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Research Article

Development and Validation of a Diagnosis System for Lung Infection Using Hybrid Deep-Learning Techniques

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Abstract

A fast and accurate test is necessary to detect COVID-19. A computed tomography (CT) scan has shown diagnostic accuracy. CT scan processing using a deep learning architecture may improve illness diagnosis and treatment. We proposed a deep learning system for COVID-19 detection using CT images, including using and comparing transfer-learning, fine-tuning, and the embedding process. This paper presents the development of a COVID-19 case identification model using deep learning techniques. The suggested model utilized a modified visual geometry group (VGG16) architecture as the deep learning framework. The model was trained and validated using a chest CT image dataset. The SARS-COV-2 dataset contains 2482 CT scans of 210 patients from publicly available sources. The modified model demonstrated encouraging outcomes by greatly enhancing the sensitivity measure (95.82±1.75)%, which is an essential criterion for accurately detecting instances of COVID-19 infection. In addition, the model achieved higher values for the accuracy metric (91.67±1.68)%, the specificity meter (88.08±3.72)%, the precision metric (87.51±3.27)%, the F1 score (91.43±1.55)%, and the area under the curve (91.98±1.55)%. Deep learning effectively detects COVID-19 in chest CT scan images. Clinical practitioners may employ the suggested approach to study, identify, and effectively mitigate a greater number of pandemics.

1. Introduction

The World Health Organization (WHO) has classified the epidemic as a public health emergency of international concern [1]. There have been about 2.5 million confirmed coronavirus cases in Iraq until October 2023, with more than 25 thousand deaths, according to reports to the WHO. As of January 2020, COVID-19 has already spread to every corner of the globe. COVID-19, a leading cause of pneumonia, easily spreads from person to person [2]. According to data compiled by the WHO, the virus is responsible for a 2-3% fatality rate [3]. To quickly identify and isolate infected individuals, it is crucial to do diagnostic tests using clinical symptoms and reverse-transcription polymerase chain reaction (RT-PCR) [4]. The sensitivity of the RT-PCR test may not be high enough to use it for early detection [5, 6].

Computed tomography (CT) appeared as an imaging method capable of recognizing lung infections linked to the COVID-19 disease [7-9]. Despite the positive conclusion of a chest CT scan in some people, the RT-PCR test produced negative results. Lung inflammation and COVID-19 are both detectable via CT scans, an indispensable diagnostic instrument [10, 11]. Artificial intelligence (AI) that combines machine learning (ML) and deep learning (DL) has been highly successful in the field of medical image interpretation due to its feature extraction capabilities and unique classification [12-15]. Many researchers use convolutional neural networks (CNN) for disease detection using DL in CT images. CNN has high efficacy in extracting features and employing spatial filters to collect structural data [16].

The objective of this research is to develop and use a reliable system for detecting and classifying COVID-19 using image processing and deep learning methods to achieve a high level of accuracy in classification. Furthermore, the research aims to underscore the significance of ML and DL techniques in addressing the COVID-19 pandemic; specifically, the focus is on elucidating the role of DL methodologies. The remainder of this research is as follows: Section 2 shows related work, while Section 3 details the methodology and describes the pre-processing, work environment, and evaluation parameters. Section 4 presents the results and discussions, while Section 5 presents the conclusions.

2. Related Work

The development of DL and ML methods now allows for the use of clinical imaging, such as CT scans, in diagnosing COVID-19. This section provides a summary of current developments in the realm of COVID-19 detection systems that have included DL methods. S. Mohammad et al. [17] suggested a distinguishable architecture for DL in which this model's pooling layer combines pooling with the SE-block layer. To improve COVID-19 diagnostic performance and convergence time, the suggested model employs batch normalization and the Mish function. The suggested approach was assessed using data from two public hospitals. Also, it was contrasted with several other widely used deep neural networks (DNN). The outcomes showed an accuracy of 99.03% with the graphics processing unit (GPU). The suggested model produces the best network outcomes for real-time applications and classification metric parameters.

M. Yousefzadeh et al. [18] presented a DL method for detecting COVID-19 in chest CT scans and a radiologist helper. The framework includes a feature extractor that is based on EfficientNetB3. They used the Mosmed Data cohort, patients from Masih Daneshvari Hospital, and the CC-CCII cohort. These datasets comprise the non-COVID-19, COVID-19, non-pneumonia, common pneumonia, normal classifications, and 7184 images from 5693 participants. The framework was tested on the MDH cohort, the CC-CCII test set, and the Mos MedData cohort. It achieved area under the curve (AUC) scores of 0.997, 0.989, and 0.954. The findings show that the framework performs better than the other models, and various specialists assessed the framework's diagnosing skills as an aid.

K. Ahamed et al. [19] built a DL-based COVID-19 case identification algorithm that was trained using data from a database of chest CT scans. The suggested model utilized an updated ResNet50V2 DL architecture. The dataset for training the model included four class labels: confirmed COVID-19 cases, typically confirmed, and control viral and bacterial pneumonia cases. The dataset was gathered from a wide range of freely available resources. Before feeding the information into the suggested model, the aggregated dataset underwent pre-processing with a sharpening filter. Using chest X-ray images, this model achieved an accuracy 96.452 for four clinical samples with COVID-19 bacterial pneumonia. 98.954% accuracy in two instances of COVID-19 viral pneumonia and 97.242% accuracy in three cases of COVID-19 bacterial pneumonia. Utilizing data from CT scans of the chest, the model corrected an overall accuracy of 99.012% of COVID-19 community-acquired pneumonia cases across three classes and 99.99% across two classes.

X. Li et al. [20] suggested a DL ensemble-based assisted diagnostic system. The cascade classifier is built using data from several different subsets of the training set. Experiments were done to see how well the method could separate patients with new coronavirus pneumonia from those with common pneumonia and healthy controls. It achieved an F1 score of 91.74% and a prediction accuracy of 93.57%.

