RESEARCH ARTICLE

Fatma Hilal Yagin[1]
Emek Guldogan[1]
Hasan Ucuzal[1]
Cemil Colak[1]

[1] Inonu University, Faculty of Medicine, Department of Biostatistics and Medical Informatics, Malatya, Turkey

Corresponding Author:
Fatma Hilal Yagin
Inonu University, Faculty of Medicine, Department of Biostatistics and Medical Informatics, Malatya, Turkey
mail: hilal.yagin@inonu.edu.tr
Phone: +90 422 341 0660/1321

Received: 02.06.2021
Acceptance: 12.07.2021
DOI: 10.18521/ktd.947192

Konuralp Medical Journal
e-ISSN1309–3878
konuralptipdergi@duzce.edu.tr
konuralptipdergisi@gmail.com
www.konuralptipdergi.duzce.edu.tr

A Computer-Assisted Diagnosis Tool for Classifying COVID-19 based on Chest X-Ray Images

ABSTRACT

Objective: Since COVID-19 is a worldwide pandemic, COVID-19 detection using a convolutional neural network (CNN) has been an extraordinary research technique. In the reported studies, many models that can predict COVID-19 based on deep learning methods using various medical images have been created; however, clinical decision support systems have been limited. The aim of this study is to develop a successful deep learning model based on X-ray images and a computer-assisted, fast, free and web-based diagnostic tool for accurate detection of COVID-19.

Methods: In this study a 15-layer CNN model was used to detect COVID-19 using X-ray images, which outperformed many previously published CNN models in terms of classification. The model performance is evaluated according to Accuracy, Matthews Correlation Coefficient (MCC), F1 Score, Specificity, Sensitivity (Recall), Youden's Index, Precision (Positive Predictive Value: PPV), Negative Predictive Value (NPV), and Confusion Matrix (Classification matrix). In the second phase of the study, the computer-aided diagnostic tool for COVID-19 disease was developed using Python Flask library, JavaScript and Html codes.

Results: The model to diagnose COVID-19 has an average accuracy of 98.68 % in the training set and 96.98 % in the testing set. Among the evaluation metrics, the minimum value is 93.4 % for MCC and Youden's index, and the maximum value is 97.8 for sensitivity and NPV. A higher sensitivity value means a lower false negative (FN) value, and a low FN value is an encouraging outcome for COVID-19 cases. This conclusion is crucial because minimizing the overlooked cases of COVID-19 (false negatives) is one of the main goals of this research.

Conclusions: In this period when COVID-19 is spreading rapidly around the world, it is thought that the free and web-based COVID-19 X-Ray clinical decision support tool can be a very effective and fast diagnostic tool. The computer-aided system can assist physicians and radiologists in making clinical decisions about the disease, as well as provide support in diagnosis, follow-up, and prognosis. The developed computer-assisted diagnosis tool can be publicly accessed at http://biostatapps.inonu.edu.tr/CSYX/..

Keywords: Convolutional Neural Network, COVID-19, Image Processing, Deep Learning, Computer-Aided Diagnostic Systems.

Göğüs Röntgeni Görüntülerine Dayalı COVID-19'u Sınıflandırmak için Bilgisayar Destekli Bir Tanı Aracı

ÖZET

Amaç: COVID-19 dünya çapında bir salgın olduğu için, evrişimli sinir ağı (CNN) kullanılarak COVID-19 tespiti olağanüstü bir araştırma tekniği olmuştur. Bildirilen çalışmalarda, çeşitli tıbbi görüntüler kullanılarak derin öğrenme yöntemlerine dayalı olarak COVID-19'u tahmin edebilen birçok model oluşturulmuş; ancak, klinik karar destek sistemleri sınırlı kalmıştır. Bu çalışmanın amacı, X- ışını görüntülerine dayalı başarılı bir derin öğrenme modeli ve COVID-19'un doğru tespiti için bilgisayar destekli, hızlı, ücretsiz ve web tabanlı bir tanı aracı geliştirmektir.

Gereç ve Yöntem: Bu çalışmada, sınıflandırma açısından daha önce yayınlanmış birçok CNN modelinden daha iyi performans gösteren X-ışını görüntüleri kullanılarak COVID-19'u tespit etmek için 15 katmanlı bir CNN modeli kullanıldı. Model performansı Doğruluk, Matthews Korelasyon Katsayısı (MCC), F1 Skoru, Seçiçilik, Duyarlılık, Youden Endeksi, Kesinlik (Pozitif Tahmin Değeri: PPV), Negatif Tahmin Değeri (NPV) ve Karışıklık Matrisine (Sınıflandırma matrisi) dayalı olarak değerlendirildi. Çalışmanın ikinci aşamasında Python Flask kütüphanesi, JavaScript ve Html kodları kullanılarak COVID-19 için bilgisayar destekli tanı aracı geliştirildi.

