RESEARCH ARTICLE | MARCH 27 2024

Detection of Covid-19 based on convolutional neural networks using pre-processed chest X-ray images

Arul Raj A. M. ; Sugumar R.; Padmkala S.; Jayant Giri ; Naim Ahmad ; Ahmed Said Badawy

AIP Advances 14, 035150 (2024)
https://doi.org/10.1063/5.0200397

AIP Advances ARTICLE pubs.aip.org/aip/adv

Detection of Covid-19 based on convolutional neural networks using pre-processed chest X-ray images

Cite as: AIP Advances 14, 035150 (2024); doi: 10.1063/5.0200397
Submitted: 26 January 2024 • Accepted: 8 March 2024 •
Published Online: 27 March 2024

View Online Export Citation CrossMark

Arul Raj A. M.,[1,a)] Sugumar R.,[1,b)] Padmkala S.,[1,c)] Jayant Giri,[2,d)] Naim Ahmad,[3,e)] and Ahmed Said Badawy[3,f)]

AFFILIATIONS

[1] Department of Computer and Science and Engineering, Saveetha School of Engineering (SSE), Saveetha Institute of Medical and Technical Sciences (SIMATS), Saveetha University, Chennai, India
[2] Department of Mechanical Engineering, Yeshwantrao Chavan College of Engineering, Nagpur, India
[3] College of Computer Science, King Khalid University, Alfara, Abha 61421, Saudi Arabia

[a)] arulrajam1003.sse@saveetha.com
[b)] sugumar.sse@saveetha.com
[c)] drspadmakala@gmail.com
[d)] **Author to whom correspondence should be addressed:** jayantpgiri@gmail.com
[e)] nagqadir@kku.edu.sa
[f)] bdwy@kku.edu.sa

ABSTRACT

The global catastrophe known as COVID-19 has shattered the world's socioeconomic structure. Effective and affordable diagnosis techniques are crucial for better COVID-19 therapy and the eradication of bogus cases. Due to the daily upsurge in cases, hospitals only have a small supply of COVID-19 test kits. The study describes a deep Convolutional Neural Network (CNN) design for categorizing chest x-ray images in the diagnosis of COVID-19. The lack of a substantial, high-quality chest x-ray picture collection made efficient and exact CNN categorization problematic. The dataset has been pre-processed using an image enhancement strategy to provide an effective training dataset for the proposed CNN model to achieve performance. The proposed model achieves 99.73% of accuracy, 98.95% of specificity, 99.47% of precision, 99.62% of sensitivity, and 98.71% of F1 score. A comparative study between the proposed model and numerous CNN-based COVID-19 detection algorithms is carried out to demonstrate that it outperforms other models. When evaluated on a separate dataset, the suggested model excelled over all other models, generally and explicitly.

I. INTRODUCTION

The emergence of COVID-19, caused by the novel coronavirus SARS-CoV-2, has triggered a global catastrophe of unprecedented proportions. Its rapid spread across continents has not only overwhelmed healthcare systems but also profoundly disrupted the world's socioeconomic structures. Effective and affordable diagnostic techniques have become paramount in managing the pandemic, ensuring appropriate therapy, and preventing the proliferation of false-positive cases. Among the daily upsurge in infection rates, healthcare facilities have grappled with the limited availability of COVID-19 test kits, exacerbating the challenges faced in curbing the virus's spread.

The COVID-19 pandemic has become one of the most serious concerns for public health in recent years.[1] In March 2020, the World Health Organization (WHO) proclaimed COVID-19 a global pandemic. Thousands of people have been impacted by the COVID-19 pandemic. It has an impact on both daily life and the world economy. Respiratory, gastric, and neurological symptoms may be brought on by COVID-19.[2] The most frequent symptoms include coughing, fever, and several respiratory infections. As a result, from a few hundred cases (mostly in China) in January 2020 with more than 42×10^6 cases globally distributed in November 2020.[3] As the number of COVID-19 infections increasing, there are 6.7×10^6 deaths reported until January 2023 as shown in Fig. 1.[4] Due to the lack of early detection methods globally and the presence of medical preconditions including cancer, chronic liver, lungs, renal disorders, and diabetes, COVID-19 is still a fatal disease. Real-time reverse transcription polymerase chain reaction (RT-PCR) is one of the most frequently utilized tests for COVID-19 detection.[5] Although RT-PCR detection methods are widely accessible worldwide, underdeveloped nations still lack the financial means to rapidly screen all of their citizens.[6] However, there are a few restrictions on this test. A few hours to two days are needed to find COVID-19. The test kit is also not generally accessible. In addition, it is not particularly trustworthy[7] since it has the potential to produce false negative results, misclassifying COVID-19 patients as unaffected and normal. As a result, the healthcare system and medical professionals are having significant difficulties combating this pandemic.

Patients with COVID-19 can have their lungs imaged using x rays and computed tomography (CT) scans. Lung imaging can show the geographical location of niduses and the severity of the infection. CT pictures are highly sensitive and have a quick turnaround time.[8] They are able to see how badly the lungs are infected. Numerous researchers have employed artificial intelligence and computer vision to categorize x ray or CT pictures based on the important COVID-19 properties. The COVID-19-free images and the COVID-19-infected images are separated into two categories. Other researchers separated images into COVID-19-infected, pneumonia-infected, and healthy groups.[9] Based on the characteristics of x ray or CT scans, some algorithms can determine the severity of the illness. This research aims to help doctors in precisely and rapidly diagnosing COVID-19.

Machine learning approaches have proved the usefulness and better performance of artificial intelligence (AI) in automated picture categorization problems, and it is currently being utilized to facilitate the diagnosis of several diseases.[10–14] In particular, Convolutional Neural Networks (CNNs) have already been commonly employed by the research community because it has been demonstrated to be incredibly effective in feature extraction and learning. Due to the accessibility of deep CNNs and the encouraging outcomes, they have demonstrated in various applications, deep learning approaches on chest x rays are becoming more and more popular. In addition, there is a wealth of information available for training various machine-learning models. The procedure has been greatly streamlined by the use of transfer learning technology, which allows a highly deep CNN network to be swiftly retrained using a relatively small number of images.

This research addresses a critical aspect of the battle against COVID-19 by proposing a deep CNN architecture for the classification of chest x-ray images to diagnose COVID-19. Accurate and efficient diagnosis through chest x-ray images holds immense promise as a complementary tool for COVID-19 detection, particularly in cases where molecular testing resources are scarce or when rapid diagnosis is imperative.

However, achieving a highly efficient and precise CNN classification model for COVID-19 diagnosis has been a formidable challenge, primarily due to the lack of a sufficiently large and high-quality chest x-ray image dataset. In response, this study employs a robust pre-processing and image enhancement approach to curate an effective training dataset for the proposed CNN model, thus ensuring its optimal performance.

