Prospects of Internet of Things (IoT) and Machine Learning to Fight Against COVID-19

Khandaker Foysal Haque and Ahmed Abdelgawad

Abstract IoT and Machine Learning has improved multi-fold in recent years and they have been playing a great role in healthcare systems which includes detecting, screening and monitoring of the patients. IoT has been successfully detecting different heart diseases, Alzheimer disease, helping autism patients and monitoring patients' health condition with much lesser cost but providing better efficiency, reliability and accuracy. IoT also has a great prospect in fighting against COVID-19. This chapter discusses different aspects of IoT in aiding healthcare systems for detecting and monitoring Coronavirus patients. Two such IoT based models are also designed for automatic thermal monitoring and for measuring and real-time monitoring of heart rate with wearable IoT devices. Convolutional Neural Networks (CNN) is a Machine Learning algorithm that has been performing well in detecting many diseases including Coronary Artery Disease, Malaria, Alzheimer's disease, different dental diseases, and Parkinson's disease. Like other cases, CNN has a substantial prospect in detecting COVID-19 patients with medical images like chest X-rays and CTs. Detecting Corona positive patients is very important in preventing the spread of this virus. On this conquest, a CNN model is proposed to detect COVID-19 patients from chest X-ray images. Two CNN models with different number of convolution layers and three other models based on ResNet50, VGG-16 and VGG-19 are evaluated with comparative analytical analysis. The proposed model performs with an accuracy of 97.5% and a precision of 97.5%. This model gives the Receiver Operating Characteristic (ROC) curve area of 0.975 and F1-score of 97.5. It can be improved further by increasing the dataset for training the model.

Keywords Internet of Things (IoT) · Sensors · COVID-19 · Coronavirus · Detection of COVID-19 · Deep learning · Convolutional Neural Networks (CNN)

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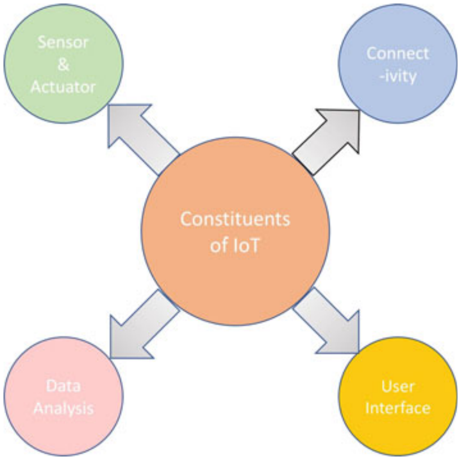

Fig. 1 Basic constituents of IoT

1 Introduction

Internet of Things (IoT) is the network of inter-connected objects that can transfer data among themselves. This is networking of the objects which usually involves sensors, actuators, communication transceivers, micro-controller or processing unit (Haque et al. 2020a). Almost every IoT architecture has four basic constituents:

- sensors and actuators,
- connectivity,
- data analysis,
- and user interface as depicted in Fig. 1.

In general, IoT architectures are based on the communicating sensor nodes. There are one or more processing units in the nodes which are equipped with different sensors and actuators depending on the field of applications. These IoT nodes collect necessary data from the deployed field which is further analyzed for monitoring or real-time decision tacking. Various kinds of sensors and actuators are used in nodes depending on the task of the deployment. Connectivity is another important part of IoT as it keeps things connected. Most IoT nodes are energy constrained as they are battery powered. So, they have to operate and communicate with very low power to last longer. Internet Engineering Task Force (IETF) has standardize Routing Protocol for Low Power and Lossy Networks (RPL) for IoT. RPL is an IPV6 routing protocol which is based on IEEE 802.15.4 with the adaptation layer of 6LoWPAN. But the communication standard for IoT is not limited to RPL rather things can be connected with any suitable wireless technology. Wi-Fi, GSM, 4G, 5G, radio communication technologies like Zigbee, LoRa, Sigfox are few popular choices for IoT connectivity. Data analysis is another component of basic IoT. This section monitors and analyzes the data which is collected from the deployment of IoT node. These analyzed data and decisions are presented to the end user through the designated websites, clouds and cell phone applications.

With the recent development of low power networks and sensors, IoT has grown forth and created numerous application fields (Haque et al. 2020b). Its application field includes industry, medical science, health monitoring, economy, weather forecasting, deep sea exploration underwater mining and daily life (Haque et al. 2020c; Yelamarthi et al. 2017; Abdelgawad and Yelamarthi 2017. The medical and health sector has always been one of the major application area of IoT. It is saving a lot of lives by detecting diseases early and remotely monitoring patients' vitals in real-time. It has made different disease detection more cheaper and a lot faster with higher accuracy and reliability.

In recent years, IoT has played an important role in healthcare by increasing the efficiency, accuracy, reliability, remote accessibility and availability of the medical devices. As IoT in the medical sector gains the popularity, it is sometimes termed as Internet of Medical Things (IoMT). IoMT architectures are used in Medical Nursing System (MNS) with Wireless Sensor Networks (WSN), Sensors, Wi-fi, Zigbee and Bluetooth for patients' data transferring (Joyia et al. 2017; Huang and Cheng 2014). An extensive research is also going on to monitor the patients' physiological condition with low cost medical sensing devices (Istepanian et al. 2011). Researchers are also interested in monitoring autism patients which can keep track of the data collected from the brain signals of the individual (Kumar and Bairavi 2016). Krishna et al. propose an IoT based algorithm to detect the abnormality in the kidney (Krishna et al. 2016). In depth research is also going to make the hospital systems more efficient by making them smart hospitals with IoT (Zhang et al. 2018; Yu et al. 2012; Catarinucci et al. 2015). IoT has a great prospect also in disease detection. Kumar and Gandhi propose an IoT based architecture with machine learning for early detection of heart diseases (Kumar and Gandhi 2018). Varatharajan et al. propose wearable sensor devices for early detection of Alzheimer's disease. Yang et al. propose an IoT-cloud based wearable ECG monitoring system which enables smart healthcare. IoT can also play a vital role in fighting against the most recent COVID-19 pandemic.

