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COVID-19 identification and analysis using CT scan images: Deep transfer learning-based approach

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1 Introduction

COVID-19 is regarded as one of the most dangerous viruses on the planet. It has the ability to spread swiftly among individuals. People lose their lives because of COVID-19. COVID-19 affects the whole world. Scientists, epidemiologists, and virologists are continuously working to get different solutions for society. The number of COVID-19 patients began to increase unexpectedly, leaving authorities and health professionals unable to deal with the problem. Hospital rooms and ICU beds are limited number in the majority of developing nations. The health services in India are a particularly complicated situation because the country has the world’s most diversified population (approx. 1.3 billion people). During the pandemic, hospitals struggled to provide adequate care to both COVID-19-infected and noninfected patients. Consequently, critically ill individuals are being refused entry to intensive care units. As a result, testing kit supplies are in short supply, and many hospitals worldwide are having difficulty detecting COVID-19 positive patients. In terms of medical professionals, it is projected that India has only one doctor for every 1666 people [1].

Healthcare services were not accessible for all COVID-19 patients in some of the worst-affected cities. As a result of a large number of verified cases, patients were returned home for quarantine and monitoring, possibly risking their loved ones to the virus. Outside of health facilities, high-risk patients must be observed regularly by examining symptoms such as fever, heart rate, oxygen saturation, and so on. Real-time monitoring technologies have a big influence on how health surveillance and treatment solutions are developed. The adoption of Healthcare 4.0 technology is one solution for this problem. Healthcare 4.0 [2–10] is driven by Industry 4.0 technology, such as wearable devices, artificial intelligence (AI), blockchain, cloud computing, IoT, robotics, 3D bioprinting, and so on. Various innovations in the e-healthcare industry, such as blockchain, AI, cloud computing, and IoT, have been combined to give dynamic medical treatments in real time. The IoT-WBAN [11] is comprised of the wireless communications of wearable devices. The information
gathered is subsequently utilized for various reasons, including in-hospital observation, remote diagnostics, outpatient monitoring, and emergency response. A wireless body area network (WBAN) has the potential to have a substantial influence on the control of COVID-19 transmission.

Inspired by that, many predictions such as plasma therapy, X-ray imaging [12, 13], and so on have come into existence. A lot of people died due to COVID-19 [14], and the disease’s origin has yet to be discovered [15]. A primary strategy for better managing this pandemic is finding, isolating, and caring for patients as soon as possible. Our research aims to develop a computational transfer learning model for COVID-19 image classification. Due to online repository availability, we get images from CT scans of COVID-19-infected people and healthy people [16]. The indication of COVID-19 is a throat infection that leads to breathing problems. The COVID-19 patient should stay in isolation to protect healthy people because COVID is a highly contagious disease that transfers from one individual to another and forms a chain. Instead, many methods are used to reduce the impact of COVID-19. One of them is medical imaging [17], which is also helpful for analysis and predicting the effect of the virus on the human body. With CT scans, images of non-COVID-19 individuals and infected persons can be analyzed [18, 19]. Fig. 1 shows sample images of CT scans for COVID positive and negative patients.

For the proper treatment of COVID-19 patients, healthcare facilities can exchange data. Sharing data securely [20, 21] and training a global model to discover affected patients is a difficult challenge. Data collection from a variety of origins is a significant problem and a barrier in the development of intelligent [22] approaches. By adopting blockchain-based [23–25] federated learning, organizations can store their data privately and spread the data among institutions. An electronic medical record (EMR) based on a blockchain system has vast potential to provide safe, dependable, and resilient EMR storage. It will also enhance access to research data for study by scientists, healthcare professionals, and government agencies who can analyze it and make better choices. The decentralized system [26, 27] for information exchange among several facilities securely exchanges data without compromising the institutions’ confidentiality. This distributed information can be analyzed to improve the global deep learning (DL) model to detect infected patients. Privacy, confidentiality, and data consistency are fundamental problems for storing and managing any patient data. As a result, blockchain-based [5] healthcare solutions are preferred for fostering user confidence, security, and privacy. Blockchain-based solutions can be used to improve the healthcare system. Healthcare systems can be enhanced with blockchain architecture and DL methods. A framework using blockchain and DL can also be used to anticipate future diseases and provide assistance to individuals.

