest diseases against Covid-19 with the model he used; and achieved a classification accuracy of 87% with ResNet152. Civit-Masot et al. [26] suggested VGG16 model as the solution of Covid-19 detection problem. They trained and tested the model on 396 X-ray images (132 Covid-19, 132 Healthy and 132 Pneumonia); and obtained 86% accuracy rate. Singh et al. [27] evaluated a CNN-based model on CT images to classify patients infected with Covid-19. Ahuja et al. [28] trained transfer learning models on CT images to determine the presence of Covid-19; and with ResNet18 model they achieved 99.4% classification performance.

As seen above, many studies have been conducted using different datasets to detect Covid-19. Apart from these, there is also a SARS-CoV-2-CT-Scan dataset consisting of 2482 CT images labeled as covid and non-covid created by Soares et al. [29]. This dataset was also used in [30-32] for Covid-19 detection. Soares et al. used various machine learning methods, but achieved the best success with eXplainable Deep Learning approach (xDNN). Silva et al. [30] have achieved 98.99% and 87.60% accuracy with the modified EfficientNetB0 using SARS-CoV-2-CT-Scan dataset and another dataset containing 812 CT scan images, respectively. Yazdani et al. [31] proposed to use attentional residual convolutional network, which can better focus on infected lung areas; and they achieved 92% classification performance. Konar et al. [32] used a semi-controlled shallow neural network containing a network they called PQIS-Net to segment the lung CT images and used fully connected layers to determine the class labels of images.

This study aims to detect Covid-19 from CT images, that is, CT images are classified as covid and non-covid. For this purpose, Xception network, one of the deep transfer learning architectures, has been trained and tested on the SARS-CoV-2-CT-Scan dataset. The main contributions of this study are as follows: (1) Covid-19 caused by the SARS-CoV-2 virus is a disease with high contagiousness and causing death. Fast and accurate detection of Covid-19 will enable early treatment and thus reduce the hospitalization rate and mortality rate of patients. (2) The model proposed in this study classifies covid and non-covid cases from chest CT images. (3) With the proposed transfer learning technique, weights related to the network that were previously trained with big data are used. Thus, classification is performed with less computational load and high performance without the need for a very large data set.

2. MATERIALS and METHODS

2.1. SARS-CoV-2-CT-Scan Dataset

In this study, a publicly available dataset consisting of 2482 CT images was used. Images were obtained from a total of 120 patients, 60 female and 60 male, who were infected with the

SARS-CoV-2 virus (covid) and were not infected by this virus but have other pulmonary diseases (non-covid). The distribution of the sexes of the patients is as follows: 32 of 60 patients belonging to the covid class are male and 28 are female. In the non-covid class, the number of male and female patients are equal, that is, 30. The dataset was created from CT images of patients admitted to hospitals in Sao Paulo, Brazil. In the dataset, there are 1252 and 1230 CT images of covid and non-covid classes, respectively. Sample CT images of these classes are shown in Figure 1.

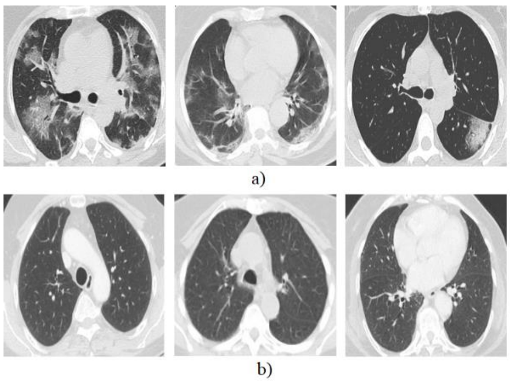

Figure 1 Chest CT images a) covid b) non-covid

In order to train and test Xception architecture, CT images are divided into two groups as 70% and 30%. Thus, 1737 of the images were used for training and 745 for test.