M. Rahimzadeh et al. [21] proposed an automatic approach for identifying COVID-19 via the images of chest CT images. The dataset includes 48,260 CT images from 282 healthy individuals and 15,589 from 95 patients. They came up with a new design to boost the performance of convolutional networks in classification tasks. When applied to images containing small but significant details, the model achieved 98.49% accuracy. This was accomplished by combining the Xception and ResNet50V2 models with a new feature pyramid network tailored for classification on over 7,996 test images.

A. Ardakani et al. [22] offered a quick and reliable approach for diagnosing COVID-19 based on artificial intelligence 120 (CT) slices from 108 patients with laboratory-confirmed COVID-19. The researchers used popular CNNs to classify individuals as either infected with COVID-19 or not. For overall performance, the best networks were Xception and ResNet-101. ResNet-101 achieved an AUC of 0.994, a sensitivity of 100%, a specificity of 99.02%, and an accuracy of 99.51%. 100% sensitivity, 100% specificity, and 99.02% accuracy were achieved using Xception, yielding an AUC of 0.994. The radiologist did only so-so work, achieving an AUC of 0.873, 89.21% sensitivity, 83.33% specificity, and 86.27% accuracy.

S. Gupt et al. [23] used the SARS-COV2 dataset intending to identify normal or COVID-19 images. The researchers used CT scans to determine whether a patient had a positive result for the COVID-19 viral imaging patterns. Several DL models extracted the characteristics of these images from the dataset, and then a variety of ML classifiers classified them as either COVID-19 or normal images. The recession classifier with the VGG19 model yields the highest possible AUC and the highest possible accuracy of 94.5%.

H. Alshazly et al. [24] adopted cutting-edge deep network topologies. They offered a transfer learning approach that utilizes carefully scaled input created for each deep architecture to attain optimal performance—conducted many different sets of investigations on the CT scan for SARS-CoV-2 and the. The data indicate that models are more accurate when compared to those obtained from past research. In the dataset, including SARS-CoV-2, the best models had average values of 99.4% for accuracy, 99.6% for precision, 99.8% for sensitivity, and 99.6% for specificity, respectively. Their F1 scores also averaged 99.4%.

3. Methodology

3.1 Proposal Method

This research presents a combination method for the automated identification of COVID-19 patients. CNN and ML techniques were used in the design process of this building's architectural layout to produce the final product. In this work, the VGG16 model was used to extract automated features from the images. As shown in Figure 1, we then fed these features to classifiers, proposing a fine-tuning approach or combining them with ML models like random forest (RF), the K-nearest neighbor (KNN), and the support vector machine (SVM).

3.2. Dataset and Work Environment

For this study, we utilized the Python programming language. The Keras library, an open-source Python library for DL compatible with TensorFlow, has been used. We have implemented this by using Colab notebooks. The Kaggle website [25] makes the provided dataset public. SARS-COV-2 is a descriptive designation for the 2482 images they obtained for the initial data set. The biggest image is 534x341 pixels, and the smallest is 244x145 pixels; all images are in jpg format. There are 210 patients represented on 2482 thoracic CT segments. Fifty people were negative for SARS-CoV-2 on CT (757 slices), whereas 80 tested positive (2,168 slices). The other 80 patients did not participate because they did not meet the criteria for the trial due to different lung problems. The dataset came from hospitals in Sao Paulo, Brazil, and RT-PCR testing verified patients' SARS-CoV-2 status. All radiological abnormalities discovered by the experts were located on the most diagnostically important CT slice, so we were able to rule out this potential source of bias.

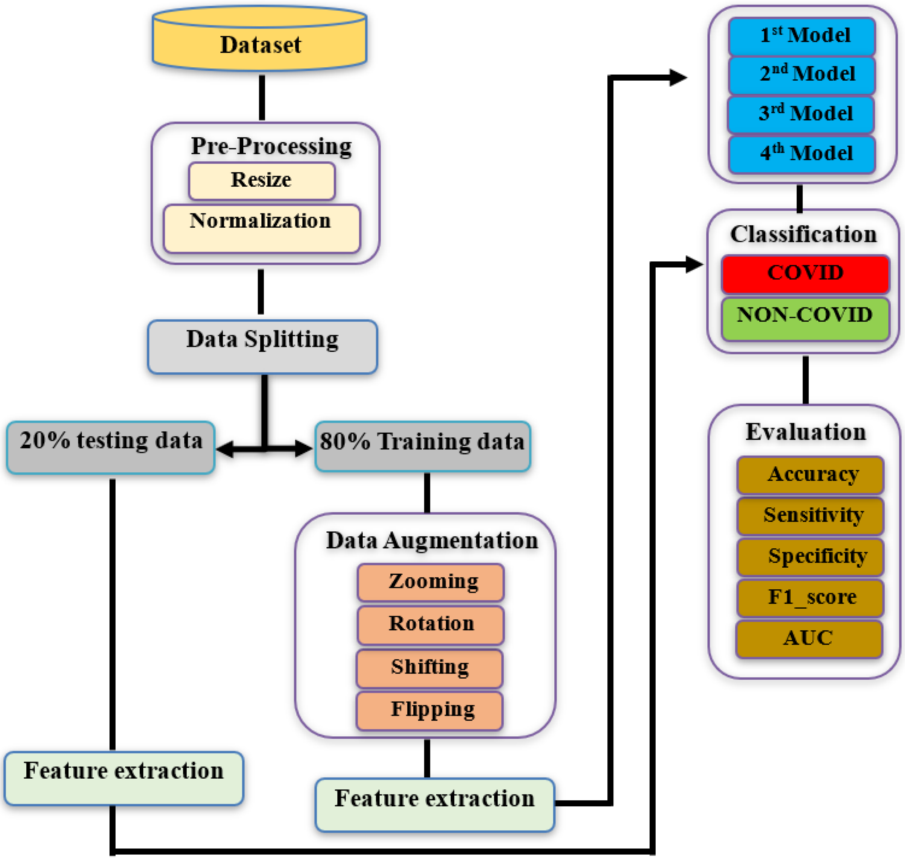


Figure 1. Block diagram for proposed COVID-19 classification system

3.3. Pre-processing

Pre-processing plays a crucial role in facilitating the system's learning process and enabling the extraction of relevant image data. The proposed study included resizing all images within both datasets to dimensions of 224×224. To improve the quality of CT images, it is essential to use image normalization as a crucial step in the suggested methodology. Pre-processing might potentially enhance the algorithm's ability to rapidly learn and extract features from images, thereby reducing the duration of the training process. We use the formula $X = x/255$ for normalization. The final pre-processing step divides the raw dataset into a smaller subset for training and testing the proposed system.

