Türkiye Klinikleri Biyoistatistik Dergisi
Turkiye Klinikleri Journal of Biostatistics
Turkiye Klinikleri J Biostat. 2022;14(1):22-31

ORİJİNAL ARAŞTIRMA ORIGINAL RESEARCH

DOI: 10.5336/biostatic.2022-88805

Artificial Intelligence Based Video Processing Methods for Predicting COVID-19: Observational Study

COVID-19'u Tahmin Etmek için Yapay Zekâ Tabanlı Video İşleme Yöntemleri: Gözlemsel Çalışma

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ABSTRACT Objective: The aim of this study is to develop a high-performance model and web-based clinical decision making method to successfully distinguish and classify COVID-19 from bacterial pneumonia, viral pneumonia and healthy controls with lung ultrasound (LUS) videos using appropriate video processing techniques and artificial intelligence (AI) methods development of the support system. **Material and Methods:** In this study, the open source LUS video dataset at https://github.com/jannisborn/covid19_ultrasound was used. The dataset includes 32 healthy controls, 24 COVID-19, 24 bacterial pneumonia and 12 viral pneumonia class videos. In the video processing stage, 300 image frames were taken from the videos in each class. The images were divided into 80% (960) training and 20% (240) test datasets. In the modeling phase, the convolutional neural network (CNN) method, one of the deep neural network architectures in the keras library, was used. Accuracy, sensitivity, specificity, precision, Matthews' correlation coefficient and F1 score criteria are given to evaluate the performance of the model. A web-based system has been developed that can successfully detect COVID-19 using the, with the help of the AI-based model, Python Flask Library. **Results:** The accuracy in the test dataset was calculated as 93.39% for healthy control, COVID-19 and viral pneumonia, and 95.07% for bacterial pneumonia. **Conclusion:** According to the performance criteria values obtained with the video processing-based CNN model, it can be said that the developed system gives very successful predictions in the diagnosis of COVID-19, bacterial pneumonia and viral pneumonia.

Keywords: COVID-19; deep learning; video processing; image processing; convolutional neural networks

ÖZET Amaç: Bu çalışmanın amacı, uygun video işleme teknikleri ve yapay zekâ yöntemleri kullanılarak akciğer ultrason videoları ile COVID19'u bakteriyel pnömoni, viral pnömoni ve sağlıklı kontrollerden başarılı bir şekilde ayırt ederek sınıflandırmak için yüksek performansa sahip bir modelin ve web tabanlı klinik karar destek sisteminin geliştirilmesidir. **Gereç ve Yöntemler:** Bu çalışmada, https://github.com/jannisborn/covid19_ultrasound adresindeki açık kaynaklı akciğer ultrason video veri seti kullanılmıştır. Veri setinde bulunan videoların 32'si sağlıklı kontrol, 24'ü COVID-19, 24'ü bakteriyel pnömoni ve 12'si viral pnömoni şeklinde klinik olarak sınıflandırılmıştır. Video işleme aşamasında, her bir sınıftaki videolardan 300 görüntü karesi alınmıştır. Görüntülerin %80'i (960) eğitim ve %20'si (240) test veri seti olarak bölünmüştür. Modelleme aşamasında, keras kütüphanesinde bulunan derin sinir ağları mimarilerinden evrişimli sinir ağları CNN yöntemi kullanılmıştır. Oluşturulan modelin performansını değerlendirmek için doğruluk, duyarlılık, seçicilik, kesinlik, Matthews'in korelasyon katsayısı ve F1 skoru ölçütleri verilmiştir. Bunlara ek olarak oluşturulan yapay zekâ tabanlı model ile, Python Flask Kütüphanesi kullanılarak COVID-19'U başarılı bir şekilde tespit edebilen web tabanlı bir sistem geliştirilmiştir. **Bulgular:** Test veri setinde doğruluk sağlıklı kontrol, COVID-19 ve viral pnömoni için %93,39 ve bakteriyel pnömoni için ise %95,07 olarak hesaplanmıştır. **Sonuç:** Önerilen video işleme tabanlı CNN modeli ile elde edilen performans ölçütlerine göre geliştirilen sistemin COVID-19, bakteriyel pnömoni ve viral pnömoni tanısında oldukça başarılı tahminler verdiği ve klinik karar destek amacıyla kullanılabileceği söylenebilir.

Anahtar kelimeler: COVID-19; derin öğrenme; video işleme; görüntü işleme; evrişimli sinir ağları

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Peer review under responsibility of Turkiye Klinikleri Journal of Biostatistics.

Received: 07 Feb 2022 ***Received in revised form:*** 07 Mar 2022 ***Accepted:*** 08 Mar 2022 ***Available online:*** 20 Apr 2022

Coronavirus disease-2019 (COVID-19) was first detected on December 31, 2019 in Wuhan, Hubei province, China. The rapidly transmitted disease was first identified as severe acute respiratory syndrome-coronavirus-2 (SARS-CoV-2) and later named COVID-19 by the World Health Organization (WHO). The virus is quite common in animals, and due to the zoonotic presence of the virus, it was first transmitted from animals to humans, and then quickly spread through contact all over the world. It took 30 days for this new and rapidly spreading virus to spread from Wuhan city to other parts of China. COVID-19 was declared an International Emergency of Public Health on January 30, 2020, and then declared a pandemic by WHO on March 11, 2020. As of the end of January 2021, with more than 100 million confirmed new cases of coronavirus (SARS-CoV-2) worldwide, it caused numerous deaths worldwide, with more than 200 million cumulative deaths, and had a very negative impact on people's lives. The disease has flu-like symptoms such as fever, dry cough, fatigue, and difficulty breathing. In more serious cases, COVID-19 often causes fatal pneumonia.[1,2]

