AN IOT BASED WEB APPLICATION FRAMEWORK FOR COVID DETECTION FROM CT SCAN IMAGES

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Abstract–
Purpose: Pandemic condition almost everywhere due to COVID-19. The health and life of people have been severely impacted globally and derails the physical activities. Early detection of the infected persons for special care is crucial step to sustain in such situation. One of the fastest ways to diagnose the patients is to detect the disease from radiography and radiology images. Earlier studies have shown that patients infected with COVID-19 have specific abnormalities in the chest radiograms. Radiologists certify the presence of COVID-19 by observing the images.
Method: In this paper, the deep learning model is utilized by consideration of CT images to detect COVID-19 infection in the patients. Initially, a dataset of *746* CT images from the publicly available datasets is prepared. Transfer learning is used to train "Convolutional Neural Networks (CNN)" using VGG19, to identify COVID-19 disease in the analyzed CT scan images. Further it has been framed with IoT based application and verified.
Result: The model is evaluated with 521 images as training,112 images for validation, and the rest 113 for testing. The precision, recall, F-Score, and confusion matrix parameters are considered to evaluate the efficiency of the model.
Conclusion: The work is implemented and verified successfully. The result found is excellent as compared to earlier work and shown in result section. Even though the performance of the model is very encouraging, to have a more reliable estimation of the accuracy rates, further analysis is required on a larger set of COVID-19 images.

Keywords: Internet of Things; Classification; Convolutional Neural Networks; COVID 19; VGG 19.

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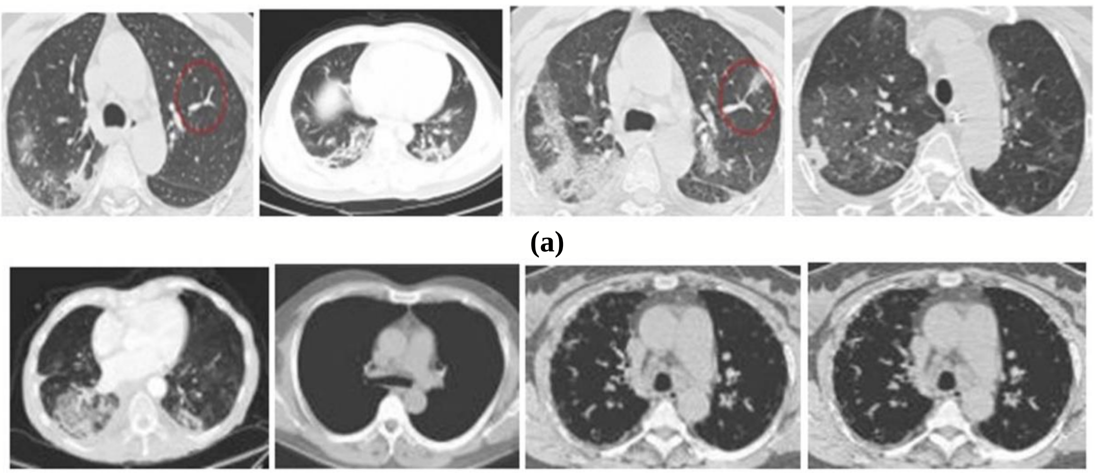
Introduction

In recent times, no other technology has created quite a buzz in the world of computing as much as the Internet. It is virtually present in every sphere of the human enterprise through the sheer power and sweep of its boundless applications. It has revolutionized the global workplace by introducing new-age technologies such as the Internet of Things (IoT) with mind-blowing applications, often disruptive, in almost every conceivable field: creating smart homes, smart grids or providing smart solutions in medical, education, communication, retail, business, government services, and agriculture, etc. In contemporary times, we have witnessed remarkable agility and ease with people and businesses connect, thanks to the help of a wide network of wireless sensor networks, healthcare services, smart phones as well as multiple types of pervasive real-time monitoring systems. With the introduction of the Internet of Things, people, as well as devices, seamlessly connect in real-time, thus creating great services and values for millions of people around the world [1]. “Internet of Things (IoT)” has organically evolved into a massive technology platform by utilizing the inherent strength of the Internet in the collection, analysis, and distribution of massive amounts of data, which is simply turned into information and knowledge in a real-time environment [2]. Riding on the enormous network of the Internet, today, IoT has emerged as the new age convergence technology with its ability to 2 effortlessly integrates multiple technologies from different domains into a unique arrangement. In essence, it connects virtually any object found on the earth through the Internet via remote sensing and control. A host of technologies such as “Radio Frequency Identification (RFID)”[3], “Networking and Communication”, “Wireless Sensor Network (WSN)”, “Real-Time Systems (RTS)”, “Cloud computing”, “Machine to Machine (M2M) Interaction”, “Mobility support” are amalgamated to form an IoT cluster [4]. However, despite the fast advancement of IoT in recent times, it is still in the process of firming up as a mature and universally validated system. Hence, a lot of research is still required to make IoT attain optimum levels of interoperability and mutual trust between various stakeholders through seamless connectivity.

