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IoT Based Model for COVID Detection from CT Scan Images Using Deep Learning

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Abstract: - The global impact of the COVID-19 pandemic has reached virtually every part of the world, significantly impacting people's health and daily routines. It has disrupted physical activities and necessitates early identification of infected individuals for proper care. Identifying the disease through radiography and radiology images stands out as one of the quickest approaches. Previous research indicates that COVID-19 patients often exhibit distinct abnormalities in chest radiographs. Radiologists have the ability to detect the existence of COVID-19 by analyzing these images. This study employs a deep learning model that utilizes CT scan images to identify COVID-19 disease in patients. In the beginning, a dataset comprising 746 CT scan images from openly accessible sources is compiled, and then same dataset had been applied for augmentation which creates total 2984 images. Transfer learning is employed to train Convolutional Neural Networks (CNN) using VGG19, enabling the recognition of COVID-19 disease in the examined CT scan images. Additionally, it integrates an IoT-based application and validates the framework. The model undergoes assessment using 521 images for training, 112 images for validation, and the remaining 113 for testing, and then same images created a new dataset using the concept of augmentation and total 2984 images were spitted into 2088 images for training, 449 images for testing and remaining 447 images for validation. The model's efficiency is evaluated by assessing parameters such as precision, recall, FScore, and the confusion matrix. The implementation and validation of the study have been successful. The results obtained demonstrate significant improvement compared to previous efforts, as

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detailed in the results section. While the model's performance is highly promising, conducting additional analysis on a larger dataset of COVID-19 images is necessary to obtain more reliable accuracy estimations.

Keywords: Component; Internet of Things (IoT), Convolutional Neural Networks (CNN), VGG19, COVID19

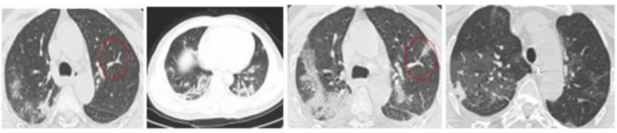
I. INTRODUCTION

In recent times, few technologies have garnered as much attention in the computing world as the Internet. Its influence spans across virtually every aspect of human activity, driven by its expansive range of applications. The advent of the Internet of Things (IoT) has particularly transformed various sectors globally, with its innovative and sometimes disruptive implementations. From enabling smart homes and grids to revolutionizing fields like medicine, education, agriculture, retail, business, government services, and communication, the impact of IoT is profound. Contemporary society has experienced a significant enhancement in connectivity among individuals and businesses, facilitated by wireless sensor networks, healthcare services, smart phones, and various realtime monitoring systems. With IoT, both people and devices seamlessly interact in real-time, generating immense value for millions worldwide (Biswalet al. 2021).

The Internet of Things has naturally developed into a vast technological platform, leveraging the inherent capabilities of the Internet to gather, analyze, and disseminate massive volumes of data, swiftly transforming it into actionable insights in real-time (Rath and Pattanayak 2019). Capitalizing on the extensive reach of the Internet, IoT has now become the cutting-edge convergence technology, seamlessly incorporating various technologies from diverse domains into a cohesive system. Essentially, It enables virtually any earthly object to link up with the internet via remote sensing and control.

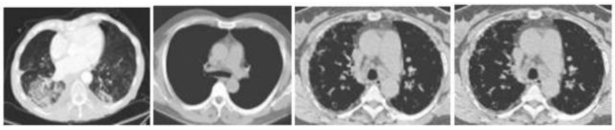
This is achieved by amalgamating a range of technologies such as Radio Frequency Identification (RFID), networking, Wireless Sensor Network (WSN), Real-Time Systems (RTS), cloud computing, Machine to Machine (M2M) Interaction, and Mobility support to construct an IoT cluster (Panda and Pattanayak, 2020).Despite the rapid improvement of IoT in recent years, it is still evolving towards becoming a mature and universally recognized system. Consequently, extensive research is still necessary to achieve optimal levels of interoperability and common trust among various participants, ensuring unbroken connectivity.

