MEDICAL RECORDS-International Medical Journal

Research Article

Development of Artificial Intelligence Based Clinical Decision Support System on Medical Images for the Classification of COVID-19

Cemil Colak[1], Ahmet Kadir Arslan[1], Hasan Ucuzal[1], Adem Kose[2], Ismail Okan Yildirim[3], Emek Guldogan[1], M. Cengiz Colak[4]

[1]Inonu University, Faculty of Medicine, Department of Biostatistics and Medical Informatics, Malatya, Türkiye
[2]Inonu University, Faculty of Medicine, Department of Internal Diseases, Malatya, Türkiye
[3]Inonu University, Faculty of Medicine, Department of Radiology, Malatya, Türkiye
[4]Inonu University, Faculty of Medicine, Department of Cardiovascular Surgery, Malatya, Türkiye

Abstract

Aim: The first imaging method to play an vital role in the diagnosis of COVID-19 illness is the chest X-ray. Because of the abundance of large-scale annotated picture datasets, convolutional neural networks (CNNs) have shown considerable performance in image recognition/classification. The current study aims to construct a successful deep learning model that can distinguish COVID-19 from healthy controls using chest X-ray images.

Material and Methods: The dataset in the study consists of subjects with 912 negative and 912 positive PCR results. A prediction model was built using VGG-16 with transfer learning for classifying COVID-19 chest X-ray images. The data set was split at random into 80% training and 20% testing groups.

Results: The accuracy, F1 score, sensitivity, specificity, positive and negative values from the model that can successfully distinguish COVID-19 from healthy controls are 97.3%, 97.3%, 97.8%, 96.7%, 96.7%, and 97.8% regarding the testing dataset, respectively.

Conclusion: The suggested technique might greatly improve on current radiology-based methodologies and serve as a beneficial tool for clinicians/radiologists in diagnosing and following up on COVID-19 patients.

Keywords: COVID-19, image processing, convolutional neural networks, classification

INTRODUCTION

The new Coronavirus pneumonia, which arose in Wuhan, China, in December 2019 and was subsequently called COVID-19, is extremely infectious and pathogenically distinct from SARS-CoV, avian flu, influenza, MERS-CoV and other widespread respiratory viruses (1,2). Later, within a few months, this illness spread quickly from one nation to another, and COVID-19 has been notified a global pandemic by the World Health Organization (WHO) (3,4). With the outbreak of COVID-19, many undesirable situations such as economic crisis, loss of life, etc., have emerged. Furthermore, no clinically licensed antiviral medication or vaccination for COVID-19 has been established (5).

COVID-19 clinical symptoms include muscular soreness, shortness of breath, fever, cough, sore throat, headache, lethargy, and others. If a person with similar symptoms is encountered, it is tested with real-time reverse transcriptase-polymerase chain reaction (RT-PCR), which is employed to determine viral nucleic acids and is considered the gold test to diagnose such viruses (6). However, this procedure often takes many hours, if not days, to diagnose the illness. In addition, the sample must be tested more than once at regular intervals for the results to be reliable. So in the case of a severe infection, this process can be harmful. Chest X-rays may thus be a less expensive, quicker, and more validated to routine COVID-19 testing (7-9). On the other hand, early diagnosis of COVID-19 is required to limit the

CITATION
Colak C, Arslan AK, Ucuzal H, et al. Development of Artificial Intelligence Based Clinical Decision Support System on Medical Images for the Classification of COVID-19. Med Records. 2023;5(1):20-3. DOI: 10.37990/medr.1130194

Received: 13.06.2022 **Accepted:** 31.07.2022 **Published:** 03.01.2023
Corresponding Author: Cemil Colak, Inonu University, Faculty of Medicine, Department of Biostatistics and Medical Informatics, Malatya, Türkiye, **E-mail**: cemilcolak@yahoo.com

spread of the disease and hinder transmission by isolating infected individuals and tracking and quarantining close contacts. In addition, accurate monitoring of the course of infection in infected patients is an essential element in managing the disease. Thus, chest X-ray medical imaging plays a vital role in confirming a positive diagnosis for COVID-19 pneumonia and monitoring the course of the disease (10,11).