2.2. Convolutional Neural Networks

Convolution was first described by LeCun et al. [33] in 1989. Convolution is simply a mathematical operation in which two matrices are multiplied on an element-by-element basis and then summed [34]. Networks using convolution process are called convolutional neural networks (CNN). CNNs usually consist of five layers:

1) Convolution layer: In this layer, the filter matrix, which will automatically extract the features from the image with the image matrix is subjected to the convolution process. First, the filter is placed in the upper left corner of the image. Here, pixels of the image matrix and filter matrix with the same index are multiplied by each other and all results are summed. This sum is then recorded in the output matrix called the feature map. Then the filter is shifted to the right and the multiplication operations are repeated. At the end of the row, the filter is shifted downwards and the same operations are repeated from left to right. After all rows are scanned from left to right with these operations, an output matrix is created.

2) Non-linearity layer: This layer is used after the convolution layer; and transform the linear output of the previous layer into a nonlinear structure using an activation function. In this way, the learning of the network is accelerated. Rectified Linear Unite (ReLU) [35], which has the ability to pull negative values to zero, is generally preferred as the activation function.

3) Pooling layer: This layer is typically used after non-linearity layer. The main function of this layer is to reduce the dimension of the feature map. With the dimension reduction process, both the computational load is reduced and the system is prevented from overfitting. As in the convolution layer, the filter sizes can be different from each other in this layer. Thanks to these filters, average pooling, where the values in the input matrix are averaged, or maximum pooling, where the maximum is taken, is performed.

4) Flattening layer: This layer transforms the matrix into a vector by successively adding the rows of the output matrix obtained from the previous layer, so that one-dimensional data can be input to fully connected layers.

5) Fully connected layer(s): All neurons in this layer are connected to every neuron of the next layer. By using the softmax activation function in the last layer, the images are labeled and the classes they belong to are determined.

2.3. Xception Architecture

With the spread of CNNs in computer vision, different structured models using CNN have been created. Firstly, the LeNet-style models [36] were introduced in 1995, and then various models were created to be used in classification and recognition problems. One of these models is Inception. The Inception architecture, also known as Inception-v1 [37], was created in 2014 by Szagedy et al. Later it was updated as Inception-v2, Inception-v3 [38] and Inception-ResNet [39]. The Xception network [40] used in this study can be called an interpretation of the Inception modules. The name Xception also comes from "extreme inception". Therefore, it will help to understand the Xception architecture to talk briefly about Inception first.

The object to be detected in object recognition or image classification may be large in some images and small in some images. In other words, the size of the object can be of different sizes in different images. Different object sizes can make it difficult to determine the filter size for the convolution process. A large filter size should be preferred for the object that looks large in the images, and a small filter size should be preferred for small objects. Inception architecture offers a solution to the problems caused by objects of different sizes by proposing to use more than one filter of different sizes at the entrance. It also suggests sending the output of this module to another inception module again. Figure 2 shows a simplified Inception module.

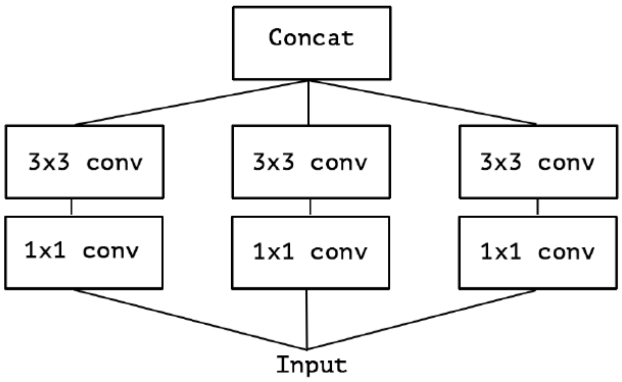

Figure 2 Simplified inception module [40]

In Xception architecture, differently from Inception architecture, a convolution operation almost same with depthwise separable convolution [41] is used. This type of convolution contains a depthwise convolution and a pointwise convolution that follows it. In depthwise convolution each filter independently processes only one channel of the input image; and in pointwise convolution, 1x1 dimensional filter iterates every single point of the input.

The module in Xception architecture uses depthwise separable convolution in different order; in other words, as seen in Figure 3, 1x1 convolution is used first and then channel-wise spatial convolution.