Now, after the discovery of the Kent version and South African virus variations, there's no other mutant stress sparking off purple flags. With the latest reports, a new 'double mutant version' of COVID-19 inflicting SARS-COV-2 has been detected in India, similarly to other versions observed in as many as 18 states across India. Many experts additionally worry that the alarming spread of the newer mutant traces could also make India's second wave of contamination worse than the first one, whilst government steps up a shield to vaccinate India's millions' at-hazard populace.

Fig. 1shows the CT scan images of those affected by COVID and under normal conditions.



(a)

(b)

Fig. 1 a) Four sample COVID-19 images, and the corresponding marks are given by our radiologist, **b)** Samples of Normal images

The Internet of Things (IoT) is being used in many sectors including healthcare. Today, to improve affordability and reachability, IoT technologies are used in most healthcare-related services starting from remote healthcare to in-hospital patient care. In developing countries, this can be a promising solution, especially where healthcare services are provided and the service providers are inadequate compared to the total population. In the recent past, many artificial intelligence-driven devices have been developed using IoT technologies for automated detection and monitoring of "electrocardiogram", "glucose and blood pressure" and "epilepsy" etc. [5]. In that work, the authors have used ResNet18 for training the classification model and achieved an accuracy of 89%. In healthcare applications, effective communication between the patients and the physicians can be provided by IoT. IoT can be effectively used for regular monitoring of the physiological parameters of the patient in an IoT-based health care system. Now-a-days, chronic heart failure has become a very serious problem. This occurs when the natural pumping action of the heart is disrupted because the heart muscle gets damaged or becomes weak. The current healthcare model has turned into a tedious job for the patients [6] The Authors have used a dataset collected from the public which is given in [6] and used transfer learning. Data augmentation was used before training by the DenseNet model and got an accuracy of 84.7% and 0.85 F1-score. As it is mostly in-hospital based and includes periodic visits to the hospital. Nowadays, the diagnosis of many diseases is successfully carried out by using medical imaging techniques. The diagnostic accuracy can be increased with the integration of eHealth with advanced technologies such as "deep learning" and "artificial intelligence" and also reduces the duration. A complete and integrated healthcare model can be designed which will enable "Chronic Heart Failure(CHF)" patients to collect vital signs at home and sending them using the Internet of Things (IoT) [7]. This helps the physicians to take periodic action in case of necessity while monitoring patients at a distance. Researchers have identified five parameters i.e., "Electrocardiogram (ECG)", "Pulse rate", "Weight, Temperature and Position" for classification of fatty liver from ultrasound images [8]. The use of technologies can help in improve homecare especially for patients with chronic diseases and the elderly, reduce healthcare costs and decrease pressure on hospital systems and healthcare providers [9]. In the healthcare environment, IoT devices generate a huge volume of data. Cloud computing technology can handle a large volume of data and also provide ease of use [10]. We can get the data from different devices such as "radio frequency identification (RFID)", "wireless sensor network (WSN)", "smart mobile technologies" and wearable devices [11].