With the rapidly developing computer technology, image processing technology is commonly utilized in the field of medicine to support medical diagnoses. Artificial intelligence (AI) is a subfield of computer science that can evaluate huge amounts of medical/clinical data. Thanks to its ability to identify meaningful associations from a dataset, AI can be used to predict diagnosis, treatment, and outcome in many clinical scenarios (7,12-14). Deep learning (DL) networks are mathematically built networks that are taught to categorize illnesses into one of many subgroups using particular inputs. Rapid DL models must be trained and evaluated in the present COVID-19 epidemic to give quick support and reliable findings. So far, the RT-PCR test's inadequacy, high cost, and delay to get findings have been major constraints. Deep learning combined with chest X-ray pictures may assist address such issues and overcome the shortcomings of RT-PCR (15,16).

The current study aims to create a successful DL model that can distinguish COVID-19 from healthy controls using chest X-ray images. Thanks to the created model, clinicians and radiologists can use it as an auxiliary tool in diagnosing and following COVID-19 infection to screen patients in emergency medical support services.

MATERIAL AND METHOD

Data collection and features

The current study employed an open-source dataset containing augmented X-ray images for COVID-19 (https://data.mendeley.com/datasets/2fxz4px6d8). The relevant dataset contains 1824 X-ray scan images, of which 912 are COVID-19 positive and 912 COVID-19 negative patients based on the RT-PCR test results. Figure 1 presents the sample X-ray images of COVID-19 negative and positive individuals in the relevant data set (17).

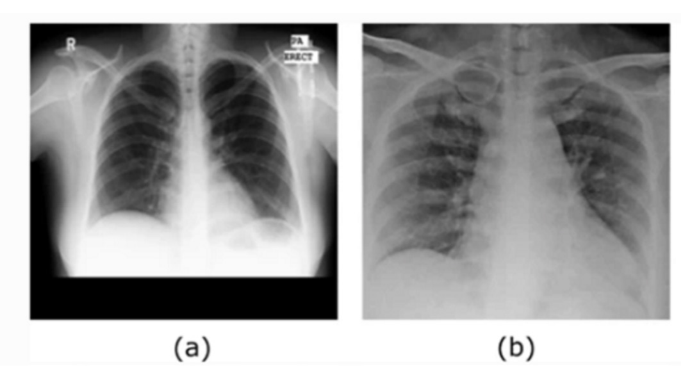

Figure 1. a) COVID-19 Negative X-ray image, **b)** COVID-19 Positive X-ray image

Convolutional Neural Networks (CNNs)

CNNs have gained popularity in machine learning in recent years because to their great predictive capacity in classification tasks requiring extremely high dimensional data and hundreds of distinct classes. CNN is a simple expansion of the multilayer perceptron (MLP) (18). The interest in CNN started with the AlexNet (Krizhevsky et al. 2012) deep learning architecture winning the 2012 ILSVRC ImageNet Large-scale image recognition competition held in 2012. CNN recognizes significant traits without human intervention and is computationally efficient. It has three fundamental layers: the convolution layer, the subsampling layer, and the fully linked layer. Depending on the implementation, the convolution and subsampling layers are iterated and eventually linked to the fully related layer. Utulizing a collection of filter masks, the convolution layer transmits 2D convolution on the pictures in the relevant dataset. All negative values are converted to zero via a non-linear function known as the linear unit (ReLU). The downsampling layer conducts curved image downsampling, lowering spatial resolution. Maximum pooling is the most often utilized subsampling method. Subsampling's purpose is to make the network more resilient and immutable. With ReLU and downsampling, many convolution rounds are performed. Flattening and connecting the last convolutional layer to the fully related layer. This information is subsequently passed on to the categorization layer (7,19).