Following the emergence of the “Kent and South African virus variants”, there hasn't been another mutant strain raising significant concerns. However, recent reports indicate the detection of “a new double mutant variant” of COVID19 influence SARS-CoV-2 in India, similar to new variants noticed across 18 states in the country. Experts express concerns that the rapid spread of these new mutant strains could exacerbate India's 2nd wave of infections, prompting the government to intensify efforts to vaccinate the millions of atrisk individuals.



(a)

Figure 1"shows the CT scan images of persons affected by COVID and under usual situations".



(b)

Figure1 "a) four sample COVID-19 images, and the conforming marks are given by our radiologist

b) Samples of Usual images"

In numerous industries, including healthcare, the Internet of Things (IoT) is increasingly utilized. Presently, IoT technologies are employed across a wide range of healthcare services, from remote healthcare solutions to hospital patient care, with the aim of enhancing affordability and accessibility. In developing nations, this approach holds significant promise, particularly in areas where healthcare services are limited compared to the overall population. Recently, numerous AIpowered devices have been created using Internet of Things technologies to automate the detection and intensive care of conditions such as electrocardiogram abnormalities, glucose and blood pressure levels, and epilepsy (Minaee et al., 2020).In the study, the classification model was trained using ResNet18, resulting in an accuracy of 89 percent. Where as in healthcare situations, IoT facilitates efficient announcement between patients as well as doctors to enables regular monitoring of patients' physiological parameters within IoT-based healthcare systems. Nowadays, chronic heart failure presents a significant challenge, resulting from damage or weakening of the heart muscle, disrupting its natural pumping action. The conventional healthcare model has become burdensome for patients (Yang et al., 2020). The authors utilized a publicly available dataset, as described in Yang et al. (2020), and employed transfer learning techniques in their approach. Prior to training with the DenseNet model, data augmentation techniques were applied, leading to an accuracy of 84.7 percent and an F1-score of 0.85. Since it primarily focuses on inhospital settings and entails periodic hospital visits, there is a growing reliance on medical imaging techniques for diagnosing various diseases. Incorporating e-Healthcare with sophisticated tools like deep learning and artificial intelligence has the potential to improve diagnostic accuracy and shorten diagnosis timeframes. A systematic healthcare framework could be formulated, enabling individuals through Chronic Heart Failure (CHF) to gather vigorous symbols from their homes and send them through the Internet of Things (IoT) (Jibadurai and Peter, 2018). This enables physicians to take timely action when necessary while remotely monitoring patients. Researchers have recognized five(5) parameters i.e.“Electrocardiogram (ECG), Pulse rate, Weight,

Temperature, and Position” for classifying fatty liver from ultrasound scan (Reddy and Rajalakshmi, 2019). The utilization of technologies has the potential to greatly improve in-home healthcare, especially for individuals with chronic illnesses and older adults, resulting in lower healthcare expenses and easing the burden on hospital systems and healthcare professionals(Sohn et al., 2015). Within the healthcare setting, IoT devices cause substantial amounts of data. Tools of Cloud computing are adapted at managing such large volumes of data while providing ease of use (Mano et al., 2016). Data can be sourced from various devices including, wireless sensor networks (WSN), smart mobile technologies, radio frequency identification (RFID) and wearable devices (Balaji, 2019).

The authors employed VGG16 for extraction of feature and devised a model named SDD300 specifically designed to classify(Saiz and Barandianran, 2020), achieving a combined model accuracy of 94.92%. In another study, ResNet50 was employed for feature extraction, followed by classification using an SVM classifier, resulting in an accuracy of 94.7% (Ismael and Sengur, 2020). However, this method requires further enhancement for improved accuracy. In a different approach, the authors applied ResNet-101 with 5 cross validations, obtaining an accuracy of 94.04% (Jain et al., 2020). Additionally, a proposed algorithm called nCOVnet was introduced for detecting COVID-19 patients, achieving an accuracy of 88% (Panwar et al., 2020). COVID-19 detection has been explored through both image classification and segmentation techniques (Amyar et al., 2020), with preprocessing steps resulting in an accuracy of 95.23%, suggesting room for perfection. Image segmentation and edge detection methods are also essential elements of image processing used for the identification, recognition, and categorization of objects(Mallik et al., 2015). Authors have conducted an extensive investigation into various edge detection methods prior to training for colloidal crystal detection (Behera et al., 2012). In another study, morphological segmentation was proposed for tumor detection from brain MR images (Jyoti et al., 2014), where various segmentation methods were assessed, with morphological segmentation yielding the lowest mean square error. Unlike traditional methods that involve preprocessing steps such as segmentation or edge detection, Deep learning (DL) models possess the ability to automatically extract features. Models like SqueezeNet and GoogleNet which are based on Deep learning (DL) have been employed for detecting COVID-19 infection (Das et al., 2021), with GoogleNet demonstrating higher accuracy compared to SqueezeNet. Additionally, a 16-layered Convolutional Neural Network (CNN) model was proposed for COVID-19 detection from chest X-ray images (Das and Mohanty, 2020), achieving a training accuracy of 73.45%, which suggests the need for improvement. CNN models have also been engaged for categorizing intricate images, such as breast histopathology images,

