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COVID -19 Predictions using Transfer Learning based Deep Learning Model with Medical Internet of Things

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Abstract— Early detection of COVID-19 may help medical expert for proper treatment plan and infection control. Internet of Things (IoT) has vital improvement in many areas including medical field. Deep learning also provide tremendous improvement in the field of medical. We have proposed a Transfer learning based deep learning model with medical Internet of Things for predicting COVID-19 from X-ray images. In the proposed method, the X ray images of patient are stored in cloud storage using internet for wide access. Then, the images are retrieved from cloud and Transfer learning based deep learning models namely VGG-16, Inception, Alexnet, Googlenet and Convolution neural Network models are applied on the X-rays images for predicting COVID 19, Normal and pneumonia classes. The pre-trained models helps to the effectiveness of deep learning accuracy and reduced the training time. The experimental analysis show that VGG -16 model gives accuracy of 99% for detecting COVID19 than other models.

Keywords- Medical IOT, Deep Learning, Transfer Learning, X-rays, COVID-19

I. INTRODUCTION

The pandemic which affects the entire world is COVID19.There are wide range of COVID-19 infection with mild symptoms to severe illness. Virus takes 2 to 14 days to exposure its severity. The common significant symptoms of COVID-19 are sore throat, headache, body or muscle aches, fever, and dry cough, running nose, vomiting, sleepiness and diarrhoea. Difficulty in breathing leads to death in several cases. The asymptotic carriers, some of the individuals have no or minor symptoms. The asymptotic carriers more risky and it's very hard to trace the silent carriers [1]. There are 5% of infected people require ventilation or oxygen, asymptotic symptoms or mild symptoms are of 80% infections and severe symptoms of 15%, according to WHO [2].

IoT campaigns are extensively used in huge sum of application areas like medicine, smart cities, home automation and manufacturing in recent years [3]. To capture the information about physical world by using these devices the sensors are used. Due to this COVID-19 pandemic, the world is overwhelmed with healthcare system. As of December 19, 2020, round 185 countries, there have been 55 million recovered cases, confirmed cases are around 21 million and deaths were reported around 1.6 million. In order to stop this outbreak, early diagnosis of COVID infected patients is more essential. IoT devices are used to extract the COVID-19 patient's dataset remotely. The information related to

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diagnosis of COVID-19, is moved to healthcare workers. Using IoT- enabled devices, the healthcare workers afford better treatment for the COVID-19 affected people [4].

Deep learning with Transfer learning for COVID 19 prediction plays a major role and there are lot advantages [31]. For handling image classification and disease detection from biological images Deep learning has become unavoidable method because of its large computing power with high accuracy in detection of anomaly. In transfer learning, the source domain knowledge obtained through its learning activity is brought to study comparable learning activity of target domain. For example, person who studied piano, can study faster to play violin as both are musical instrument. Transfer learning shown in figure 1.

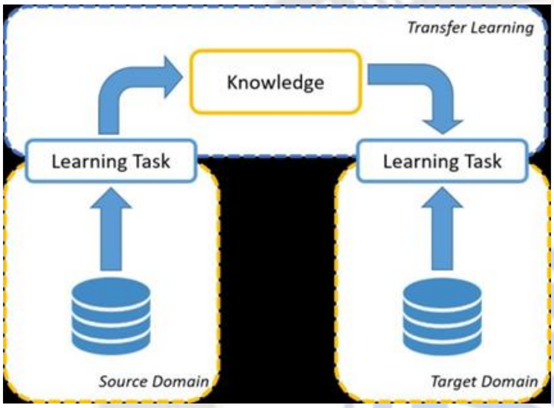


Figure 1. Transfer Learning

The image recognition context is same in the transfer learning context. In order to handle a specific take with previously trained data is handled by deep Convolutional Neural Network (CNN), and it handles a vast amount of data [29]. The task of the target domain are handled using the classification layers of the CNN and finally, we frozen the trained convolution and pooling layers of the model. There are many advantages provided by transfer learning. Test and train dataset which are not required for transfer learning. In the next case, identify the collected training data which are not required.