3.4. Data Augmentation

The use of deep convolutional models in our work necessitates a substantial quantity of images for training to enhance performance while mitigating the risk of overfitting. However, the quantity of images in our collection is inadequate. The system's robustness will increase in proportion to the diversity of the training data. We used data augmentation to increase the number of training images and enhance their diversity. Additionally, this aids in improving the accuracy of predictions and mitigates the overfitting issue. We used several transformation techniques to enhance the dataset, including rotation, flipping, shearing, and zooming. We randomly selected the rotation angle from 0 to 30 degrees. The range of random zooming was between 90% and 110%.

3.5. VGG16 and Proposed Model

The Visual Geometry Group at the University of Oxford built the VGG16 model to achieve a win in the 2014 International Large-Scale Visual Recognition Challenge (ILSVRC2014) [26]. The model starts with a set of weights acquired by training on the ImageNet dataset, which comprises more than 14 million images annotated with 1000 distinct categories. The VGG16 model has 138,357,544 parameters. Figure 2 shows the architecture of the proposed models.

3.6 Evaluation Metrics

We compared the performance of several classifiers used in the SARS-COV-2 dataset's image classification using AUC, accuracy, precision, sensitivity, and F1 score. The percentage of successfully classified images as COVID-19 can indicate the system's accuracy. Similarly, precision can be defined as accurately forecasting the total [27]. The equations show these metrics: [28]

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{1}$$

$$sensitivity = \frac{TP}{TP + FN} \tag{2}$$

$$Precision = \frac{TP}{TP + FP} \tag{3}$$

$$\text{F1 score} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{4}$$

$$\text{Specificity} = \frac{TN}{TN + FP} \tag{5}$$

where the abbreviations for true positive, true negative, false positive, and false negative are (TP), (TN), (FP), and (FN), respectively [8].

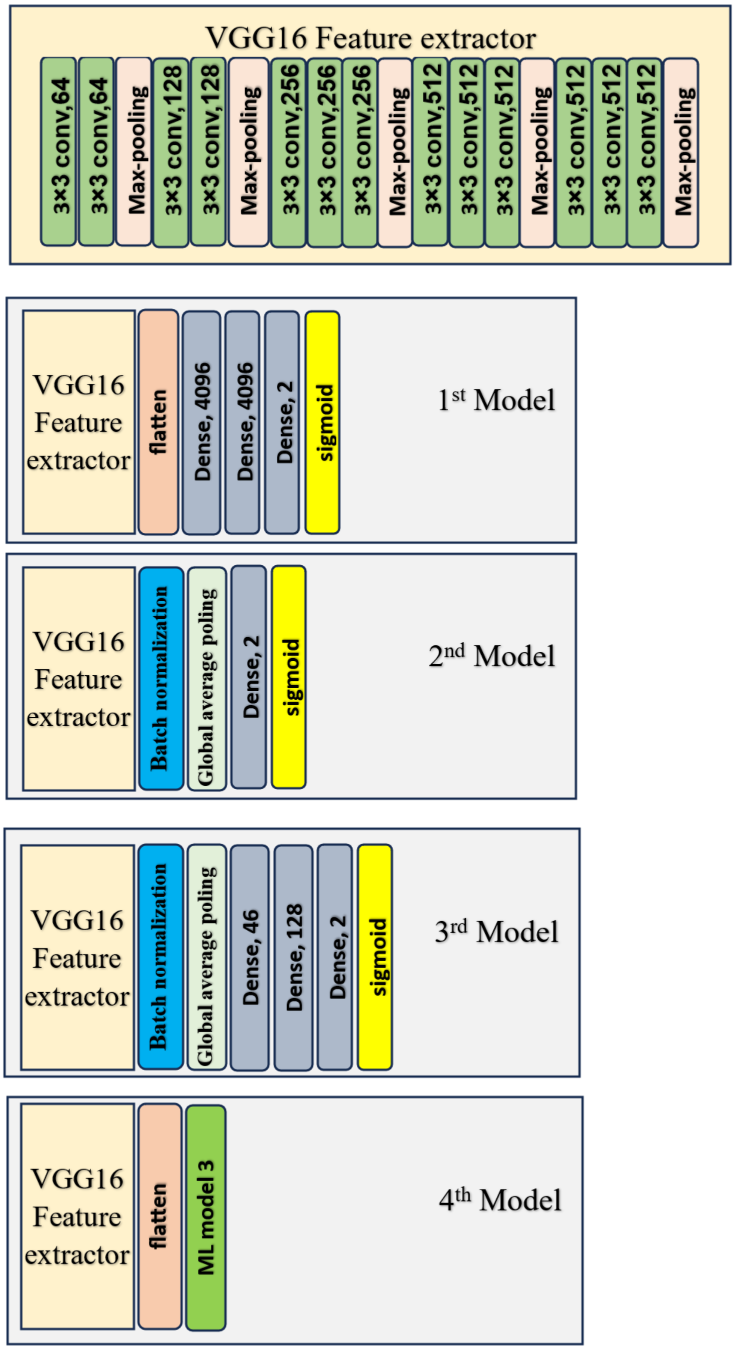
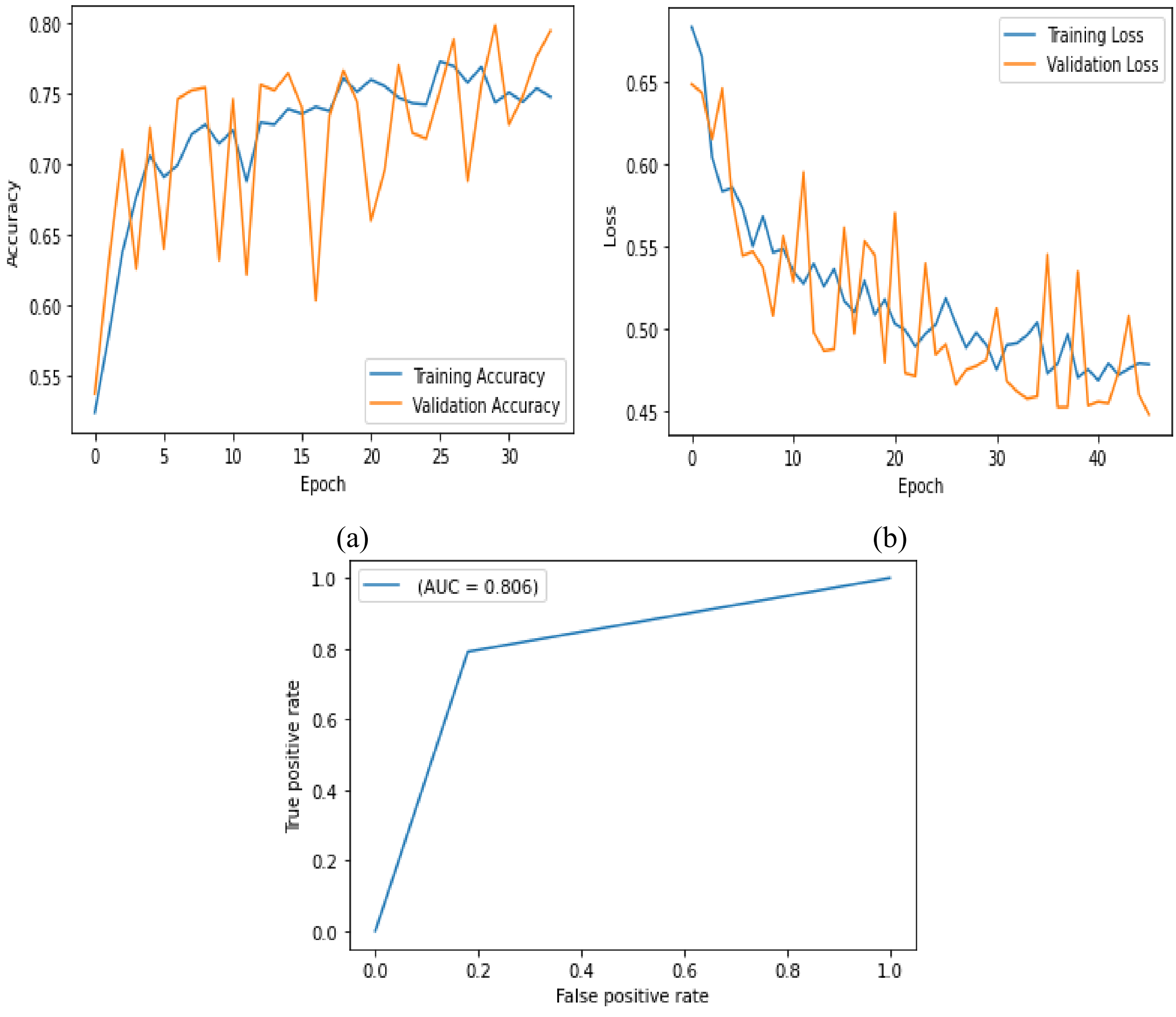