images derived from genetic data, and chest X-ray images (Das et al., 2021), with competitive performance observed in the ground of image processing.

The literature review reveals that CNN models exhibit performance a kin to that of humans across diverse domains of medical image processing. Many research investigations have utilized deep learning (DL) models to detect COVID-19 from chest X-ray and CT images. However, there remains potential for the development of highly accurate models to identify the existence of COVID-19 disease.

This research paper primarily concentrates on constructing a specialized web application support customized for COVID19 classification, employing IoT technology in conjunction with medical images from CT scans. Medical imaging is crucial for disease diagnosis, treatment, and research, entails capturing internal images of the human body. One indispensable requirement in hospitals is medical imaging. Incorporating the Internet of Things (IoT) into medical imaging within the healthcare sector enables real-time knowledge sharing, diagnoses, and data retrieval, addressing concerns regarding data loss. For more than a year, the COVID-19 deadly disease has presented an unprecedented crisis for both India and the global community. Despite vaccine introductions, the battle against the virus persists, with ongoing challenges exacerbated by recent mutations and variants. Key contributions of this paper include:

1) An e-Health infrastructure, utilizing IoT and designed to be cost-effective and adaptable, has been created to classify COVID-19 through the analysis of CT scan images.

2) A proposed web-based tool aims to facilitate sonographers in remote regions by providing them with a userfriendly platform for classifying COVID-19 infections, ensuring convenient access.

3) The enhanced VGG19 model is made available on a cloud-based server for online usage.

II. METHODOLOGY:

Figure 2 displays the architecture of the inventive, costeffective, and scalable eHealth project designed for COVID-19 classification.

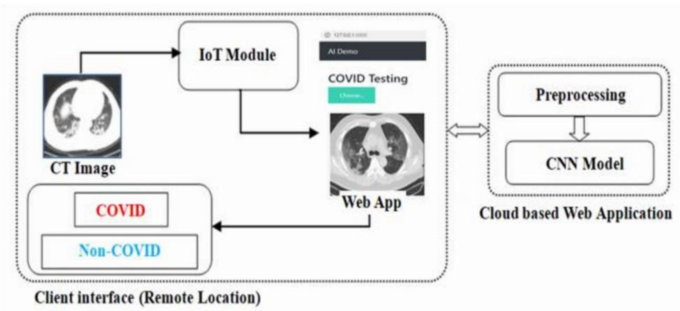


Figure 2 "Suggested innovative, cost-effective and scalable e-Healthcare framework for precise web-based COVID-19 classification"

The subsequent sections outline the complete architecture, which is divided into two main efficient units.

Client interface (remote location)

Semi-skilled clinicians perform CT scans on patients. After the CT scanning process, the resulting ultrasound images are uploaded to the web-based interface via the IoT module. Upon successful upload, a cloud-based web application will classify the images as either normal or abnormal. Afterward, the categorized data will be sent back to the client.

B. “Cloud-based web application architecture for COVID19 Classification using CT scan images”

To detect the presence of COVID-19, a cloud-based web application has been created, utilizing the CT images uploaded by the IoT Module. The framework employs a trained model based on Convolutional Neural Network (CNN) for development. This model, along with the widely used Flask framework, is utilized to build the web application for classification purposes. Flask, as a lightweight backend framework, utilizes Python and is mainly used for deploying pre-trained models over internet connections.