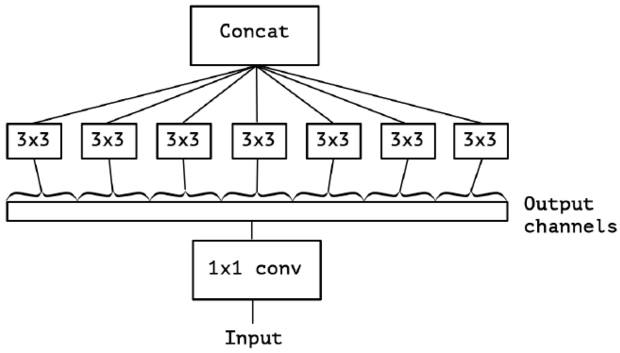

Figure 3 Extreme version of Inception module [40]

Xception architecture consists of three structures: Entry flow, middle flow and exit flow. These three structures consist of 14 modules (4, 8 and 2 modules, respectively) containing 36 convolution layers in total. There are residual connections in modules except the first module of entry flow and the last module of exit flow. The Xception architecture starts with entry flow, which contains 4 modules and each module has two convolution layers. In the first module, convolution is performed with 32 and 64 filters with 3x3 filter size. In the other three modules in this flow, separable convolution is realized with 128, 256 and 728 filters in 3x3 filter size. The entry flow accepts 299x299x3 size images as input and creates a 19x19x728 size feature map at the output. In middle flow, three separable convolution processes with 728 filters in 3x3 size are repeated 8 times. Middle flow creates a 19x19x728 feature map at the output. The feature map, which is the output of middle flow, is given as input to exit flow. Exit flow has two modules. In the first module, separable convolution is performed with 728 and 1024 filters in 3x3 sizes, while in the last module it is performed with 1536 and 2048 filters. Afterwards, the architecture is terminated with the addition of fully connected layers. The flows and modules related to the Xception architecture are shown in the Figure 4.

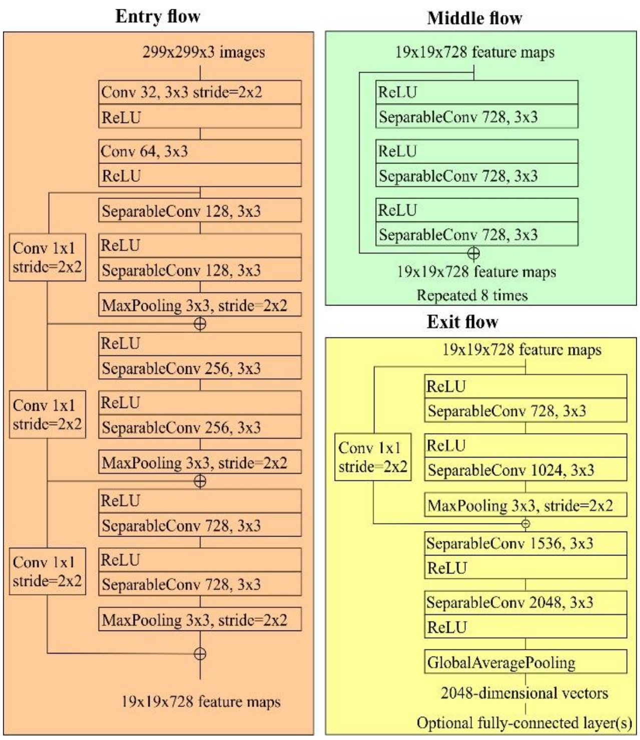

Figure 4 Xception architecture

3. EXPERIMENTAL RESULTS

In this study, chest CT images of cases with and without Covid-19 disease were trained and tested using Xception, ResNet50V2 and VGG16 deep learning architectures. While these models were used to extract features from images, a 2-layer FCNN was used for classification purpose. The first layer of FCNN was formed with 16 neurons; in the last layer where softmax was used, as many neurons are used as the number of classes. Experimental results were compared with the results determined by the experts in terms of precision (1), recall (2), f1-score (3) and accuracy (4) metrics. The mathematical expressions for these metrics are as follows:

$$Precision = \frac{TruePositive}{TruePositive+FalsePositive} \tag{1}$$

$$Recall = \frac{TruePositive}{TruePositive+FalseNegative} \tag{2}$$

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

$$Accuracy = \frac{TP+TN}{TP+FP+TN+FN} \times 100 \tag{4}$$

Proposed model was trained and tested on Google Colab using the Keras [42] and Tensorflow [43] libraries. The dataset was split by 70% and 30% as training and test, and has been trained and tested with Xception, ResNet50V2 and VGG16 architectures.