Medical image enhancement is required to aid physicians in providing accurate disease diagnoses.[15,16] A variety of techniques are employed in the image enhancement process to enhance an image's aesthetic appeal, such as reducing blur and noise from the image to boost contrast and reveal more of the image's details. The primary

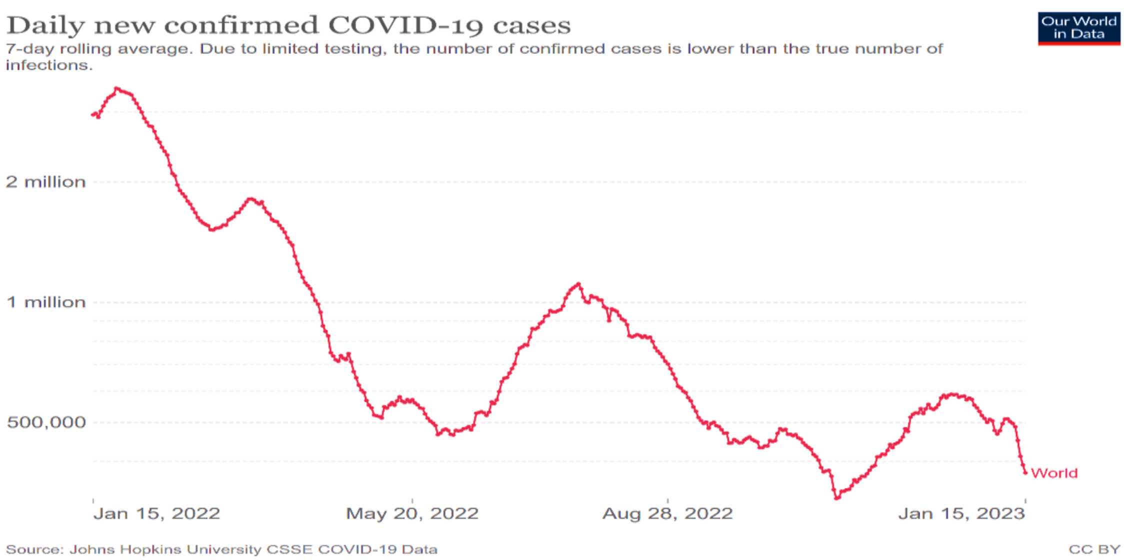


FIG. 1. Statistics of confirmed new COVID-19 cases from John Hopkins University.

goal of image enhancement is to increase interoperability or perception of image information for human viewers or feature extraction. By altering the input image's pixel intensity, enhancement produces an image that is qualitatively better than the original image. The information should not be changed during the image-enhancing procedure.

For the purpose of identifying COVID-19 from chest x ray (CXR), Oh *et al.*[17] employed gamma correction enhancement and Histogram Equalization (HE) approaches. For the diagnosis of COVID-19, they suggested a patch-based convolutional neural network technique with only a few trainable parameters, and it demonstrated 92.5% sensitivity. A three-channel technique and a VGG-19 pre-trained network are proposed by Heidari *et al.*[18] using 8474 CXR pictures that included COVID-19, community-acquired pneumonia, and normal patients. The augmented CXR and original images were employed in the three-channel technique, which successfully classified COVID-19 images with 94.5% accuracy. It can be concluded from the aforementioned studies, and several models are developed and validated using a small dataset. As a result, a large dataset may be used to examine image-enhancing approaches and compare their performance to that of the original x-ray image-based performance. Since the results cannot be guaranteed to be replicated when these models are tested on a larger dataset, it is challenging to characterize their findings.

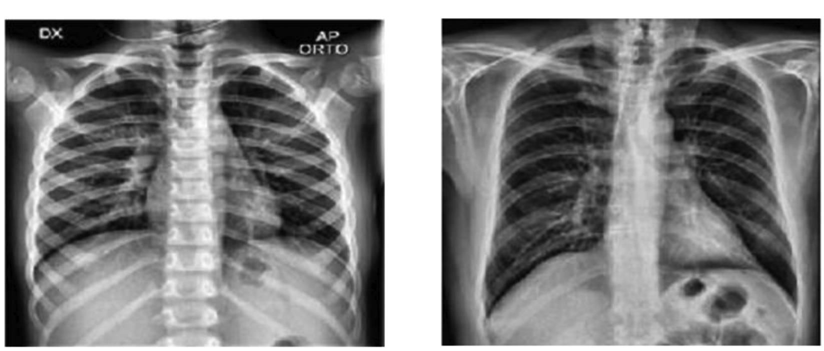
This research is arranged as follows: The recent research on COVID-19 detection based on CNN from CT scans or chest x-ray radiology images is summarized in Sec. II. Section III explains the proposed CNN model, and Sec. IV provides the dataset, results, and comparative analysis. Section V concludes with remarks and future perspectives.

In light of the ongoing battle against the pandemic and the pressing need for accurate and accessible diagnostic tools, our research contributes a significant step forward in the development of image processing solutions for COVID-19 detection, compared with other research solutions. The results presented herein offer not only a promising avenue for enhanced diagnostic accuracy but also a potential resource-efficient solution to alleviate the burden on healthcare systems worldwide.

II. RELATED WORKS

To better comprehend the subject under discussion and present the most recent information, this section gave an overview of various connected studies. One of the best deep learning (DL) models, convolutional neural networks (CNNs), have demonstrated their superiority to traditional approaches in several fields, including classification tasks and pattern recognition.[19] Although several scholars have considered computed tomography (CT) images, few academics have presented various DL models for the category of chest x-ray (CXR) images. The symmetrical pattern of peripheral hazy lung opacities and air space consolidation are visible on chest x-ray (CXR) images of COVID-19 patients.[20] The chest x ray is the preferred imaging technique when COVID-19 is suspected as shown in Fig. 2. CXR images are less expensive than CT scans, have a lower radiation dosage, and can lower the danger of COVID-19 infection during testing because it is portable and simple to clean. Even though the sensitivity of CXR outcomes is only 69% in Ref. 21, according to Wong,[22] chest x rays can be utilized to establish the order of treatment for COVID-19-infected individuals. Chest x-ray diagnosis can help the overburdened healthcare system even during the COVID-19 pandemic.