Figure 2. The Architecture of the proposed models

4. Results and Discussion

Here, we provide the findings from our effort to categorize lungs as COVID or non-COVID, as well as comparisons to previous studies in the field. The proposed model takes a CT scan image with dimensions of 224×224×3 as input to the output of the probabilistic results from the network's last layer. The following performance metrics, as shown in Figure 3, determine the CNN performance: accuracy, sensitivity, specificity, precision, F1 score, and AUC. Then, the first model was achieved after calculating the confusion matrix on the testing set, and the results were respectively as follows: 73.52±6.69%, 58.58±2.75%, 86.44±8.45%, 80.25±4.24%, 64.86±1.52%, and 72.5±7.87%. The VGG16 model was used by adding feature extraction. Then, trainable layers false and including the top true, removing the last layer Denes (1000) without a fully connected layer and adding classifier Denes (2) to it by COVID and non-COVID as shown in Figure 3.



(c)

Figure 3. First model results using SARS-CoV-2: (a) accuracy, (b) loss, and (c) ROC curve

After incorporating feature extraction, we used the second VGG16 model, setting the trainable layers to false and including the top layer to false. Subsequently, the model included three blocks, including the batch normalization layer, global average pooling 2D, and dense (2). Afterward, we incorporated the categorizations of COVID-19 and non-COVID-19. Figure 4 displays the training accuracy, validation accuracy, loss retractions, and receiver operating characteristic (ROC) curve. The performance indicators are shown.

We determined the correctness of the model by evaluating the confusion matrix. The accuracy values obtained on the testing set were as follows: 79.07±0.92%, 79.39±3.51%, 78.80±2.73%, 76.40±1.63%, 77.81±1.30%, and 79.08±0.99%, as shown in Figure 4.