Transfer Learning and VGG-16

CNNs are recognized to provide excellent results when given a big amount of data with thousands of examples. Because this is not realistic in most circumstances, transfer learning is utilized, in which a previously trained network is taught employing data from the novel dataset. Transfer learning has the significant advantage of reducing the time required to construct and train an algorithm by reusing the weights of previously generated model(s) (20).

VGG-16 is one of the deep CNN networks that aired in 2015 (21). VGG stands for "Visual Geometry Group" in VGG-16. The University of Oxford's Visual Geometry Group came up with the concept for the bespoke 16-layer mesh and trained it using the ImageNet dataset. A conventional VGG-16 model is made up of numerous 33 core size filters that improve the depth of the mesh and assist the model in learning more complicated characteristics. Three fully linked layers follow the convolutional layers in VGG (22).

Modeling and performance assessment

All coding was performed on Intel (R) Xeon (R) Gold 5122 server with 1.5 TB RAM, 16 core @ 3.60 GHz CPU, and Tesla P40 24GB GPU on a virtual server with Python software. Keras and Tensorflow 2.0 libraries in Python programming language were used for program coding. The input size of X-ray images was initially resized to 224x224 pixels for compatibility with deep learning models. 80% of the image dataset, the training set, and 20% of the image dataset were randomly split as the testing set to validate the deep learning model. Transfer learning was performed by a pre-trained VGG-16 model in the study. Softmax was used as the activation function. In the model, the lot size was set to 16, the learning rate to 0.0001, and the period value to 20. Accuracy, F1 score, sensitivity, specificity, positive and negative predictive values (PPV and NPV) were estimated to evaluate performance of the algorithm(s) (23).

RESULTS

The dataset in the study consists of the subjects with 912 negative and 912 positive PCR results. The relevant dataset includes 1824 X-ray scan pictures, 912 of which are from patients with COVID-19, and 912 of which are from patients without COVID-19. Table 1 presents the confusion matrix in the testing dataset for the VGG-16 model.

Table 1. Performance measures obtained in the testing dataset

Test / True	True Positive	True Negative	Total
Test Positive	178	6	184
Test Negative	4	177	181
Total	182	183	365

Table 2 presents the accuracy, F1 score, sensitivity, specificity, NPV and PPV obtained from the VGG-16 model and their confidence intervals regarding the testing dataset.

The accuracy, F1 score, sensitivity, specificity, PPV and NPV from the model that can successfully distinguish COVID-19 from healthy controls are 97.3%, 97.3%, 97.8%, 96.7%, 96.7%, and 97.8% regarding the testing dataset, respectively.

Table 2. Performance metrics obtained in the testing dataset

Metric	Value	95% Confidence Interval Lower Limit	95% Confidence Interval Upper Limit
Accuracy	0.973	0.956	0.989
F1 Score	0.973	0.956	0.989
Sensitivity	0.978	0.945	0.994
Specificity	0.967	0.93	0.988
PPV	0.967	0.93	0.988
NPV	0.978	0.944	0.994

DISCUSSION

Medical imaging methods such as computed tomography (CT) and X-rays are critical in the worldwide battle against COVID-19, while artificial intelligence technologies enhance the power of imaging instruments and aid specialized clinicians. By accurately identifying infections on X-ray and CT images, work efficiency can be increased and subsequent evaluations facilitated. Artificial intelligence is a system that is quickly being utilized in various sectors to increase performance, accuracy, time efficiency, and cost efficiency all at the same time. In medicine, this technology is used for better patient care through early diagnosis and treatment, improved workflow, reduced medical errors, reduced medical costs, and reduced morbidity and mortality (24,25). It is widely recognized that AI technologies can potentially play a vital role in facilitating and expediting the classification of COVID-19 patients.