The parameters for experiment, the number of epochs and batch size, were set to 50 and 16, respectively. Adadelta [44], Adam and SGD were chosen as optimizers for Xception, ResNet50V2 and VGG16 transfer learning models, respectively, due to their better performance. Adadelta, Adam, and SGD were used with learning rates of 1.0, 0.0001, and 0.0001, respectively. Experiments related to models were run 10 times. The average accuracy values for, Xception, ResNet50V2 and VGG16 were obtained as 98.89%, 96.95% and 97.72%, respectively. Since Xception gives better results than the other two methods, this study focuses on the Xception model and its results. So the results related to Xception obtained from these 10 experiments are shown in Table 1.

Table 1 Experimental results of Xception network

Exp. No	Precision	Recall	F1-score	Acc. (%)
1	1.00	1.00	0.99	99.19
2	0.99	0.99	0.99	98.79
3	0.99	0.99	0.99	99.33
4	0.99	0.99	0.99	98.93
5	0.99	0.99	0.99	99.06
6	0.98	0.98	0.98	97.72
7	0.98	0.98	0.98	98.26
8	0.99	0.99	0.99	99.46
9	0.98	0.98	0.98	98.66
10	1.00	1.00	1.00	99.59
Ave.	0.99	0.99	0.99	98.89

According to Table 1, covid and non-covid class images are classified with an average accuracy of 98.89%. The best classification performance is obtained from the 10th experiment with an accuracy of 99.56%. The Receiver Operator Characteristic (ROC) curve is an evaluation metric often used in classification problems. It is created by plotting True Positive Rate against False Positive Rate at various threshold values. Area Under Curve (AUC) is a measure of the classifier's ability to distinguish between classes and takes values between 0 and 1. The closer the

AUC value to 1, the better the classifier's performance. The ROC curve for the model with the AUC values can be seen from Figure 5. Confusion matrix and accuracy-loss graphs of the model for experiment 10 are shown in Figures 6 and 7, respectively. As seen from the confusion matrix, 375 of 376 images with covid and 367 of 369 images without covid are classified correctly; that is, the recall values for the covid and non-covid classes are calculated as 0.997 and 0.995, respectively. For this reason, the average recall values of the classes are stated as 1.00 in the Table 1 due to the rounding of the numbers.

In addition, the obtained classification results prove that even with a small number of FCNN layers and a small number of neurons such as 16 used in this layer, covid and non-covid classes are distinguished from each other with high performance.