Real-time reverse transcription-polymerase chain reaction is the most widely used method worldwide to detect COVID-19 disease, but many countries also have immunological tests to diagnose it. Rapid tests have proven to be the most effective method for limiting the spread of easily transmitted COVID-19, leading researchers to seek a quick diagnosis. Therefore, in most studies in the literature, 3 types of radiological imaging methods are mainly used for COVID-19 detection: computed tomography (CT), X-ray, and lung ultrasound (LUS). Other research papers have employed a combination of wearable medical sensors to eliminate physiological signals in addition to these 3 strategies.[3] CT scanning is a type of radiological imaging that provides a three-dimensional image of the lungs and can detect COVID-19 at various stages of the disease's course.[4,5] On the other hand, CT screening is expensive and exposes patients to radiation that may be hazardous in the future.[6] Due to its versatility, low cost, and somewhat speedier approach, X-ray scans are another way used to detect the condition.[7] However, due to the low resolution and overlapping projections of X-ray scans, the characteristics of the disease and its pulmonary consolidation at various stages are not clearly visible.[8] LUS, on the other hand, provides clear and real-time pictures of the lungs and is therefore more beneficial for bedside therapy and daily checkups due to its effective functionality. According to a visual examination by specialists in the relevant domains, LUS has long been utilized to detect respiratory disorders and performs better for pneumonia diagnosis than X-rays.[9]

One of the deep learning methods, convolutional neural networks (CNNs), is often used in artificial intelligence (AI) based studies for both classification and segmentation problems. CNN said, "We're not saying X-ray is an effective method to support clinical decisions using medical images or videos such as CT or LUS." There is a very good CNN-based research to classify and identify COVID-19, especially using LUS datasets.[5] However, in these studies, the development of web-based clinical decision support systems in order to diagnose the disease quickly has been inadequate.

A computer-aided system can help healthcare professionals make clinical decisions about the disease and support disease diagnosis, follow-up, and prognosis. In this study, a highly successful deep learning model based on LUS videos was created and a computer-aided, fast, free, and web-based clinical decision support system was developed to accurately distinguish COVID-19 from healthy control, bacterial pneumonia, and viral pneumonia. The developed system can be accessed free of charge at http://biostatapps.inonu.edu.tr/CVSY/.

MATERIAL AND METHODS

DATASET

The study used an open source LUS video data set from https://github.com/jannisborn/covid19_ultrasound address, which included COVID-19, viral pneumonia, bacterial pneumonia, and healthy controls.[10] Of the 92 convex ultrasound videos in the data set, 24 are in the COVID-19, 12 are in the healthy control class, 24 are in the class of viral pneumonia, 24 are bacterial pneumonia, and 32 are in the healthy control class. The general characteristics of the data set are given in Table 1.

TABLE 1: General characteristics of the dataset.

File format	.avi
Method	Hold-out
Data set type	Open source
Total videos	92
Number of images from videos for each class	300
Number of training images	960
Number of test images	240
Total number of images	1,200
Width	64 pixel
Height	64 pixel

DATA PRE-PROCESSING

All analyses were carried out on data (videos) recorded with convex ultrasound probes, a standard probe that allows comprehensive vision of the lung. 92 convex ultrasound videos were processed and converted into images with 300 frames for each class. As a result, a database of 1,200 images was created. Normalization of images has been performed.[11] All images with different resolutions have been resized to 64×64 pixels. Standardized images were obtained through this resizing process.

CONVOLUTIONAL NEURAL NETWORKS (CNNs)

The CNN architecture is a type of artificial neural network that uses sensors and a controlled machine learning algorithm to analyze high-dimensional data. It is a multilayered forward-feed neural network created by the overlap of many hidden layers in turn. This is because it has this sequential design that allows CNNs to learn hierarchical features.[1] CNNs are built to learn the spatial hierarchies of features automatically and adaptively by re-dissemination using several building blocks like convolution, pooling, and fully connected layers. The convolution and pooling layers extract features, while the fully connected third layer gives output for categorizing the extracted attributes. The evolution layer plays an important role on CNN. A convolution layer performs property inference, which consists of a combination of linear and nonlinear operations, namely the convolution process and activation function. The pooling layer provides an overblog process that reduces the in-plane size of property maps to add displacement immutability to minor distortions and reduce the number of subsequent learnable parameters. The output property maps of the last convolution or pooling layer are typically flattened and linked to one or more fully linked layers, also known as dense layers. After properties are created that are subtracted by convolution layers and downsized by pooling layers, these properties are mapped to the network's final outputs by a subset of fully connected layers. The last fully bound layer must have the same number of output nodes as the number of classes.[1] The structure of the CNN model used is as in Figure 1.

Callbacks are important for executing code and automatically interacting with the training model process. Keras supports an early halt to training through a callback called "an early stop." This callback allows you to specify the performance criteria and the trigger to follow, and stops the training process once triggered. An early stop callback was used in model training in the study. The number of training laps (epochs) of the model is set at 15. In the study, the hyper-parameters of the model were adjusted by the ADAM optimization method.