COVID-19 infects millions of people all over the world and still causes the death of hundreds of thousands of individuals. A major problem in controlling the spread of this disease is the inefficiency and lack of medical testing and other diagnostic methods. Recently, there has been a substantial surge in attempts to build AI and DL-based systems to diagnose COVID-19 based on several medical imaging (X-ray, CT, MR, and so on). A machine learning-based medical assistance platform may help radiation physicians make clinical choices as well as screen, diagnose, and treat patients. In a study, Xception and Xception + SVM models were used on 1102 chest X-ray images, and the diagnostic accuracy values were 96.75% and 99.33%, respectively (26). Another research contrasted deep learning-based feature extraction, which is often used to construct an automated model of COVID-19 categorization. MobileNet, DenseNet, Xception, ResNet, InceptionV3, InceptionResNetV2, VGGNet, and NASNet were opted from a pool of deep CNNs to achieve the most accurate feature. The models' performance was verified using a publicly accessible COVID-19 data of chest X-ray and CT images. While the deep learning model created with the bagging tree classifier DenseNet121 feature extractor has the highest accuracy with 99.0% classification accuracy, the deep learning model created with the ResNet50 feature extractor with LightGBM classifier has the second-highest accuracy with 98.0% classification accuracy (5). Finally, in a study by Rasheed et al., the developed models that automatically diagnose COVID-19 infection with high oerformance metrics from X-ray images with Logistic Regression (LR) and CNNs, which are frequently utulized ML methods. The models were developed using 500 X-ray images, and a dimensionality reduction method based on principal component analysis (PCA) was also used to accelerate the learning process and boost prediction accuracy by selecting highly differentiating properties. According to the experimental data, the LR and CNN models for positive case identification had an overall accuracy of 95.2 percent to 97.6 percent without PCA and 97.6% to 100% with PCA, respectively (27). The present study intends to assess the prediction performance and classification of COVID-19 disease using transfer learning and VGG-16 with X-ray images. The model predicted COVID-19 infection with 97.3% accuracy. In addition, in the model test set, F1-score, sensitivity, specificity, PPV and NPV were obtained as 97.3%, 97.8%, 96.7%, 96.7%, and 97.8%, respectively.

CONCLUSION

Given the high classification rate achieved for the diagnosis of COVID-19, the resulting model could be advantageous in assisting in the screening of patients in emergency medical support services and assisting clinicians for emergencies. Overall, It is concluded that the suggested technique may greatly enhance the current radiology- established methodology and may be a useful tool for medical practitioners/radiologists to assist them in diagnosing and following up on COVID-19 patients.

Acknowledgment: *We would like to thank Inonu University Scientific Research Projects Coordination Unit for supporting our project with TOA-2020-2204 code.*

Financial disclosures: *The authors declared that this study was supported by Inonu University Scientific Research Projects Coordination Unit .*

Conflict of Interest: *The authors declare that they have no competing interest.*

Ethical approval: *Ethical approval was not obtained in this study as open source datasets were used.*