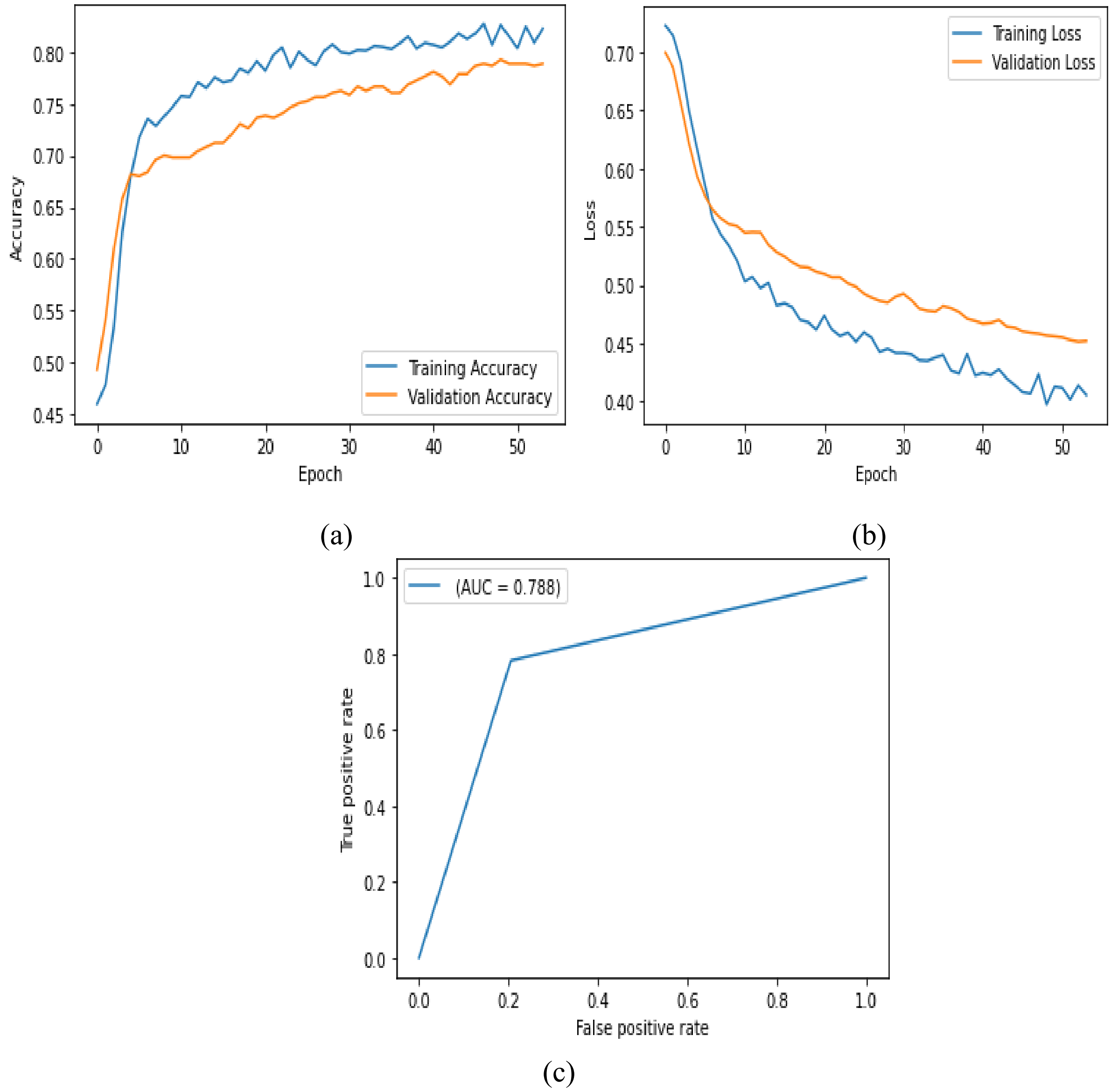
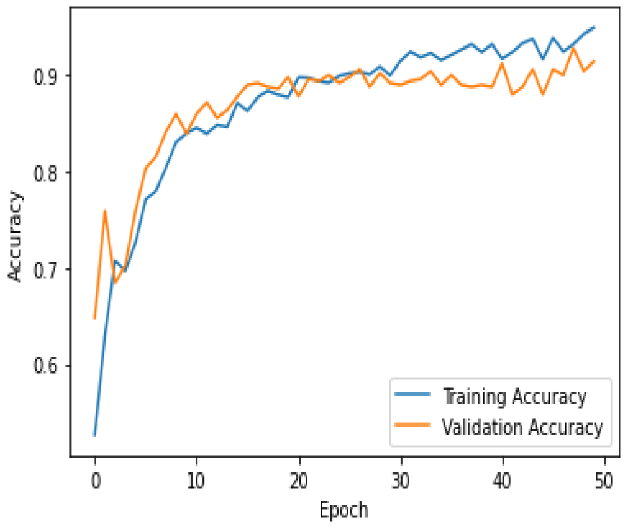
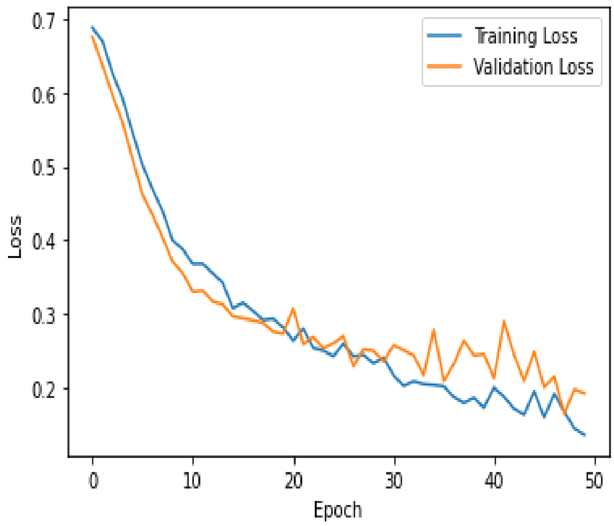