The authors have used VGG16 for feature extraction and made a model SDD300 for classification [12]. The combined model resulted in 94.92% accuracy. The authors have implemented ResNet50 for the extraction of features and used an SVM classifier for classification [13]. In that work, the method provided 94.7% accuracy that needs to be further increased using an improved method. The authors have implemented ResNet-101 with five cross-validations and got 94.04% accuracy [14]. Authors have proposed an algorithm n CO Vnet to detect the COVID-19 patients by which they got an accuracy of 88% [15]. Both image classification and image segmentation have been applied for COVID-19 detection in [16]. Though authors have used such preprocessing steps in their work, still the accuracy of 95.23% was achieved that needs further improvement. Edge detection and segmentation methods are the other aspects of image processing for detection, recognition, and classification [17]. For colloidal crystal detection, authors have provided a detailed study on various edge detection methods before training [18]. Morphological segmentation has been proposed in [19] for tumor detection from brain MR images. Authors have verified various methods of segmentation whereas the morphological segmentation provided the lowest mean square error. The deep learning models are capable of automatic feature extraction and avoid such preprocessing steps as edge detection or segmentation. Deep learning-based models like Squeeze Net and Google Net have been utilized to detect the presence of COVID-19 infection [21]. The Google Net provided higher accuracy than that of the SqueezeNet. A 16 layered CNN model has been proposed in [20] for COVID-19 detection from chest X-ray images. Using that model, the authors achieved 73.45% training accuracy that needs to be increased with an improved method. CNN models are also applied for the classification of complex images including breast histopathology images, images generated from gene data, and chest X-ray images as well [22]. The performance of CNN models is found to be competitive in the field of image processing. As for this medical image processing a large amount of data to be stored and to be processed [23] by using Wavelet Transform and Metaheuristic Algorithm. The movement of Covid patient also can be monitored using IOT with help of some sensor [24].

From the literature survey, it is observed that the CNN models are providing human-like performance in various fields of medical image processing. Different works have been developed using deep learning models for COVID-19 detection from chest X-ray and CT images. Still, the scope is there for highly accurate model designing to diagnose the presence of COVID-19 infection.

This paper especially focuses on the web application framework for the classification of COVID Using IoT and CT scan medical images.

Medical imaging is the process of obtaining internal photographs of the human body to diagnose, treat, or study diseases. One of the most important requirements of a hospital is medical imaging. In the medical sector, the internet of things (IoT) in imaging allows for real-time knowledge exchange, diagnosis, and retrieval, avoiding data loss problems. The COVID-19 pandemic has been an unparalleled crisis for India and the world for over a year now. Even now, with the arrival of vaccines, our fight hasn't ended. Recent mutations and variations of the virus are adding to our problems. The main contributions of the paper include:

1) IoT based low-cost and scalable e-Health architecture has been developed for classifying the COVID-19 using CT scan images.
2) A web application that enables sonographers in remote areas for classifying COVID-19 infected is proposed for easy access.
3) The improved VGG19 model is provided in the cloud-based server for online access.
4) Instead of directly providing the CT image dataset, we have passed the dataset through data augmentation stage to improve the training.

Method

The innovative low-cost and scalable e Health projected architecture for COVID-19 classification is shown in Fig. 2.

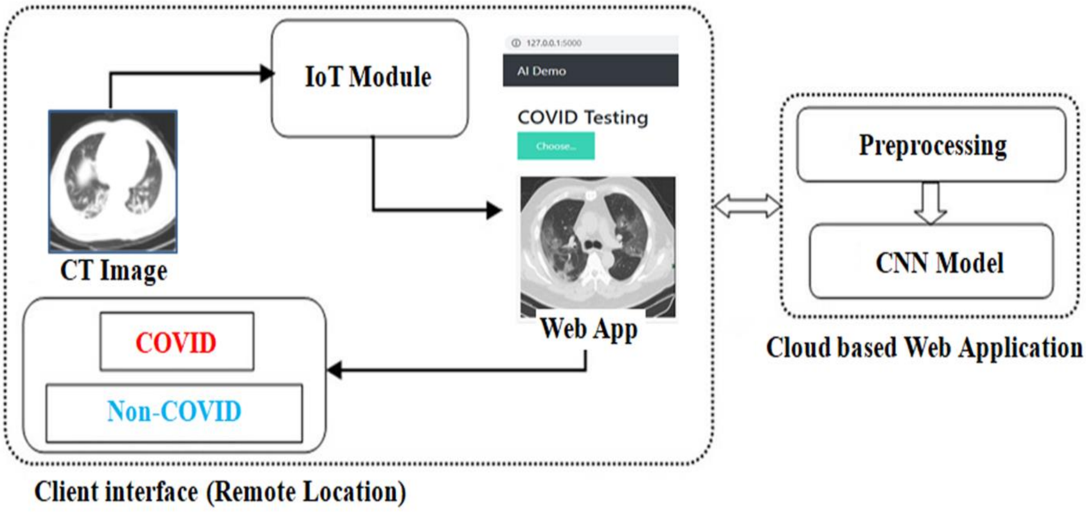


Fig. 2 Proposed novel low-cost and scalable e-Health architecture for accurate web-based COVID-19 classification

The following subsections describe the entire architecture which is broadly classified into two functional units.