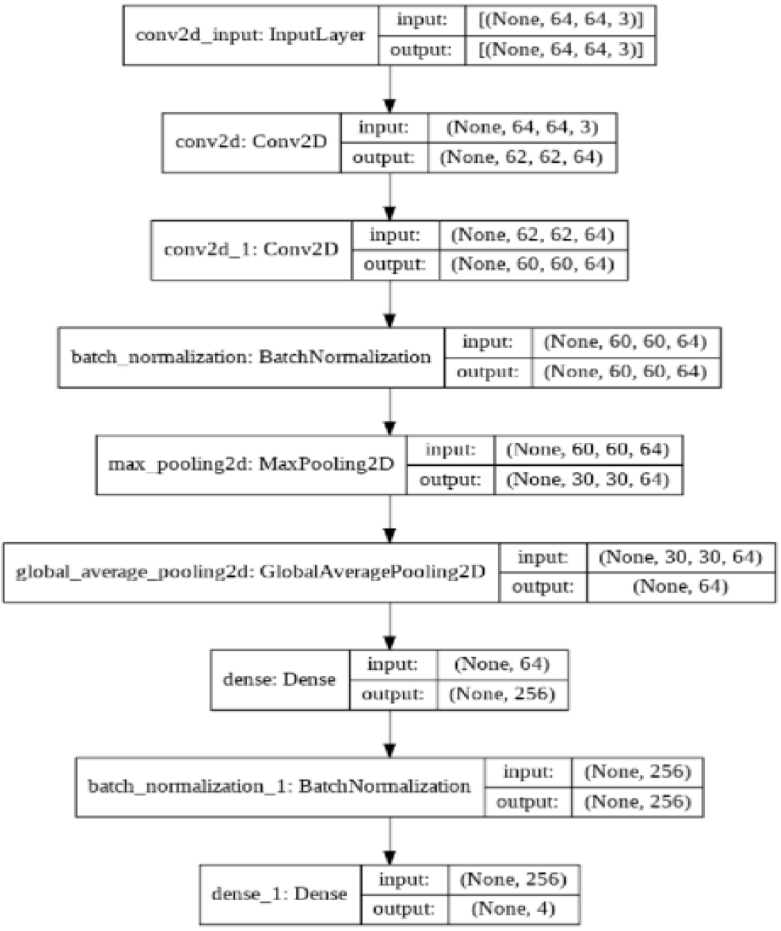

FIGURE 1: Convolutional neural network architecture.

PERFORMANCE EVALUATION CRITERIA

Confusion matrix was used to calculate the performance criteria of classification models. Accuracy, sensitivity, specificity, precision, Matthews' correlation coefficient (MCC) and F1 score criteria for each class are given to evaluate the performance of the model.

DEVELOPMENT OF WEB BASED SYSTEM

In the second phase of the study, a clinical decision support system was developed that can be accessed free of charge from any internet-connected device (mobile phone, desktop computer, laptop, etc.) to distinguish COVID-19 from viral pneumonia, bacterial pneumonia, and healthy controls. This web-based system was developed with the help of the Python Flask Library and JavaScript, with the HTML5 engine.[12] The system has 2 language options: English and Turkish. When LUS videos of people with suspected COVID-19 are uploaded, the developed system can detect COVID-19 in a few minutes or less. The system consists of 3 parts. The first section contains a brief description of the system. In the second part, when the user uploads the LUS video to the system and clicks on the "analyze" button, the classification estimate is displayed in the third part. Video files with .mov, .mp4, or .avi extensions are supported by the system. The computer-aided diagnostic tool developed can be accessed at http://biostatapps.inonu.edu.tr/CVSY/. The main menu of the developed web-based system is as in Figure 2.

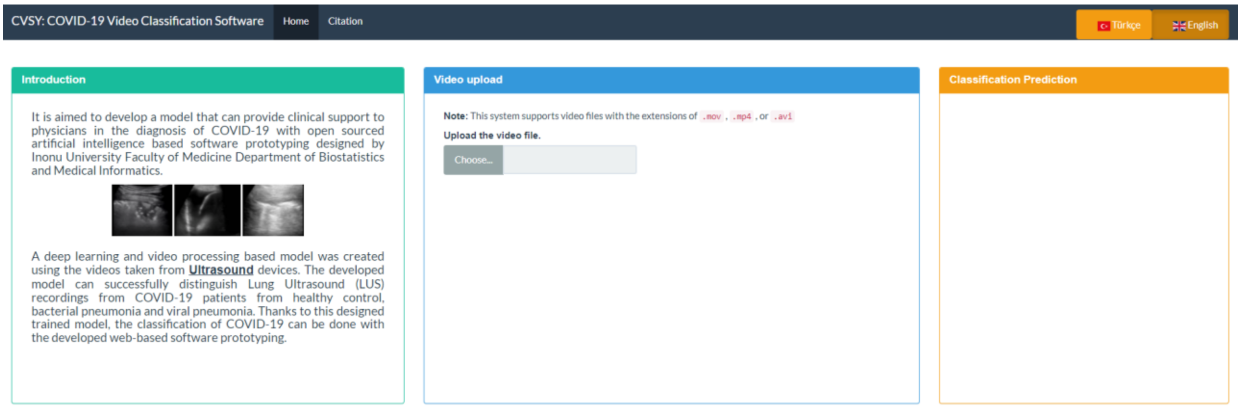

FIGURE 2: Main menu of the developed web-based system.