The world has been suffering the formidable outbreak of the novel Coronavirus which was first detected in December 2019. This creates a respiratory infectious disease which has been emerging and spreading very fast causing a real threat to the public health. Transmission rate and mode of transmission are very important factors for any contagious disease like COVID-19. According to the World Health Organization (WHO), respiratory droplets of size greater than 5–10 μm acts as a mode of transmission which potentially involve airborne transmission (WHO Organization 2020). This creates an alarming threat to the public health as interaction without necessary safety measures can be highly contagious. So, this disease poses a high growth factor with an estimated fatality rate of 2–5% (Wu et al. 2020). According to WHO, to the date of 6 July 2020, the worldwide total confirmed COVID-19 cases are 11.327 M with the fatality of 0.532 M (WHO coronavirus disease 2020a). Figure 2, Shows the time-series graph of total confirmed cases and deaths over the time to the date.

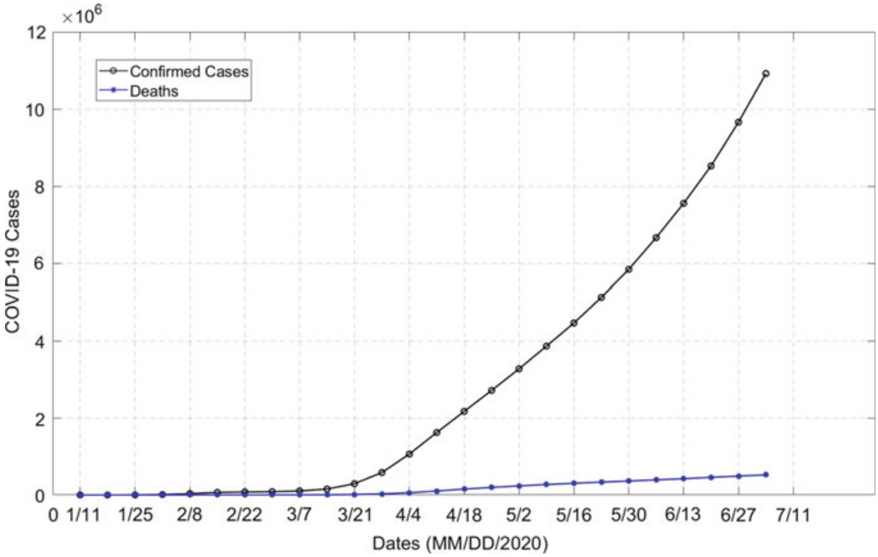

Fig. 2 Time-series graph of world-wide total confirmed cases and deaths due to COVID-19

It shows that this spreads very fast with geometric progression. Early detection of COVID-19 patients is one of the most important aspects to limit the spread of this virus. WHO listed a few rapid and detailed diagnostic tests for COVID-19 detection including genesig Real-Time PCR Coronavirus (COVID-19) testing and cobas SARS-CoV-2 for use on the cobas 6800/8800 systems (WHO coronavirus disease 2020b). These tests take a lot of time and money whereas IoT and Machine Learning can play a major role in automatic positive patient detection and patients' health monitoring. This can save both time and money which will eventually save lives. To find the cure and vaccine for this disease is another important aspect of this critical time to save lives and bring the world back to normal. The combined approach of IoT and Machine learning is vastly helping the humanity to fight against this pandemic. The next part of the chapter focuses on the different aspects of IoT and Machine Learning in fighting against COVID-19.

2 Fight Against COVID-19: An IoT Perspective

IoT is one of the most creative platforms to fight against this pandemic. IoT provides higher reliability and accuracy in screening, detecting and treatment of the COVID-19 patients. It can be used for thermal screening, measuring blood pressure, measuring heart rate and SpO_2 level, measuring glucose level and many other aspects of the detection and treatment of the disease (Sing et al. 2020; Mohammed et al. 2020;

Vaishya et al. 2020). The next part of this section discusses designing two such model to aid COVID-19 detection and treatment.

2.1 Thermal Monitoring with IoT

High temperature is one of the symptoms in COVID-19 affected people. Thermal screening using infrared thermometers is one of the ways to sort out suspected patients for further testing. But this involves the possibility for healthy people to be exposed to affected patients as they have to report to testing center for screening. A continuous real-time monitoring is needed to sort out the suspected patients for further testing. IoT can offer this much needed thermal monitoring accurately in real-time for 24/7. AMG8833 8x8 Infra-Red (IR) thermal camera is an excellent choice for distant monitoring of the thermal profile. It can measure the heat profile from a distance of 7 m (23 feet) and has the sensitivity of $\pm 2.5\,^{\circ}$C. It has the versatility of working with different micro controller platforms. It works really well with Arduino and Raspberry Pi. Here, an IoT node is designed to monitor the real-time thermal temperature from a distance and transfer the data to the cloud for monitoring 24/7. This can be mounted in the front door of the house or testing center for remote monitoring and early suspect detection. Feather Huzzah ESP8266 WI-Fi micro-chip is used as the processing unit as it provides full Wi-Fi stack. A TFT LCD display is also used to monitor the thermal activity. The system has some important components:

- thermal monitoring node,
- wireless connectivity,
- IoT cloud,
- user interface,
- and notification system.

Thermal monitoring node is equipped with ESP8266, AMG8833 IR thermal camera and TFT LCD display. It reads the subjects thermal profile with the IR thermal camera and the thermal image is simultaneously displayed in the LCD display. The node is connected to the Wi-Fi and it transfer the collected data to the cloud. ThingSpeak, Adafruit IO or Google Drive are a few common cloud storage that can be used for such implementation. The data is displayed in any desired interface such as: personal websites or Android/iOS applications. The working principle of the system is depicted the Fig. 3

The thermal node keeps monitoring the temperature and the thermal profile of the subjects put in front of it. ESP8266 is connected to the cloud over Wi-Fi, and it sends the collected data to the designated cloud. The node sends the temperature and thermal image of the subject to the cloud which can be analyzed further for screening out the abnormalities. User can access the collected data and thermal profile from the designed website or phone applications from anywhere in the world.