A. Client interface (remote location)

The client who performs the CT scanning on the patients is a semi-skilled clinician. After the CT scanning is performed, using the IoT module, the ultrasound images that are generated are uploaded into the web-based interface. Upon successful upload, the web application present in the cloud will classify the image regarding whether it is normal or abnormal. The classified information will then be sent back to the client.

B. Cloud-based web application architecture for COVID-19 Classification using CT scan images

For identifying the COVID condition, a cloud-based web application has been developed that uses the CT image uploaded by the IoT Module. A "Convolution Neural Network (CNN)" based trained model is used for developing the framework and then the developed model along with the popular "Flask framework" is used for the development of the web application which is then used for classification. Flask is a lightweight backend framework. It runs on Python its main use is to serve the pre-trained models over the internet connectivity.

Dataset Description

The publicly available datasets [6] for CT Scan images are used here. The dataset consisted of 746 representative CT images comprising of both COVID (349 images) and normal conditions (397 images). The information like hospital name, time of diagnosis, etc. which are not related to the diagnostic are removed from the dataset. Also, the images of our dataset were resized to 224×224 pixels for compatibility since the models are trained with an image size of 224×224 pixels. The data splitting is mentioned in image 3.

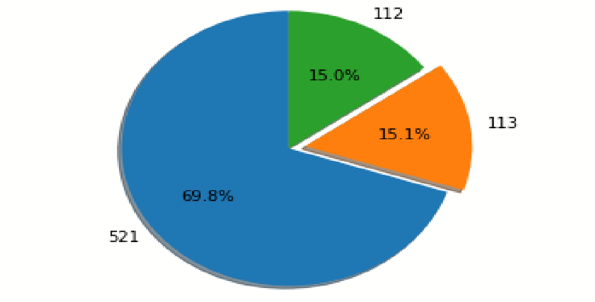


Figure 3 Pi chart representing data splitting

Data Augmentation

Data augmentation is another way to mitigate data deficiency i.e., creating new image-label pairs and adding the synthesized pairs into the training set from the limited training data. Each training image is augmented by random transformation, random crop, and flip. The random transformation consists of translation and rotation. In Fig. 4 the augmented images are displayed where the batch size is 40.

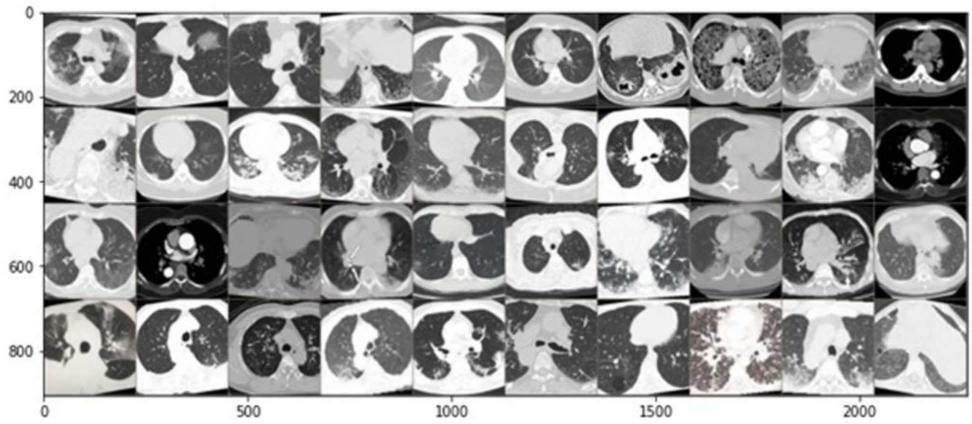


Fig. 4 After augmentation images when bath size is 40

Algorithm 1: Data Augmentation

Input: CT Image Dataset
Initialization: Load the Data Transformer model
Training:
Train _transform=transforms Compose (transforms)
{ transforms. Random Rotation=value;
transforms. Random Horizontal Flip=probability value;
transforms. Resize=img Size
transforms. Center Crop=crop Size
transforms. To Tensor=a Num Py array or PIL image
transforms.Normalize=([mean Of Channel 1, mean Of Channel 2, mean Of Channel 3], [std Of Channel 1, std Of Channel 2, std Of Channel 3]);
Return transforms;
])train_ data=images. train_ transform;
Output: Augmented dataset

Here we 1st create one transforms Compose function which is passing one transforms object as parameter. Then we are initializing value for the attributes of transforms, and finally returning that object. So based on our created transform object we are changing the dataset and finally we are getting one new augmented dataset for training purpose.