For severe health issues such as COVID-19, the time and resources required to collect and marked images are difficult to acquire considerably large and openly accessible medical photographic data to train DL models. A different way of training DL models is transfer learning, which involves assigning precalculated weights to a DL network. The weights are acquired from previous experiments in various applications. This approach is commonly used for initializing DL techniques; other parameters are
finalized using corpus available for clinical samples [28]. This analysis would look at how transfer learning can be incorporated to classify COVID-19 in CT scans. This could help physicians and academics provide a method to help highly constrained health providers decide about the next course of action. We have used the VGG-19 pretrained model to identify and classify the COVID positive and negative CT scan samples. The paper’s key contributions include:

- We suggest a novel DL technique and evaluate it on a dataset with 5000 images to identify COVID-19 quicker.

Fig. 1 Sample patient images of dataset. (A) Positive patient images; (continued)
The proposed model is a transfer learning model based on VGG-19 architecture that can obtain an accuracy of 95%.

We also discover in the experimental findings that our proposed model performs better in comparison to CNN and Xception Net.

We begin with a summary of the study relevant to this research in Section 2. After that, we discuss the suggested transfer DL model and compare the results with another model in Section 4. In Section 5, we present the output results along with discussions. Finally, we conclude the work and explain some future directions.

Fig. 1, cont’d (B) negative patient images.
2 Related works

Afshar et al. [29] introduced a model using a capsule network to classify COVID-19 by analyzing CT scans. In this model, capsules and various convolution layers were used, which eliminates the class imbalance problem. In the experimental result, the authors showed the model’s performance. They used the trained model that is publicly accessed on GitHub [30]. They showed that this model’s accuracy is 95.7% sensitivity as 90%, the specificity of the model is 95.80%. In Ref. [31], the author proposed an AI model, in which machine learning (ML) and DL algorithms are utilized to identify the COVID-19-patient’s X-ray. In Refs. [32, 33], the authors provide an analysis of MERS’ radiologic features for treating sick individuals using X-rays. Still, they considered only a 30-year-old individual as having fever, stomach pain, and diarrhea. Further, this model applied on the X-ray and CT scans proved helpful. Also, in Ref. [34], the authors explain some protocols that should be implemented in hospitals to reduce the risks of spreading COVID-19 from infected persons to healthy persons.

In Ref. [35], the authors discussed the breakout cause of COVID-19. They raised the question of the cause of COVID-19. In their study, they assessed the impact of COVID-19 spread. In Ref. [36], the author proposed a model using the support vector machine (SVM) technique to classify the pneumothorax characteristics of a lung image mine using a local binary pattern. In the proposed model, they segmented the region of abnormal lungs using multiscale texture segmentation, which removes the chest image’s impurities and gives us the area of interest. Later on, this transformation is used for a shift in texture to find multiple overlapping frames. Sobel edge detection identifies rib boundaries. Finally, the rib border is filled in between the aberrant patches to get a full disease region. In Ref. [37], the author uses CT scans of 21 COVID-19-infected individuals to demonstrate their work. In Ref. [38], the author extracted the features by using convolutional neural network (CNN) and SVM algorithms for classification by using COVID-19 corpus. This proposed model can be utilized to cure COVID-19 positive individuals. In Ref. [13], the author identified the impact of this viral disease from person-acquired lung diseases and pneumonia using deep algorithms applied on a chest CT scan. In Ref. [39], the author demonstrated the impact of COVID-19 on acute renal failures. In Ref. [40], the authors classified the collection of 50 COVID-19 patients within two classes as good and poor. Further, the potential risk for pulmonary infections and low recovery was found by the authors. Table 1 depicts a summary of works done for COVID-19 identification using various approaches.

In Ref. [48], the author analyzed COVID-19-infected persons and death due to the virus worldwide. In Ref. [41], the author introduced a DL model to diagnose a COVID-19-infected person with help from images. This method is very effective in the rapid identification of an infected person. This method gives 97.48% accuracy for lung classification by using different matrix parameters. In Ref. [49], the author demonstrated how the COVID-19 virus is revealed as a pneumonia infection. The authors’ main aim is to propose a DL algorithm that is Covidx-net to cure COVID-19 automatically with the help of images. In Ref. [50], the authors proposed
a distinct approach to identify COVID-19 positive individuals. It was concluded that COVID-19 automatically prevents the spread of coronaviruses through touch. Besides, the study of the COVID-19 correlation to pneumonia was performed and it was found that it is challenging to predict pneumonia caused by the coronavirus or any other symptoms. In Ref. [51], the author tried to find the lung abnormality by using chest radiography and concluded that the medical community depends on chest radiography due to the convenience and less spread control. In Ref. [30], the author used the front view of 123 X-ray samples to treat COVID-19 patients. In Ref. [42], the author presented the different AI techniques in medicine and the challenges faced using corpus-less image samples. They incorporate the pretrained AlexNet model and CNN to train on the dataset. As a result, the method has 98%, and modified CNN has 94.1% accuracy. In [52], the author extracted two subsets (16 × 16 and 32 × 32) generated from 530 X-rays and 150 CT scan samples labeled for COVID or non-COVID.

