An IoT-Based Deep Learning Framework for Early Assessment of Covid-19

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Abstract—Advancement in the Internet of Medical Things (IoMT), along with machine learning, deep learning, and artificial intelligence techniques, initiated a world of possibilities in healthcare. It has an extensive range of applications: when connected to the Internet, ordinary medical devices and sensors can collect valuable data, deep learning, and artificial intelligence techniques utilize this data and give an insight of symptoms, trends and enable remote care. Recently, Covid-19 pandemic outbreak caused the death of a large number of people. This virus has infected millions of people, and still, the rate of infected people is increasing day by day. Researchers are endeavoring to utilize medical images and deep learning-based models for the detection of Covid-19. Various techniques have been presented that utilize X-Ray images of the chest for the detection of Covid-19. However, the importance of regional-based convolutional neural networks (CNNs) is currently confined. Thus, this research aimed to introduce an IoT-based deep learning framework for early assessment of Covid-19. This framework can reduce the working pressure of medical experts/radiologists and contribute to the pandemic control. A deep learning-based model, i.e., faster regions with CNNs (Faster-RCNN) with ResNet-101, is applied on X-Ray images of the chest for Covid-19 detection. It uses region proposal network (RPN) to perform detection. By employing the model, we achieve a detection accuracy of 98%. Therefore, we believe that the system might be capable in order to assist medical expert/radiologist, to verify early assessment toward Covid-19.

Index Terms—Covid-19, deep learning, faster regions with CNN (Faster-RCNN), Internet of Medical Things (IoMT), ResNet-101.

I. INTRODUCTION

INTERNET of Medical Things (IoMT) plays a pivotal part in the healthcare sector and increases the accuracy, reliability, and productivity of electronic devices. Researchers continuously pay attention to a digitized healthcare system via interconnecting the convenient medical devices/resources and healthcare services. IoMT helps in reducing unnecessary appointments and the burden on healthcare organizations by connecting subjects to their medical experts and supporting the transfer of

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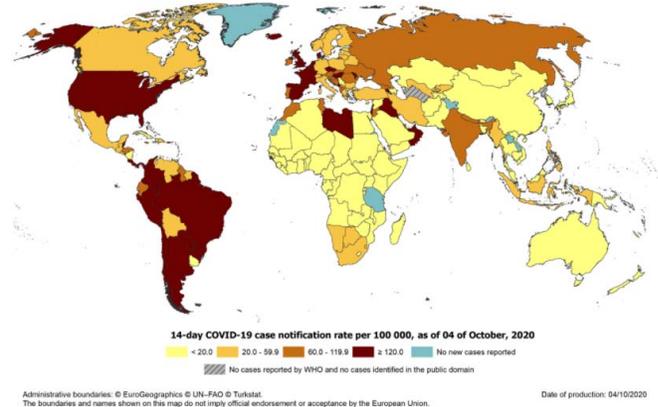
Fig. 1. Worldwide Statistics: Covid-19 infected people [4].

medical data. In December 2019, the Covid-19 infection (virus originated from animals) appeared in Wuhan Province, China, and quickly spread worldwide [1]. The virus transmits through the air, and physical contact with an infected person [2] and inserts itself into the lungs through the respiratory system, where it replicates and destroys lung cells [3]. On March 11, 2020, the disease is declared a pandemic by the World Health Organization. It is recently considered the leading cause of fatality for thousands of countries, including China, Iran, Italy, the USA, Spain, and the United Kingdom. The latest number of infected peopled due to pandemic is shown in Fig. 1.

At the early stages, the detection of Covid-19 is crucially vital and significant. The medical industry is seeking novel technologies and methods to monitor and control the spread of the virus. The IoMT, along with artificial intelligence and deep learning techniques, might enable the healthcare system to properly monitor Covid-19 subjects. It helps to enhance patient satisfaction and decreases readmission rates in the hospital. It might help to trace the virus spread quickly, recognizes the high-risk patients, and is beneficial for infection control. Likewise, it can help to predict the fatality risk by sufficiently investigating the patients' earlier data.