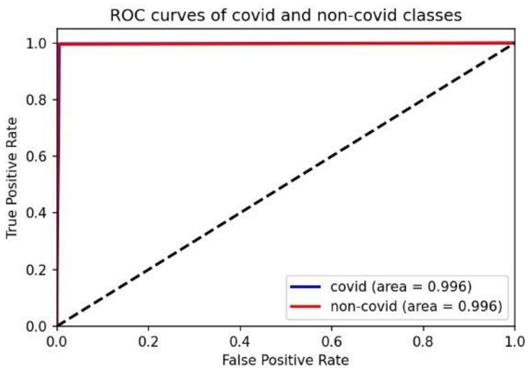

Figure 5 ROC curve for the Xception model

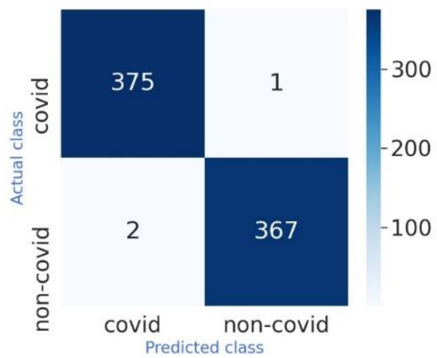

Figure 6 The confusion matrix of the 10th best performing experiment

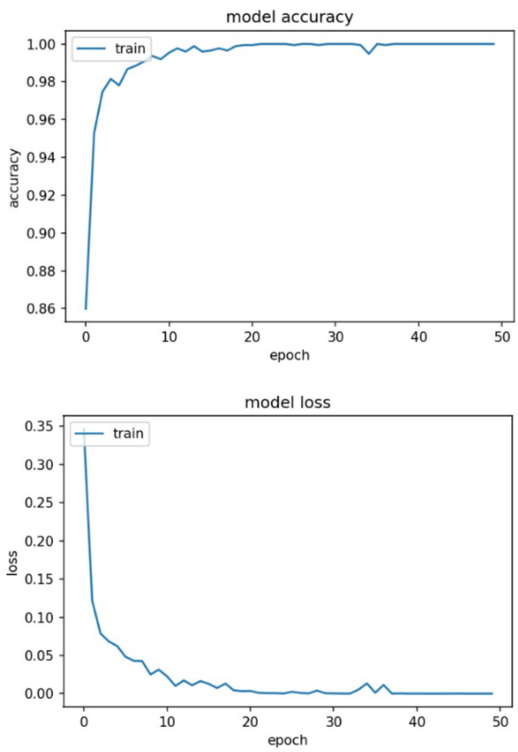

Figure 7 Accuracy and loss graphics of the classifier

Since 2019, many studies have been carried out on different datasets in order to detect Covid-19 from CT images with computer-aided technologies and help experts in the diagnosis of the disease. In these studies, both classical machine learning methods and frequently deep learning techniques were used. Table 2 shows the comparative results related to proposed study and other studies in the literature using the same dataset. As can be seen from Table 2, other studies have also used CNN-based deep learning; and the Xception model outperforms other models using the same dataset.

Table 2 Performance comparison

Authors	**Methods**	**Acc. %)**
Soares et al. [29]	xDNN	97.38
Silva et al. [30]	Modified EfficientB0	98.99
Yazdani et al. [31]	Attentional Residual Conv. Network	92.00
Konar et al. [32]	PQIS-Net	93.10
Proposed	Xception	99.59

4. CONCLUSION

With the onset of the Covid-19 epidemic and its globalization, studies in the field of computer technologies have started and continue rapidly, as in other fields. The definitive diagnosis of Covid-19 is possible with the RT-PCR test; however, this test gives results between 4 and 6 hours and this period is not too short. For this reason, computer-aided technologies have begun to be produced that will help experts in the detection of the disease and give results within seconds. There are various transfer learning models in the literature. In this study, Xception, ResNet50V2 and VGG16 models were examined. The models were trained and tested, on a public dataset of 2482 images. As a result, images belonging to the covid and non-covid classes were classified with an average performance of 98.89%, 96.95% and 97.72% for the Xception, ResNet50V2 and VGG16 models, respectively. Because it is more successful than other models, Xception is recommended as a transfer learning method for the detection of Covid-19. In addition, the best 99.59% classification performance was achieved with Xception. The achievements are at a level that can compared with the literature, and the proposed model gives better results than studies using the same dataset. This is promising in that the proposed model will assist experts in medical decision making.

In future study, it is aimed to detect Covid-19 by applying hybrid models consisting CNNs on more data using data augmentation techniques.

Funding

The author has no received any financial support for the research, authorship or publication of this study.

The Declaration of Conflict of Interest/ Common Interest

No conflict of interest or common interest has been declared by the authors.

The Declaration of Ethics Committee Approval

This study does not require ethics committee permission or any special permission.

The Declaration of Research and Publication Ethics

The authors of the paper declare that they comply with the scientific, ethical and quotation rules of SAUJS in all processes of the paper and that they do not make any falsification on the data collected. In addition, they declare that Sakarya University Journal of Science and its editorial board have no responsibility for any ethical violations that may be encountered, and that this study has not been evaluated in any academic publication environment other than Sakarya University Journal of Science.