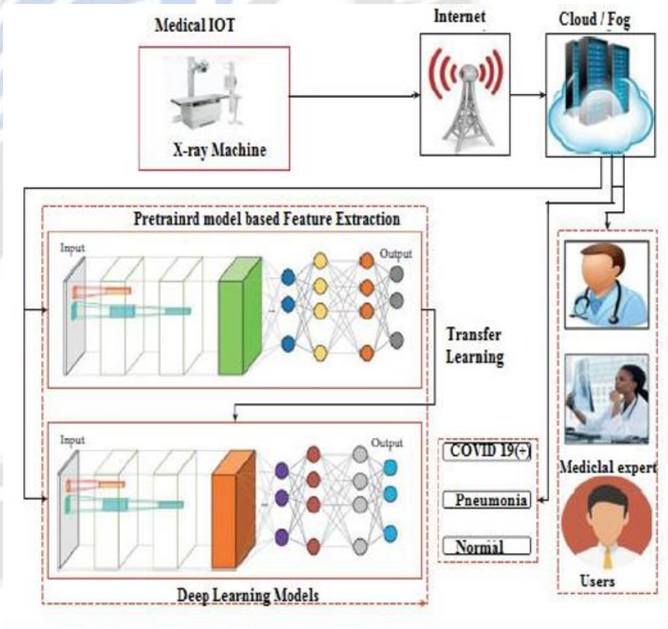
As compared with traditional deep learning method, transfer learning approached can be implemented very quickly, and experts from various domain and doctors are also reduced. Such conditions are required in Transfer learning. One of the challenging task, is collecting a vast amount of X-ray images with the same distribution of classes in both training and test sets of Covid 19. Training deep learning models with millions of parameters from scratch, requires large amount of data and time. But Transfer learning does not require much amount data to be trained from scratch. The large amount of sufficient data is used to pre-train the transfer learning and qualified again with a small quantity of data. Therefore it requires less time for training COVID 19 data [5].

Therefore, we have proposed a method to detect COVID 19 from X-ray images using Transfer learning based deep learning with medical IOT. In the proposed method, the patient X-ray images from the dataset or hospital transferred through network and stored in cloud storage. Those images can be taken from cloud by the data analysis for COVID prediction. Transfer learning based deep learning model is applied for predicting classes namely normal, Pneumonia and COVID classes [6]. The models namely CNN, Alexnet, Google Net, Inception V3 and VGG-16 are used for COVID prediction. Those results can be again stored in cloud for use by medical experts, Medical Analyst and patients for finding COVID results.

The main contribution of the proposed method,

(i) Applying Transfer learning approach to reduce information size and minimize training and testing time ofdeep learning models
(ii) A deep learning model is developed to predict COVID-19 efficiently in terms of accurateness and other enactment metrics.
(iii) Enhancing the effectiveness of the model by integrating IOT with COVID-19 prediction mode

II. RELATED WORKS



Various deep learning models for COVID-19 we have analysed in this section. COVID-19 is a risky illness and it blowouts fastly, when compared with other viruses. As well as we have labelled, different fields of life to mend the living principles with various IOT [30] based systems with different techniques. In order to predict it, there are various ensemble-based Deep learning models is used widely. Till now various researchers have completed many works to predict Covid-19 in an effective and efficient manner [32].

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A significant role of a medical treatment is to diagnosis the suspected COVID-19 patients. To encounter the COVID-19 outbreaks, an automated deep transfer learning models for the diagnosis of COVID-19 chest X-ray is primary required [33]. By employing deep transfer learning model, early diagnosis of suspected COVID-19 patients is done with the help of IoT outline. In paper [7], the authors proposed the real-time communication and diagnosis of COVID-19 suspected cases. ResNet152V2, DenseNet201, InceptionResNetV2, and VGG16 models were used for IoT framework. The chest X-ray diagnosis and modalities the infection by using deep ensemble model which is stored on the cloud server, in which the medical sensors are utilized for this purpose [13].