To improve AlexNet, Oh *et al.*[23] implemented CNN to learn transfer. For images with a single intensity, the first layer of AlexNet is substituted. The enhanced AlexNet architecture was used by Kaur *et al.*[24] Parameters are optimized using the Strength Pareto evolutionary algorithm-II (SPEA-II). To categorize chest x-ray pictures, Narin *et al.*[25] evaluated different layers of ResNet. The most effective classification performance is offered by ResNet50. DenseNet201 did well in the investigation of Chowdhury *et al.*[26] when identifying chest x-ray pictures with image augmentation. Hernandez *et al.* used ResNet-50, DenseNet, and VGG-16 to apply transfer learning in the study, fine-tuning them to increase accuracy.[27] The attention module was added by Sitaula and Hossain[28] to the adaptive convolution layer of VGG16. Three datasets of chest x-ray images from the COVID-19 system were used for classification trials. GoogleNet was used by Haritha *et al.*[29] to categorize x-ray pictures and forecast COVID-19. The angle transformation (AT) was originally used to transform CXR images by Kaya *et al.*[30] The images are then



(a) Healthy (b) COVID 19

FIG. 2. An illustration of normal and COVID-19 CXR images.

trained using GoogleNet and LSTM. They eventually achieved a higher accuracy rate. Haque *et al.* proposed a CNN-based model for COVID-19 detection with precision of 96.72% and accuracy of 98.3%.[31]

To classify the three categories of COVID-19, pneumonia, and normal with an accuracy of 96.06%, Fu *et al.*[32] employed UNet on chest segmentation and suggested the DenseANet model. A two-step classification approach between COVID-19 and normal was proposed by Aswathy *et al.*,[33] and the accuracy was 98.50%. Arora *et al.*[34] used MobileNet to classify COVID-19 and pneumonia patient groups, reporting a 96.11% classification accuracy. The Fractal CovNet network was proposed by Munusamy *et al.*[35] to concentrate the CT image and carry out the classification task. It combines the Fractal module and UNet. To classify three categories of COVID-19, pneumonia, and normal chest x-ray images, Vinod *et al.*[36] suggested the Deep Covix-Net network; classification accuracy between COVID-19 and healthy using CT images was 97.00%; the accuracy for classifying COVID-19 and pneumonia using x-ray images was 96.80%.

As the COVID-19 outbreak threatens to frustrate healthcare systems globally, CXR may be explored as a technique for diagnosing COVID-19 if diagnostic performance with CXR is improved. The major objective of this research is to propose a CNN-based method to identify COVID-19 in chest x rays.

- To identify patients with COVID-19, the research proposes a simple CNN architecture that extracts deep information from CXR images.
- Initially, the images are pre-processed using contrast-limited adaptive histogram equalization (CLAHE) which is an image enhancement technique that improves the local contrast and edges to improve the detection accuracy using CNN architecture.
- This proposed CNN model achieves 99.73% of accuracy in detecting COVID-19 infection trained on images from the Kaggle dataset.[37]

III. PROPOSED METHODOLOGY

Using openly available data and CNN models, one of the key objectives of this research is to produce accurate classification results. The CXR pictures in the collection are initially pre-processed for improvement. Then, the improved photos are fed into a CNN-based deep learning model that is suitable for an inquiry into COVID-19 image categorization. The main goal is to compare existing deep-learning techniques for COVID-19 detection with the proposed simple deep-learning-based CNN model to get the best accuracy on a small CXR dataset with high performance.

A. Dataset preparation

The experiment is conducted using Kaggle, a chest x-ray database that includes 10 192 (normal), 6012 (lungs opacity), and 1345 (viral pneumonia) images. Kaggle dataset is one of the best-known public x-ray databases.[37] It contains 3616 COVID-19 cases. However, for this investigation, only COVID-19 (3616) and normal (10 192) images are collected. Following image enhancement, CNN architecture used the enhanced images in a ratio of 20% data for testing and 80% for training. The Kaggle dataset is notable for its substantial size, encompassing the total of 13 808 chest x-ray images. It includes a diverse range of cases, such as normal cases, COVID-19 cases, and images depicting lung opacity and viral pneumonia. This diversity is crucial for developing and evaluating machine learning models for various lung-related conditions. One of the key strengths of this dataset is its inclusion of 3616 COVID-19 cases. This is a substantial number of cases compared to many other publicly available datasets. Given the unique challenges posed by COVID-19 and the importance of accurate diagnosis, a dataset with a significant number of COVID-19 cases is valuable for training and testing models specific to this disease.

Although the Radiological Society of North America (RSNA) Pneumonia Detection Challenge Dataset primarily focused on pneumonia, this dataset contains a subset of COVID-19 cases, making it suitable for comparative studies. The Mendeley COVID-19 Dataset includes x ray and CT scan images and has been used in numerous COVID-19 image analysis studies. Each of these datasets serves a specific purpose and may be suited to different research questions or experimental setups with very few data. In this research, Kaggle dataset is chosen based on their specific requirements, such as the need for a larger COVID-19 case count and the inclusion of additional lung conditions which overcomes the other dataset issues.

ALGORITHM 1. Data Preprocessing using CLAHE.

Input : - Chest x-ray image dataset with COVID-19 and normal cases (K) from Kaggle dataset.
- CLAHE parameters (e.g., clip limit, grid size).
Output: Enhanced image dataset
i is the number of images in K
$n \leftarrow 1$
while $n \le i$ *do*
Step 1 : $image \leftarrow READ(K(n))$ # Read the nth image from the dataset
Step 2 : *Enhance image ←ApplyCLAHE(image, CLAHE_parameters) # Apply CLAHE to enhance the image*
Step 3 : Save enhanced_image to the enhanced dataset
Step 6: $n \leftarrow n + 1$
End While

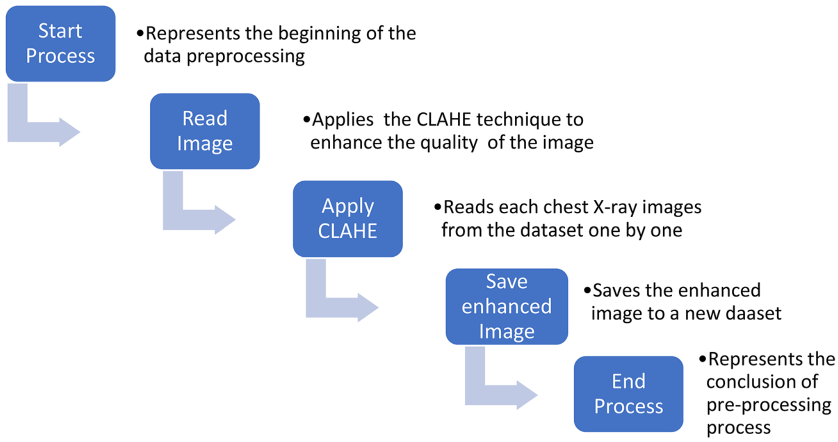


FIG. 3. Data Flow Diagram for Data Preprocessing using CLAHE.

B. Image enhancement using CLAHE

Adaptive Histogram Equalization is a better HE variant (AHE). Small patches in the image are subjected to histogram equalization in AHE, which increases the contrast of each patch independently, as shown in Fig. 3. As a result, rather than employing the image's overall information, it improves localized contrast and edges in each region based on the distribution of pixel intensities. AHE may over-amplify the image's noise component.[38] The enhanced images with Contrast Limited Adaptive Histogram Equalization (CLAHE) appear more realistic than HE images. It is observed that the HE approach can over-saturate some areas when used on the x-ray images. The same methodology as AHE is used by CLAHE to overcome this issue, but a threshold parameter controls how much contrast enhancement can be produced within the chosen region. Below is a simplified algorithm for the research described, focusing on the data preprocessing step using the Contrast Limited Adaptive Histogram Equalization (CLAHE) technique (Algorithm 1).