Hathaliya et al. [2] introduced a permissioned blockchain-based medical care ecosystem to improve the safety and confidentiality of client records. Remote health surveillance becomes increasingly sophisticated and versatile in Healthcare 4.0, allowing patients to be seen at any time and from any location via wearable sensors. The current telesurgery technology has security, privacy, and interoperability concerns, limiting its potential use in healthcare institutions throughout the world. To address these concerns, the authors [3] offered HaBiTs (blockchain-based telesurgery), a system in which security is accomplished by integrity and extensibility via smart contracts. To appropriately administer medicine, access to the health history of patients is vital, and blockchain may substantially strengthen the healthcare system. Various approaches are evaluated in this chapter [4], comprising tools and techniques to assess the performance of such systems for addressing existing limits of healthcare systems leveraging blockchain technologies, such as Hyperledger Fabric and Composer.

### Table 1 Comparative review of the existing work.

| S. no. | Authors | Year | Approach | Accuracy (%) |
|-------|---------|------|----------|--------------|
| 1.    | Hassanien et al. [41] | 2020 | Deep-based methodology with vector gadget classifier | 98.48 |
| 2.    | Afshar et al. [29] | 2020 | Capsule network | 95.7 |
| 3.    | Maghdid et al. [42] | 2020 | AlexNet pretrained | 98 |
| 4.    | Maghdid et al. [42] | 2020 | Modified CNN | 94 |
| 5.    | Thejeshwar et al. [43] | 2020 | KE Sieve Neural Network | 98 |
| 6.    | Jain et al. [44] | 2021 | Inception Net V3 | 93 |
| 7.    | Jain et al. [44] | 2021 | Xception | 97 |
| 8.    | Aras et al. [45] | 2021 | ResNet50 | 94.7 |
| 9.    | Ying et al. [46] | 2021 | DRE-Net | 86 |
| 10.   | Wang et al. [47] | 2021 | CNN | 93 |
3 Proposed model

3.1 Convolutional neural networks

This is DL model, that is mostly used for image analysis and classifications [53–55]. A CNN model comprises one or more convolution layers, pooling layers, and fully connected layers. It has various applications such as handwriting recognition, medical image processing, sentiment analysis, and so on [56]. CNN can handle noisy images in image classification as well as overfitting problems in datasets [57, 58]. Nahid et al. proposed an image processing model to identify pneumonia [59]. In this model, they used X-ray images in the CNN framework and got 97.2% accuracy. In this work, they used feature learning and classification strategy together. Feature engineering comprises different convolutional and pooling layers. COVID-19 has been identified for 2020. After that various research works are carried out to identify COVID-19 using DL methods. We have also employed the CNN model for COVID-19 image identification with the following parameters (Table 2).

3.2 Transfer learning

It is a way of using one task’s experience to increase the widespread use of another. The understanding of a previously qualified DL model is used to migrate the parameters learned by a network on any “task A” to a new “task B” [60].

It is often used in the processing of computer vision. The natural language where the labeled data are too small for a model to be trained from scratch and a network with a lot of information are preentrained on an identical problem (Fig. 2).

Following strategies can be used for transfer learning:

- **Use as a feature extractor**: DL networks are a layered architecture where multiple layers learn distinct features. All layers are connected to the last layer or the fully connected layer for final results. For other models, it can use DL models without their final layer as a fixed feature extractor (Fig. 3).
- **Use to fine-tuning**: In this method of transfer learning, we replace the final layer of the network and also selectively retrain some of the previous layers, which is shown in Fig. 4.

Table 2 CNN model parameter details.

| Parameter                | Value          |
|--------------------------|----------------|
| Learning rate            | 0.001          |
| Hidden layers            | 32             |
| Batch size               | 32             |
| Pooling                  | Maxpooling 2D  |
| Activation function      | Softmax        |
| Number of classes        | 2              |
| Optimizer                | Adam           |
3.3 Xception Net

At Google, Xception CNN has been created by Francois Chollet. It is an advancement to the inception net; the changes are made in the structure by replacing the regular inception module of the inception net by depth-wise separable convolutions [62]. It has a parameter size close to that of the inception net, but it performs somewhat better [63]. It consists of a combined layer containing $1 \times 1$, $3 \times 3$, and $5 \times 5$ convolution, and it has 48 levels and hires an inception component. It is even known by the name GoogLeNet [64]. It is shown in Fig. 5.
Fig. 4 Transfer learning using fine-tuning [61].
The experiments were conducted using the following parameters for Xception Net classification (Table 3).