IoMT, along with artificial intelligence and deep learning, helps to fight with the virus through medical assistance, population screening, notification, and recommendations about infection control [5]. As an evidence-based medical tool, this technology can enhance the treatment, planning, and reported issues of the Covid-19 [6]. To diagnose Covid-19, several techniques have been introduced, including numerous medical imaging techniques, polymerase chain reaction (PCR), and blood tests (CBCs) [7].
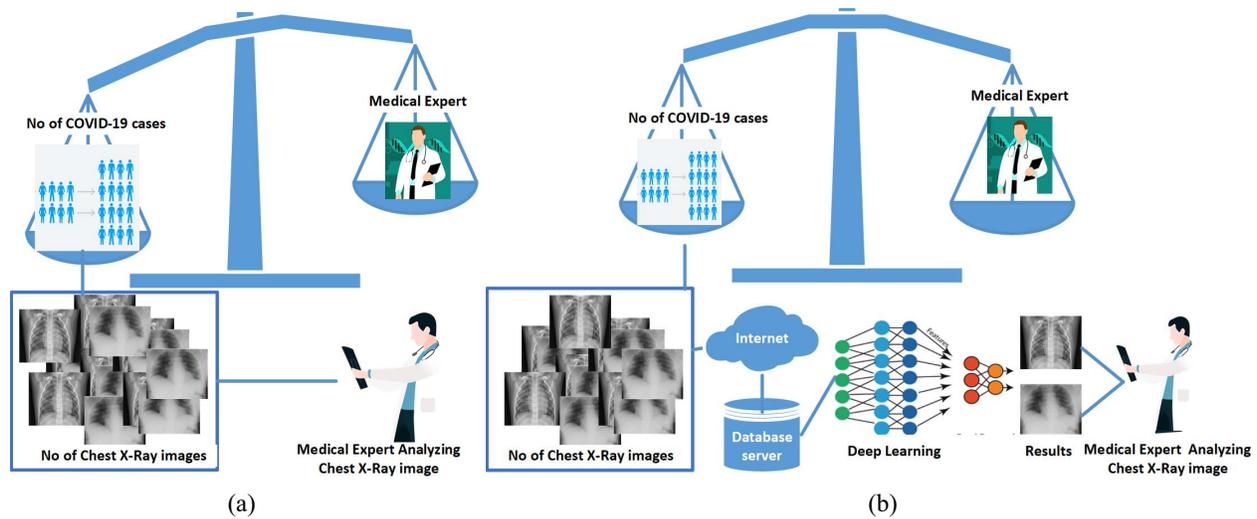
Fig. 2. (a) Traditional workflow applied for screening and clinically diagnosing of Covid-19. The number of radiologists or medical experts is relatively small in comparison with the number of cases reported. (b) Analysis of X-Ray images can be significantly improved for Covid-19 diagnosis with IoMT and deep learning.

The problem statement is, how two Covid-19 patients, one with normal and the other with infection in the lungs caused by Covid-19, can be treated the same? Therefore, the significance of using X-Ray images parallel with PCR and CBC is that it can give a better estimation of Covid-19. Using other test data with X-Ray images, we might better diagnose the severity of diseases and then perform appropriate treatment. In the traditional X-Ray analysis methods, Covid-19 detection is a comparatively complicated task, as shown in Fig. 2(a). To diagnose Covid-19, X-Ray modality is used, which is economical and low-risk from radiation hazards to human health [8] and [9]. In X-Ray images, the radiologist needs to attentively recognize the white spots or viruses that contain pus and water, which is quite problematic and lengthy. A specialist doctor or radiologist might mistakenly diagnose other diseases such as Covid-19 as pulmonary tuberculosis [10].

Inspired from successful results of earlier methods [11], in this work, an Internet of Things (IoT)-based deep learning framework is introduced for Covid-19 detection. The framework can assist the medical expert and radiologist and may help to decrease the workload pressure (examination of X-Rays), stimulating the diagnosis and treatment process of patients, hence contributing to the control of the pandemic Fig. 2(b). For detection of Covid-19 in X-Ray samples, we applied a deep learning architecture, i.e., faster regions with CNN (Faster-RCNN), [12] with ResNet-101 [13] as a backbone network. To the best of our knowledge, Faster-RCNN with ResNet-101 architecture is used for the first time for Covid-19 detection. The X-Ray images are collected from different online available data sources for testing and training of the model. This article mainly focuses on the following.

1) An IoT-based framework is introduced for the early assessment of Covid-19. The medical sensors/devices collected chest X-Ray samples that are directly fed into a deep learning architecture for the detection of Covid-19.

2) The framework is capable of assisting medical experts or radiologists, relieve the working pressure, and might help in the control of pandemic.

3) Regional-based convolutional neural networks (RCNNs), i.e., Faster-RCNN and ResNet-101, are utilized for Covid-19 detection.