The capability of the system is improved further by enabling the auto facial recognition with machine learning and automatic notification system. For this, Raspberry

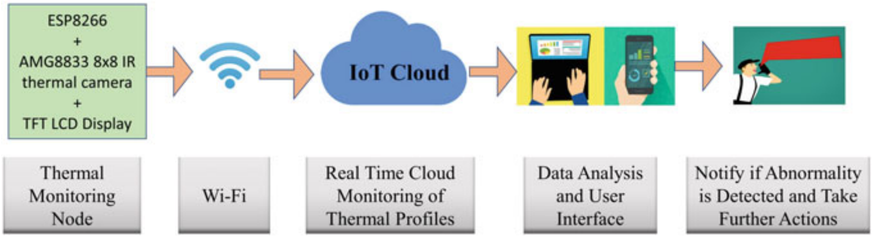

Fig. 3 Architecture of the thermal monitoring system with IoT

Pi is used as the node's processing unit which is equipped with AMG8833 IR thermal camera, Raspberry Pi camera and TFT LCD display. Here, IR thermal camera is used to measure the temperature and to get the thermal image whereas the Raspberry Pi camera takes the corresponding face images for detecting the person. Eigenface algorithm is used for facial recognition of the subjects (Gunawan et al. 2017). The system measures each of the subject's thermal profiles and puts the profile corresponding to the identified person's name. Upon detecting any abnormalities in the thermal profile, the system sends an email notification to the corresponding person. This makes the system fully autonomous and it does not require any human interaction. But the system needs to be trained with all the subjects' images to detect them later while testing.

2.2 *Heart Rate and SpO_2 Monitoring for Primary COVID-19 Screening*

SpO_2 is the measurement of the oxygen carrying hemoglobin in the blood compared to the hemoglobin that is not carrying oxygen. The normal SpO_2 percentage of a healthy human is 96–99%. SpO_2 or oxygen saturation play an important role in early detection of the disease. COVID-19 causes severe respiratory distress which eventually decrease the oxygen saturation in the blood which can cause severe damage to the patient's health and might cause death. One of the early symptoms of the COVID-19 affected patient is lower SpO_2 rate, according to WHO, SpO_2 rate goes down to less than 90% causing severe respiratory problem (WHO Organization Coronavirus disease 2019). Moreover, hospitals treating COVID-19 patients need to monitor this rate to support the patients with respiratory aid. So, the remote real-time monitoring of SpO_2 would help the medical sectors to detect and treat the patients better with more distancing and safety.

A real time heart-rate and SpO_2 monitoring system is designed in this section of the chapter. Arduino pro mini along with ESP8266 is used due to its smaller dimension such that it can be used as wearable device. Arduino pro mini is based on ATmega328 micro-controller and ESP8266 micro chip provides Wi-Fi connectivity

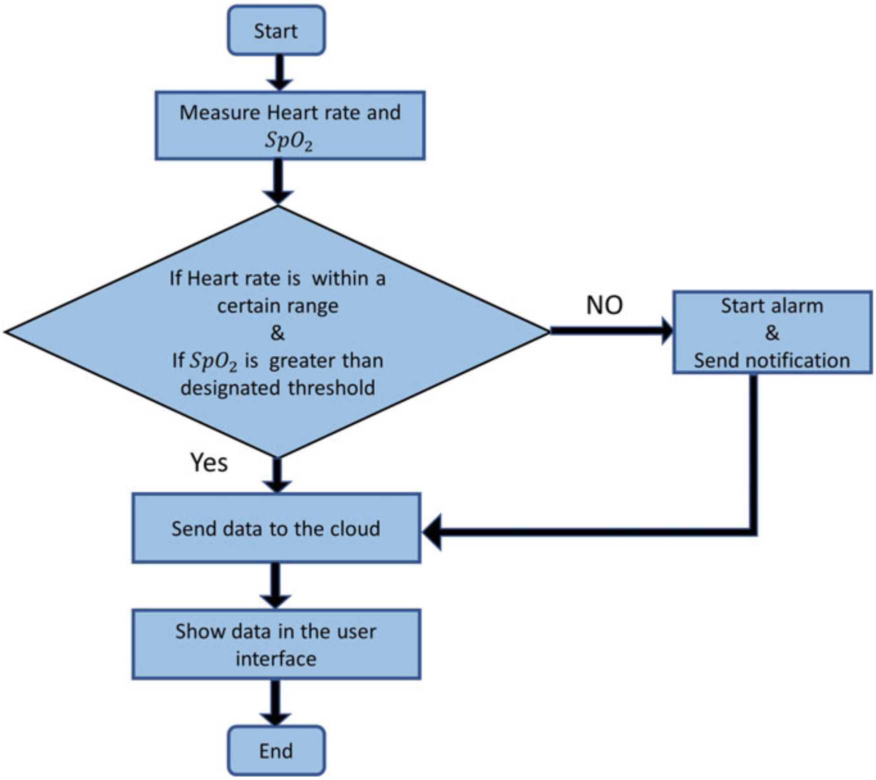

Fig. 4 Flow chart for real-time heart rate and SpO_2 measuring system

to the processing unit. MAX30102 pulse oximeter and heart rate monitor sensor is integrated to the node for measuring the heart rate and SpO_2 rate. It is connected to the Arduino pro mini board with I2C bus. A buzzer is also added to the node for alarming when heart rate or SpO_2 rate go beyond the specified threshold values. This can be used as a wearable device to monitor the heart rate and oxygen saturation at a regular interval. The working principle of the whole system is depicted in Fig. 4.