In the above algorithm, first, we read each chest x-ray image from the dataset, apply the CLAHE technique to enhance it, and save the enhanced image to a new dataset. The CLAHE parameters (e.g., clip limit and grid size) were chosen based on the research requirements.

This algorithm represents the crucial data preprocessing step in the research, which enhances the quality of chest x-ray images before feeding them into the Convolutional Neural Network (CNN) for COVID-19 detection. Figure 3 illustrates the flow of data and actions involved in enhancing chest x-ray images using the CLAHE technique, which is a critical step in the research for COVID-19 detection.

First, the original image is changed from RGB (red, green, and blue) to HSV (hue, saturation, and value) color space since the HSV is more closely related to how people perceive color. Second, CLAHE processes the value portion of HSV without altering the hue or saturation. Each gray level is dispersed once again among the pixels in the original histogram after it has been cropped. Each pixel's value is decreased until it reaches a preset limit. The image that has undergone HSV processing is then converted back to RGB color space. Then, using the CLAHE technique, images are normalized and highlighted for classification models to examine small features. The histogram of original and enhanced images is shown in Fig. 4, and the design flow of image enhancement and CNN classification is shown in Fig. 5.

1. CNN architecture

The proposed CNN architecture is shown in Fig. 6. RGB images with a resolution of 128 × 128 × 2 are input into the CNN model to train it. The convolutional layer is the top layer. The first layer's kernel is 3 by 3. Filters with a size of 5 × 5 and a stride of 1 are used in the first three convolutional layers. The remaining two convolution layers employ 3 × 3 kernels without any strides, totaling 64 across both layers. The dropout function helps to reduce the possibility of overfitting and is used to activate each of these convolution layers using the rectified linear unit (RELU) activation function (Af). Dropout is a regularization technique where a predetermined number of hidden layers are arbitrarily disregarded or eliminated during training. In this technique, training hyperparameters are calculated and modified utilizing numerous parallel architectures with various numbers of nodes and permutations. The random selection is carried out in accordance with the probabilistic search strategy supplied to the dropout function. The first two convolution layers in the proposed approach employ a dropout rate of 0.2, while the last three convolutions use a dropout rate of 0.1, signifying that during any training set, 20% and 10% of nodes, respectively, will be dropped out.

FCL is made up of 64 neurons in the proposed CNN architecture. To the second FCL, the first FCL transmits output activation. The input to the activation function (Af) is normalized in this layer using the batch normalization. In the output layer, the model finally uses "SoftMax" activation to predict the class label between COVID-19 and normal images. Table I shows the hyperparameters and overall architecture of the proposed CNN model.

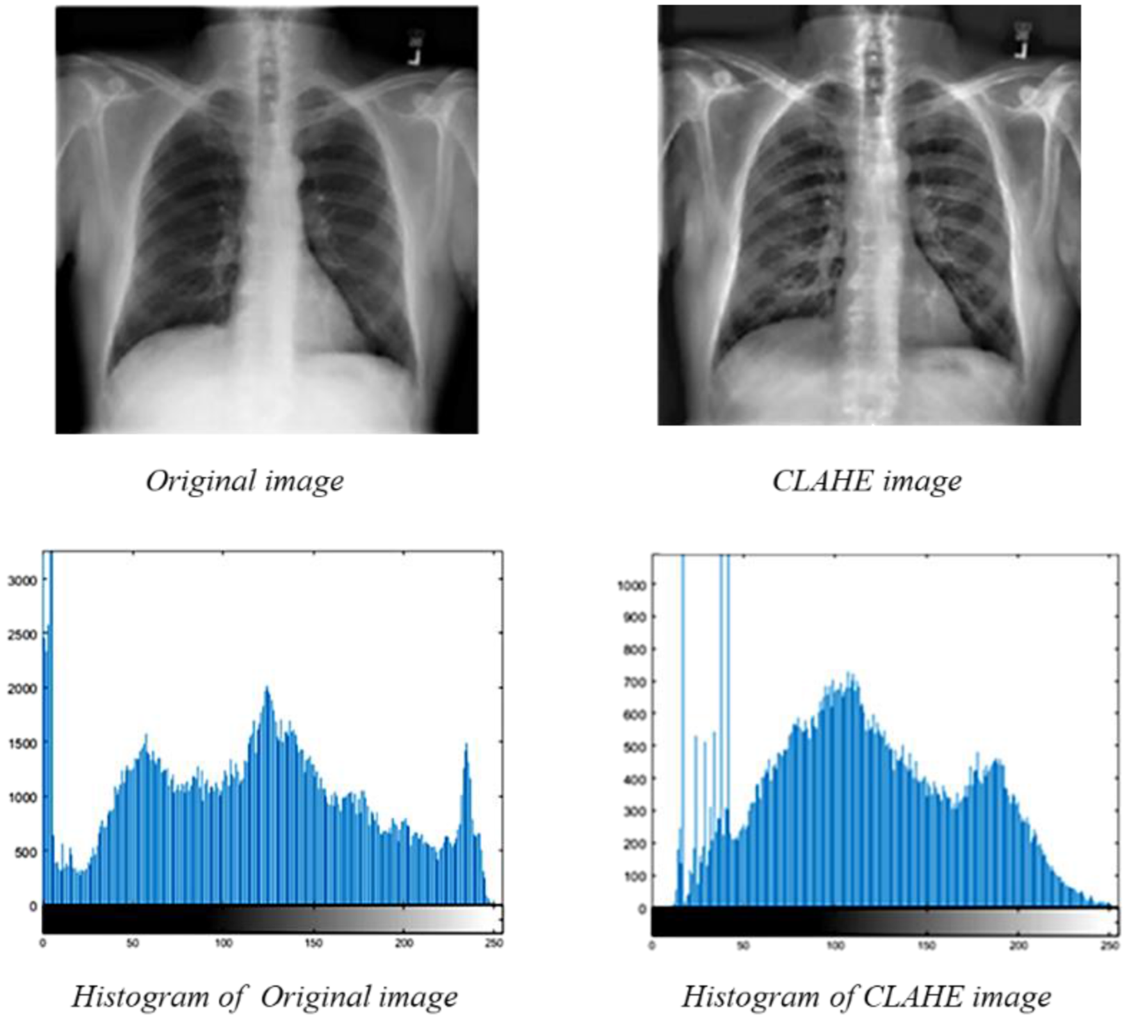


FIG. 4. Histogram of original and enhanced images.