During this pandemic, Artificial Intelligence (AI) and Machine Learning (ML) played a major role in the field of designing efficient diagnosis policies, predictions of disease spread, and medicine development. An automated drug delivery, pursuing the grounds of illness blow-out and responding to patient queries were efficiently managed by IoT [8]. In various fields like healthcare systems, smart security, electronic and mechanical monitoring systems, IoT is playing a major role. In control and monitoring mechanical, electronic, smart security, and healthcare systems IoT is being used [9]. In paper [10] and [11], the examples of IoMT and IoT applications of healthcare were provided by the authors. To swear the implementation of quarantine, track pandemic outbreaks the applications can be trained in order to suggest aid to medical experts in hospitals. The various diagnosis and treatment of Covid-19 subjects, there are various emerging technologies were applied [17]. For Covid-19 classification, researcher's used different machine learning and artificial intelligence [18-19]. Some researchers used artificial intelligence-based methods for investigation of Covid-19 X-Rays [12]. For the investigation and recognition of Covid-19, by the developed methods, a limited number of CT-scans and X-Rays are used [14]. There were 50 sample images which contains 25 healthy subject samples and 25 COVID positive samples, and employed with a limited data set and several deep learning architectures [15]. There are 800 images in data set which contains the X-Ray samples classification into normal, Pneumonia and Covid-19. The authors [16] introduced CNN architecture termed COVID-Net and testified with sensitivity 80% and overall accuracy is 92.4%. In order to categorize the X-Rays trials into bacterial pneumonia, viral, infested and fit the authors [17] used the model ResNet-50. The complete precision is 96.23% and sensitivity is 100%. There were 931 subjects of bacterial pneumonia, 1203 healthy subjects, 68 Covid-19 X-rays of 45 Covid-19 subjects and 660 subjects of Non-Covid- 19 viral pneumonia used by the authors [16]. An automatic detection model by using the X-Ray samples the researchers developed by retaining transfer learning with neural networks [18]. In paper [19], the authors completed their research work of Covid-19 recognition using chest X-Ray. Most of the researchers used classification based methods like ResNet-50, SqueezeNet, VGG, Inception, ResNet-101, AlexNet and Xception for image classification of chest X-Rays. In paper [20] the researchers employed U-Net, 3-D U-Net, VBNet, MiniSeg, DeepLab, and Dense-Net of segmentation models. The authors used Chest X-Ray sample images as pneumonia data set for their research work [21].

For the automatic diagnosis of Covid-19 from thoracic X-Rays, and to evaluate the effectiveness of the pre- trained convolutional neural networks, the work proposed by the experts and the scientific community. the collection of 1427 thoracic X-ray scans are administered, in order to train and test the CNNs. Transfer learning is the desirable approach to train the CNNs and 224 images samples were tested. The authors considered large- scale datasets, in order to perform the feature extraction and classification. The key requirement to extract the knowledge and to perform an alternative task, the powerful entity is transfer learning [15].

III. PROPOSED MIoT ARCHITECTURE

In this section, we propose a MIoT architecture, where the framework has been deployed.

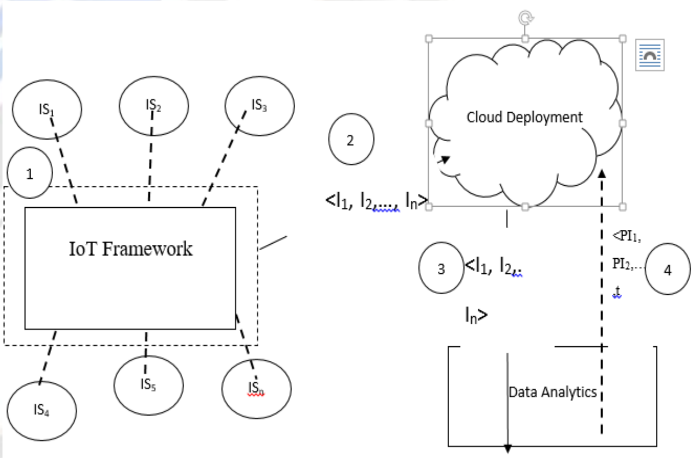

Figure 3. Proposed MIoT Architecture

The general IoT architecture is nothing but collection of various sensors (depending on the need) to different IoT boards such as Arduino/NodeMCU/Intel Galileo/Raspberry PI boards. After establishing such a connection, the data received from the sensors are gathered through various IoT boards and transferred to the cloud environment in a wireless manner. After storing the data in the cloud or fog environment, the data can be retrieved for the data analysis part. Such an IoT architecture can be deployed for different applications such as Medical IoT, Industrial IoT, and Cognitive IoT [22-24]. In this paper, we try to attempt to deploy the MIoT application. When MIoT comes into picture the following sensors play a major