Bulgular: COVID-19 tanısına yönelik model, eğitim setinde ortalama %98.68 ve test setinde %96.98 doğruluk oranına sahiptir. Değerlendirme ölçütlerinden minimum değerler MCC ve Youden Endeksi için %93.4, maksimum değer ise duyarlılık ve NPV ölçütlerinde % 97.8 olarak elde edilmiştir. Daha yüksek bir duyarlılık değeri, daha düşük bir yanlış negatif (FN) değeri anlamına gelir ve düşük bir FN değeri, COVID-19 vakaları için cesaret verici bir sonuçtur. Bu sonuç çok önemlidir, çünkü gözden kaçan COVID-19 vakalarını (yanlış negatifler) en aza indirmek bu araştırmanın ana hedeflerinden biridir.

Sonuç: COVID-19'un dünya çapında hızla yayıldığı bu dönemde, ücretsiz ve web tabanlı COVID-19 X-Ray klinik karar destek aracının oldukça etkili ve hızlı bir tanı aracı olabileceği düşünülmektedir. Bilgisayar destekli sistem, doktorlara ve radyologlara hastalık hakkında klinik kararlar vermede yardımcı olabileceği gibi, teşhis, takip ve prognoz konusunda da destek sağlayabilir. Geliştirilen bilgisayar destekli tanı aracına http://biostatapps.inonu.edu.tr/CSYX/ adresinden genel erişim sağlanabilmektedir.

Anahtar Kelimeler: Evrişimli Sinir Ağı, COVID-19, Görüntü İşleme, Derin Öğrenme, Bilgisayar Destekli Tanı Sistemleri.

INTRODUCTION

The COVID-19 outbreak first started on December 31, 2019, to detect unknown causes of pneumonia in Wuhan City, Hubei Province, China (1, 2). The rapidly transmitted disease was first described as SARS-CoV-2, and later this disease was identified as COVID-19 by the World Health Organization (WHO). It took 30 days for this new and rapidly spreading virus to extended from Wuhan city to other parts of China (3). The COVID-19 was declared an Internationally Important Public Health Emergency on 30 January 2020, and later declared as a pandemic by WHO on 11 March 2020 (4).

This virus is common in animals. However, due to the zoonotic presence of the virus, it was transmitted from animals to humans and then quickly spread around the world through contact between people. Extremely Acute Respiratory Syndrome Virus (SARS-CoV) and the Middle East Respiratory Syndrome Virus (MERS-CoV), which are members of the coronavirus family, have previously caused severe respiratory illnesses and deaths (5). From past to present, the genome of the COVID-19 virus has been mutated. For example; A study from University College London (UCL) reported 198 recurrent mutations for COVID-19 (6). Fever, cough, sneezing, sore throat, severe headache, malaise, and shortness of breath are known to be the most prevalent symptoms of COVID-19 disease (7).

Real-time reverse transcription-polymerase chain reaction (RT-PCR) is the most widely used technique worldwide for detecting COVID-19 disease, but many countries also have immunological tests to diagnose this disease. Radiological images such as computed tomography (CT) and X-ray scans have played a significant role in the early diagnosis of the disease and are used for this purpose (8). X-ray images are thought to have a distinctive potential among screening methods in monitoring various lung-related diseases such as tuberculosis, atelectasis, and pneumonia. Chest X-ray scans are beneficial for observing and tracking the impact of COVID-19 illness in the lungs.

Early diagnosis and treatment can be provided by determining the disease's pathological effects by evaluating COVID-19 with lung scan images of the patients since the RT-PCR test has a sensitivity value between 60% -70% and is time-consuming for the diagnosis of COVID-19 (9). It was recognized that X-ray and CT scans are a more effective way to detect COVID-19 and can be used in conjunction with RT-PRC (10).

Many countries around the world are struggling with deficiency kits for testing and a lack of qualified laboratory staff at the beginning of this pandemic, resulting in increases in false-negative rates for a high incidence of disease. For such reasons, clinicians often focus on chest x-ray and CT scans findings to determine the COVID-19 status (11, 12). In countries where test kits are deficient, CT and X-ray scanning images are widely used to identify COVID-19. Researchers claim that COVID-19 was detected earlier by observing radiological imaging outputs and laboratory findings together (13-15).

In the literature, the Convolutional Neural Network (CNN) method, one of the deep learning algorithms, is frequently used in artificial intelligence (AI) based studies. CNN, MRI (16), X-ray (17), CT scans (18), ultrasonography (19), etc. It has been used effectively for clinical purposes, such as for medical image processing. Besides, through a process very close to human brain function, CNN is a collection of methods that detect relationships.

There are numerous deep learning and machine learning methods that use X-ray images to diagnose diseases in the current literature. A new CNN model that classifies X-ray scans has been proposed in a research article (20). As pre-trained CNNs are to available difficulties in practical implementations, the authors implement a small-sized CNN architecture. The researchers used a 12-class X-Ray dataset, with an 86 percent precision rate recorded in their studies. Another work proposed a different deep learning approach to tuberculosis detection. The authors propose a new CNN model in their method that used an X-Ray dataset. A large dataset including X-Ray scans was created by another study to which they implemented CNN models for binary and multi-class classifications. The relevant dataset, transfer learning, was used with pre-trained ResNet, AlexNet, and VGG16 methods. Though an 82.2 percent accuracy score was recorded for the binary classification, over 90% accuracy rate results were reported for the other classifications. By Ioannis et al., another done work proposed VGG19 and obtained an accuracy of 93.48 percent using X-ray images (21). In another latest study, a model known as COVID-Net received an accuracy rate of 92.4% in the X-ray image dataset (22).