IV. RESULTS AND DISCUSSION

The test was conducted using Google Collaboratory. Google Collaboratory is a cloud service for sharing information and working on machine learning that is built on Jupyter notebooks. The use of Google Collaboratory benefits the research in several ways. First, it provides a cloud-based platform for sharing information and collaborating on machine learning projects, enabling researchers to work together seamlessly. In addition, Google Collaboratory offers access to a stable graphics processing unit (GPU) and a fully optimized runtime for deep learning tasks, ensuring that researchers

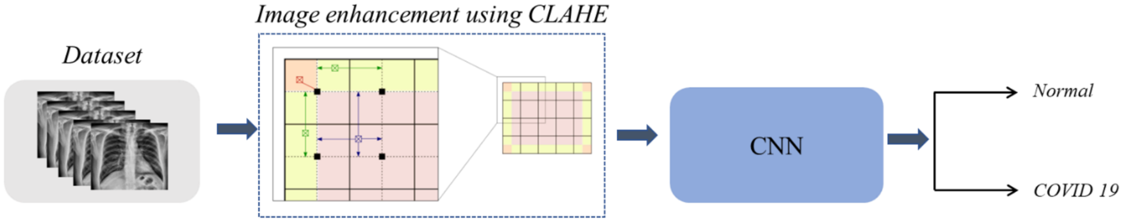


FIG. 5. Design flow of the proposed COVID-19 detection.

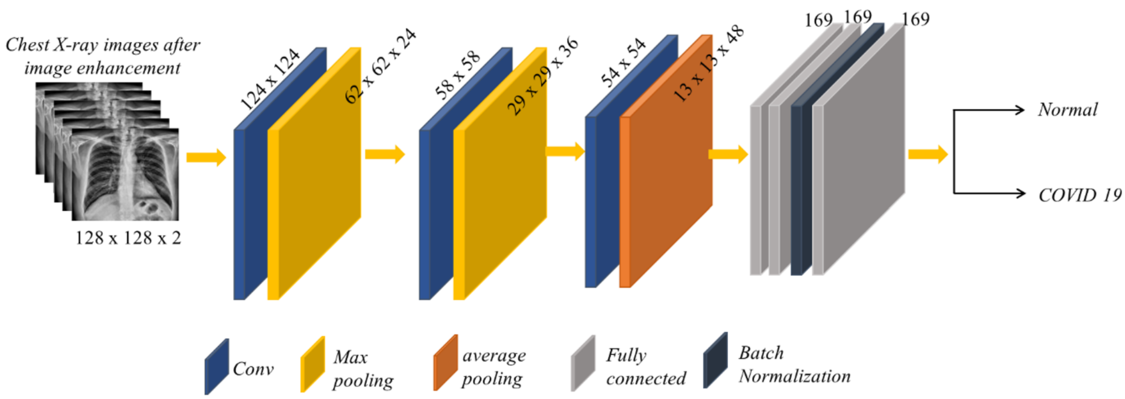


FIG. 6. Proposed CNN architecture.

TABLE I. Overview of the proposed CNN architecture.

Layer	Kernel size	Af	Stride	Input	Output	Parameters
Conv2D	24	⋯	2	128 × 128 × 2	62 × 62 × 24	2424
Conv2D	36	⋯	2	62 × 62 × 24	29 × 29 × 36	21 636
Con2D	48	RELU	2	29 × 29 × 36	13 × 13 × 48	43 248
Flatten	⋯	⋯	⋯	⋯	⋯	8112
Dense	⋯	Softmax	⋯	⋯	⋯	169

have the necessary computational resources to train complex models efficiently. This accessibility to powerful computing resources enhances the scalability and reproducibility of the research, ultimately contributing to the advancement of knowledge in the field of deep learning.

The trained algorithms are evaluated using five-fold cross-validation in order to compare various deep learning algorithms classified CXR images under two different classes—COVID-19 and normal. Five performance indicators, including accuracy (ACC), precision (PR), sensitivity or recall (SN), specificity (SP), and F1 score, are used to compare the effectiveness of the proposed model as represented in Eqs. (1)–(5). In the analysis, the proposed CNN is performed on CXR images after image enhancement using the CLAHE technique and achieved 99.73% of accuracy, 99.47% of precision, 99.62% of sensitivity, 98.95% of specificity, and 98.71% of F1 score, as shown in Table II. It is evident that COVID-19 detection of pre-processed CXR images using CLAHE and CNN architecture achieved the best performance when compared with CXR images without pre-processing as shown in Fig. 7,

$$\boldsymbol{Acc} = \frac{\boldsymbol{TP} + \boldsymbol{TN}}{\boldsymbol{TP} + \boldsymbol{TN} + \boldsymbol{FP} + \boldsymbol{FN}}, \tag{1}$$

$$\boldsymbol{PR} = \frac{\boldsymbol{TP}}{\boldsymbol{TP} + \boldsymbol{FP}}, \tag{2}$$

$$\boldsymbol{SN} = \frac{\boldsymbol{TP}}{\boldsymbol{TP} + \boldsymbol{FN}}, \tag{3}$$

$$\boldsymbol{SP} = \frac{\boldsymbol{TN}}{\boldsymbol{TN} + \boldsymbol{FP}}, \tag{4}$$

$$F1 - \boldsymbol{score} = \frac{2\,\boldsymbol{x}\,\boldsymbol{PR}\,\boldsymbol{x}\,\boldsymbol{SN}}{\boldsymbol{PR} + \boldsymbol{SN}}. \tag{5}$$

TABLE II. Performance evaluation of the proposed CNN with and without CLAHE technique.

Method	Accuracy (%)	Precision (%)	Specificity (%)	Sensitivity (%)	F1-score (%)
Without image enhancement	92.45	91	91.55	90.45	89.63
With image enhancement	99.73	99.47	99.62	98.95	98.71

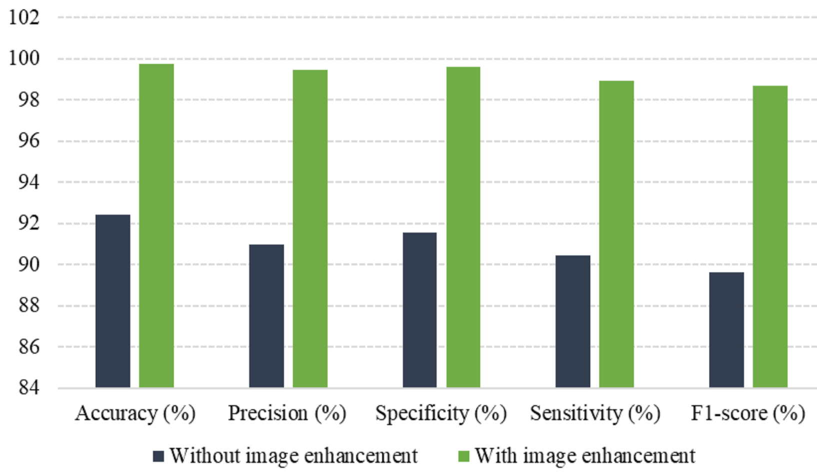


FIG. 7. Proposed CNN architecture.