### 3.4 VGG19 model

VGG is a deep CNN used for image classification. The Visual Geometry Group created it at Oxford in 2014. VGG19 is a 19-layer version of the VGG network (3 fully connected, 16 convolutional, 1 softmax, and 5 maxpool layers) [65].

The input to VGG-based CNN is a 224 × 224 RGB image that is preprocessed by a preprocessing layer. After preprocessing, they are passed to through the weight layers of the VGG19 model to 19 weight layers and 3 fully connected layers (Fig. 6). It comprises two fully connected layers of 4096 channels, followed by a completely connected 1000 channel layer to anticipate 1000 labels. Softmax feature is used for grouping by the last FC layer [65]. The experiments were conducted using the following parameters and architecture for VGG19 classification (Table 4 and Fig. 7).
Fig. 6 VGG19 model architecture [65, 66].
4 Experiments

4.1 Dataset detail

The non-COVID and COVID instances of CT scan samples are included in this COVID-19 dataset [67]. A total of 5000 CT scan samples are utilized from the associated dataset for conducting this research. The dataset is divided into two subfolders of 2500 non-COVID images and 2500 COVID images.

4.2 Experimental setting

We use Python for the proposed model to analyze COVID-19 on a Windows 10 machine with an Intel Core i7-8700 CPU of a 3.20 GHz processor and RAM of 32 GB. First, we trained the models to extract the features. After that image classification was performed using different parameters in the transfer learning model.

4.3 Performance evaluation

Classifiers evaluate their performance based on precision, accuracy, recall, F1 score, accuracy, and area under the receiver operating characteristic curve (AUC). The measure shown by the confusion matrix is as shown in Table 5. These are used to retrieve the performance. The definitions of the various performance variables are shown in Table 6.

4.4 Experimental outcomes

We contrasted the experimental outcomes with other DL and transfer techniques, such as CNN, VGG19, and Xception Net, to assess the proposed DL model’s efficiency. A comparison has been made based on accuracy, loss, AUC, F1 score, precision, recall, and confusion matrix. The proposed model VGG19 uses two classes, COVID and non-COVID. Figs. 8–10 show the accuracy and loss history of our model’s test set.

### Table 4 CNN model parameter details.

| Parameter            | Value                                      |
|----------------------|--------------------------------------------|
| Input shape          | (224, 224, 3)                             |
| Weights              | ImageNet                                  |
| Optimizer            | Adam                                      |
| Loss function        | Categorical_crossentropy                   |
| Activation function  | Softmax                                   |
| Epochs               | 60                                        |
| Batch size           | 32                                        |
| Dropout rate         | 0.5                                       |
| Regularization       | Nil                                       |
| Pooling              | Maxpooling2D                               |

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| Layer (type)       | Output Shape       | Param # |
|-------------------|--------------------|---------|
| input_1 (InputLayer) | ([None, 224, 224, 3]) | 0       |
| block1_conv1 (Conv2D) | (None, 224, 224, 64) | 1792    |
| block1_conv2 (Conv2D) | (None, 224, 224, 64) | 36,928  |
| block1_pool (MaxPooling2D) | (None, 112, 112, 64) | 0       |
| block2_conv1 (Conv2D) | (None, 112, 112, 128) | 73,856  |
| block2_conv2 (Conv2D) | (None, 112, 112, 128) | 147,584 |
| block2_pool (MaxPooling2D) | (None, 56, 56, 128) | 0       |
| block3_conv1 (Conv2D) | (None, 56, 56, 256) | 295,168 |
| block3_conv2 (Conv2D) | (None, 56, 56, 256) | 590,080 |
| block3_conv3 (Conv2D) | (None, 56, 56, 256) | 590,080 |
| block3_conv4 (Conv2D) | (None, 56, 56, 256) | 590,080 |
| block3_pool (MaxPooling2D) | (None, 28, 28, 256) | 0       |
| block4_conv1 (Conv2D) | (None, 28, 28, 512) | 1,180,160 |
| block4_conv2 (Conv2D) | (None, 28, 28, 512) | 2,359,808  |
| block4_conv3 (Conv2D) | (None, 28, 28, 512) | 2,359,808  |
| block4_conv4 (Conv2D) | (None, 28, 28, 512) | 2,359,808  |
| block4_pool (MaxPooling2D) | (None, 14, 14, 512) | 0       |
| block5_conv1 (Conv2D) | (None, 14, 14, 512) | 2,359,808  |
| block5_conv2 (Conv2D) | (None, 14, 14, 512) | 2,359,808  |
| block5_conv3 (Conv2D) | (None, 14, 14, 512) | 2,359,808  |
| block5_conv4 (Conv2D) | (None, 14, 14, 512) | 2,359,808  |
| block5_pool (MaxPooling2D) | (None, 7, 7, 512) | 0       |
| flatten (Flatten) | (None, 25088) | 0       |
| dropout (Dropout) | (None, 25088) | 0       |
| dense (Dense) | (None, 2) | 50,178  |