At first, the wearable node measures the heart rate and SpO_2 with MAX30102 sensor. This sensor passes a beam of light through the finger tip and receives the reflected light which depends on the absorption of the light by blood. It can measure the oxygen saturation rate of blood as absorption rate of the oxygenated blood varies from the deoxygenated one. This sensor can also measure the heart rate of the patient. After measuring, data is sent to the micro-controller where it compares if the heart rate is within a designated range and if SpO_2 value is greater than a designated value. If the obtained values are as expected it sends the data to the cloud and publishes the data in desired user interface. If the measured values are not within the designated range it creates an alarm with a buzzer and sends an email notification to the assigned authority. This system helps in screening and treating COVID-19 patients to a great extent and increase the safety and reliability of the treatment.

3 Machine Learning in Fighting Against COVID-19

Deep Learning (DL) is a branch of Machine Learning (ML) which is inspired by the working procedure of the human brain. DL has the capability of unsupervised learning i.e. to learn from the examples with unlabeled data. The features like unlabeled data utilization, working without feature engineering, and prediction with high accuracy and precision make DL very popular with Artificial Intelligence (AI) and Big Data analysis. DL has been vastly used in industries, self driven cars, face recognition, object detection, image classification and in many other fields. Convolutional Neural Network (CNN) is a DL algorithm which has been performing very well in solving problems like document analysis, different sorts of image classification, pose detection, action recognition. Medical imaging is another field where CNN has been showing promising results in recent years.

CNN is an Artificial Neural Network (ANN) based deep learning algorithm which has grown significantly in recent times. CNN is based on the principle of human nervous system specially human brains which is formed of billions of neurons. The idea of artificial neuron was first conceptualized in 1943 (McCulloch and Pitts 1943). Hubel and Wisel first found that for detecting lights in the receptive fields, visual cortex cells have a major role which greatly inspired the building of a model like Neocognitron (Gu et al. 2018). This model is considered to be the base and predecessor of CNN. CNN is formed of artificial neurons which has the property of self optimization with learning like the brain neurons. Due to this self optimizing property, it can extract and classify the features extracted from images more precisely than any other algorithm. Moreover, it needs very limited preprocessing of the input data though it yields highly accurate and precise results. CNN is vastly used in object detection and image classification including medical imaging.

CNN has been performing really well with medical imaging. For recent years, it has been used vastly for a different disease or anomaly detection. CNN does the diagnosis of Coronary Artery Disease (CAD), recognition of stages from bright-field microscopy images of malaria-infected blood, detection of Parkinson's disease from electroencephalogram (EEG) signals, the study of Alzheimer's disease and classification of many other diseases. CNN can also play a great role in COVID-19 detection from CT or X-ray images.

In the rest part of the section, a CNN model is proposed to detect COVID-19 positive patients from chest X-ray images as in authors' earlier work (Haque et al. 2020d). With very little time and resources, this model successfully detects Coronavirus patients with high accuracy. This work also includes the comparative analytical analysis of the CNN models in detecting COVID-19. This can help to implement testing of COVID-19 on a much greater scale which would save both money and time.

3.1 Related Works

Extensive research work is going on for classifying COVID-19 patient image data. Few researchers have proposed different DL models for classifying chest x-ray images whereas some others have taken CT images into consideration. Narin et al. proposed three CNN models based on pretrained ResNet50, InceptionV3, Inception-ResNetV2 for detecting COVID-19 patient from chest X-ray radiographs (Narin et al. 2020). These models are pretrained on ImageNet database and use 2×2 average pooling layers and two fully connected layers on the top of the pre-trained layers. It is mentionable that ImageNet provides a huge number of a generalized dataset for image classifications. The Softmax activation function is used for each of the models to finally classify the images. It is found that ResNet50 gives the classifying accuracy of 98% whereas InceptionV3 and Inception-ResNetV2 perform with the accuracy of 97% and 87% respectively. But these models have taken only 100 images (50 COVID-19 and 50 normal Chest X-rays) into consideration for training which might result in declined accuracy for a higher number of training images. Zhang et al. propose a CNN model for Coronavirus patient screening using their chest X-ray images (Zhang et al. 2020). This research group has used 100 chest X-ray images of 70 COVID-19 patients and 1431 X-ray images of other pneumonia patients where they are classified as COVID-19 and non-COVID-19 respectively. This model is formed of three main parts: backbone networks, classification head, and anomaly detection head. The backbone network is a 18 residual CNN layer pre-trained on ImageNet dataset. This model can diagnose COVID-19 and non-COVID-19 patients with an accuracy of 96% and 70.65% respectively. But this model also have few drawbacks like– using smaller dataset and its false positive rate is almost 30%. Hall et al. also worked on finding COVID-19 patients from a small set of chest X-ray images with DL (Hall et al. 2020). They have used pre-trained ResNet50 and VGG 16 along with their own CNN and this model generates the overall accuracy of 94.4% and false positive rate of 6%. The model shows the true positive rate of 0.969 whereas the true negative rate is 0.94. Sethy and Behea have also utilized deep features for Coronavirus disease detection (Sethy and Behera 2020). Their model is based on ResNet50 plus SVM where the features extracted from each CNN layers are utilized by SVM for classification. This model achieved the accuracy and F1-score of 95.38% and 91.41% respectively. The false positive rate and F-1 scores are 95.52 % and 91.41% which is better than other discussed models. But this model is trained with a very small dataset of 25 images for each of the class: COVID-19 and Normal.