REFERENCES

[1] S.E. Park, “Epidemiology, virology, and clinical features of severe acute respiratory syndrome – coronavirus-2 (SARS-CoV-2; Coronavirus Disease-19)” Clin Exp Pediatr vol. 63, no. 4, pp. 119-124, 2020. doi:10.3345/cep.2020.00493

[2] C.C. Lai, C.Y. Wang, Y.H. Wang, S.C. Hsueh, W.C. Ko et al., “Global epidemiology of coronavirus disease 2019 (COVID19): disease incidence, daily cumulative index, mortality, and their association with country healthcare resources and economic status” Int J Antimicrob Agents, vol. 55, no. 4, pp. 105946, 2020. doi:10.1016/j.ijantimicag.2020.105946

[3] WHO. Coronavirus disease (covid-2019) r&d. https://www.who.int/blueprint/priority-diseases/key-action/novel-coronavirus/en/ Last access date 02.04.2021.

[4] V.M. Corman, O. Landt, M. Kaiser, R. Molenkamp, A. Meijer et al., “Detection of 2019 novel coronavirus (2019-nCoV) by

real-time RT-PCR", Euro Surveill, vol. 25, no. 3, pp. 2000045, 2020.

[5] Y. Yang, M. Yang, C. Shen, F. Wang, J. Yuan et al. "Evaluating the accuracy of different respiratory specimens in the laboratory diagnosis and monitoring the viral shedding of 2019-nCov infections", medRxiv, 2020. doi:10.1101/2020.02.11.200214

[6] M. Chung, A. Bernheim, X. Mei, N. Zhang, M. Huang et al., "CT imaging features of 2019 novel coronavirus (2019-nCoV)", Radiology, vol. 295, no. 1, pp. 202-207, 2020. doi:10.1148/radiol.2020200230

[7] T. Ai, Z. Yang, H. Hou, C. Zhan, C. Chen et al., "Correlation of chest CT and RT-PCR testing for coronavirus disease 2019 (COVID-19) in China: A report of 1014 cases", Radiology, vol. 296, no. 2, pp. E32-E40, 2020. doi:10.1148/radiol.2020200642

[8] G. Litjens, T. Kooi, B.E. Bejnordi, A.A.A. Setio, F. Ciompi et al., "A survey on deep learning in medical image analysis", Medical Image Analysis, vol. 42, pp. 60-88, 2017. doi:10.1016/j.media.2017.07.005

[9] H. Panwar, P.K. Gupta, M.K. Siddiqui, R. Morales-Mendenez, V. Singh, "Application of deep learning for fast detection of COVID-19 in X-Rays using nCOVnet", Chaos, solitons and fractals, vol. 138, pp. 109944, 2020. doi:10.1016/j.chaos.2020.109944

[10] I.D. Apostolopoulos, T.A. Mpesiana, "Covid-19: automatic detection from x-ray images utilizing transfer learning with convolutional neural networks", Phys Eng Sci Med, vol. 43, pp. 635-640, 2020. doi:10.1007/s13246-020-00865-4

[11] L. Li, L. Qin, Z. Xu, Y. Yin, X. Wang et al., "Using artificial intelligence to detect COVID-19 and community-acquired pneumonia based on pulmonary CT: Evaluation of the diagnostic accuracy", Radiology, vol. 269, no. 2, pp. E65-E72, 2020. doi:10.1148/radiol.2020200905

[12] G. Jain, D. Mittal, D. Thakur, M.K. Mittal, "A deep learning approach to detect Covid-19 coronavirus with X-ray images", Biocybernetics and Biomedical Engineering, vol. 40, no. 1, pp. 1391-1405, 2020. doi:10.1016/j.bbe.2020.08.008

[13] S. A. Harmon, T.H. Sanford, S. Xu, E.B. Turkbey, H. Roth et al., "Artificial intelligence for the detetion of Covid-19 pneumonia on chest CT using multinational datasets", Nat Commun, vol. 11, pp. 4080, 2020. doi:10.1038/s41467-020-17971-2