The results obtained from comparing the performance of the CNN models with and without CLAHE enhancement provide insights into the impact of image preprocessing on COVID-19 detection accuracy. The conclusion drawn from this evaluation highlights any observed improvements or limitations associated with the use of the CLAHE technique in enhancing the performance of the CNN model for COVID-19 detection from CXR images.

The performance of the proposed model is compared with existing CNN models for COVID-19 detection as shown in Table III. ResNet-50[25] achieved 99.5% of accuracy, which is almost equivalent to our proposed model with image enhancement. VGG19+CNN[39] achieved 98.05% of accuracy trained on CXR images for detection of our classes (Normal, Pneumonia, Lung cancer, and COVID-19). The performance and reliability of the proposed system are compared to existing and recent COVID-19 detection methods. In comparison to earlier experiments, the model has the best accuracy and precision values, but the values of specificity and recall are almost similar. The proposed work has evaluated the model against each of the four performance characteristics, but the majority of research have not supplied information about all four of them. The proposed method exhibits excellent performance that is more efficient than existing approaches as shown in Fig. 8.

The key performance indicators used to evaluate the effectiveness of the proposed CNN model for COVID-19 detection in chest x-ray images are accuracy (ACC), precision (PR), sensitivity or recall (SN), specificity (SP), and F1 score. These metrics provide comprehensive insights into the performance of the model across different aspects, including overall correctness, ability to correctly identify positive cases, ability to avoid false positives, and overall balance between precision and recall. By considering these metrics, we can assess the robustness and reliability of the CNN model in accurately detecting COVID-19 from pre-processed chest x-ray images using the CLAHE technique.

TABLE III. Comparison of performance evaluation of various CNN models for COVID-19 diagnosis.

Ref	Models	Accuracy (%)	Precision (%)	Specificity (%)	Sensitivity (%)	F1-score (%)
Bharati *et al.* (2020)[14]	VDSNet	73	69	⋯	63	68
Huang and Liao (2022)[11]	LightEfficientNetV2	83.42	81.94	⋯	82.76	82.39
Jaiswal *et al.* (2020)[39]	COVIDPEN	96	96.4	⋯	87.1	94
Narin *et al.* (2021)[25]	ResNet50	99.5	98.3	99.8	98.8	98.5
Hernandez *et al.* (2020)[27]	ResNet50 + fine tuning	90.63	90.00	⋯	91.67	90.72
Rajawat *et al.* (2022)[19]	C-COVIDNet	97.5	95.1		96.2	95.1
Chowdhury *et al.* (2020)[26]	DenseNet201	97.94	97.95	98.80	97.94	97.94
Zhang *et al.* (2021)[16]	5L-DCNN-SP-C	93.64	93.96	94.00	93.28	93.62
Ibrahim *et al.* (2021)[39]	VGG19+CNN	98.05	98.43	99.5	98.05	98.24
Kaur *et al.* (2021)[24]	mAlexNet + SPEA-II	96.5	⋯	91.7	98.0	⋯
Proposed work	**CNN**	**99.73**	**99.47**	**99.62**	**98.95**	**98.71**

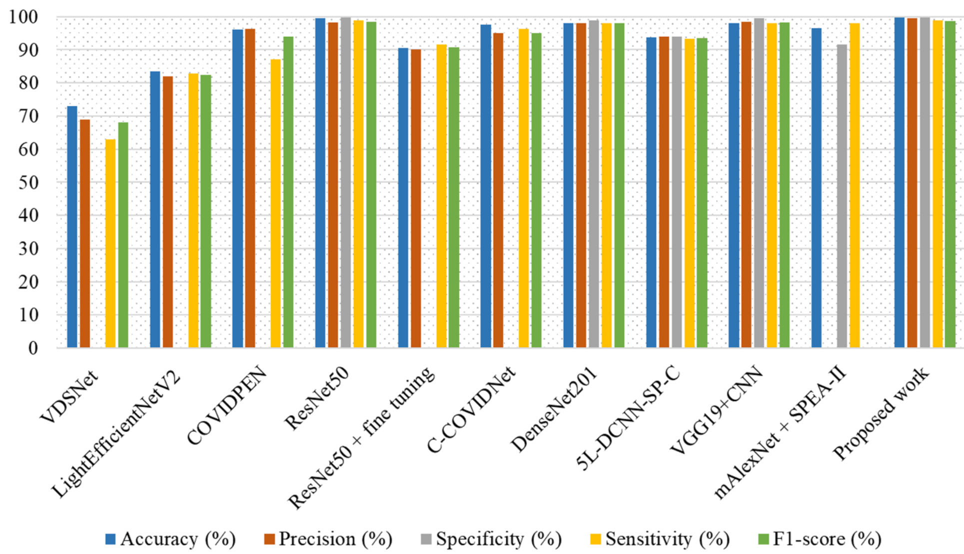


FIG. 8. Comparison of the proposed CNN model with existing CNN models for detection of COVID-19.

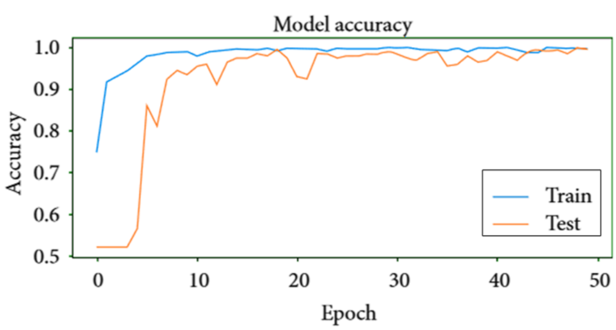


FIG. 9. Model accuracy for training and testing (50 epochs).

The training accuracy and validation accuracy with regard to epochs are displayed in Fig. 9. There were 50 iterations of the CNN model run. The highest accuracy possible was 99.73% for training and 99.33% for validation. These results showed that our model learned effectively and could distinguish between COVID-19 and normal cases with accuracy. According to Fig. 10, the CNN's training accuracy has not changed after five epochs, and the CNN likewise exhibits a constant validation accuracy after 25 epochs. The loss experienced by CNN during training and validation is depicted in Fig. 10. The validation loss becomes minimal after five epochs and remains minimal until the last epoch, while the training loss of CNN is minimal and steady from the first epoch.

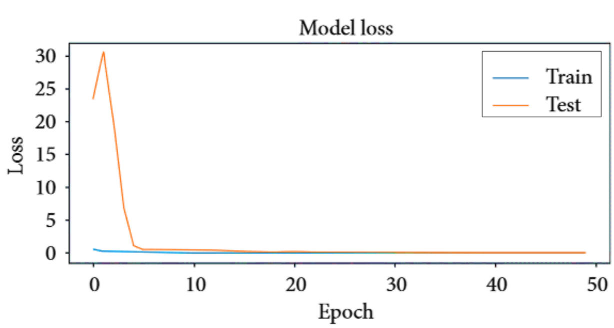


FIG. 10. Model loss for training and testing.