3.2 Proposed CNN Model for COVID-19 Detection

3.2.1 Dataset Collection and Modeling

For training the proposed model, 161 chest X-ray images of COVID-19 patients are used which are obtained from open Github repository by Cohen et al. (2020). This repository contains patients' chest X-ray images of COVID-19, SARS, ARDS, Pneumocystis, Streptococcus, Chlamydophila, E.Coli, Legionella, Varicella, Lipoid, Bacterial, Pneumonia, Mycoplasma Bacterial Pneumonia, Klebsiella and Influenza. For training, only the COVID-19 positive X-rays have been taken into consideration and the patient age ranges from 12–93 years. The training also needs the normal or non-COVID-19 chest X-rays, which is obtained from Kaggle dataset naming "Chest X-ray Images (pneumonia)" (Mooney 2020). This repository contains 5863 images in two categories- normal and pneumonia. But we have taken 161 (same number as the COVID-19 chest X-ray images) normal chest X-ray images for the training purpose. The whole dataset is primarily split into two categories: training and validation maintaining the ratio of 80% and 20% respectively. Each group of training and validation dataset contains two subcategories: 'Normal' and 'COVID-19', containing the respective types of X-ray images. So, for the training, both the categories- 'Normal' and 'COVID-19' contain 161 chest X-ray images each whereas, the validation dataset contains 40 images for each of the 'Normal' and 'COVID-19' sub-categories. For maintaining unanimity and the image quality at the same time, all the images are converted to 224×224 pixels. Moreover, all the X-ray images that are used for training and validation of the model are in Posteroanterior (PA) chest view.

3.2.2 CNN Modeling

CNN has been playing a great role in classifying images, in particular medical images. This has opened new windows of opportunities and made the disease detection much more convenient. It also successfully detects recent novel Coronavirus with higher accuracy. One of the constraints that researchers encounter is a limited dataset for training their model. Being a novel disease, the chest X-ray dataset of COVID-19 positive patients is also limited. Therefore, to avoid overfitting, a sequential CNN model is proposed for classifying X-ray images. Figure 5 depicts the proposed CNN model for COVID-19 detection. This model has 4 main components:

- input layers,
- convolutional layers,
- fully connected layers,
- and (iv) output layers.

The tuned data set is fed into the input layers of the model. This model is trained on 165 X-ray images of each category: normal and COVID-19. It has four convolutional

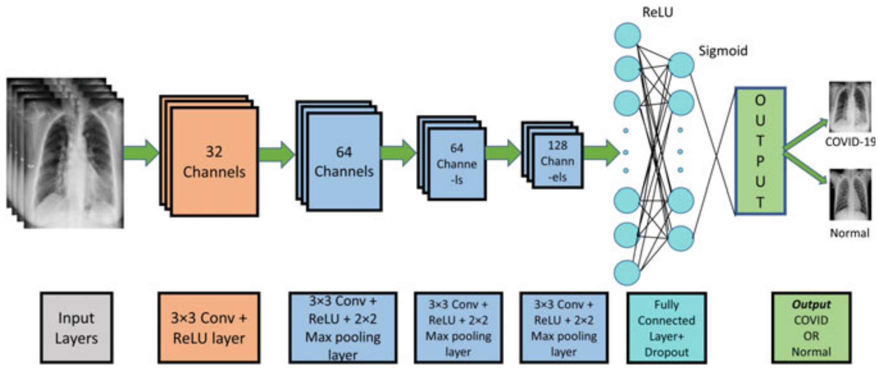

Fig. 5 Workflow diagram of the proposed CNN model for COVID-19 detection

layers, first one is a 2D convolutional layer with 3×3 kernels and Rectified Linear Unit (ReLU) activation function. ReLU is one of the most popular and effective activation functions that are being widely used in DL. ReLU does not activate all the neurons at the same time making it computationally efficient in comparison to other activation functions like tanh.

The next three layers are 2D convolutional layer along with the ReLU activation function and Max pooling. Max pooling accumulates the features of the convolutional layer by convolving filters over it. It reduces the computational cost as it minimizes the number of parameters thus it helps avoid overfitting. In each of three layers a 2×2 Max pooling layer is added after the convolutional layer to avoid overfitting and to make the model computationally efficient. In the next step of the model, the output of the convolutional layers is converted to a long 1D feature vector by a flatten layer. This output from the flatten layer is fed to the fully connected layer with dropout. In a fully connected layer, every input neuron is connected to every activation unit of the next layer. All the input features are passed through the ReLU activation function and this layer categorizes the images to the assigned labels. The Sigmoid activation function makes the classification decision depending on the classification label of the neurons. Finally, in the output layer, it is declared if the input X-ray image is COVID-19 positive or normal. This model is termed as 'Model 1'.

For comparative analysis, two more CNN models are also developed with 3 and 5 conv layers respectively instead of the 4 conv layers of the Model 1. These models with 3 and 5 conv layers are termed as 'Model 2' and 'Model 3' respectively. Model 2 has one 3 3 conv layer with ReLU having 32 channels and two more layers with 3 conv layers with ReLU and 2 Max Pooling layers having 64 channels each.

This work also takes few pretrained models into consideration in terms of their performance with COVID-19 image classification. Three pretrained models based on ResNet50, VGG-16 and VGG-19 are also developed and tuned to detect the COVID-19 cases from the same chest x-ray datasets (He et al. 2016; Simonyan and Zisserman 2014). ResNet is based on ImageNet and it has achieved excellent results with only 3.57% error. It has five stages each having one convolution and one

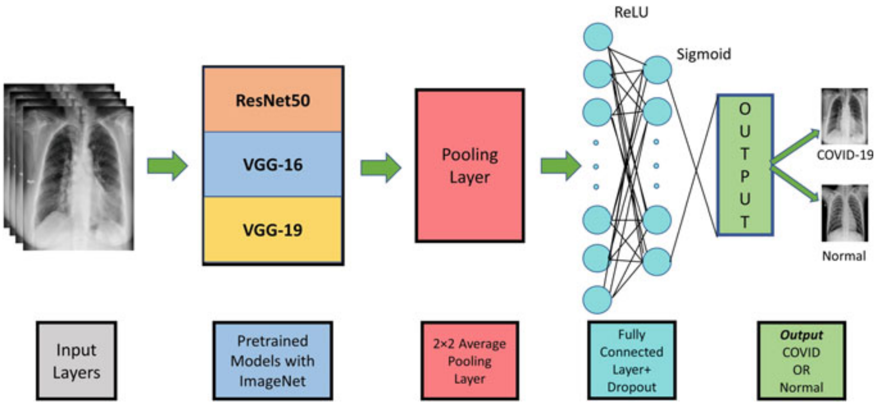

Fig. 6 Workflow diagram of the pretrained models for COVID-19 detection

identity block. Each of the convolution and identity blocks have 3 convolution layers. VGG-16 is CNN model which is 16 layers deep as its name suggests. This is one of the most excellent CNN architecture for image classification. This model doesn't have a large number of hyper -parameters rather it use 3 × 3 convolution layers and 2 max pooling layer with stride of 1 and 2 respectively. The whole architecture is based on this consistent convolution and max pooling layer. VGG-19 is of the same architecture as VGG-16 except for VGG-19 has 19 deep layers instead of 16. The pretrained model of these three CNN architecture are used to extract features and outputs are fed to 2 × 2 pooling layer. A flatten layer converts the outputs to a 1D feature vector. The output from the flatten layer is fed to the fully connected layer with dropout which has the same architecture as Model 1, Model 2 and Model 3. Figure 6 depicts the workflow diagram of the pretrained models.