RESULTS

As a result of the video processing stage; 300 image frames belonging to each class were obtained (total 1,200). An example of the image frames obtained from healthy, COVID-19, bacterial pneumonia and viral pneumonia patients are as in Figure 3, Figure 4, Figure 5, and Figure 6, respectively.

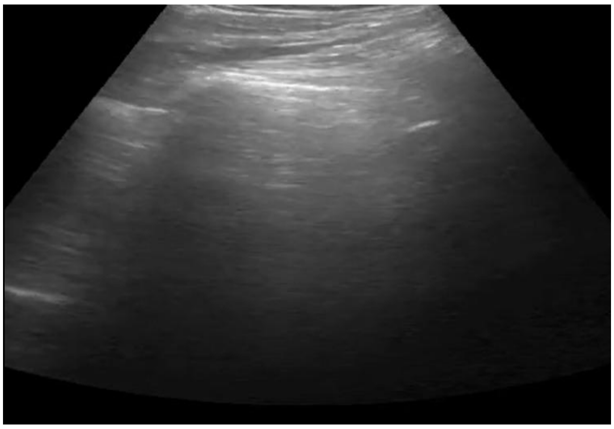

FIGURE 3: An example of the image frame obtained by processing from the ultrasound video of a healthy patient.

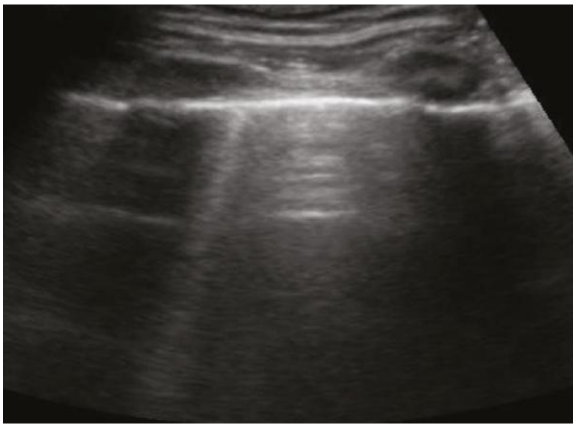

FIGURE 4: An example of the image frame obtained by processing from the ultrasound video of a COVID-19 patient.

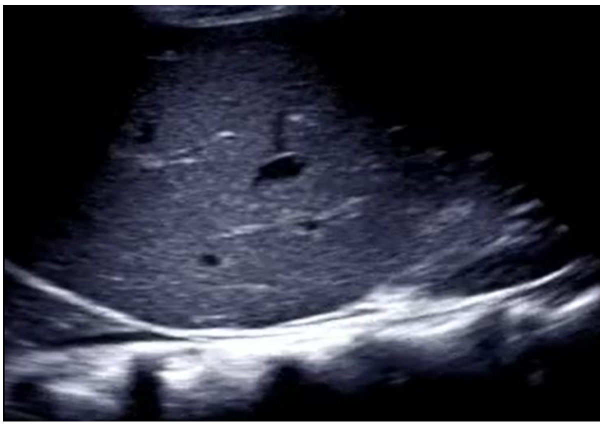

FIGURE 5: An example of the image frame obtained by processing from the ultrasound video of a bacterial pneumonia patient.

FIGURE 6: An example of the image frame obtained by processing from the ultrasound video of a viral pneumonia patient.

After training the CNN model videos created, he correctly estimated 52 in the healthy class for the test set (n=60 in each group), 53 in the COVID-19 class, 55 in the viral pneumonia class, and 52 in the bacterial pneumonia class.

When performance criteria for the healthy control class are taken into account, accuracy was 93.39% (90.25%-96.53%), precision was 86.67% (82.37%-90.97%), sensitivity was 88.14% (84.04%-92.23%), specificity was 95.24% (92.54%-97.93%), F1-score was 87.39% (83.2%-91.59%) and MCC was 82.92% (78.16%-87.68%).

When performance criteria for the COVID-19 class are taken into account, accuracy was 93.39% (90.25%-96.53%), precision was 88.33% (84.27%-92.39%), and sensitivity was 86.89% (82.61%-91.53%), specificity was 95.78% (93.24%-98.33%), F1-score was 87.6% (83.43%-91.77%) and MCC was 83.1% (78.36%-87.85%).

When performance criteria for viral pneumonia class are taken into account, accuracy was 93.39% (90.25%-96.53%), precision was 91.67% (88.17%-95.16%), sensitivity was 84.62% (80.05%-89.18%), specificity was 96.91% (94.73%-99.1%), F1-score was 88% (83.89%-92.11%) and MCC was 83.58% (78.89%-88.27%).

When performance criteria for the bacterial pneumonia class are taken into account, accuracy was 95.07% (92.33%-97.81%), precision was 86.67% (82.37%-90.97%), sensitivity was 94.55% (91.67-97.42), specificity was 95.24% (92.54-97.93), F1-score was 90.43% (86.71%-94.16%) and MCC was 87.27% (83.05%-91.49%). The performance criteria for the classes in the developed model are given in Table 2.

TABLE 2: Performance criteria of the CNN model for healthy control, COVID-19, viral pneumonia and bacterial pneumonia classes.