Since COVID-19 is a worldwide pandemic, COVID-19 classification using a CNN model has been an extraordinary research technique. Excellent CNN-based investigations are available to classification and identify COVID-19 using different X-ray image datasets. Although promising results have been obtained from these CNN techniques, they are not yet an option for real test methods. Many models that can predict COVID-19 based on commonly deep learning methods using various medical images have been created; however, web-based clinical decision support systems have been limited.

In this period when COVID-19 is declared a worldwide pandemic, the web-based systems for COVID-19 on X-Ray imaging may be a highly useful and fast diagnostic tool. A computer-aided system can assist physicians and radiologists in making clinical decisions about the disease and supporting disease diagnosis, follow-up, and prognosis. In this study, a highly successful deep learning model-based on X-ray images is developed for correctly the detection of COVID-19, and a computer-assisted, fast, free, and web-based computer-assisted diagnosis tool that can accurately predict COVID-19 is proposed and accessed at http://biostatapps.inonu.edu.tr/CSYX/.

The remainder of this article is regulated as follows. In Part II, the deep learning method used in the study and the web-based diagnostic tool developed were explained. The experimental results in Part III and the discussion in Part IV are presented.

MATERIAL AND METHODS

Dataset: The design of this research is an experimental clinical study, and the analyzed images were obtained from the related research in an open-access manner. In the study, an open-source data set containing augmented X-ray images for COVID-19 at https://data.mendeley.com/datasets/2fxz4px6d8 was used (23). The data set used in the study was augmented published online. In CNN models, it is a common technique to augment the image data set for preventing over-fitting and for the model from not memorizing all the training data details. The data set includes a total of 1824 X-Ray scan images; 912 COVID-19 positive and 912 COVID-19 negative scans. Figure 1 shows some example X-ray images in the dataset.

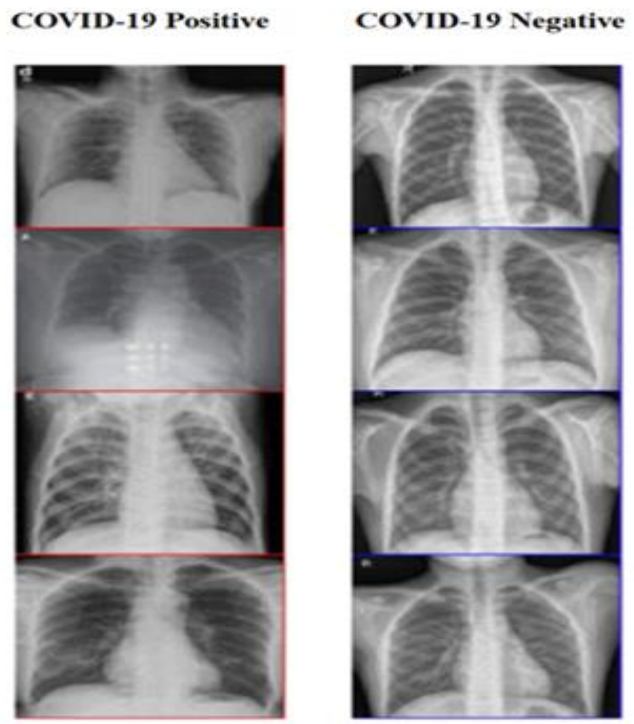

Figure 1. Sample Images of X-Ray Scan Dataset

Methods: All encodings were performed with PYTHON software on the virtual server with 1.5 TB RAM, 16 core @ 3.60 GHz CPU, and Tesla P40 24GB GPU on Intel (R) Xeon (R) Gold 5122 server. The X-ray images' input size is initially resized to 224 x 224 pixels for compatibility with CNN models. CNN model was implemented using Keras and Tensorflow 2.0 libraries. In the study's experiments, 80% of the image data set and the remaining 20% of the training set were randomly divided as testing set to validate the CNN model. The CNN model used in the study contains 15 layers.

Firstly, two sequential convolutional layers are built, with a 224x224x32 output shape with 3x3 cores with the similar size padding to ensure the output's size. A 2x2 top pool layer is then added to the model to reduce the size of the features. Then another convolutional layer of 64 depth is added. A maximum pool layer of size 2×2 results in these curved layers for size reduction, and an activation function is used ReLU in all layers. The features add a flatten layer and add a dense layer in 64depth, with a dropout layer of 0.5. A rigidly connected layer incorporates the characteristics of the previous layers, and the final output of the exactly-connected layers is standardized with a Sigmoid activation function. In the constructed model, the batch size is 16, the learning rate is 0.0001, and the epoch value is 20. Hyperparameters of the model were chosen intuitively and tuned by Adam's optimization method during the experiment. The model performance is evaluated according to Accuracy, Matthews Correlation Coefficient (MCC), F1

Score, Specificity, Sensitivity (Recall), Youden's Index, Precision (Positive Predictive Value: PPV), Negative Predictive Value (NPV), and Confusion Matrix (Classification matrix).

Finally, the CNN model's methodology is depicted in Figure 2, and the layers of the created CNN model are presented in Figure 3.