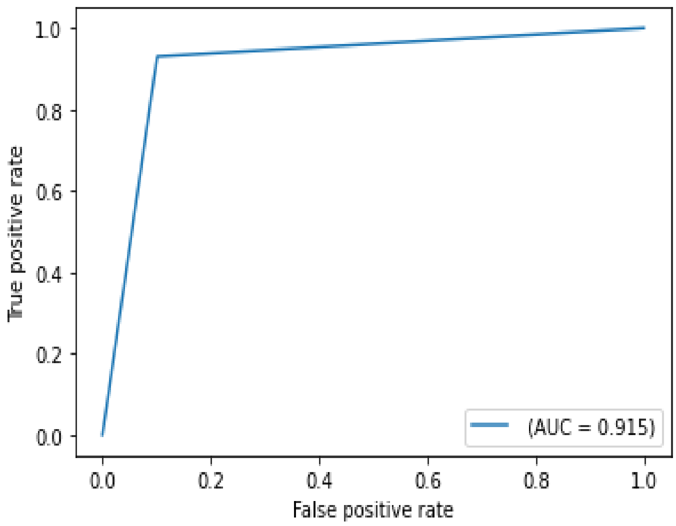
Figure 4. The second model results using SARS-CoV-2: (a) accuracy, (b) loss, and (c) ROCcurve

In the third model, it is now possible to train only the three layers at the bottom. We made some changes to the parameters and added the three blocks of dense layer (64), dense layer (128), and dense layer (2), along with the classifier. This created a new model that was 91.67±1.58% more accurate overall than the old model. The final sensitivity, specificity, precision, F1 score, and AUC are higher than the second model. These values are 95.82±1.75%; 88.08±3.27%; 87.51±3.27%; 91.43±1.50%; and 91.98±1.55%, respectively. Figure 5 presents the model's training accuracy, validation accuracy, loss, and ROC.





(a) (b)

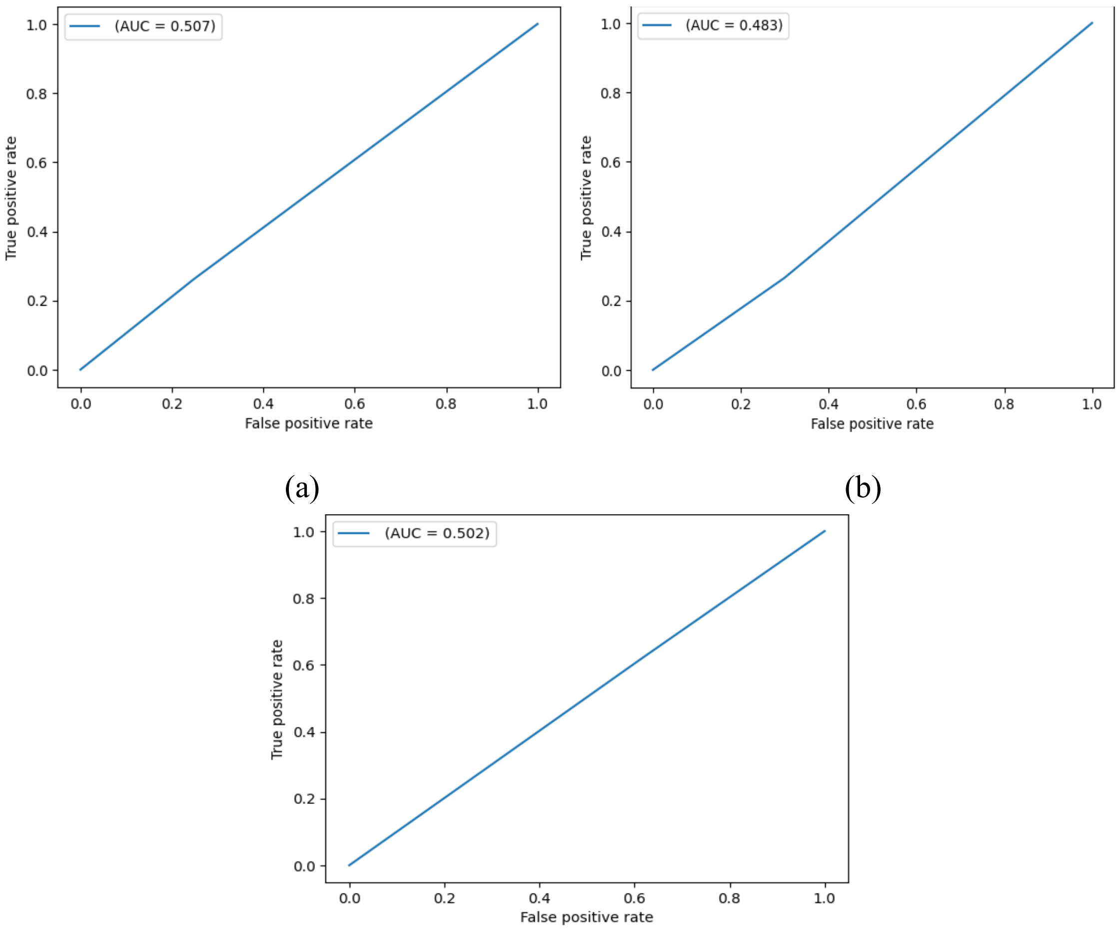


(c)

Figure 5. The third model results using SARS-CoV-2: (a) accuracy, (b) loss, and (c) Roc curve

The fourth model uses the VGG16 model as a feature extractor. We built the model as follows: first, we set the trainable layer to false; then, we added a flattening layer; and finally, we appended the ML models. We utilized three algorithms to instantiate the machine-learning model: the RF, KNN, and SVM classifiers. The outcomes showed a somewhat reduced degree of efficacy in both situations compared to earlier methods. Combining DL with ML can achieve a more effective computational model, as demonstrated by this study. This enhanced efficiency, however, does not come without a cost, as seen by the results provided in Figure 6. The results show that the RF classifier achieved 52.51±3.15%, 28.26±3.53%, 71.16±3.61%, 45.77±6.17%, 34.94±4.32%, and 50.7±3.13%, respectively. The mean accuracy for the KNN classifier ranged from 51.87±1.95% to 26±1.20%, 74±3.66% to 46±3.64%, and 33.34±1.51% to

50.08±1.84%. The accuracy for the SVM classifier ranged from 50.30±1.88%, 57.82±4.75%, 43.82±4.54%, 46.99±1.69%, 51.79±2.53%, and 50.82±1.88%, respectively. The E method demonstrates that combining DL with ML results in faster model execution time. However, the combined accuracy is lower than that of the first model, and the third model is used separately.