Metric	Healthy control	COVID-19	Viral pneumonia	Bacterial pneumonia
	Prediction value (95% CI)	Prediction value (95% CI)	Prediction value (95% CI)	Prediction value (95% CI)
Accuracy	93.39 (90.25-96.53)	93.39 (90.25-96.53)	93.39 (90.25-96.53)	95.07 (92.33-97.81)
Precision	86.67 (82.37-90.97)	88.33 (84.27-92.39)	91.67 (88.17-95.16)	86.67 (82.37-90.97)
Sensitivity	88.14 (84.04-92.23)	86.89 (82.61-91.16)	84.62 (80.05-89.18)	94.55 (91.67-97.42)
Specificity	95.24 (92.54-97.93)	95.78 (93.24-98.33)	96.91 (94.73-99.1)	95.24 (92.54-97.93)
F1-score	87.39 (83.2-91.59)	87.6 (83.43-91.77)	88.0 (83.89-92.11)	90.43 (86.71-94.16)
MCC	82.92 (78.16-87.68)	83.1 (78.36-87.85)	83.58 (78.89-88.27)	87.27 (83.05-91.49)

CI: Confidence interval; MCC: Matthews' correlation coefficient.

The healthy control rate for COVID-19 and viral pneumonia was estimated to be 93.39%, and 95.07% for bacterial pneumonia. The proposed system is able to successfully distinguish COVID-19 according to the uploaded ultrasound video. Classification estimates of ultrasound videos of healthy, COVID-19, bacterial pneumonia and viral pneumonia patients uploaded to the system are given in Figure 7, Figure 8, Figure 9, and Figure 10, respectively.

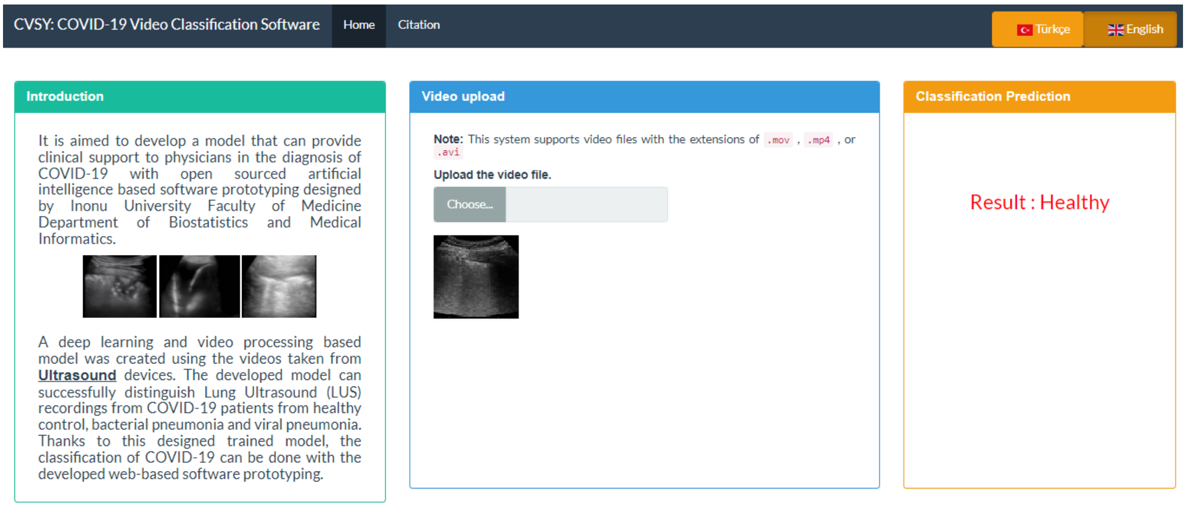

FIGURE 7: Prediction results of lung ultrasound video of healthy patient.

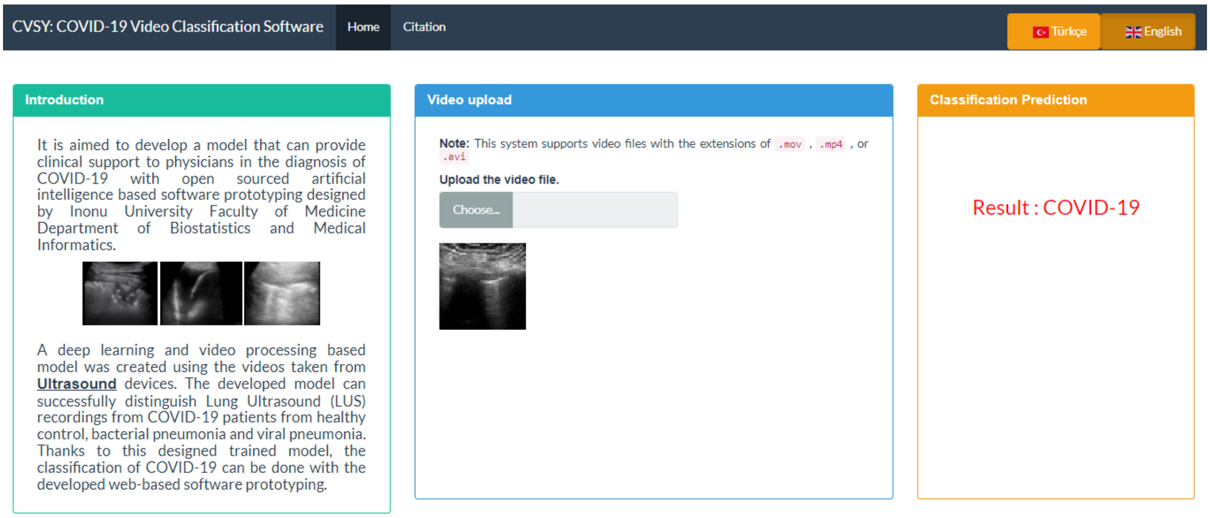

FIGURE 8: Prediction results of lung ultrasound video of COVID-19 patient.