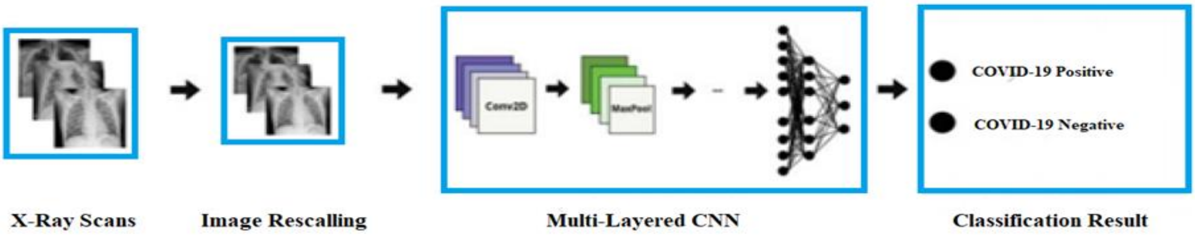

Figure 2. The methodology of the proposed CNN model

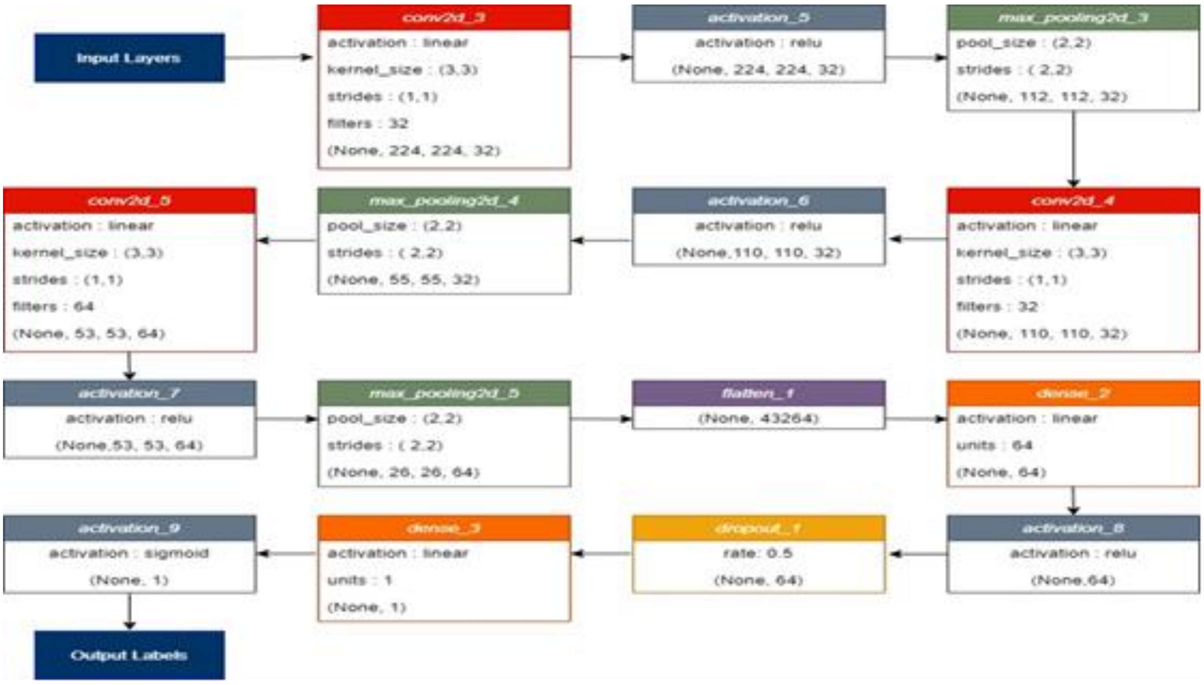

Figure 3. The layers of the CNN Model

Convolution Neural Networks (CNNs): A significant extension of artificial neural learning is deep learning, employed in several scientific and application fields. The basic architecture of the deep learning concept is regarded as neural networks with convolution (CNNs). Different layers are used to create a CNN model. In the CNN model, while a convolution layer is liable for extracting local features, a normalization layer is liable for normalizing local features. The pooling layer is used to down sample local features. The convolution layer is the layer where the convolution stage occurs, and the CNN models learn. This layer performs most of the calculations in the model. Convolution is the most important stage of these networks. Several parameters and hyperparameters are available on all layers. These greatly affect the performance of the model. One of these parameters, filters, extract the necessary functions for the convolution layers and then learn the data using these functions. In CNN, the pooling layer is often used for image size reduction. With this layer, the speed of computation increases, the problem of the over-fitting problem is prevented, reducing the available memory. A common approach used for ordering layers within a convolutionary neural network that can be replicated one or more times in a given model is the inclusion of a pooling layer and after convolutional layer. To build a new collection of the same number of pooled feature maps, the pooling layer operates separately on each feature map. Pooling requires selecting a pooling operation to be implemented to function feature maps, just like a filter. And the flattening layer converts the pooled overall feature (attribute) map matrix into only a single column. It will then be transmitted to the neural network for processing. This layer is also known as a dense layer because it is a fully connected layer. The input from the previous layers becomes flattened in this layer into a vector. After flattening, the past layer's volume is given as an input to the precisely bonded layer. This layer tries to determine which features fit into a particular class by looking at the past layer's output. As finally, it acts on high-level characteristics that have unique weights. Therefore, as it computes the weights and the previous layer's results, a rigidly connected layer ensures the distinct groups' right probabilities. The outputs are defined by the use of the activation function (24, 25).