Dataset Explanation

In this study, widely accessible datasets (Yang et al., 2020) containing CT scan images are utilized. The dataset comprises 746 images obtained from CT scans, representing both COVID cases (349 images) and normal health conditions (397 images). Non-diagnostic details such as hospital names and diagnosis times are not included in the dataset. Additionally, all images in our dataset are adjusted to a size of 224×224 pixels to align with the models, as they are trained on images of this dimension. The dataset splitting procedure is depicted in Figure 3.

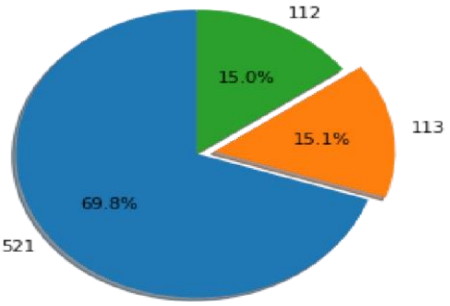


Figure 3: "Pi chart representing data splitting"

Data Augmentation:

Data augmentation offers an alternative approach to address limited data availability by generating new image-label pairs and integrating them into the training dataset. This involves augmenting each training image through random transformations, crops, and flips, encompassing translation and rotation adjustments. As we are going for four types of augmentation the total dataset will be multiple of four. The augmented dataset is illustrated below in Figure 4.

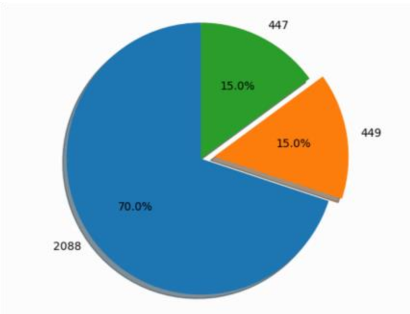


Figure 4: "Pi chart representing data splitting of augmented data"

Later on data augmentation the data would be passed through loader of size 40. which is reflected with the figure 5.

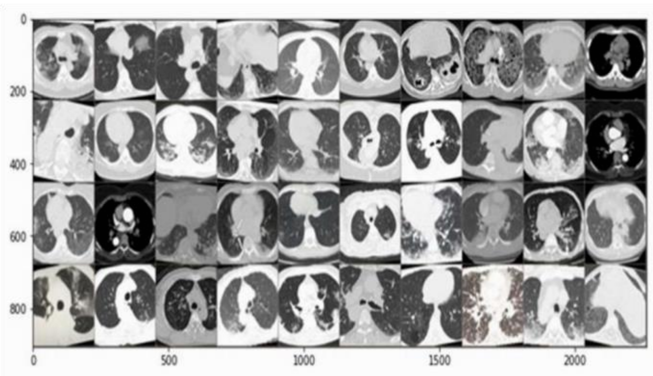


Fig. 5 after augmentation images when bath size is 40

Transfer Learning Approach Using VGG-19

In transfer learning, a model originally trained on a specific task can be adapted to perform a related task through adjustments. This method is especially beneficial in situations such as medical image classification of uncommon or newly identified illnesses, where acquiring an adequate amount of training data to construct a model from the ground up is difficult (Kapoor et al., 2016). This challenge is especially pronounced with deep neural networks that entail a substantial number of parameters to train. In transfer learning, refining the already proficient initial values of model parameters can lead to improved and more precise outcomes (Rajgopalan et al., 2018). Researchers have effectively showcased the utilization of artificial neural networks for time series prediction (Das et al., 2015).

There are primarily two methods for leveraging a pretrained model for a relatedjob. In the first methodology, the internal weights of the pre-trained model remain unchanged, and it functions as a feature extractor. A classifier is then trained atop these extracted features to perform classification (Elhosery et al., 2018). The second approach involves finetuning either the entire network or a subset of it for the new task. The initial values for the new task are derived from the pre-trained model's weights and are fine-tuned during training. Figure 5 illustrates the structure of the VGG 19 model.