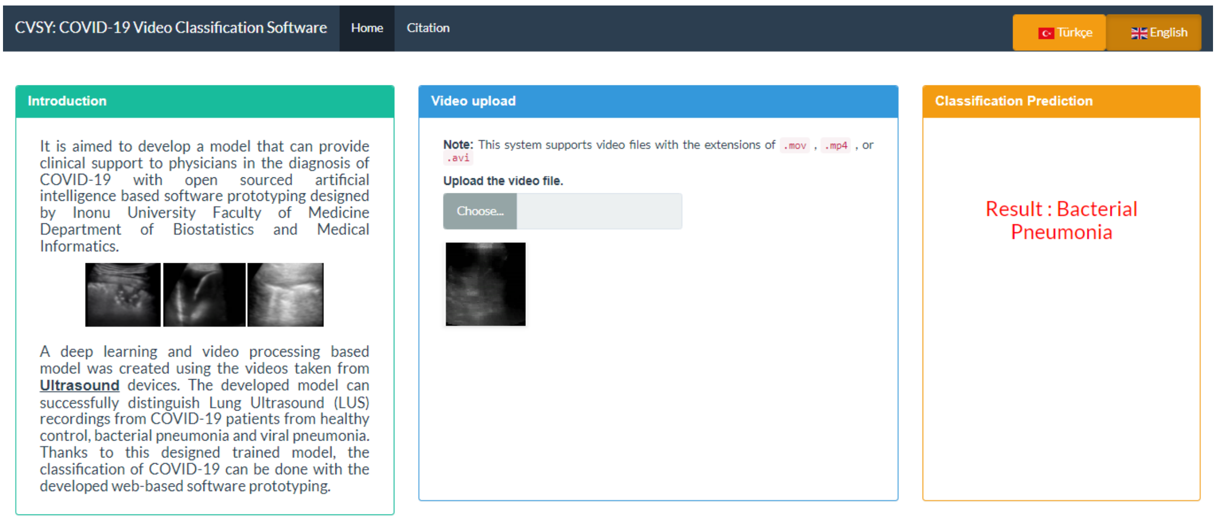

FIGURE 9: Prediction results of lung ultrasound video of bacterial pneumonia patient.

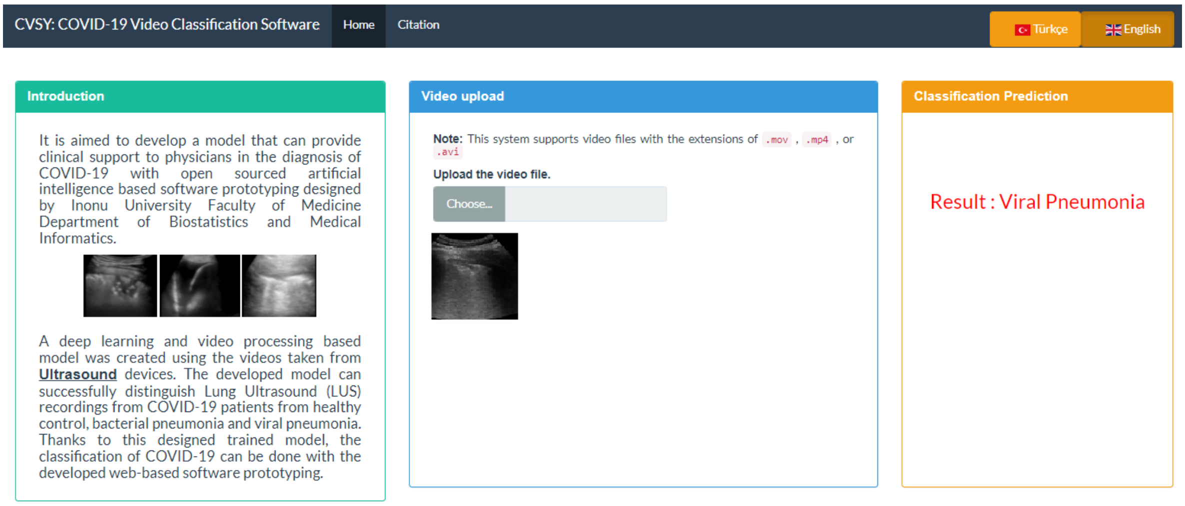

FIGURE 10: Prediction results of lung ultrasound video of viral pneumonia patient.