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role in gathering the (medical) data. The sensors which are frequently used in MIoT are temperature, pressure, force, airflow, gyroscope, heart rate, and respiration rate and image sensor. As, the proposed methodology is based on the images, we consider only the image sensor. In the proposed MIoT architecture IS- represents the Image sensor. In the proposed IoT framework, the image sensors (IS) will be installed to gather the information. Such information will be collected through different IoT boards. Such collected information will be transferred as images $<I_1,I_2,\ldots,I_n>$ to the cloud or fog environment. In practical, when the number of image sensors are increased as $<IS_1,IS_2,\ldots,IS_n>$, the data received from the sensors may be collected at different time intervals (t_1, t_2, t_3, ..., t_n) and will be represented as a (image) sequence (S_1, S_2, $S_3,\ldots,S_n$) where each S_i is representation of the images received from one image sensor IS_1. The proposed methodology is applied to one such image sequence S_1. Medical IOT is liable for accumulating several image scans such as X-rays, CT, MRI images. Here, X-rays images of patients are collected and such an image sequence is transferred to cloud or fog environment for further processing through internet. The images are retrieved from the cloud for data analysis. Transfer learning based Deep learning method is applied on the retrieved images for analysis of three classes namely normal, COVID 19 and Pneumonia. The processed images or results are stored back into the cloud for further necessary actions. These result can be accessed by Doctor, Medical experts and patients for further action.

IV. TRANSFER LEARNING BASED DEEP LEARNING MODELS

In this section, data pre-processing, structure of the convolutional neural network architectures, transfer learning models architecture are specified. Data pre-processing is done to resize the image to fit each model.

A. Convolution Neural Network)

In our work, to detect a Chest X-ray images in three classes: Normal, Pneumonia, and COVID-19. In our proposed model, the Chest X-ray images for COVID-19 positive cases along with images of Normal and Viral Pneumonia were identified and classified. The other lung infection dataset is released for normal and COVID-19 cases. By applying the transfer learning method for training models, we calibrated these five pre-trained models which is much quicker and tranquil than the training a prototype from scrape with arbitrarily primed masses. When we feed our dataset, we established the output layer of these pre- trained replicas as no-trainable. By freezing the weights and other trainable parameters in each layer which is not be modified or trained and for the further process we included an output layer in order to train on our dataset. In our proposed model this output layer would be the only trainable layer. There are five pre-trained deep learning models, were used which are VGG-16, Inception V3, AlexNet, GoogleNet, and CNN. With a learning rate of 0.0001, and accuracy for our matrix we used the Adam optimizer. The architecture of CNN model is shown in Figure 4.

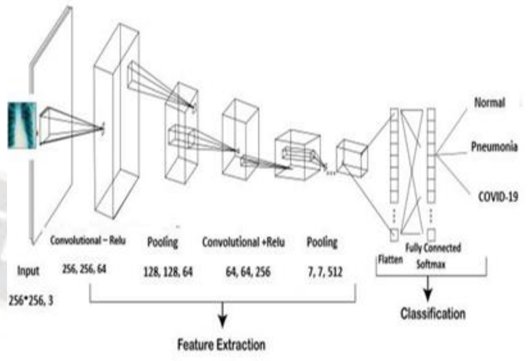

Figure 4. Architecture of CNN Model

The layers like multiple hidden layers, an input layer and an output layer are present in the CNN architecture. Further, a convolutional layers, fully connected layers, normalization layers (ReLU) and pooling layers are typically present in the hidden layers. Three RGB channels and the images with symptoms like normal, Pneumonia and COVID-19 is this network's input of size 256 by 256. Relu function is the first layer in a convolutional layer, and the kernel size is 256 by 256 with 64 output channels combination, which is shown in equation (1),