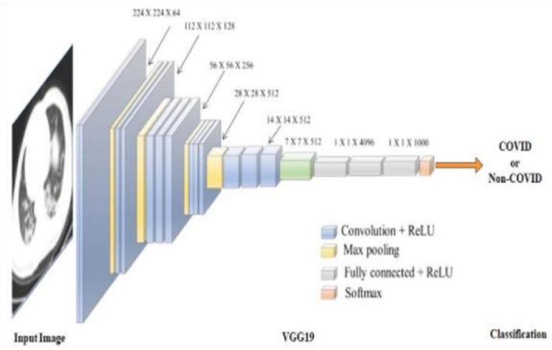


Figure 6 “Architecture diagram of VGG 19”

“Covid-19 detection using enhanced VGG-19 model”

In this study, we utilize the VGG-19 model by means of the base for pre-training. By adjusting the transformation function through fine-tuning.We optimize the parameters, despite the fact that the VGG-19 model was originally intended for 1000 classifications, our task requires a binary classification model. The framework incorporates a pre-trained VGG-19 model via transfer learning and fine-tuning. VGGNet, utilizing convolutional neural networks (CNNs) for image recognition, was originally developed with various layer depths. Initial assessments of VGGNet, validated on the ImageNet dataset consisting of 14 million images across 1000 number of classes, demonstrated an encouraging accuracy of 92.7 percent (Minaee et al., 2020). Here the 19 layers of VGG-19 model serve as a fully connected classifier, comprising "convolution blocks" consisting of "convolution layers" and "max-pooling layers". The pre-trained VGG-19 model undergoes fine-tuning utilizing PyTorch. Conventionally, the convolutional 2D layers in VGG-19 consist of 512 nodes. However, in our study, the output is tailored to two layers corresponding to two classes: normal or abnormal. These layers are fine-tuned, gradually reducing from 4096 nodes to 502 nodes, and ultimately to classify two classes. To mitigate overfitting during model training, a dropout rate of 0.3 is applied, along with using "CrossEntropyLoss" as the loss function and "Adam" as the optimizer. The training process spans 100 epochs.

III. RESULTS

Utilizing Python 3 on the Google Colaboratory platform the described approach was executed. The system employed ran on Windows 10 and was equipped with 16GB of RAM and an i5 processor.

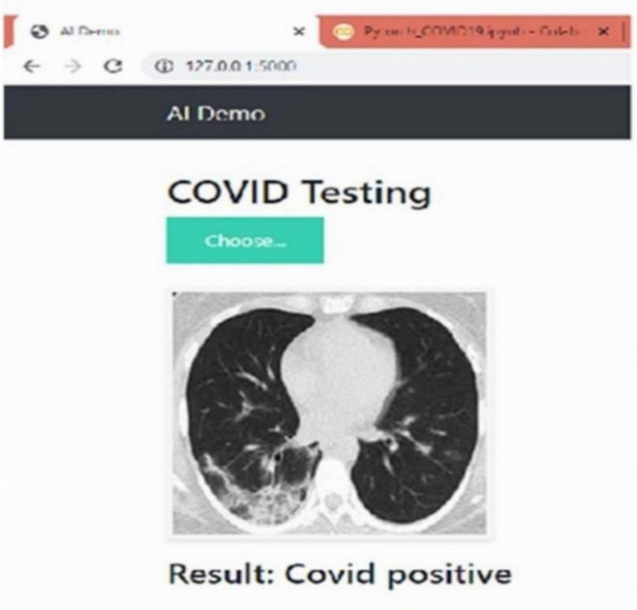


Figure 7 “illustrates the created web interface, showcasing the CT scan alongside the prediction results when tested with a COVID image”