DISCUSSION

AI-powered systems can find significant links in unprocessed data and can be used in practically every aspect of medicine and epidemiology, including drug research, treatment decisions, patient care, and financial and operational decisions. AI allows healthcare providers to readily solve complicated problems that would be difficult, time-consuming, or inefficient to solve on their own.[13-19]

COVID-19 is a longstanding threat to healthcare systems and the economies of nations. Millions of people around the world have died due to COVID-19. Most of the deaths are caused by respiratory failure, which causes the loss of other organs. As there are many emergencies, hospital capacities are full and clinicians have limited time. For this reason, clinical decision support systems are needed. Combining medical imaging methods with AI technologies is clinically important, as speed, accessibility, and ease of implementation are crucial in clinical diagnosis of the current state of COVID-19.[1]

In this study, a successful CNN architecture was created to distinguish between COVID-19, viral pneumonia, bacterial pneumonia, and healthy controls based on LUS videos. The model created classified COVID-19 with 93.39%, viral pneumonia with 93.39%, bacterial pneumonia with 95.07% accuracy, and healthy controls with 93.39% accuracy in the test set. The sensitivity criterion from the additional CNN model is another important result. A higher sensitivity value means a lower false negative (FN) value. A low FN value minimizes overlooked cases of COVID-19 or pneumonia (FN).

Many published studies on COVID-19 prediction have been reported using different structures of CNN models. In a study using the X-ray image data set in the literature, CNN, CNN/random forest, and CNN-support vector machine (SVM) methods were used in a study and obtained from CNN with the highest accuracy rate of 95.2%.[20] In another study, 95.18%, 94.39%, 95.75%, and 96.49% accuracy rates were obtained using the combination of MobileNet, ResNet50, InceptionV3, and InceptionV3 and MobileNet models, respectively.[21] In a study using the ResNet18, ResNet50, ResNet101, VGG16, and VGG19 models in COVID-19 X-ray scanning image data sets, a SVMs classifier was created with some core functions to classify features. The ResNet50 model and the SVM classifier achieved an accuracy rate of 94.7%, the highest of all the results.[22]

In a different COVID-19 X-ray image data set, different CNN models (AlexNet, VGG19, ResNet, and SqueezeNet) have been created for transfer learning, called DeTraC. DeTraC achieves a 93.1% accuracy rate in detecting COVID-19.[23] In a study, 94.39% accuracy, 82.28% accuracy, and 76.27% sensitivity values were obtained with the ResNeXt (MCRFNet) model based on ultrasound images.[24] In another study, for the automatic detection of COVID-19 from the LUS imaging data set, a deep CNN (POCOVID-Net) was trained and 89% accuracy was achieved.[25]

Many studies in the literature have produced outstanding results for COVID-19 prediction. However, many of these studies have classified positive and negative samples, and the development of web-based clinical decision support systems for the models created has also been limited. A significant difference between the current study and similar studies in the literature is that the developed system can predict viral pneumonia and bacterial pneumonia in addition to COVID-19.

As a result, this study is one of the few studies that can distinguish between COVID-19, viral pneumonia, bacterial pneumonia, and healthy controls from LUS videos and give prediction results in a matter of seconds. With the effective use of the proposed AI-based system, it is expected to support the diagnosis processes of the disease and reduce the possible financial burden and inappropriate medical procedures. The additionally developed system significantly affects the current approach focused on radiology and can be a useful tool to help healthcare professionals and radiologists detect, diagnose, and track cases of COVID-19, viral pneumonia, and bacterial pneumonia.

CONCLUSION

A highly successful deep learning model based on LUS videos was developed, as well as a computer-aided, quick, free, and web-based computer-aided diagnostic tool. The web-based system developed in the study is estimated to provide support to physicians in clinical decision-making for the diagnosis of COVID-19, viral pneumonia, and bacterial pneumonia.

Conflict of Interest

No conflicts of interest between the authors and/or family members of the scientific and medical committee members or members of the potential conflicts of interest, counseling, expertise, working conditions, share holding and similar situations in any firm.

Source of Finance

During this study, no financial or spiritual support was received neither from any pharmaceutical company that has a direct connection with the research subject, nor from a company that provides or produces medical instruments and materials which may negatively affect the evaluation process of this study.

This study was approved way İnönü University Scientific Research Projects Coordination Unit within the scope of TYL-2021-2539 (ID: 2539) numbered research project. For this reason, we would like to thank İnönü University Scientific Research Projects Coordination Unit for their support.

Authorship Contributions

***Idea/Concept:** Burak Yağın, Emek Güldoğan, Cemil Çolak; **Design:** Burak Yağın, Emek Güldoğan; **Control/Supervision:** Emek Güldoğan, Cemil Çolak; **Data Collection and/or Processing:** Burak Yağın, Emek Güldoğan; **Analysis and/or Interpretation:** Burak Yağın, Emek Güldoğan, Cemil Çolak; **Literature Review:** Burak Yağın, Emek Güldoğan; **Writing the Article:** Burak Yağın, Emek Güldoğan, Cemil Çolak; **Critical Review:** Emek Güldoğan, Cemil Çolak; **References and Fundings:** Emek Güldoğan; **Materials:** Burak Yağın, Emek Güldoğan.*

REFERENCES

1. Yağın FH, Güldoğan E, Ucuzal H, Çolak C. A Computer-assisted diagnosis tool for classifying COVID-19 based on chest X-Ray images. Konuralp Medical Journal. 2021;13(S1):438-45. [Crossref]
2. Muhammad G, Shamim Hossain M. COVID-19 and non-COVID-19 classification using multi-layers fusion from lung ultrasound images. Inf Fusion. 2021;72:80-8. [Crossref] [PubMed] [PMC]
3. Hassantabar S, Stefano N, Ghanakota V, Ferrari A, Nicola GN, Bruno R, et al. Coviddeep: Sars-cov-2/covid-19 test based on wearable medical sensors and efficient neural networks. arXiv preprint arXiv. 2020;200710497. [Crossref]
4. Ai T, Yang Z, Hou H, Zhan C, Chen C, Lv W, et al. Correlation of chest CT and RT-PCR testing for coronavirus disease 2019 (COVID-19) in China: A report of 1014 cases. Radiology. 2020;296(2):E32-E40. [Crossref] [PubMed] [PMC]