Computer-Assisted Diagnosis Tool for COVID-19: In the second phase of the study, a computer-assisted diagnosis tool, which can be accessed free of charge from any internet-enabled device (mobile phone, desktop computer, laptop, etc.), was developed for the COVID-19 disease using X-Ray scan images. This web-based system is developed using Python Flask library, JavaScript, and Html codes (26-28). It has two language options, English and Turkish. When X-Ray scan images of people with suspected COVID-19 are uploaded, the developed system results as COVID-positive or COVID-negative within a few minutes or less. The main menu of the COVID-19 computer-assisted diagnosis tool is displayed in Figure 4. The system consists of three sections. The first section contains a short explanation of the system. In the second section, when any user can upload an X-Ray scan image and click analyze button, the estimate of the COVID-19 diagnosis is displayed in the third section. The system supports image files with the extensions of .dcm , .jpeg , .jpg , or .png. The developed computer-assisted diagnosis tool can be accessed at http://biostatapps.inonu.edu.tr/CSYX/.

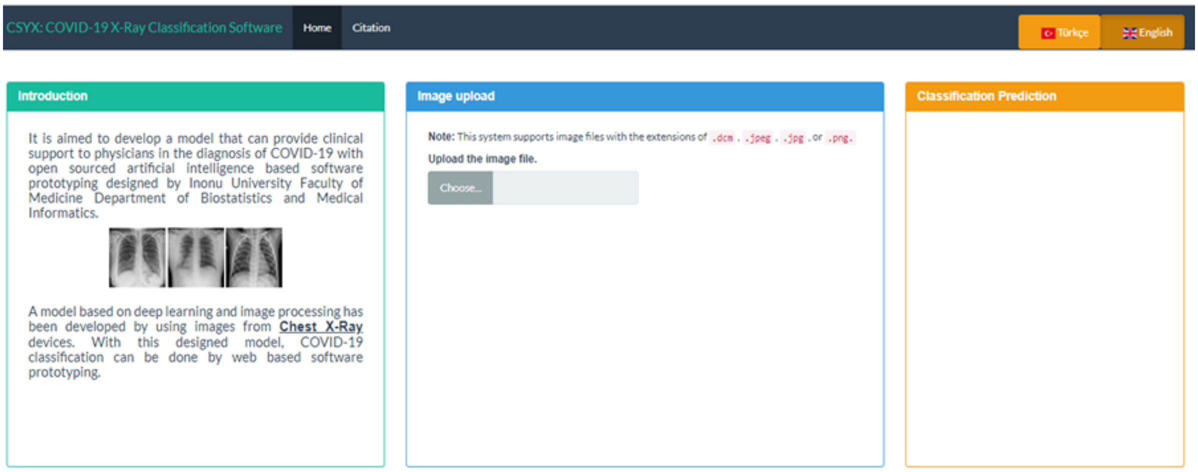

Figure 4. The System Main Menu

RESULTS

Findings of CNN Model: The confusion matrix for the COVID-19 X-Ray scan test data set of the created model is given in Figure 5. Performance metrics obtained from the CNN model created for the diagnosis of COVID-19 are listed in Figure 6. When the experimental results of the trained and tested CNN model are examined, our proposed model achieved an overall accuracy of 96.7% in the testing set, and more importantly, the Precision and Sensitivity (Recall) rates for COVID-19 cases were 95.7% and 97.8% for the COVID-19 classification, respectively.

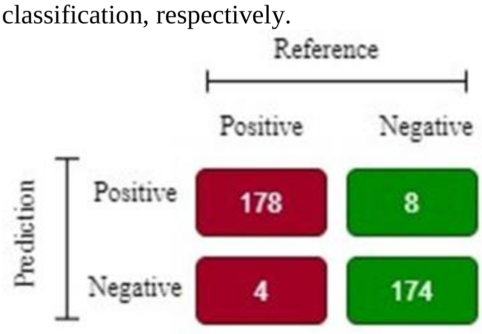

Figure 5. The confusion matrix for the COVID-19 X-Ray testing dataset

As the calculated performance metrics are evaluated with a 95% confidence interval (CI), the minimum value is 93.4% for MCC and Youden's index, and the maximum value is 97.8 for sensitivity and NPV in Figure 6.

Metric	Value (%)	%95 CI (%)
Accuracy	96.7	(94.9-98.5)
F1-Score	96.7	(94.9-98.6)
Sensitivity (Recall)	97.8	(94.5-99.4)
Specificity	95.6	(91.5-98.1)
MCC	93.4	(91-96)
Youden's Index	93.4	(86-97)
Precision (PPV)	95.7	(91.7-98.1)
Negative Predictive Value (NPV)	97.8	(94.3-99.4)

Figure 6. Performance criteria for the CNN model in the testing dataset

Findings of Developed COVID-19 X-Ray Computer Assisted Diagnosis Tool: The results for the COVID-19 X-Ray positive and negative images randomly loaded from outside to the system are illustrated in Figures 7 and 8, respectively. As can be seen, the system can successfully classify COVID-19 status as positive and negative based on the uploaded X-Ray image.