[14] M. Rahimzadeh and A. Attar, "A modified deep convolutional neural network for detecting Covid-19 and pneumonia from chest x-ray images based on concatenation of Xception and ResNet50V2", Informatics in Medicine Unlocked, vol. 19, pp. 100360, 2020. doi:10.1016/j.imu.2020.100360

[15] T. Ozturk, M. Talo, E.A. Yildirim, U.B. Baloglu, O. Yildirim et al., "Automated detection of Covid-19 cases using deep neural networks with X-ray images", Computers in Biology and Medicine, vol. 121, pp. 103792, 2020. doi:10.1016/j.compbiomed.2020.103792

[16] L. Wang, Z.Q. Lin, A. Wong, "COVID-Net: A tailored deep convolutional neural network design for detection of Covid-19 cases from chest radiography images", arXiv, arXiv:2003.09781, 2020. https://arxiv.org/abs/2003.09871

[17] P.K. Sethy, S.K. Behera, P.K. Ratha, P. Biswas, "Detection of coronavirus disease (Covid-19) based on deep features ansd support vector machine", International Journal of Mathematical, Engineering and Management Sciences, vol. 4, no. 5, pp. 642-651, 2020. doi:10.33889/IJMEMS.2020.5.4.052

[18] E.E.D. Hemdan, M.A. Shouman, M.E. Karar, "COVIDX-Net: A framework of

deep learning classifiers to diagnose Covid-19 in X-ray images", arXiv, arXiv:2003.11055, 2020. https://arxiv.org/abs/2003.11055

[19] A. Narin, C. Kaya, Z. Pamuk, "Automatic detection of coronavirus disease (Covid-19) using x-ray images and deep convolutional neural networks", arXiv, arXiv:2003.10849, 2020. https://arxiv.org/abs/2003.10849

[20] S. Ying, S. Zheng, L. Li, X. Zhang, X. Zhang et al., "Deep learning enables accurate diagnosis of novel coronavirus (Covid 19) with CT images", medRxiv, 2020. doi:10.1101/2020.02.23.20026930

[21] S. Wang, B. Kang, J. Ma, X. Zeng, M. Xiao et al., "A deep learning algorithm using CT images to secreen for coronavirus disease (Covid-19)", medRxiv, 2020. doi:10.1101/2020.02.14.20023028

[22] X. Wang, X. Deng, Q. Fu, Q. Zhou, J. Feng et al., "A weakly-supervised framework for Covid-19 classification and lesion localization from chest CT", IEEE Trans Med Imaging, vol. 39, no. 8, pp. 2615-2625, 2020. doi:10.1109/TMI.2020.2995965

[23] X. Xu, X. Jiang, C. Ma, P. Du, X. Li et al., "Deep learning system to screen coronavirus disease 2019 pneumonia", arXiv, 2002.09334, 2020. https://arxiv.org/abs/2002.09334

[24] S.H. Yoo, H. Geng, T.L. Chiu, S.K. Yu, D.C. Cho et al., "Deep learning-based decision-tree classifier for Covid-19 diagnosis from chest X-ray imaging", Front Med, vol. 7, no. 427, pp. 1-8, 2020. doi: 10.3389/fmed.2020.00427

[25] S. Albahli, "A deep neural network to distinguish covid-19 from other chest diseases using X-ray images", Curr Med Imaging Rev, vol. 16, pp. 1-11, 2020. doi: 10.2174/1573405616666200604163954

[26] J. Civit-Masot, F. Luna-Perejon, M.D. Morales, A. Civit, "Deep learning system for Covid-19 diagnosis aid using X-ray pulmonary images", Appl Sci, vol. 10, no. 13, pp. 4060, 2020. doi:10.3390/app10134640

[27] D. Singh, V. Kumar, K. Vaishali, M. Kaur, "Classification of Covid-19 patients from chest CT images using multi-objective differential evolution-based convolutional neural networks", Eur J Clin Microbiol Infect Dis, vol.39, pp. 1379-1389, 2020. doi: 10.1007/s10096-020-03901-z

[28] S. Ahuja, B.K. Panigrahi, N. Dey, V. Rajinikanth, T.K. Gandhi, "Deep transfer learning-based automated detection of Covid-19 from lung CT scan slices", Appl Intell, pp. 1-15, 2020. doi:10.1007/s10489-020-01826-w

[29] E. Soares, P. Angelov, S. Biaso, M.H. Froes, D.K Abe, "SARS-CoV-2 CT Scan Dataset: A large dataset of real patients CT scans for SARS-CoV-2 identification", MedRxiv, 2020.