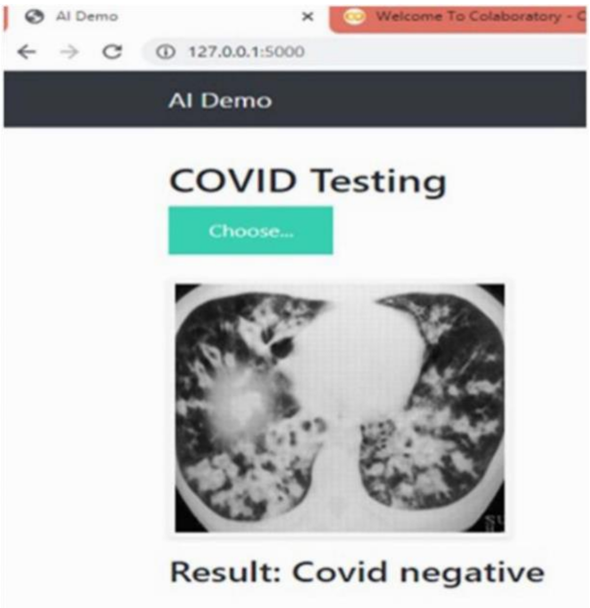


Figure 8 “displays the developed web interface, presenting the CT scan alongside the prediction outcomes when assessed with a normal image”.

The effectiveness of the suggested model is assessed based on key metrics such as "classification accuracy," "confusion matrix," "F-score," "Precision," and "Recall." The process for calculating these performance metrics is sketched below:

$$\text{“Precision”} = \frac{N(TP)}{N(TP)+N(FP)} \tag{1}$$

$$\text{“Recall”} = \frac{N(TP)}{N(TP)+N(FN)} \tag{2}$$

$$\text{“Fscore”} = 2 \times \frac{precission * recall}{precission + recall} \tag{3}$$

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

Figure 9 illustrates information concerning cumulative true positives (N(TP)), cumulative false positives (N(FP)), cumulative true negatives (N(TN)), and cumulative false negatives (N(FN)). These measurements are computed for individual classes. To obtain a comprehensive assessment of the algorithm's performance, the averages of these metrics across both classes are taken into account.

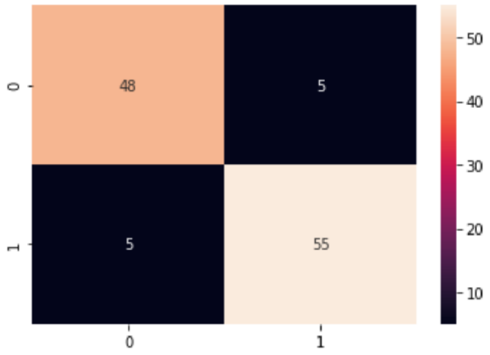


Figure9 Confusion matrix for without augmentation.

Table 1 presents the confusion matrix derived from the validation of the constructed framework using the dataset. Upon examination of the table, it is apparent that out of the 53 COVID-19 images, 48 are precisely classified, while the remaining 5 images are labeled as normal. This results in a COVID-19 correct classification rate of 90.56%. Similarly, among the 60 normal images, 55 are accurately classified, with only 5 images being misclassified as abnormal, leading to a correct classification rate of 91.66%. As a result, the overall correct classification rate is computed to be 91.15%.

Table 1 “Confusion matrix of the suggested algorithm”

True Class	Predicted	
	Abnormal	Normal
"Abnormal (53)"	48	5
"Normal(60)"	5	55

Table 2 presents the achieved "F-score," "Precision," "Support," and Recall. Ultimately, the computed "F-score" for abnormal is 91%, for normal is 92%, and the average is 91%.

Table 2 "Performance analysis of the proposed algorithm for detection and correctly classified, with only 7 image being misclassified as

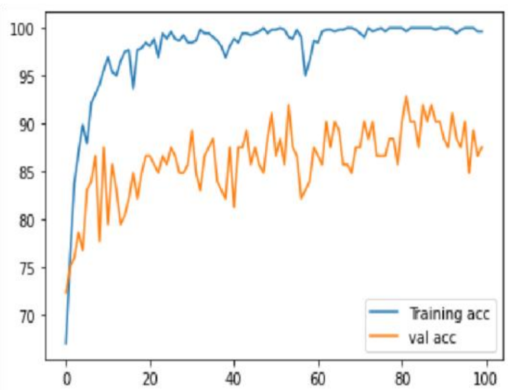


Figure 10 "The Accuracy curve of the training and validation dataset used in the proposed model"

But when we are implementing the same dataset to the same model with applying augmentation then, we found a better accuracy compared to previous one. Figure 11 represents the confusion matrix of augmented data after passed to the proposed model.