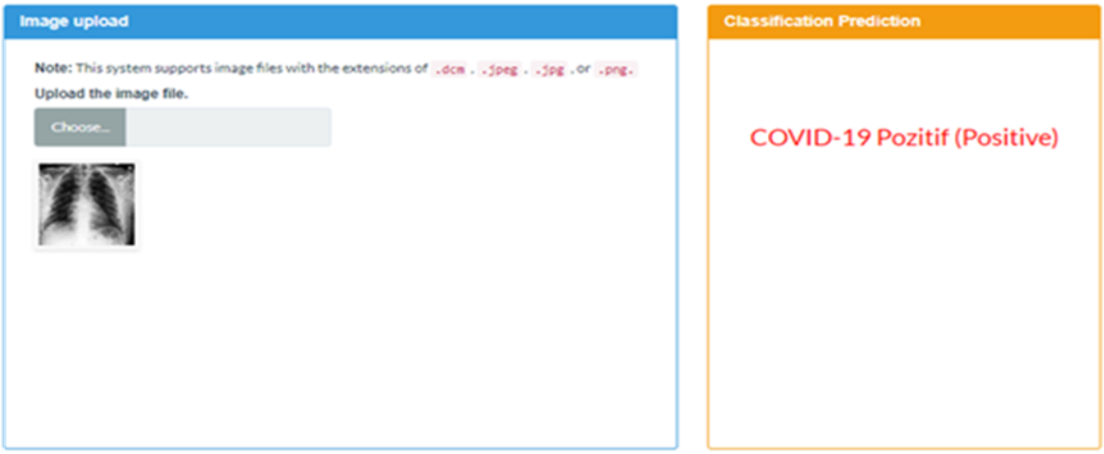

Figure 7. Prediction Result of COVID-19 Positive X-Ray Scan Image in System

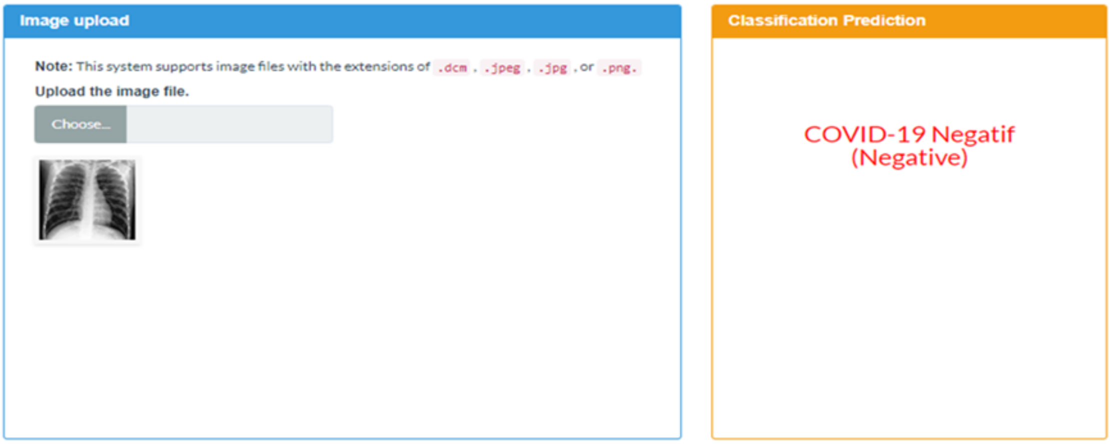

Figure 8. Prediction Result of COVID-19 Negative X-Ray Scan Image in System.

DISCUSSION

COVID-19 is a long-time danger to the healthcare systems and economies of nations. In the world, millions of people have died due to the disease. Deaths have been caused by respiratory failure, resulting in the loss of other organs. As there are many emergencies, hospital capacities are full, and clinicians have limited time. Therefore, computer-aided diagnostic systems can save lives. There is also a great deal of variation in the sample scan images taken from X-ray machines because of differences in the radiologist's expertise (5, 14). Since speed, accessibility, and ease of application are extremely important in the clinical diagnosis of the current state of COVID-19, combining medical imaging methods with artificial intelligence technologies would be very useful from clinical aspects.

In this study, a successful CNN architecture was created to classify COVID-19 as positive and negative (to detect the disease) from X-Ray scan images. The created model achieved 96.7% accuracy in the testing set. Another significant result is achieving the positive predictive value and sensitivity metrics obtained from the model for COVID-19 cases. A higher sensitivity value means a lower false negative (FN) value, and a low FN value is an encouraging result for COVID-19 cases. This considerable result is significant because minimizing the overlooked COVID-19 cases (false negative) is one of this research's main aims.