(a) (b)

(c)

Figure 6. Fourth model ROC curve using SARS-CoV-2: (a) RF (b) KNN (c) SVM

Accuracy, sensitivity, specificity, F1-score, precision, and AUC are measures shown in Table 1. The findings demonstrated that the first approach had less-than-desirable results when compared to other approaches. In this instance, we used a subset of the first approach, the first model. The unfreezing of the third model method's last three layers sets it apart from standard transfer-learning procedures and ultimately leads to the desired effect. We credit the last three layers, Denes Layers 64, Denes Layers 128, and Denes Layers 2, for improving the output quality by acting as extra classifiers for COVID and non-COVID situations. The fourth model generally represents the least efficient strategy. After creating a flattening layer, this method combines ML and DL by adding an ML model.

Table 1. Results for all methods

Method	Accuracy %	Sensitivity %	Specificity %	Precision %	F1 score %	AUC %
1st model	79.07±0.92	79.39±3.51	78.80±2.73	76.40±1.63	77.81±1.30	79.08±0.99
2nd model	73.52±6.69	58.58±2.5	86.44±8.45	80.25±4.24	64.86±1.52	72.50±7.87
3rd mode	91.67±1.68	95.82±1.75	88.08±3.72	87.51±3.27	91.43±1.55	91.98±1.55
4th model_RF	52.51±3.15	28.26±3.53	71.16±3.61	45.77±6.17	34.94±4.32	50.70±3.13
4th model_KNN	51.87±1.95	26.00±1.20	74.15±3.62	46.61±3.64	33.34±1.51	50.08±1.84
4th model_SVM	50.30±1.88	57.82±4.75	43.82±4.54	46.99±1.69	51.79±2.53	50.82±1.88

Table 2 presents a comprehensive summary of the results from several experiments on the diagnostic system for COVID-19. The assessment was based on the correctness of the comparison. It is important to emphasize that direct comparisons are unfeasible due to discrepancies between the data sets, such as variations in the number of images and different methodologies used. However, our study achieved superior results, reliability, and resilience for the present model compared to earlier works.

Table 2. Comparison with other studies

Ref.	Method	Accuracy	Sensitivity	Specificity	Precision	F1 score	AUC
JavadiMoghaddam and Gholamalinejad [17]	WCNN4	99.03	98.91		98.71	98.43	
Yousefzadeh, et al. [18]	EfficientNB3		97.02	96.08		97.00	99.07
Ahamed, et al. [19]	ResNet/class1	99.01	99.06	99.06	99.00		
	ResNet/class2	89.90	89.91	90.15	89.70		
Li, et al. [20]	VGG16	93.57	94.21	93.93	89.40	91.74	
Rahimzadeh, et al. [21]	Xception	98.49	94.96				
	ResNet50V2	96.55	98.02				
Ardakani, et al. [22]	VGG-19	85.29	92.16	87.43			94.30
	AlexNet,	79.92	89.21	68.63			89.00
	VGG-16	83.33	80.39	86.27			92.60
	SqueezeNet	82.84	87.43	87.25			89.90
Gupta, et al. [23]	VGG19	93.90	93.90		93.90	94.00	94.60
	VGG16	94.20	94.20		94.20	94.20	98.20
Proposed model	3rd Model	91.67±1.8	95.82±1.75	88.08±3.72	87.51±3.27	91.43±1.5	91.98±1.55

5. Conclusion

This study presents the development of a DL VGG16 model to diagnose COVID-19 based on chest CT scan images. We compared the redesigned model with other pre-existing models. The optimized model exhibited encouraging outcomes by significantly enhancing the sensitivity metric of 95.82±1.75%, a critical factor in accurately detecting COVID-19 infection. Furthermore, the resulting model showed notable performance in terms of accuracy 91.67±1.68%, specificity 88.08±3.72%, precision 87.51±3.27%, F1 score 91.43±1.55%, and AUC 91.98±1.55%. DL methodologies effectively identify and diagnose COVID-19 in chest CT scan images. DL has shown exceptional performance in the field of radiology. In future scenarios, the suggested methodology has the potential for clinical practitioners to use it to analyze, identify, and subsequently prevent and manage pandemics more effectively.

Declaration of Competing Interest: The authors declare no known conflicts of interest.

References

[1] Y. Karadayi, M. N. Aydin, and A. S. Öğrencí, "Unsupervised Anomaly Detection in Multivariate Spatio-Temporal Data Using Deep Learning: Early Detection of COVID-19 Outbreak in Italy," *IEEE Access,* vol. 8, pp. 164155-164177, 2020.

[2] R. G. Babukarthik, V. A. K. Adiga, G. Sambasivam, D. Chandramohan, and J. Amudhavel, "Prediction of COVID-19 Using Genetic Deep Learning Convolutional Neural Network (GDCNN)," *IEEE Access,* vol. 8, pp. 177647-177666, 2020.

[3] G. Zazzaro, F. Martone, G. Romano, and L. Pavone, "A Deep Learning Ensemble Approach for Automated COVID-19 Detection from Chest CT Images," (in English), *JOURNAL OF CLINICAL MEDICINE,* vol. 10, no. 24, DEC 2021.

[4] V. Chang, M. Abdel-Basset, R. Iqbal, and G. Wills, "Guest Editorial:Advanced Deep Learning Techniques for COVID-19," *IEEE Transactions on Industrial Informatics,* vol. 17, no. 9, pp. 6476-6479, 2021.

[5] P. Bhowal, S. Sen, J. H. Yoon, Z. W. Geem, and R. Sarkar, "Choquet Integral and Coalition Game-Based Ensemble of Deep Learning Models for COVID-19 Screening From Chest X-Ray Images," *IEEE Journal of Biomedical and Health Informatics,* vol. 25, no. 12, pp. 4328-4339, 2021.

[6] N. N. Das, N. Kumar, M. Kaur, V. Kumar, and D. Singh, "Automated deep transfer learning-based approach for detection of COVID-19 infection in chest X-rays," *Irbm,* vol. 43, no. 2, pp. 114-119, 2022.