Transfer Learning Approach Using VGG-19

In transfer learning, through some adaption towards a new task, a model trained on one task can be used for a similar related task. Transfer learning is mainly useful for tasks such as medical image classification for rare or emerging diseases where sufficient training samples are not obtainable to train a model from scratch [25]. This is especially the case for models which have a large number of parameters to train based on deep neural networks. In the case of transfer learning, better and accurate results can be achieved by carrying out small modifications to the already good initial values of the model parameters [26]. Researchers have successfully demonstrated the use of the artificial neural network for time series prediction [21].

Mainly, there are a couple of ways in which a pre-trained model can be used for a similar assignment.

In the first approach, the weights, which are internal to the pre-trained model are not altered to and the pre-trained model is treated as a feature extractor. On top of it, a classifier is trained to perform the classification [3].In the second approach, the whole network or a subgroup thereof is fine-tuned for the new assignment. The weights of the pre-trained prototypical are treated as the primary values for the new assignment and are updated during the training stage. Figure 5 illustrate the architecture of VGG 19 model.

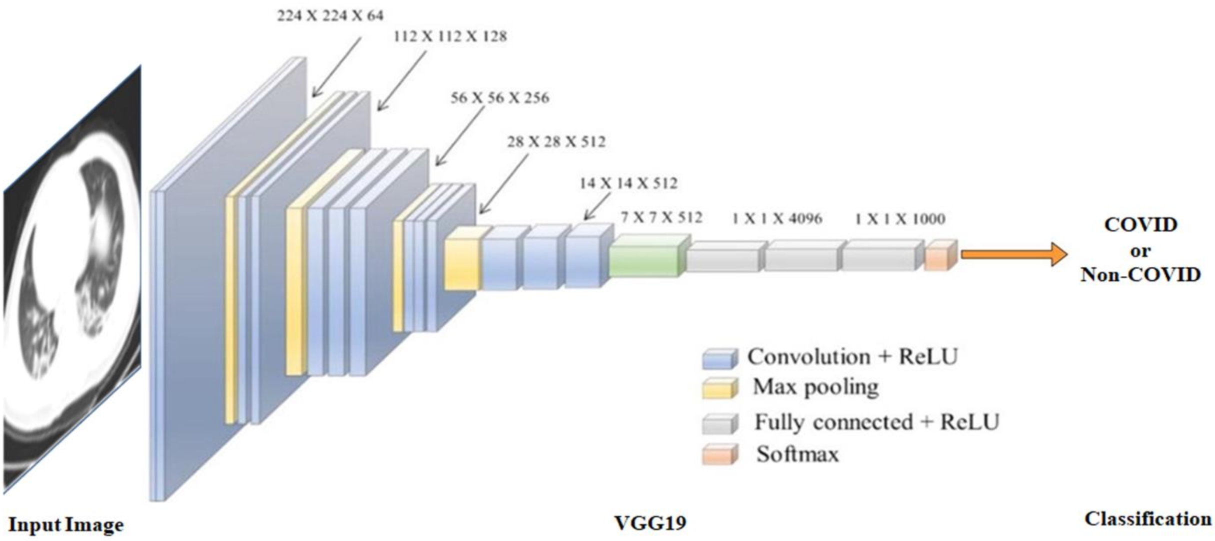


Figure 5 Architecture diagram of VGG 19

Covid-19 detection using enhanced VGG-19 model

In this model we are using VGG 19 as the pre-trained model. By fine tuning the transform function, the parameters got optimized. VGG 19 model is designed for 1000 classification but we required a model which is classified 2 classification. The architecture consists of a pre-trained VGG-19 model along with transfer learning and fine-tuning. VGGNet using CNN for image recognition task is initially designed with different layer depths. Preliminary analysis of VGGNet when validated using the Image Net dataset comprising of 14 million images from 1000 classes offered a promising accuracy of 92.7% (Minaee *et al.* 2020). In this paper, the 19 layers of VGG-19 act as a fully connected classifier with “convolution blocks” consisting of “convolution layers” and “max-pooling layers”. Py Torch is used for carrying out the fine-tuning of the pre-trained VGG-19 model. Traditionally, there are 512 nodes in the convolution 2D layers in VGG-19. In this study, the output consists of two layers whose output corresponds to two classes i.e. normal or abnormal, and are fine-tuned for connections having 4096 nodes to 502 nodes and then 502 to 2 classification classes. During the training of the model, to avoid over-fitting we have added Dropout of 0.3, and “Cross Entropy Loss” is used as the loss parameters and “Adam” as the optimizer. The training is performed over 100 epochs.