Published research articles on the prediction of COVID-19 have been reported using different structures of CNN models. In a study conducted using the same data set in the literature, CNN, CNN / Random Forest, and CNN-support vector machine (SVM) methods were used, and the highest accuracy rate was obtained from the CNN model with 95.2% (29). In another study using the same data set in the literature, using the combination of MobileNet, ResNet50, InceptionV3, and InceptionV3 and MobileNet models, 95.18%, 94.39%, 95.75%, and 96.49% accuracy rates were obtained, respectively (30).

In another study, ResNet18, ResNet50, ResNet101, VGG16, and VGG19 models were used in different COVID-19 X-Ray scan image datasets. For the classification of features, the Support Vector Machines (SVM) classifier was created with some kernel functions. The ResNet50 model and the SVM classifier achieved an accuracy score of

94.7%, the highest among all results (31). In another study, different CNN models (AlexNet, VGG19, ResNet, and SqueezeNet) were created for the transfer - learning called DeTraC in a different COVID-19 X-Ray scan image dataset. An accuracy rate of 93.1% was achieved with DeTraC for detecting COVID-19 (32). In another recent study, a CNN method named CNN-COVID was developed using X-ray scan images, and the method was tested in two different data sets. With this method, accuracy of 0.9722 for the first data set and 0.9884 for the second data set was obtained (33).

In many studies, outstanding results have been obtained for COVID-19 prediction. However, in these studies, a web-based diagnostic system for COVID-19 has not been developed. Compared to such studies in the literature, the superiority of the current study is a web-based diagnostic system that can quickly predict COVID-19 and is developed for use worldwide.

The web-based system developed in the second phase of this study using a highly successful deep learning architecture for detecting COVID-19 is one of the few studies that can be classified from X-Ray scan images for COVID-19 disease. It is thought that the developed system will help clinicians and other healthcare professionals in clinical evaluations. It is envisaged that the disease's diagnosis and treatment processes will be carried out more effectively with the development of a system that can help medical methods used to diagnose individuals with suspected COVID-19. In addition, with the effective use of the proposed artificial intelligence-based software, it is expected to support the disease's diagnosis processes and reduce the possible financial burden and inappropriate medical procedures. The proposed model and developed system significantly advance the existing approach focused on radiology and can be a useful tool for healthcare professionals and radiologists to help them detect and diagnose, and follow-up COVID-19 cases during the COVID-19 pandemic. We believe that with this computer-aided diagnostic system, diagnostic time for COVID-19 will be reduced, and diagnostic accuracy will be significantly improved.

As a result, the article's primary contributions are as follows:

1. The model constructed with a 15-layer CNN architecture for COVID-19 classification provided 98.68% accuracy in the training set and 96.98% in the test set.

2. The system developed based on the CNN model can predict COVID-19 accurately and effectively. Also, it performs the estimation process in a minute or two.

3. It is thought that the web-based system developed can provide support to physicians in the clinical decision-making process to diagnose COVID-19.

Taken together, the preliminary results of the current study are auspicious, and the results can be further improved as more data for training becomes available. Future studies plan to create a model with higher performance criteria by using more training data sets of the system.

CONCLUSION

It is thought that the deep learning-based web-based diagnostic tool will help physicians and radiologists in the diagnosis of COVID-19 by significantly shortening the diagnosis time.

ACKNOWLEDGEMENT

This study was supported by Inonu University Scientific Research Projects Coordination Unit within the scope of TOA-2020-2204 (ID: 2204) numbered research project. For this reason, we would like to thank Inonu University Scientific Research Projects Coordination Unit for their support.

Conflict of Interest: The authors report no conflict of interest.

Funding: This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

REFERENCES

1. Wu F, Zhao S, Yu B, Chen Y-M, Wang W, Song Z-G, et al. A new coronavirus associated with human respiratory disease in China. Nature. 2020;579(7798):2652.
2. Huang C, Wang Y, Li X, Ren L, Zhao J, Hu Y, et al. Clinical features of patients infected with 2019 novel coronavirus in Wuhan, China. The lancet. 2020;395(10223):497-506.
3. Wu Z, McGoogan JM. Characteristics of and important lessons from the coronavirus disease 2019 (COVID-19) outbreak in China: summary of a report of 72 314 cases from the Chinese Center for Disease Control and Prevention. Jama. 2020;323(13):1239-42.
4. Timeline-COVID W, Organization WH. Apr 27. URL: https://www who int/news-room/detail/27-04-2020-who-timeline---covid-19 [accessed 2020-04-27]. 2020.
5. Kong W, Agarwal PP. Chest imaging appearance of COVID-19 infection. Radiology: Cardiothoracic Imaging. 2020;2(1):e200028.
6. van Dorp L, Acman M, Richard D, Shaw LP, Ford CE, Ormond L, et al. Emergence of genomic diversity and recurrent mutations in SARS-CoV-2. Infection, Genetics and Evolution. 2020;83:104351.
7. Mishal A, Saravanan R, Atchitha SS, Santhiya K, Rithika M, Menaka SS, et al. A Review of Corona Virus Disease-2019. History. 2020;4:07.