3.3 Results and Analysis

The proposed model is trained for 25 epochs with 10 steps per epoch. In this section, the proposed model (Model 1) is analyzed along with Model 2 and Model 3 and pretrained ResNet50, VGG-16 and VGG-19. These six models are trained and validated with the same dataset and machine. The validation accuracy and corresponding epochs for all the six models are plotted in Fig. 7.

The overall accuracy is 97.5%, 93.75%, and 95% for Model 1, Model 2, and Model 3 respectively whereas the pretrained model achieved the accuracy of 88.5%, 78.75% and 60% respectively by ResNet50, VGG-16 and VGG-19. It clearly shows that the proposed model (Model 1) performs better than the other models in terms of accuracy. The performance of the models is more evident from the metrics like precision, recall, and F-1 score. These performance metrics are calculated from the

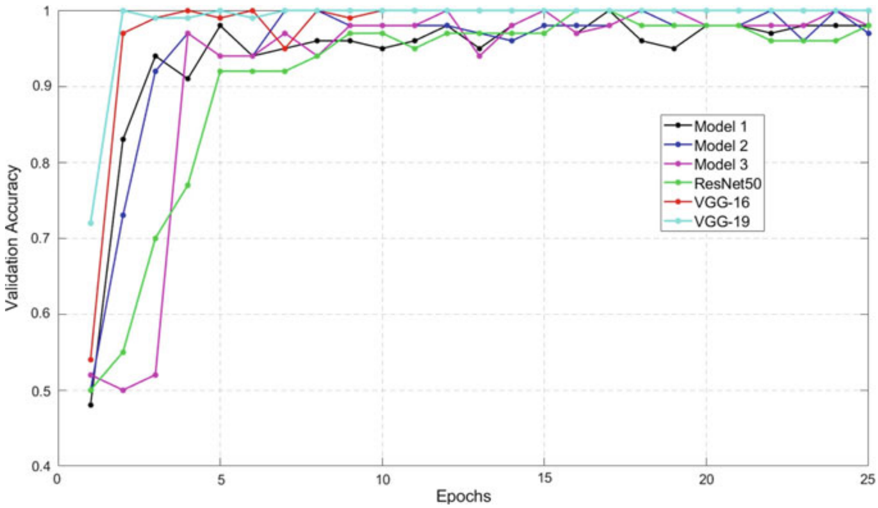

Fig. 7 Validation accuracy and corresponding epochs for all the six models

possible outcomes of the validation dataset which is obtained by the confusion matrix. A confusion matrix has four different outcomes: True Positive (TP), True Negative (TN), False Positive (FP), False Negative (FN). In this case, TP denotes the number of Corona positive patients detected as positive, TN denotes the number of Corona negative cases detected as negative, FP presents the number of cases which are actually negative but detected as Corona positive and FN gives the cases which are actually Corona positive but detected as negative. Receiver Operating Characteristics (ROC) curve represents the performance of the classifier at different threshold values which plot the TP rates vs FP rates. Confusion Matrices and corresponding ROC curves for all the six models is depicted in Figs. 8 and 9 respectively for analytical analysis.

Model 1 detects 39 TP and 39 TN cases, Model 2 finds 35 TP and 40 TN cases whereas, Model 3 detects 40 TP and 36 TN cases. On the other hand, the pretrained models perform very well in detecting the TN cases which is 40 for each models whereas the TP cases detected are 31, 23 and 8 by ResNet50, VGG-16 and VGG-19 respectively. The ROC curve area of the Model 1 is 0.975 which outperforms the other discussed models. On the contrary, VGG-19 achieved the lowest ROC curve area of 0.60 in compared to others. It is evident from the confusion matrix that Model 1 performs better in terms of case detection.

Accuracy defines how close the generated result is to the actual value whereas precision measures the percentage of the relevant results. Recall or sensitivity is another important factor for evaluating a CNN model. It is defined by the percentage of the total relevant results that a model can correctly classify. F1-score combines both precision and recall and it is designated as the weighted average of these two. Equations 1–4 represents accuracy, precision, recall, and F-1 sore respectively.