$$\mathrm{Relu}(y)=\max(0,y) \tag{1}$$

Relu function which returns the value for any positive value of y and returns zero if it endures any negative input. The dwindling the image stack which involves in the next layer of the architecture of max pooling. To pool an image we have used the window size of (128 × 128, 64) output channels. The variations of all the negative values within the filtered image is shown in Equation (1). Also in the max pooling layer we have a Rectified Linear Unit (Relu) process is known as a normalization layer. On all the filtered images this process is repeated until there is an increase in no-linear properties of the model. The process images in a convolutional layer, with a kernel size of (64, 64) and the output channels of RGB process is 256 like same as the first layer on the third layer. The kernel size of the fully connected layer of size 7 × 7 which is beforehand to the pooling layer.

B. Fine turning with transfer learning

Better Classification performance is provided by DNN (Deep Neural Network) because of which it has gained significant importance than other algorithm. But DNN needs huge computation power, resources and lengthy training for developing its models. In order to overcome the complexity,

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Transfer learning techniques have been introduced to transfer the neural network trained knowledge of parametric weights to the new model. In the proposed method, we have used five pertained models namely VGG -16, Inception V3, GoogLeNet Alexnet and CNN. The 1000 different classes can be classified by VGG-16, InceptionV3. To support the proposed method for classifying 3 classes namely Normal, Pneumonia and COVID-19, we replaced 1000 output features of the VGG-16, InceptionV3 with 3 output features of the proposed method. We only trained the fully connected layer rather than training the convolution layer. The fine-tuned model is shown in the figure.

VGG-16

Loss function (cross-entropy) and the optimizer is also used by us. Learning rate is set a 0.002 and 0.1 is the decreasing factor set for StepLR object for every seven epoch. All the training batches are iterated for every epoch. Based on loss Backward () and optimizer. Step () methods we computed the loss and made adjustment to weights. Performance over the test data is also evaluated subsequently. We exhibited the network programs (loss and accurateness) at the end of epoch. Numbers of corrected predictions are obtained from accuracy. The pre trained model VGG-16 [25] used after fine-tuning it using Keras. The model is pertained to classify images as normal, pneumonia and Covid, VGG-16 is replicated to new sequential model excluding output layer. Freezing of weight is done to set non trainable output layer. Further new proposed output layer is set and it is only one trainable output layer.

Inception V3

In the proposed method, we also used the Inception V3 model [26] for our experimentations. It is used in proposed method to flatten and produce one dimensional output layer. It adds 1024 hidden units of fully connected layer and Relu activation function, a dropout rate of 0.5, and sigmoid layer for classification. The over fitting is prevented by using data argumentation layer for training images. Data argumentation works directly in memory.

GoogleNet

Another type of convolutional neural network is GoogleNet [27] is used for the proposed method. To replicate the entire process, we used GoogLeNet and the embedding approach. The new output layer with three nodes is added for normal, Pneumonia and Covid classes.

AlexNet

Another type of convolutional neural network is AlexNet [28] is applied for the proposed method. The same embedding approach applied for various network to reproduce the entire process, is also used for the GoogLeNet. The new output layer with three nodes is added for normal, Pneumonia and Covid-19 classes.

CNN

In the propose method, two convolutional layers CNN architecture is used. Here, 200 kernels of the first layer of size 3*3 and 100 kernels of the second layer of size with 3*3 is proposed for CNN. A flattening layer transforms a 2D feature matrix fed to the linking convolution layer and completely connected layer within a fully connected neural network classifier. Subsequently, there is 50 neuron dense layer, neural network primary layer, separate layers and then gives one output to subsequent layer. At last, there will be a three neuron final dense layer that provides output as normal class or pneumonia class or COVID 19 class [28].

The following section describes the experimental results

.