8. Zu ZY, Jiang MD, Xu PP, Chen W, Ni QQ, Lu GM, et al. Coronavirus disease 2019 (COVID-19): a perspective from China. Radiology. 2020;296(2):E15-E25.
9. Kanne JP, Little BP, Chung JH, Elicker BM, Ketai LH. Essentials for radiologists on COVID-19: an update—radiology scientific expert panel. Radiological Society of North America; 2020.
10. Lee EY, Ng M-Y, Khong P-L. COVID-19 pneumonia: what has CT taught us? The Lancet Infectious Diseases. 2020;20(4):384-5.
11. Bernheim A, Mei X, Huang M, Yang Y, Fayad ZA, Zhang N, et al. Chest CT findings in coronavirus disease-19 (COVID-19): relationship to duration of infection. Radiology. 2020:200463.
12. Long C, Xu H, Shen Q, Zhang X, Fan B, Wang C, et al. Diagnosis of the Coronavirus disease (COVID-19): rRT-PCR or CT? European journal of radiology. 2020;126:108961.
13. Li Y, Xia L. Coronavirus disease 2019 (COVID-19): role of chest CT in diagnosis and management. American Journal of Roentgenology. 2020;214(6):1280-6.
14. Shi H, Han X, Jiang N, Cao Y, Alwalid O, Gu J, et al. Radiological findings from 81 patients with COVID-19 pneumonia in Wuhan, China: a descriptive study. The Lancet infectious diseases. 2020;20(4):425-34.
15. Zhao W, Zhong Z, Xie X, Yu Q, Liu J. Relation between chest CT findings and clinical conditions of coronavirus disease (COVID-19) pneumonia: a multicenter study. American Journal of Roentgenology. 2020;214(5):1072-7.
16. Zou L, Zheng J, Miao C, Mckeown MJ, Wang ZJ. 3D CNN based automatic diagnosis of attention deficit hyperactivity disorder using functional and structural MRI. IEEE Access. 2017;5:23626-36.
17. Liu C, Cao Y, Alcantara M, Liu B, Brunette M, Peinado J, et al., editors. TX-CNN: Detecting tuberculosis in chest X-ray images using convolutional neural network. 2017 IEEE international conference on image processing (ICIP); 2017: IEEE.
18. Zhao X, Liu L, Qi S, Teng Y, Li J, Qian W. Agile convolutional neural network for pulmonary nodule classification using CT images. International journal of computer assisted radiology and surgery. 2018;13(4):585-95.
19. Liu J, Li W, Zhao N, Cao K, Yin Y, Song Q, et al., editors. Integrate domain knowledge in training CNN for ultrasonography breast cancer diagnosis. International Conference on Medical Image Computing and Computer-Assisted Intervention; 2018: Springer.
20. Kesim E, Dokur Z, Olmez T, editors. X-ray chest image classification by a small-sized convolutional neural network. 2019 scientific meeting on electrical-electronics & biomedical engineering and computer science (EBBT); 2019: IEEE.
21. Apostolopoulos ID, Mpesiana TA. Covid-19: automatic detection from x-ray images utilizing transfer learning with convolutional neural networks. Physical and Engineering Sciences in Medicine. 2020;43(2):635-40.
22. Wang L, Lin ZQ, Wong A. Covid-net: A tailored deep convolutional neural network design for detection of covid-19 cases from chest x-ray images. Scientific Reports. 2020;10(1):1-12.
23. Alqudah AM, Qazan S. Augmented COVID-19 X-ray images dataset. Mendeley Data. 2020;4.
24. O'Shea K, Nash R. An introduction to convolutional neural networks. arXiv preprint arXiv:151108458. 2015.
25. Li Y, Hao Z, Lei H. Survey of convolutional neural network. Journal of Computer Applications. 2016;36(9):2508-15.
26. Sanner MF. Python: a programming language for software integration and development. J Mol Graph Model. 1999;17(1):57-61.
27. Baxter G, Frean M, Noble J, Rickerby M, Smith H, Visser M, et al., editors. Understanding the shape of Java software. Proceedings of the 21st annual ACM SIGPLAN conference on Object-oriented programming systems, languages, and applications; 2006.
28. Raggett D, Le Hors A, Jacobs I. HTML 4.01 Specification. W3C recommendation. 1999;24.
29. Alqudah AM, Qazan S, Alquran H, Qasmieh IA, Alqudah A. COVID-2019 detection using X-ray images and artificial intelligence hybrid systems. Biomedical Signal and Image Analysis and Project; Biomedical Signal and Image Analysis and Machine Learning Lab: Boca Raton, FL, USA. 2019.
30. Ahmad F, Farooq A, Ghani MU. Deep Ensemble Model for Classification of Novel Coronavirus in Chest X-Ray Images. Computational Intelligence and Neuroscience. 2021;2021.
31. Ismael AM, Şengür A. Deep learning approaches for COVID-19 detection based on chest X-ray images. Expert Systems with Applications. 2021;164:114054.
32. Abbas A, Abdelsamea MM, Gaber MM. Classification of COVID-19 in chest X-ray images using DeTraC deep convolutional neural network. Applied Intelligence. 2021;51(2):854-64.
33. de Sousa PM, Carneiro PC, Oliveira MM, Pereira GM, da Costa Junior CA, de Moura LV, et al. COVID-19 classification in X-ray chest images using a new convolutional neural network: CNN-COVID. Research on Biomedical Engineering. 2021:1-11.