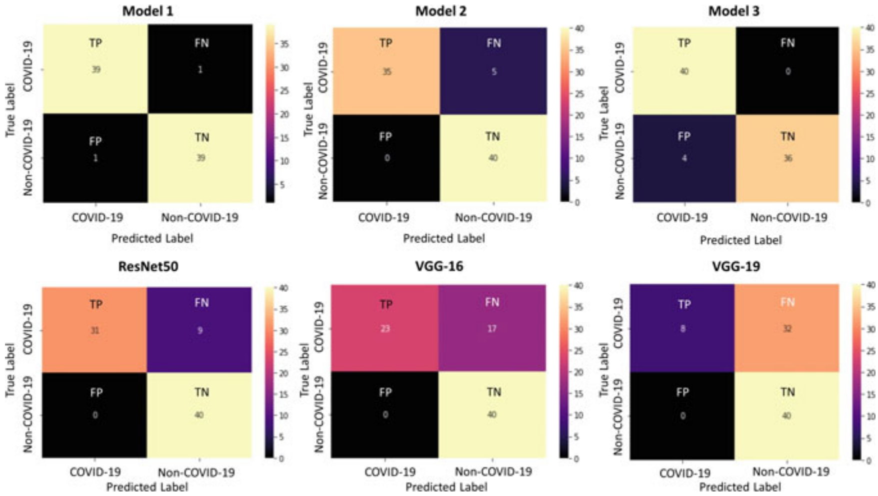

Fig. 8 Confusion matrices of all the six models on validation data set

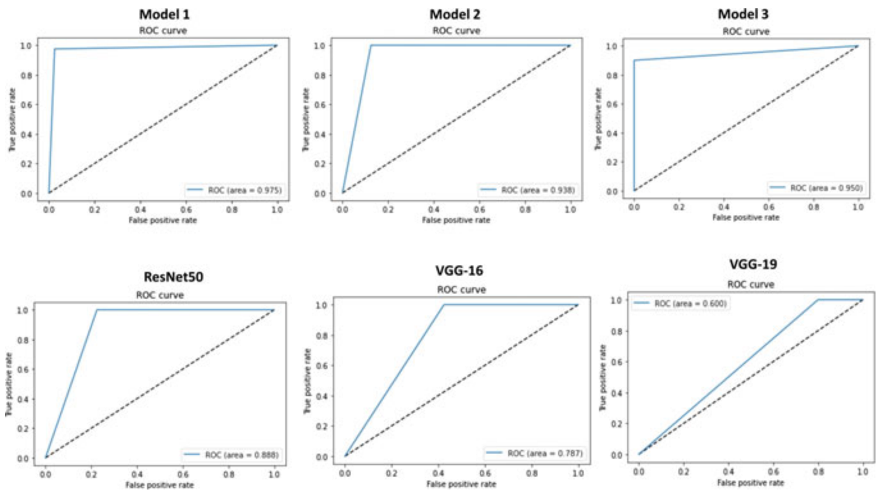

Fig. 9 ROC curves and curve area of all the six models

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

$$Precision = \frac{TP}{TP + FP} \tag{2}$$

$$Recall = \frac{TP}{TP + FN} \tag{3}$$

$$F1\ Score = 2 \times \left(\frac{Precision \times Recall}{Precision + Recall} \right) \tag{4}$$

Table 1 Confusion matrix parameters and performance metrics of the models

Model	TP	TN	FP	FN	TP (%)	TN (%)	Accuracy (%)	Precision (%)	Recall (%)	ROC Area	F1-Score
Model 1	39	39	1	1	97.5	97.5	97.5	97.5	97.5	0.975	97.5
Model 2	35	40	0	5	87.5	100	93.75	100	87.5	0.938	93.34
Model 3	40	36	4	0	100	90	95	90.9	100	0.950	95.23
ResNet50	31	40	0	9	77.5	100	88.75	100	77.5	0.888	87.32
VGG-16	23	40	0	17	57.5	100	78.75	100	57.5	0.787	73.01
VGG-19	8	40	0	32	20	100	60	100	20	0.60	33.33

Table 1 shows the confusion matrix parameters, accuracy, precision, recall, ROC curve area and F1-score of the mentioned six models.

Model 1 achieves the highest F1-score of 97.5, contrarily, VGG-19 performs with the lowest F1-score of 33.33. The overall performance and also the F1-score of the proposed model (Model 1) show better performance than that of the other models. The accuracy of the proposed model is 97.5% with the precision and recall value of 97.5% for both the parameters. Though this model lacks accuracy, the overall performance including accuracy and F1-score can be improved further by training the model with a larger dataset.

4 Conclusion

Mass testing and early detection of COVID-19 play an important role in preventing the spread of this recent global pandemic. Proper monitoring and treatment also play an important part in fighting against this. Time, cost, accuracy and reliability are the few major factors in any disease detection and treatment process, especially COVID-19. IoT and Machine Learning do a great job in addressing these issues. This chapter discusses different prospects of IoT in fighting against COVID-19. It also includes designing two different IoT model for thermal monitoring which would do the preliminary screening for detecting COVID-19 and heart rate monitoring system for affected patients. A CNN based model is proposed in the later part of the chapter for detecting COVID-19 cases from patients' chest X-rays. A set of 322 chest X-ray images which are equally divided into two classes: 'COVID-19' and 'Normal', are used for training the model. Similarly, an equally divided image set of 80 chest X-rays are used for validation of the model. This model performs with an accuracy and precision of 97.5% and 97.5% respectively. Moreover, this model is compared to pretrained ResNet50, VGG-16, VGG-19 and other two CNN models with a different number of convolutional layers. The comparative studies show better F1-score and overall performance of the proposed model (Model 1) than that of other models. This model can be improved further with the availability of the larger dataset. So, CNN has great prospects in detecting COVID-19 with very limited time, resources, and costs. Though the proposed model shows promising results, it is in no way clinically tested. This model needs further improvements and clinical testing for it to work in clinical diagnosis.

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References

Abdelgawad, A., & Yelamarthi, K. (2017). Internet of things (IoT) platform for structure health monitoring. *Wireless Communications and Mobile Computing*.

Catarinucci, L., De Donno, D., Mainetti, L., Palano, L., Patrono, Stefanizzi, M. L., & Tarricone, L. (2015). An IoT-aware architecture for smart healthcare systems. *IEEE Internet of Things Journal*, *2*(6), 515–526.

Cohen, J. P., Morrison, P., & Dao, L. (2020). Covid-19 image data collection. arXiv:2003.11597. https://github.com/ieee8023/covid-chestxray-dataset

Gu, J., Wang, Z., Kuen, J., Ma, L., Shahroudy, A., Shuai, B., et al. (2018). Recent advances in convolutional neural networks. *Pattern Recognition*, *77*, 354–377.

Gunawan, T. S., Gani, M. H. H., Rahman, F. D. A., & Kartiwi, M. (2017). Development of face recognition on raspberry pi for security enhancement of smart home system. *Indonesian Journal of Electrical Engineering and Informatics (IJEEI)*, *5*(4), 317–325.