[7] E. Jangam, A. A. D. Barreto, and C. S. R. Annavarapu, "Automatic detection of COVID-19 from chest CT scan and chest X-Rays images using deep learning, transfer learning and stacking," *Applied Intelligence,* pp. 1-17, 2022.

[8] K. Gong *et al.*, "A multi-center study of COVID-19 patient prognosis using deep learning-based CT image analysis and electronic health records," *European journal of radiology,* vol. 139, p. 109583, 2021.

[9] M. Y. Kamil, "Morphological gradient in brain magnetic resonance imaging based on intuitionistic fuzzy approach," in *Al-Sadiq International Conference on Multidisciplinary in IT and Communication Techniques Science and Applications, AIC-MITCSA 2016,* 2016, pp. 133-135.

[10] K. S. Kumari, S. Samal, R. Mishra, G. Madiraju, M. N. Mahabob, and A. B. Shivappa, "Diagnosing COVID-19 from CT image of lung segmentation & classification with deep learning based on convolutional neural networks," *Wireless Personal Communications,* pp. 1-17, 2021.

[11] S. Serte and H. Demirel, "Deep learning for diagnosis of COVID-19 using 3D CT scans," *Computers in Biology and Medicine,* vol. 132, p. 104306, 2021/05/01/ 2021.

[12] J. C. Clement, V. Ponnusamy, K. C. Sriharipriya, and R. Nandakumar, "A Survey on Mathematical, Machine Learning and Deep Learning Models for COVID-19 Transmission and Diagnosis," *IEEE Reviews in Biomedical Engineering,* vol. 15, pp. 325-340, 2022.

[13] E. Radhi and M. Kamil, "An Automatic Segmentation of Breast Ultrasound Images Using U-Net Model," *Serbian Journal of Electrical Engineering,* Article vol. 20, no. 2, pp. 191-203, 2023.

[14] R. R. Kadhim and M. Y. Kamil, "Comparison of breast cancer classification models on Wisconsin dataset," *International Journal of Reconfigurable and Embedded Systems,* Article vol. 11, no. 2, pp. 166-174, 2022.

[15] D. A. Mahmood and S. A. Aminfar, "Efficient Machine Learning and Deep Learning Techniques for Detection of Breast Cancer Tumor," *BioMed Target Journal,* vol. 2, no. 1, pp. 1-13, 2024.

[16] Y. Oh, S. Park, and J. C. Ye, "Deep Learning COVID-19 Features on CXR Using Limited Training Data Sets," *IEEE Transactions on Medical Imaging,* vol. 39, no. 8, pp. 2688-2700, 2020.

[17] S. JavadiMoghaddam and H. Gholamalinejad, "A novel deep learning based method for COVID-19 detection from CT image," *Biomedical Signal Processing and Control,* Article vol. 70, no. 102987, pp. 1-7, 2021, Art. no. 102987.

[18] M. Yousefzadeh *et al.*, "ai-corona: Radiologist-assistant deep learning framework for COVID-19 diagnosis in chest CT scans " *PLoS ONE,* vol. 16, no. 9 September, pp. 1-20, 2021, Art. no. e0257119.

[19] K. U. Ahamed *et al.*, "A deep learning approach using effective preprocessing techniques to detect COVID-19 from chest CT-scan and X-ray images," *Computers in Biology and Medicine,* Article vol. 139, no. 105014, pp. 1-19, 2021, Art. no. 105014.

[20] X. Li, W. Tan, P. Liu, Q. Zhou, and J. Yang, "Classification of COVID-19 Chest CT Images Based on Ensemble Deep Learning," *Journal of Healthcare Engineering,* Article vol. 2021, no. 5528441, pp. 1-7, 2021, Art. no. 5528441.

[21] M. Rahimzadeh, A. Attar, and S. M. Sakhaei, "A fully automated deep learning-based network for detecting COVID-19 from a new and large lung CT scan dataset," (in English), *BIOMEDICAL SIGNAL PROCESSING AND CONTROL,* vol. 68, JUL 2021.

[22] A. A. Ardakani, A. R. Kanafi, U. R. Acharya, N. Khadem, and A. Mohammadi, "Application of deep learning technique to manage COVID-19 in routine clinical practice using CT images: Results of 10 convolutional neural networks," *Computers in biology and medicine,* vol. 121, p. 103795, 2020.

[23] S. Gupta, P. Aggarwal, N. Chaubey, and A. Panwar, "Accurate Prognosis Of Covid-19 Using Ct Scan Images With Deep Learning Model And Machine Learning Classifiers," *Indian Journal of Radio and Space Physics,* Article vol. 50, no. 1, pp. 19-24, 2021.

[24] H. Alshazly, C. Linse, E. Barth, and T. Martinetz, "Explainable COVID-19 detection using chest CT scans and deep learning," *Sensors (Switzerland),* Article vol. 21, no. 2, pp. 1-22, 2021, Art. no. 455.

[25] S. Eduardo, A. Plamen, B. Sarah, F. Michele Higa, and A. Daniel Kanda, "SARS-CoV-2 CT-scan dataset: A large dataset of real patients CT scans for SARS-CoV-2 identification," *medRxiv,* p. 2020.04.24.20078584, 2020.

[26] O. Russakovsky *et al.*, "ImageNet Large Scale Visual Recognition Challenge," *International Journal of Computer Vision,* Article vol. 115, no. 3, pp. 211-252, 2015.

[27] E. Acar, E. Şahin, and İ. Yılmaz, "Improving effectiveness of different deep learning-based models for detecting COVID-19 from computed tomography (CT) images," *Neural Computing and Applications,* vol. 33, no. 24, pp. 17589-17609, 2021.

[28] M. Y. Kamil, "A deep learning framework to detect Covid-19 disease via chest X-ray and CT scan images," *International Journal of Electrical and Computer Engineering,* Article vol. 11, no. 1, pp. 844-850, 2021.