Total params: 20,074,562
Trainable params: 50,178
Nontrainable params: 20,024,384

Fig. 7 Model architecture and configuration parameters.
after each training epoch. The flow of the plot that represents accuracy is saturated very soon when the loss function comes to a minimum local level and is steadily increasing as the learning rate decreases.

Our model’s confusion matrix is seen in Tables 7–9. The model’s classification labels are represented on the $x$-axis while the input image labels are represented on the $y$-axis.

The proposed model using VGG19 architecture is compared with the recent state of the art in terms of efficiency shown in Fig. 11. Table 10 displays the outcomes of three models in the COVID-19 CT scan image dataset. Overall, the quantitative findings among all six assessment metrics, including accuracy, precision, recall, F1 score, AUC, and loss, strongly showed that the suggested method outperforms existing approaches of COVID analysis. In particular, VGG19 can achieve an accuracy of 95% with a loss of 17%. Tables 7 and 8 show that our proposed model has marginally higher accuracy and lower loss, which means that the introduced model can accurately classify the images.

Overall, the quantitative findings show that VGG19 outperforms CNN and Xception Net in all six measurement criteria. Fig. 11 compares our approach to existing methods in terms of efficiency. CNN obtained a loss of 72% and an accuracy of 93%. Xception Net obtained a loss of 85% and an accuracy of 93%. Our proposed model has 17% loss and 95% accuracy and performs better than other models.
Fig. 8  Accuracy and loss of CNN model.
5 Conclusions

In our healthcare system, AI, DL, and blockchain approaches are all vital. They give a user-friendly and efficient automated system for maintaining health. COVID-19 identification and analysis using cutting-edge computational tools are the focuses of this chapter. We also employed the transfer learning concept to improve the predicted outcomes in this chapter. For COVID-19 detection and analysis, a transfer learning-based VGG19 pretrained model was used. A CT scan image dataset was used to assess the efficacy of the VGG19 model. Following a series of tests, it was discovered that the more convolution layers, a strong dropout, a high batch size, and a large number of epochs, the better the accuracy. The VGG19 model’s findings were compared to the CNN and Xception Net models, and it was discovered that the VGG19 model outperforms the other two. The VGG19 model is based on a transfer learning technique.

Fig. 9 Accuracy and loss of VGG19 model.

5 Conclusions

In our healthcare system, AI, DL, and blockchain approaches are all vital. They give a user-friendly and efficient automated system for maintaining health. COVID-19 identification and analysis using cutting-edge computational tools are the focuses of this chapter. We also employed the transfer learning concept to improve the predicted outcomes in this chapter. For COVID-19 detection and analysis, a transfer learning-based VGG19 pretrained model was used. A CT scan image dataset was used to assess the efficacy of the VGG19 model. Following a series of tests, it was discovered that the more convolution layers, a strong dropout, a high batch size, and a large number of epochs, the better the accuracy. The VGG19 model’s findings were compared to the CNN and Xception Net models, and it was discovered that the VGG19 model outperforms the other two. The VGG19 model is based on a transfer learning technique.
Fig. 10 Xception Net model accuracy and loss.
Table 7 The confusion matrix of the CNN model.

![Confusion matrix for CNN model]

Table 8 The confusion matrix of the VGG19 model.

![Confusion matrix for VGG19 model]
Table 9 The confusion matrix of the Xception Net model.

![Confusion matrix]

Table 10 The performance comparison.

|        | Accuracy | Precision | Recall | F1 score | AUC  | Loss  |
|--------|----------|-----------|--------|----------|------|-------|
| CNN    | 0.9393   | 0.94      | 0.94   | 0.94     | 0.93 | 0.7247|
| VGG19  | 0.9500   | 0.95      | 0.95   | 0.95     | 0.95 | 0.1797|
| Xception | 0.9319  | 0.93      | 0.93   | 0.93     | 0.93 | 0.8525|

Fig. 11 Result comparison on different models.
that may be used in various domains. Blockchain architectures have several advantages over traditional systems, including seamless connectivity, faster data transfer, incident management, tracking, cost effectiveness, quick data access, and data security. We may combine DL-based models with blockchain designs in the future to increase the efficiency of healthcare systems.

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