V EXPERIMENTAL RESULT

COVID-19 Radiography Database [34] dataset has been used for experimental analysis. The chest X-ray database consists of three classes namely COVID-19 positive, Normal images and Viral Pneumonia images. These images are collected by various country researchers for the database. During various phases, these database images are released. During first phase, the following images are released. They are 219 COVID-19 images, 1341 normal images, and 1345 viral pneumonia chest x-ray images. In subsequent release, the number of COVID -19 images are enlarged to 1200. After that, along with 10,192 normal images along with 3616 COVID-19 positive cases are released. There are 1345 viral Pneumonia images were considered additionally. A resolution of 299*299 pixels is set for all images. During training phase, about 90% of datasets is used and 10% is used for testing stage. Validation is performed on the training dataset, with 10% of randomly selected images. Cross-validation with K=5 A stratified K-fold is performed. The performance of the proposed model is calculated by the following metrics:

(i) Accuracy

This measure is calculated by the total predictions divided by the total number of samples which is given in equation,

$$\text{Accuracy}= \frac{TurePos + TrueNeg}{TruePos + TrueNeg + FalsePos + FalseNeg} \qquad \text{--} \; 1$$

(ii) Sensitivity

$$\frac{TruePos}{TruePos + FalseNeg} \qquad \text{----------------} \quad 2$$

(iii) Specificity (TPR)

It is the ability of the classifier to detect negative results which is calculated as given in equation (3)

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$$TPR= \frac{TrueNeg}{TrueNeg + FalsePos} \quad \text{---------------------------------3}$$

Table 1. Comparison of different models for Normal cases identification of imbalanced dataset

Models	Accuracy	Sensitivity	Specificity
CNN	0.857	0.843	0.877
AlexNet	0.864	0.912	0.895
GoogLeNet	0.898	0.921	0.929
Inception V3	0.943	0.932	0.947
VGG-16	0.953	0.947	0.957

From Table 1, we infer that the VGG16 and Inception Net provide better performance compared to other models.

Table 2. Comparison of different models for identification Pneumonia class of imbalanced dataset.

Models	Accuracy	Sensitivity	Specificity
CNN	0.864	0.922	0.908
AlexNet	0.963	0.9413	0.929
GoogLeNet	0.972	0.978	0.949
Inception V3	0.981	0.987	0.969
VGG-16	0.987	0.99	0.989

Table 2 shows the output of Pneumonia class identification for imbalanced dataset for all the five models. From the result of Table 2, we infer that the VGG16 and InceptionNet provide better performance compared to other models.

Table 3 shows the output of COVID-19 class identification for imbalanced dataset for all the five models. From the result of Table 3, we infer that the VGG16 and InceptionNet provide better performance compared to other models

Table 3. Comparison of different models for identification COVID-19 class of imbalanced dataset .

Models	Accuracy	Sensivity	Specificity
CNN	0.854	0.894	0.878
AlexNet	0.891	0.884	0.929
GoogLeNet	0.912	0.908	0.949
Inception V3	0.921	0.917	0.971
VGG-16	0.947	0.931	0.989

From Table 8, we can infer the proposed method works better for identification of COVID 19 compare other models. Training time for various models for deep learning and transfer learning based deep learning models are predicted in the following Fig.5. There are few perceptions to be analysed in the proposed method. Due to transfer learning model approach .The information size and variation used in training is reduced. Pretained models helps to provide better results f\in faster manner. And also different deep learning designs such as AlexNet, GoogLeNet, Inception V3 and VGG-6 model and their learning capacity notifying their determination. The proposed method also modified the models for improved execution. And there exists the advantage of using IOT with deep learning models for COVID-19 identification. VGG-19 model could be applied as an appropriate deep learning-based tools for COVID-19 prediction from X-ray as it produce better result compared to other models

V. CONCLUSION

In the proposed method, we have applied transfer learning based Deep learning with Medical IOT for predicting COVID 19 from X-ray images. Here deep learning models consists of VGG-16, Incerption Net, Alexnet, Googlenet and CNN. The pre trained data of above models helps to improve accuracy and effectiveness of system with reduce time for prediction of COVID 19 using transfer learning. Integrating Medical IOT with deep learning helps for predicting COVD-19 quickly with high accuracy. Among all model, VGG 16 has shown higher accuracy of 99.1 % for COVID prediction, 96.7% for pneumonia, and 98.1 for normal class prediction.

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