Fig. 9 illustrates the model accuracy achieved during the training and testing phases across 50 epochs. The plot provides a visual representation of how the accuracy of the deep learning model evolves over the course of training, as well as its generalization performance on unseen data during testing. This visualization offers insights into the model's learning dynamics, including potential overfitting or underfitting tendencies, and provides valuable information for evaluating its overall performance and effectiveness in COVID-19 diagnosis.

V. CONCLUSION

The goal of this work is to show how COVID-19 may be effectively and precisely diagnosed using CNN that was trained on datasets of chest x-ray images. Numerous people have already passed away as a result of inadequate care, inadequate facilities, or a lack of early detection. Initially, the CXR images from the Kaggle dataset are pre-processed using the CLAHE technique for image enhancement. The pre-processed images are trained by using the proposed CNN architecture. The model achieved 99.73% of accuracy, 99.47% of precision, 99.62% of sensitivity, 98.95% of specificity, and 98.71% of F1 score. The proposed work has evaluated the model against each of the four performance characteristics, but the majority of research have not supplied information about all four of them. The positive findings of the proposed study will definitely facilitate the understanding of deep learning-based COVID-19 detection techniques based on CXR images. The authors are actively working on the use of various cutting-edge data augmentation methods and algorithms because of the tremendous impact that data augmentation techniques have on model performances. The research strength lies in its extensive dataset, with a substantial number of COVID-19 and normal cases, robust image preprocessing using CLAHE, rigorous cross-validation, and impressive model performance metrics. Future research will concentrate on this direction as well as the creation and assessment of multi-class classification models.

ACKNOWLEDGMENTS

The authors extend their appreciation to the Deanship of Scientific Research at King Khalid University, Saudi Arabia for funding this work through the Small Group Research Project under Grant No. RGP1/306/44.

AUTHOR DECLARATIONS

Conflict of Interest

The authors have no conflicts to disclose.

Ethics Approval

This article does not contain any studies with human participants or animals performed by any of the authors.

Author Contributions

Arul Raj A.M.: Validation (equal); Visualization (equal); Writing – original draft (equal); Writing – review & editing (equal). **Sugumar R.**: Conceptualization (equal); Data curation (equal); Formal analysis (equal); Writing – review & editing (equal). **Padmkala S.**: Methodology (equal); Resources (equal); Supervision (equal); Validation (equal); Writing – review & editing (equal). **Jayant Giri**: Methodology (equal); Validation (equal); Visualization (equal); Writing – original draft (equal); Writing – review & editing (equal). **Naim Ahmad**: Conceptualization (equal); Data curation (equal); Formal analysis (equal); Investigation (equal); Resources (equal); Supervision (equal); Writing – review & editing (equal). **Ahmed Said Badawy**: Funding acquisition (equal); Investigation (equal); Methodology (equal); Software (equal); Supervision (equal); Writing – review & editing (equal).

DATA AVAILABILITY

The data that support the findings of this study are available from the corresponding author upon reasonable request.

REFERENCES

[1] X. Han, Z. Hu, S. Wang, and Y. Zhang, "A survey on deep learning in COVID-19 diagnosis," J. Imaging **9**, 1 (2022).
[2] W.-J. Guan, Z.-Y. Ni, Y. Hu, W.-H. Liang, C.-Q. Ou, J.-X. He, L. Liu, H. Shan, C.-L. Lei, D. S. Hui *et al.*, "Clinical characteristics of coronavirus disease 2019 in China," N. Engl. J. Med. **382**, 1708–1720 (2020).
[3] World Health Organization, "Coronavirus Disease 2019 (COVID-19)," Situation Report No. 72, 1 April 2020, available online https://apps.who.int/iris/bitstream/handle/10665/331685/nCoVsitrep01Apr2020-eng.pdf (accessed 16 March 2020).
[4] COVID-19 Dashboard by the Center for Systems Science and Engineering (CSSE) at Johns Hopkins University (JHU) https://www.arcgis.com/apps/dashboards/bda7594740fd40299423467b48e9ecf6 (accessed 14 January 2023).
[5] P. Sun, X. Lu, C. Xu, W. Sun, and B. Pan, "Understanding of COVID-19 based on current evidence," J. Med. Virol. **92**(6), 548–551 (2020).
[6] M. Nour, Z. Cömert, and K. Polat, "A novel medical diagnosis model for COVID-19 infection detection based on deep features and Bayesian optimization," Appl. Soft Comput. **97**, 106580 (2020).
[7] G. Qiu, Z. Gai, Y. Tao, J. Schmitt, G. A. Kullak-Ublick, and J. Wang, "Dual-functional plasmonic photothermal biosensors for highly accurate severe acute respiratory syndrome coronavirus 2 detection," ACS Nano **14**, 5268–5277 (2020).
[8] M. F. Aslan, M. F. Unlersen, K. Sabanci, and A. Durdu, "CNN-Based transfer learning–BiLSTM network: A novel approach for COVID-19 infection detection," Appl. Soft Comput. **98**, 106912 (2021).
[9] A. Bhattacharyya, D. Bhaik, S. Kumar, P. Thakur, R. Sharma, and R. B. Pachori, "A deep learning based approach for automatic detection of COVID-19 cases using chest X-ray images," Biomed. Signal Process. Control. **71**, 103182 (2022).
[10] A. Gupta, Anjum, S. Gupta, and R. Katarya, "InstaCovNet-19: A deep learning classification model for the detection of COVID-19 patients using chest X-ray," Appl. Soft Comput. **99**, 106859 (2021).
[11] M. L. Huang and Y. C. Liao, "A lightweight CNN-based network on COVID-19 detection using X-ray and CT images," Comput. Biol. Med. **146**, 105604 (2022).
[12] L. Hussain, T. Nguyen, H. Li, A. A. Abbasi, K. J. Lone, Z. Zhao, M. Zaib, A. Chen, and T. Q. Duong, "Machine-learning classification of texture features of portable chest X-ray accurately classifies COVID-19 lung infection," Biomed. Eng. Online **19**, 88 (2020).
[13] T. A. Soomro, L. Zheng, A. J. Afifi, A. Ali, M. Yin, and J. Gao, "Artificial intelligence (AI) for medical imaging to combat coronavirus disease (COVID-19): A detailed review with direction for future research," Artif. Intell. Rev. **55**, 1409–1439 (2022).
[14] S. Bharati *et al.*, "Hybrid deep learning for detecting lung diseases from X-ray images," Inform. Med. Unlocked **20**, 100391 (2020).
[15] R. Sethi, M. Mehrotra, and D. Sethi, "Deep learning-based diagnosis recommendation for COVID-19 using chest X-rays images," in *Proceedings of the 2020 Second International Conference on Inventive Research in Computing Applications (ICIRCA)* (IEEE, Coimbatore, India, 2020), pp. 1–4.
[16] Y. D. Zhang, S. C. Satapathy, S. Liu, and G. R. Li, "A five-layer deep convolutional neural network with stochastic pooling for chest CT-based COVID-19 diagnosis," Mach. Vis. Appl. **32**(1), 14 (2021).
[17] Y. Oh, S. Park, and J. C. Ye, "Deep learning COVID-19 features on CXR using limited training data sets," IEEE Trans. Med. Imaging **39**, 2688 (2020).
[18] M. Heidari, S. Mirniaharikandehei, A. Z. Khuzani, G. Danala, Y. Qiu, and B. Zheng, "Improving performance of CNN to predict likelihood of COVID-19 using chest X-ray images with preprocessing algorithms," Int. J. Med. Inform. **144**, 104284 (2020).
[19] N. Rajawat, B. S. Hada, M. Meghawat *et al.*, "C-COVIDNet: A CNN model for COVID-19 detection using image processing," Arabian J. Sci. Eng. **47**, 10811–10822 (2022).
[20] I. D. Apostolopoulos and T. A. Mpesiana, "COVID-19: Automatic detection from x-ray images utilizing transfer learning with convolutional neural networks," Phys. Eng. Sci. Med. **43**, 635 (2020).
[21] C. Dennie, C. Hague, R. S. Lim, D. Manos, B. F. Memauri, E. T. Nguyen, and J. Taylor, "Canadian Society of Thoracic Radiology/Canadian Association of Radiologists consensus statement regarding chest imaging in suspected and confirmed COVID-19," Can. Assoc. Radiol. J. **71**, 470–481 (2020).
[22] H. Y. F. Wong, H. Y. S. Lam, A. H.-T. Fong, S. T. Leung, T. W.-Y. Chin, C. S. Y. Lo, M. M.-S. Lui, J. C. Y. Lee, K. W.-H. Chiu, T. W.-H. Chung *et al.*, "Frequency and distribution of chest radiographic findings in patients positive for COVID-19," Radiology **296**, E72–E78 (2020).
[23] X. Xu, X. Jiang, C. Ma *et al.*, "A deep learning system to screen novel coronavirus disease 2019 pneumonia," J. Engineering **6**, 1122–1129 (2020).