In algorithm 2 we are training the model with the following algorithm. Where TDS is the training dataset, I is the set of images and L is the labels of the images and m is the number of the image in the training dataset.

Algorithm 2: Training of proposed CNN Model

Input: TDS=$\{I_i, L_i\}_{i=1}^{m}$

Initialization:

1. Load model
2. Load train_loader
3. Epoch=100

Training:

4. for i=1 to epoch
5. for j=1 to train_loader
   y_pred=model(TDS)
   loss=lossfunction(y_pred)

predicted=max(y_pred.data,1)
train_correct=(predicted==y_train).sum()
accuracy=(train_correct/m)*100
6. End for
7. End for

Algorithm 3: Proposed Framework

1. Open the Web application using the IOT Module.
2. Enter a CT scan image.
3. Then IOT module will send the image to the cloud.
4. Data preprocessing.
5. Detection using the CNN model.
6. Result will be sent back to the client machine.

Results

The proposed method was implemented using python 3 on the Google Colaboratory platform using a system loaded with windows 10 with 8gb Ram and i3 processor.

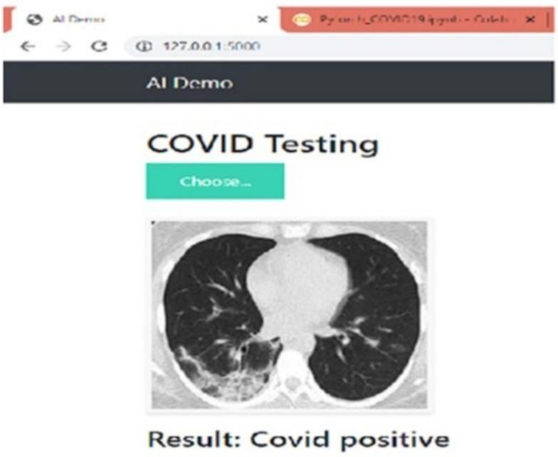


Fig. 6 Developed web interface along with the CT scan and prediction when tested using a COVID image.

Fig.7 Developed web interface along with the CT scan and prediction when tested using a normal image.

The performance of the proposed model is analyzed considering “classification accuracy”, “confusion matrix”, “F-score”, “Precision” and “Recall” as the vital metrics. The calculation carried out for obtaining the values of the performance metrics is given below:

$$\text{Precision}=\frac{N(TP)}{N(TP)+N(FP)} \quad (1)$$

$$\text{Recall}=\frac{N(TP)}{N(TP)+N(FN)} \quad (2)$$

$$\text{F-score}=2\times\frac{precission*recall}{precission+recall} \quad (3)$$

$$\text{Accuracy}=\frac{N(TP)+N(TN)}{N(TP)+N(TN)+N(FP)+N(FN)} \quad (4)$$

Fig. 8 provides the information about the total true positives indicated by N(TP), total false positives indicated by N(FP), total true negatives indicated by N(TN), and total false negatives indicated by N(FN). All these measures are computed for each class. The average of all these measures across the two classes is taken into account to compute the overall measure of the algorithm.

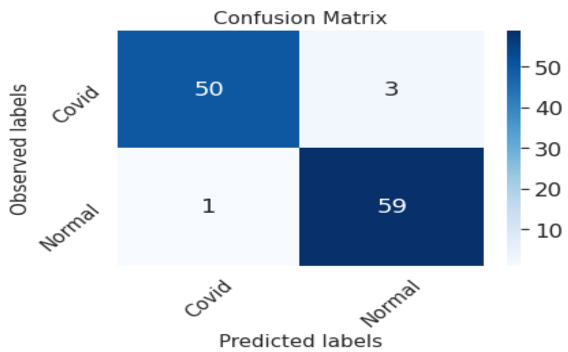


Fig. 8 Confusion matrix

Table 1 shows the confusion matrix thus obtained after the developed framework is validated using the dataset. From the table, it can be observed that out of 53 images representing COVID, 50 are classified correctly while the other 3 images are classified as normal. The correct classification rate for COVID is 94.34%. Similarly, out of the 60 normal images, 59 are classified correctly while the other 1 image is classified as abnormal, providing a correct classification rate of 98.33%. Thus, the overall correct classification rate is 97.32%.