[30] P. Silva, E. Luz, G. Silva, G. Moreira, R. Silva, D. Lucio, D. Menotti, "Covid-19 Detection in CT Images with Deep Learning: A Voting-Based Scheme And Cross-Datasets Anaşysis", Informatics in Medicine Unlocked, vol. 20, pp. 100427, 2020.

[31] S. Yazdani, S. Minaee, R. Kafieh, N. Saeedizadeh, M. Sonka, "Covid CT-Net: Predicting Covid-19 from Chest CT Images using Attentional Convolutional Network", arXiv, 2020.

[32] D. Konar, B.K. Panigrahi, S. Bhattacharyya, N. Dey, "Auto-Diagnosis of COVID-19 using lung CT images with semi-supervised shallow learning network", IEEE Access, vol. 9, pp. 28716-28728, 2020. doi: 10.1109/ACCESS.2021.3058854

[33] Y. LeCun, B. Boser, J.S. Denker, D. Henderson, R.E. Howard, W. Hubbard, L.D. Jackel, “Backpropagation applied to handwritten zip code recognition”, Neural Comput, vol. 1, no. 4, pp. 541-551, 1989. doi: 10.1162/neco.1989.1.4.541

[34] I. Goodfellow, Y. Bengio, A. Courville, "Deep Learning", MIT Press, 2016.

[35] V. Nair, G.E. Hinton, "Rectified Linear Units Improve Restricted Boltzmann Machines", In Proc.: 27th International Conference on Machine Learning (ICML'10), June 21-24, Haifa, Israel pp. 807-814, 2010.

[36] Y. LeCun, L. Jackel, L. Bottou, C. Cortes, J.S. Denker, H. Drucker, I. Guyon, U. Muller, E. Sackinger, P. Simard et al., “Learning algorithms for classification: A comparison on handwritten digit recognition”, Neural Networks: The Statistical Mechanics Perspective, pp. 261-276, 1995.

[37] C. Szegedy, W. Liu, Y. Jia, P. Sermanet, S. Reed, D. Anguelov, D. Erhan, V. Vanhoucke, A. Rabinovich, “Going deeper with convolutions”, In: Proceedings of the IEEE conference on computer vision and pattern recognition. arXiv:1409.4842, 2014. https://arxiv.org/abs/1409.4842

[38] C. Szegedy, V. Vanhoucke, S. Ioffe, J. Shlens, Z. Wojna, “Rethinking the inception architecture for computer vision”, arXiv:1512.00567, 2015. https://arxiv.org/abs/1512.00567

[39] C. Szegedy, S. Ioffe, V. Vanhoucke, A. Alemi, “Inception-v4, Inception-ResNet and the impact of residual connections on learning”, arXiv:1602.07261, 2016. https://arxiv.org/abs/1602.07261

[40] F. Chollet, “Xception: Deep learning with depthwise separable convolutions”, arXiv, arXiv:1610.02357v3, 2017. https://arxiv.org/abs/1610.02357

[41] L. Sifre, “Rigid-motion scattering for image classification”, Ph.D. thesis, 2014.

[42] F. Chollet, “Keras”, 2015. https://github.com/fchollet/keras

[43] A. Martin, A. Agarwal, P. Barham, E. Brevdo, Z. Chen et al., "TensorFlow: Large-scale machine learning on heterogeneous systems" (software available from: tensorflow.org), 2015.

[44] M.D. Zeiler, “Adadelta: An adaptive learning rate method”, ArXiv abs/1212.5701, 2012. https://arxiv.org/abs/1212.5701v1