Hall, L. O., Paul, R., Goldgof, D. B., & Goldgof, G. M. (2020). Finding covid-19 from chest x-rays using deep learning on a small dataset. arXiv preprint arXiv:2004.02060.

Haque, K. F., Zabin, R., Yelamarthi, K., Yanambaka, P., & Abdelgawad, A. (2020). An IoT based efficient waste collection system with smart bins. In *IEEE 6th World Forum on Internet of Things (WF-IoT)*. IEEE.

Haque, K. F., Abdelgawad, A., Yanambaka, P., & Yelamarthi, K. (2020). An energy-efficient and reliable RPL for IoT. In *2020 IEEE 6th World Forum on Internet of Things (WF-IoT)*. IEEE.

Haque, K. F., Kabir, K. H., & Abdelgawad, A. (2020). Advancement of routing protocols and applications of underwater wireless sensor network (UWSN)-a survey. *Journal of Sensor and Actuator Networks*, *9*(2), 19 (2020).

Haque, K.F., Haque, F.F., Gandy, L., & Abdelgawad, A. (2020). Automatic detection of COVID-19 from chest X-ray images with convolutional neural networks. In *3rd IEEE International Conference on Computing, Electronics & Communications Engineering (IEEE iCCECE'20)*.

He, K., Zhang, X., Ren, S., & Sun, J. (2016). Deep residual learning for image recognition. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition* (pp. 770–778).

Huang, C.-H., & Cheng, K.-W. (2014). RFID technology combined with IoT application in medical nursing system. *Bulletin of Networking, Computing, Systems, and Software*, *3*(1), 20–24 (2014).

Istepanian, R. S., Sungoor, A., Faisal, A., & Philip, N. (2011). Internet of m-health things 'm-IoT'. In *IET Seminar on Assisted Living*.

Joyia, G. J., Liaqat, R. M., Farooq, A., & Rehman, S. (2017). Internet of medical things (IOMT): Applications, benefits and future challenges in healthcare domain. *Journal of Communication*, *12*(4), 240–247.

Kumar, K. S., & Bairavi, K. (2016). IoT based health monitoring system for autistic patients. In *Proceedings of the 3rd International Symposium on Big Data and Cloud Computing Challenges (ISBCC–16')* (pp. 371–376). Springer.

Kumar, P. M., & Gandhi, U. D. (2018). A novel three-tier internet of things architecture with machine learning algorithm for early detection of heart diseases. *Computers & Electrical Engineering*, *65*, 222–235.

Krishna, K. D., Akkala, V., Bharath, R., Rajalakshmi, P., Mohammed, A., Merchant, S., et al. (2016). Computer aided abnormality detection for kidney on FPGA based IoT enabled portable ultrasound imaging system. *IRBM*, *37*(4), 189–197.

McCulloch, W. S., & Pitts, W. (1943). A logical calculus of the ideas immanent in nervous activity. *The Bulletin of Mathematical Biophysics*, *5*(4), 115–133.

Mohammed, M., Syamsudin, H., Al-Zubaidi, S., AKS, R. R., & Yusuf, E. (2020). Novel covid-19 detection and diagnosis system using IoT based smart helmet. *International Journal of Psychosocial Rehabilitation*, *24*(7).

Mooney, P. (2020). Chest x-ray images (pneumonia). https://www.kaggle.com/paultimothymooney/chest-xray-pneumonia

Narin, A., Kaya, C., & Pamuk, Z. (2020). Automatic detection of coronavirus disease (covid-19) using x-ray images and deep convolutional neural networks. arXiv preprint arXiv:2003.10849.

Sethy, P. K., & Behera, S. K. (2020). Detection of coronavirus disease (covid-19) based on deep features. Preprints *2020–030300*.

Singh, R. P., Javaid, M., Haleem, A., & Suman, R. (2020). Internet of things (IoT) applications to fight against covid-19 pandemic. *Diabetes & Metabolic Syndrome: Clinical Research & Reviews*.

Simonyan, K., & Zisserman, A. (2014). Very deep convolutional networks for large-scale image recognition. arXiv preprint arXiv:1409.1556.

Vaishya, R., Javaid, M., Khan, I., & Haleem, A. (2020). Artificial intelligence (AI) applications for covid-19 pandemic. *Diabetes & Metabolic Syndrome. Clinical Research & Review*.

WHO Organization Coronavirus Disease (covid-19). (2019). https://www.who.int/emergencies/diseases/novel-coronavirus-2019.

WHO Organization. (2020). *Modes of transmission of virus causing covid-19: Implications for IPC precaution recommendations: Scientific brief, 27 March 2020*. Technical report, World Health Organization.

WHO Coronavirus Disease (COVID-19) Dashboard. (2020). Geneva world health organization. https://covid19.who.int/.

WHO Coronavirus Disease (COVID-19) Newsroom. (2020). Geneva world health organization. https://www.who.int/news-room/detail/07-04-2020-who-lists-two-covid-19-tests-for-emergency-use.

Wu, Y.-C., Chen, C.-S., & Chan, Y.-J. (2020). The outbreak of covid-19: An overview. *Journal of the Chinese Medical Association*, *83*(3), 217.

Yelamarthi, K., Aman, M. S., & Abdelgawad, A. (2017). An application-driven modular IoT architecture. *Wireless Communications and Mobile Computing*, *2017*, 2017.

Yu, L., Lu, Y., & Zhu, X. (2012). Smart hospital based on internet of things. *Journal of Networks*, *7*(10), 1654.

Zhang, H., Li, J., Wen, B., Xun, Y., & Liu, J. (2018). Connecting intelligent things in smart hospitals using NB-IoT. *IEEE Internet of Things Journal*, *5*(3), 1550–1560.

Zhang, J., Xie, Y., Li, Y., Shen, C., & Xia, Y. (2020). Covid-19 screening on chest x-ray images using deep learning based anomaly detection. arXiv preprint arXiv:2003.12338.