5. Chung M, Bernheim A, Mei X, Zhang N, Huang M, Zeng X, et al. CT imaging features of 2019 novel coronavirus (2019-nCoV). Radiology. 2020;295(1):202-7. [Crossref] [PubMed] [PMC]
6. Roy S, Menapace W, Oei S, Luijten B, Fini E, Saltori C, et al. Deep learning for classification and localization of COVID-19 markers in point-of-care lung ultrasound. IEEE Trans Med Imaging. 2020;39(8):2676-87. [Crossref] [PubMed]
7. Mahmud T, Rahman MA, Fattah SA. CovXNet: A multi-dilation convolutional neural network for automatic COVID-19 and other pneumonia detection from chest X-ray images with transferable multi-receptive feature optimization. Comput Biol Med. 2020;122:103869. [Crossref] [PubMed] [PMC]
8. Fan L, Li D, Xue H, Zhang L, Liu Z, Zhang B, et al. Progress and prospect on imaging diagnosis of COVID-19. Chin J Acad Radiol. 2020:1-10. [Crossref] [PubMed] [PMC]
9. Amatya Y, Rupp J, Russell FM, Saunders J, Bales B, House DR. Diagnostic use of lung ultrasound compared to chest radiograph for suspected pneumonia in a resource-limited setting. Int J Emerg Med. 2018;11(1):8. [Crossref] [PubMed] [PMC]
10. Born J, Wiedemann N, Brändle G, Buhre C, Rieck B, Borgwardt K. Accelerating covid-19 differential diagnosis with explainable ultrasound image analysis. arXiv preprint arXiv. 2020;200906116. [Crossref]
11. Yağın FH, Güldoğan E, Çolak C. A web-based software for the calculation of theoretical probability distributions. The Journal of Cognitive Systems. 2021;6(1):44-50. [Crossref]
12. Yağın B, Yağın FH, Gözükara Bag HG, Çolak C. A web-based software for reporting guidelines of scientific researches. The Journal of Cognitive Systems. 2021;6(1):39-43. [Crossref]
13. Yağın FH, Yağın B, Çolak C. An interactive web-based software for epidemiological research designs. Middle Black Sea Journal of Health Science. 2021;7(1):122-31. [Crossref]
14. Yılmaz R, Yağın FH. Early detection of coronary heart disease based on machine learning methods. Medical Records. 2022;4(1):1-6. [Link]
15. Yılmaz R, Yağın FH. A comparative study for the prediction of heart attack risk and associated factors using MLP and RBF neural networks. The Journal of Cognitive Systems. 2021;6(2):51-4. [Link]
16. Perçin İ, Yağın FH, Güldoğan E, Yoloğlu S. ARM: An interactive web software for association rules mining and an application in medicine. 2019 International Artificial Intelligence and Data Processing Symposium (IDAP); IEEE. 2019. [Crossref]
17. Perçin İ, Yağın FH, Arslan AK, Çolak C. An interactive web tool for classification problems based on machine learning algorithms using java programming language: data classification software. 2019 3rd International Symposium on Multidisciplinary Studies and Innovative Technologies (ISMSIT); IEEE. 2019. [Crossref]
18. Yagin FH, Kucukkakcali Z, Cicek IB, Gozukara Bag HG. The effects of variable selection and dimension reduction methods on the classification model in the small round blue cell tumor dataset. Middle Black Sea Journal of Health Science. 2021;7(3):390-6. [Crossref]
19. Yagin FH, Cicek IB, Kucukakcali Z. Classification of stroke with gradient boosting tree using smote-based oversampling method. Medicine. 2021;10(4):1510-5. [Crossref]
20. Kang Z, Li X, Zhou S. Recommendation of low-dose CT in the detection and management of COVID-2019. Eur Radiol. 2020;30(8):4356-7. [Crossref] [PubMed] [PMC]
21. Ahmad F, Farooq A, Ghani MU. Deep ensemble model for classification of novel coronavirus in chest X-ray images. Comput Intell Neurosci. 2021;2021:8890226. [Crossref] [PubMed] [PMC]
22. Ismael AM, Şengür A. Deep learning approaches for COVID-19 detection based on chest X-ray images. Expert Syst Appl. 2021;164:114054. [Crossref] [PubMed] [PMC]
23. Abbas A, Abdelsamea MM, Gaber MM. Classification of COVID-19 in chest X-ray images using DeTraC deep convolutional neural network. Appl Intell (Dordr). 2020:1-11. [Crossref] [PubMed] [PMC]
24. Hu Z, Liu Z, Dong Y, Liu J, Huang B, Liu A, et al. Evaluation of lung involvement in COVID-19 pneumonia based on ultrasound images. Biomed Eng Online. 2021;20(1):27. [Crossref] [PubMed] [PMC]
25. Born J, Brändle G, Cossio M, Disdier M, Goulet J, Roulin J, et al. POCOVID-Net: automatic detection of COVID-19 from a new lung ultrasound imaging dataset (POCUS). arXiv preprint arXiv. 2020;200412084. [Link]