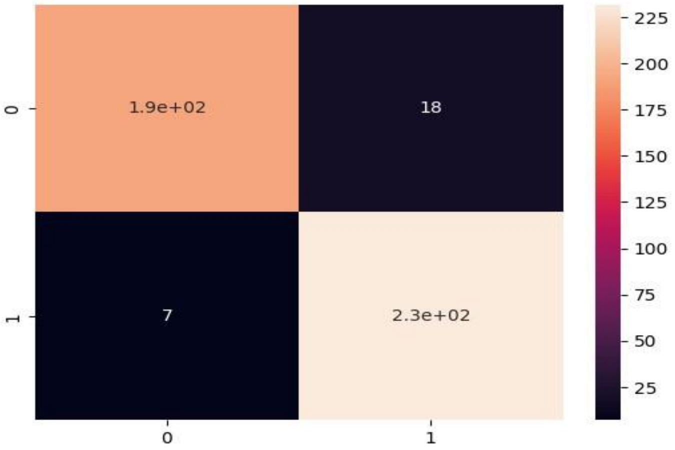


Figure 11 Confusion matrixafter implementing augmentation

Table 3 illustrates the confusion matrix resulting from the validation of the developed framework using the augmented dataset. Upon inspection of the table, it is evident that among the 210 images depicting COVID, 192 are accurately classified, while the remaining 18 images are categorized as normal. This yields a correct classification rate for COVID of 91.45%. Likewise, among the 239 normal images, 232 are "Abnormal (210)"

Table 4 presents the acquired values for "F-score", "Precision", "Support", and Recall. Ultimately, the computed "F-score" for abnormal is 94%, for normal is 95%, and the average is 94%.

Table 4"Performance analysis of the proposed algorithm for detection and classification of CT scan images"

"Class"	"Pre cision"	"R ecall"	"Fscore"	"Sup port"
"Abnorm al"	0.96	0.9 1	0.9 4	210
"Normal"	0.93	0.9 7	0.9 5	239
"Average "	0.95	0.9 4	0.9 4	449

Figure 12 illustrates the accuracy observed during both the training and validation phases.

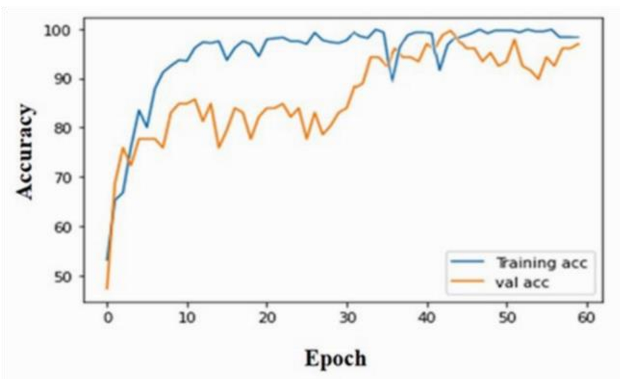


Figure12"TheAccuracy curve of the training and validation dataset used in the planned model with augmented data"

IV. DISCUSSION

Previously, most research efforts have focused solely on classification and detection tasks. In contrast, our proposed approach integrates classification capabilities into both IoT devices and a web application. While Reddy and Rajalakshmi have previously proposed an IoT model, their claimed accuracy falls short. To address this, we have modified the existing VGG19 neural network model using transfer learning techniques for enhanced performance. Additionally, we have fine-tuned the model using a large dataset. Our framework facilitates contactless operation to mitigate disease transmission, and through the implementation of a web application, accurate data can be authenticated and stored in the cloud.

V. CONCLUSION

Amidst the global COVID-19 pandemic, healthcare sectors grapple with numerous diagnostic challenges. This paper introduces a web application designed to classify scanned patient images, leveraging a cloud-based platform integrating a Convolutional Neural Network (CNN) model. Patient scans are uploaded to the cloud using web application and via an IoT module, which then transfers them to the cloud-based system for classification. Experimental findings demonstrate that our proposed model achieves an accuracy of 94.45% with augmented data and 91.15% without augmentation. Nonetheless, we anticipate that employing alternative deep learning methodologies could potentially enhance this accuracy further.

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