REFERENCES

1. Guo H, Zhou Y, Liu X, Tan J. The impact of the COVID-19 epidemic on the utilization of emergency dental services. J Dental Sci. 2020;15:564-7.
2. Akbulut S, Yağın FH, Çolak C. Prediction of COVID-19 based on genomic biomarkers of metagenomic next-generation sequencing (mNGS) Data using artificial intelligence technology. Erciyes Med J. 2022;44:544–8.
3. Cansel N, Karaca Y, Yağin FH. Evaluation of Coronavirus Phobia and Depression in Patients With Cardiovascular Disease. Kahramanmaraş KSU Medical Journal.17:163-71.
4. Yaylaci S, Dheir H, Şenocak D, et al. The effects of favipiravir on hematological parameters of covıd-19 patients. Revista Associação Méd Brasileira. 2020;66:65-70.
5. Kassania SH, Kassanib PH, Wesolowskic MJ, et al. Automatic detection of coronavirus disease (COVID-19) in X-ray and CT images: a machine learning based approach. Biocybern Biomed Eng. 2021;41:867-79.
6. Huang P, Liu T, Huang L, et al. Use of chest CT in combination with negative RT-PCR assay for the 2019 novel coronavirus but high clinical suspicion. Radiology. 2020;295:22-3.
7. Perçin İ, Yağin H, Arslan AK, Çolak C, editors. 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); 2019: IEEE.
8. Aggarwal P, Mishra NK, Fatimah B, et al. COVID-19 image classification using deep learning: Advances, challenges and opportunities. Comput Bio Med. 2022:144:105350.
9. Madaan V, Roy A, Gupta C, et al. XCOV Net: chest X-ray image classification for COVID-19 early detection using convolutional neural networks. New Gener Comput. 2021;39:583-97.
10. Reshi AA, Rustam F, Mehmood A, et al. An efficient CNN model for COVID-19 disease detection based on X-ray image classification. Complexity. 2021;1-12.
11. Al-Zubaidi EA, Mijwil MM. Medical image classification for coronavirus disease (COVID-19) using convolutional neural Networks. Iraqi Jo Sci. 2021:2740-7.
12. Perçın İ, Yağin FH, Güldoğan E, et al. ARM: an interactive web software for association rules mining and an application in medicine. 2019 International Artificial Intelligence and Data Processing Symposium (IDAP); 2019: IEEE.
13. Yağin FH, Yağin B, Arslan AK, Çolak C. Comparison of performances of associative classification methods for cervical cancer prediction: observational study. Turk Clinics J Biostatistics. 2021;13.
14. Yilmaz R, Yağin FH. Early Detection of Coronary Heart Disease Based on Machine Learning Methods. Medical Records. 2022;4:1-6.
15. Yousri D, Abd Elaziz M, Abualigah L, et al. COVID-19 X-ray images classification based on enhanced fractional-order cuckoo search optimizer using heavy-tailed distributions. Applied Soft Computing. 2021;101:107052.
16. Apostolopoulos ID, Mpesiana TA. Covid-19: automatic detection from x-ray images utilizing transfer learning with convolutional neural networks. Phys Eng Sci Med. 2020;43:635-40.
17. Alqudah AM. Augmented COVID-19 X-ray images dataset. Mendeley Data, v4. 2020.
18. Yilmaz R, Yağin FH. A Comparative Study for the Prediction of Heart Attack Risk and Associated Factors Using MLP and RBF Neural Networks. J Cognitive Systems. 2021;6:51-4.
19. Theckedath D, Sedamkar R. Detecting affect states using VGG16, ResNet50 and SE-ResNet50 networks. SN Computer Sci. 2020;1:1-7.
20. Tammina S. Transfer learning using VGG-16 with deep convolutional neural network for classifying images. Int J Scientific Research Publications (IJSRP). 2019;9:143-50.
21. Simonyan K, Zisserman A. Very deep convolutional networks for large-scale image recognition. arXiv preprint arXiv:14091556. 2014.
22. Srivastava S, Kumar P, Chaudhry V, Singh A. Detection of ovarian cyst in ultrasound images using fine-tuned VGG-16 deep learning network. SN Computer Science. 2020;1:1-8.
23. Yasar S, Yagin FH, Arslan AK, et al. Interactive web-based software for evaluating diagnostic tests and roc curve analyses in health sciences. Annals Med Research. 2021;28:2012-8.
24. Paksoy N, Yağin FH. Artificial intelligence-based colon cancer prediction by identifying genomic biomarkers. Med Records. 2022;4:196-202.
25. Yağin FH, Güldoğan E, Ucuzal H, Çolak C. A Computer-Assisted Diagnosis Tool for Classifying COVID-19 based on Chest X-Ray Images. Konuralp Med J. 2021;13:438-45.
26. Wang D, Mo J, Zhou G,et al. An efficient mixture of deep and machine learning models for COVID-19 diagnosis in chest X-ray images. PloS One. 2020;15:e0242535.
27. Rasheed J, Hameed AA, Djeddi C, et al. A machine learning-based framework for diagnosis of COVID-19 from chest X-ray images. Interdiscip Sci. 2021;13:103-17.