Table 1 Confusion matrix of the proposed algorithm

True Class	**Predicted**	
	Abnormal	**Normal**
Abnormal (53)	50	3
Normal (60)	1	59

Table 2 provides the obtained “F-score”, “Precision”, “Support” and Recall”. Finally, the calculated “F-score” for abnormal is 96%, for normal is 97% and the average is 96.5%.

Table 2 Performance analysis of the proposed algorithm for detection and classification of CT scan images

Class	**Precision**	**Recall**	**F-score**	**Support**
Abnormal	0.94	0.98	0.96	53
Normal	0.98	0.95	0.97	60
Average	0.96	0.97	0.965	113

The training and validation accuracy are shown in Fig. 9.

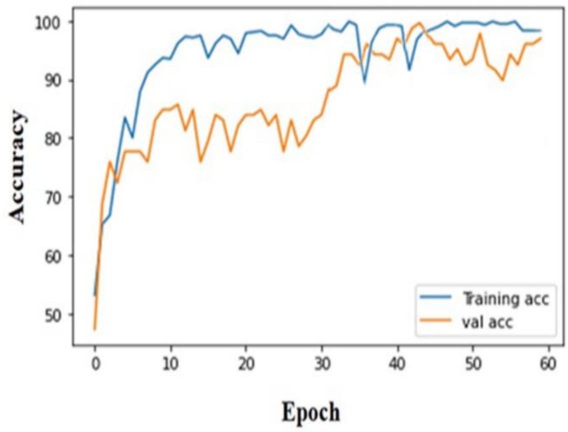


Fig. 9 The Accuracy curve of the training and validation dataset used in the proposed model

Discussion

A comparative analysis of the classification accuracy with some other techniques and Image type is provided in Table 3, which provides an insight into the efficacy of the proposed technique.

Table 3 External Validation

Author	**Image Type**	**Classification Model**	**Accuracy(%)**
Yang, X *et al.*(2020)	chest CT images	DenseNet	84.7
Minaee *et al.*(2020)	X-Ray	ResNet18	89
Saiz, F. A., & Barandiaran(2020)	X-Ray	SDD300	94.92
Ismael, A. M., & Şengür, A. (2021))	X-Ray	ResNet50	94.7
Jain, G *et al.* (2020)	X-Ray	ResNet-101	94.04
Panwar, H. ,*et al.* (2020)	X-Ray	nCOVnet	88
Amyar, A., *et al.* (2020)	chest CT images	Segmentation	95.23
Proposed	chest CT images	Improved VGG19	97.32

Most of the works proposed earlier is for classification and detection purpose only. However, the proposed work provides the classification with IoT and web application. Tough Reddy, D. S., & Rajalakshmi, P have been proposed for IoT model the accuracy claimed by them is a poor enough. Due to transfer learning method used in existing VGG19 net model, it has been modified for better performance. Also the tuning of the model is being made for large dataset. As shown in the frame work the work can be used in contactless manner to avoid further spreading of the disease. simultaneously due to web application implementation the exact data can be recorded and stored in the cloud. The implementation of the IoT module as depicted in Fig.2 contributes to the improved performance of the proposed model.

Conclusion

In the era of the global pandemic arising from COVID-19, health care industries face a lot of challenges in the context of diagnosis. In this paper, we present a web application for the classification of scanned images of patients with the help of a cloud-based application that incorporates a CNN model for the purpose. The scanned images are uploaded to the web application through an IoT module and that is further forwarded to a cloud-based application that performs the necessary classification.

Experimental results show that the proposed by us model provides an accuracy of 97.32%. External validation of the proposed technique is provided in Table 3, which provides an insight into the efficacy of the proposed technique. However, as per our presumption, this accuracy can be further enhanced using other deep learning approaches.

Declarations

Funding: The authors did not receive support from any organization for the submitted work.

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

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

Informed Consent: This article does not contain patient data.

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