[24]M. Kaur, V. Kumar, V. Yadav, D. Singh, N. Kumar, and N. N. Das, "Metaheuristic-based deep COVID-19 screening model from chest X-ray images," J. Healthc. Eng. **2021**, 8829829.
[25]A. Narin, C. Kaya, and Z. Pamuk, "Automatic detection of coronavirus disease (COVID-19) using X-ray images and deep convolutional neural networks," Pattern Anal. Appl. **24**, 1207–1220 (2021).
[26]M. E. Chowdhury, T. Rahman, A. Khandakar, R. Mazhar, M. A. Kadir, Z. B. Mahbub, K. R. Islam, M. S. Khan, A. Iqbal, N. A. Emadi *et al.*, "Can AI help in screening viral and COVID-19 pneumonia?," IEEE Access **8**, 132665–132676 (2020).
[27]D. Hernandez, R. Pereira, and P. Georgevia, "COVID-19 detection through X-Ray chest images," in *Proceedings of the 2020 International Conference Automatics And Informatics (ICAI), Varna, Bulgaria* (IEEE, 2020), pp. 1–5.
[28]C. Sitaula and M. B. Hossain, "Attention-based VGG-16 model for COVID-19 chest X-ray image classification," Appl. Intell. **51**, 2850–2863 (2021).
[29]D. Haritha, N. Swaroop, and M. Mounika, "Prediction of COVID-19 cases using CNN with X-rays," in *Proceedings of the 2020 5th International Conference on Computing, Communication And Security (ICCCS)* (IEEE, Patna, India, 2020), pp. 1–6.
[30]Y. Kaya, Z. Yiner, M. Kaya, and F. Kuncan, "A new approach to COVID-19 detection from X-ray images using angle transformation with GoogleNet and LSTM," Meas. Sci. Technol. **33**, 124011 (2022).
[31]K. F. Haque, F. F. Haque, L. Gandy, and A. Abdelgawad, "Automatic detection of COVID-19 from chest X-ray images with convolutional neural networks," in *Proceedings of the 2020 International Conference on Computing, Electronics & Communications Engineering (iCCECE)* (IEEE, Southend, UK, 2020), pp. 125–130.
[32]Y. Fu, P. Xue, and E. Dong, "Densely connected attention network for diagnosing COVID-19 based on chest CT," Comput. Biol. Med. **137**, 104857 (2021).
[33]A. L. Aswathy, H. S. Anand, and S. S. Vinod Chandra, "COVID-19 diagnosis and severity detection from CT-images using transfer learning and back propagation neural network," J. Infect. Public Health **14**(10), 1435–1445 (2021).
[34]V. Arora, E. Y. K. Ng, R. S. Leekha, M. Darshan, A. Singh, and A. Singh, "Transfer learning-based approach for detecting COVID-19 ailment in lung CT scan," Comput. Biol. Med. **135**, 104575 (2021).
[35]H. Munusamy, K. J. Muthukumar, S. Gnanaprakasam, T. R. Shanmugakani, and A. Sekar, "FractalCovNet architecture for COVID-19 chest X-ray image classification and CT-scan image segmentation," Biocybern. Biomed. Eng. **41**(3), 1025–1038 (2021).
[36]N. Vinod, B. R. Jeyavadhanam, A. M. Zungeru, and S. R. S. Prabaharan, "Fully automated unified prognosis of Covid-19 chest X-ray/CT scan images using Deep Covix-Net model," Comput. Biol. Med. **136**, 104729 (2021).
[37]Kaggle dataset, COVID-19 Radiography Database https://www.kaggle.com/datasets/tawsifurrahman/covid19-radiography-database.
[38]J. B. Zimmerman, S. M. Pizer, E. V. Staab, J. R. Perry, W. McCartney, and B. C. Brenton, "An evaluation of the effectiveness of adaptive histogram equalization for contrast enhancement," IEEE Trans. Med. Imaging **7**(4), 304–312 (1988).
[39]D. M. Ibrahim, N. M. Elshennawy, and A. M. Sarhan, "Deep-chest: Multiclassification deep learning model for diagnosing COVID-19, pneumonia, and lung cancer chest diseases," Comput. Biol. Med. **132**, 104348 (2021).
[40]A. K. Jaiswal, P. Tiwari, V. K. Rathi, J. Qian, H. M. Pandey, and V. H. C. Albuquerque, "COVIDPEN: A novel COVID-19 detection model using chest X-rays and CT scans," medRxiv:2020.07.08.20149161 (2020).