4) For training and testing of the model, Chest X-Ray images are customized using different online available data sets.

5) The detection results are compared with other deep learning approaches of Covid-19.

The remainder of this article is organized as follows. The literature work summarizes in Section II. A concise overview of the data sets utilized in this work is presented in Section III. The method used for Covid-19 detection is elaborated in Section IV. The detail of the experimental outcomes is elaborated in Section V, and finally, the conclusion of the work done in this article, and future guidelines, is presented in Section VI.

II. LITERATURE SURVEY

Researchers have done much work until now to provide an efficient and effective solution for Covid-19 prediction and detection. Singh *et al.* [14] and Yang *et al.* [15] provided examples of the IoT and the IoMT applications in healthcare. The applications can be practiced to offer assistance to medical experts in hospitals, assure quarantine implementation, and track pandemic outbreaks. Vafea *et al.* [16] presented a review of various emerging technologies applied for the treatment and diagnosis of Covid-19 subjects. Researchers used different artificial intelligence [17], machine learning [18], and deep learning approaches [7], [11], and [19] for Covid-19 classification, and detection as shown in Fig. 3. Some researchers [17] did a review of artificial intelligence-based methods applied for segmentation and investigation of Covid-19 X-Rays. In the literature, most of the developed methods employed a limited number of CT-scans and X-Rays for
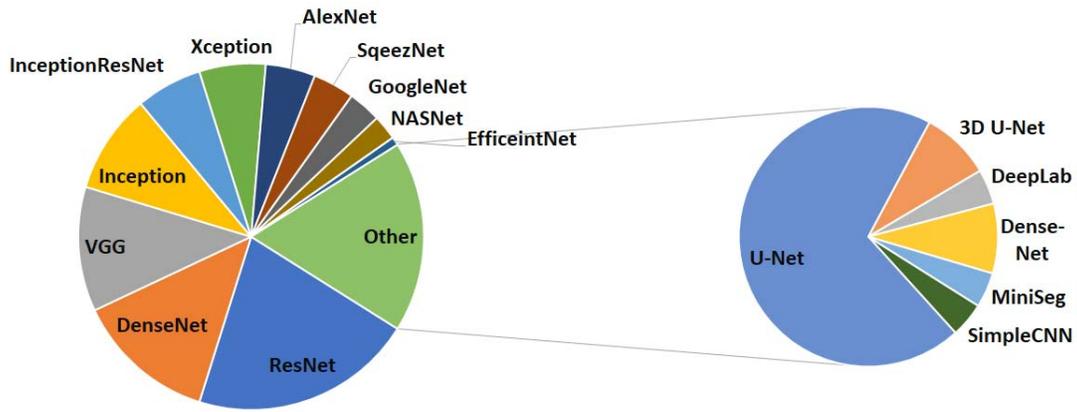
Fig. 3.   Different deep learning methods used by researchers in literature for Covid-19 detection [7] and [11].

TABLE I
LIST OF SOME AVAILABLE BENCHMARK DATA SETS USED FOR COVID-19 DETECTION

S.No	Dataset Name or Paper	Type	Dataset Link
1	Covid-chestxray-dataset [17]	CT and X-Ray	https://github.com/ieee8023/covid-chestxray-dataset
2	SIRM	CT and X-Ray	https://www.sirm.org/category/senza-categoria/covid-19
3	UCSD-AI4H [18]	CT	https://github.com/UCSD-AI4H/COVID-CT
4	Actualmed COVID-19 Chest X-ray Dataset Initiative	X-Ray	https://github.com/agchung/Actualmed-COVID-chestxray-dataset
5	Twitter COVID19 CXR dataset	X-Ray	https://twitter.com/ChestImaging
6	COVID-19 [19]	CT	ttps://github.com/KevinHuRunWen/COVID-19
7	BIMCV COVID-10+ [20]	CT and X-Ray	https://bimcv.cipf.es/bimcv-projects/bimcv-covid19/
8	COVID-19 X-ray dataset (COVID-CAPS) [21]	X-Ray	https://github.com/ShahinSHH/COVID-CAPS
9	COVIDGR-1.0 [22]	X-Ray	https://github.com/ari-dasci/covidgr
10	European Society of Radiology	CT and X-Ray	https://www.eurorad.org/advanced-search?search=COVID
11	BSTI	CT and X-Ray	https://www.bsti.org.uk/covid-19-resources
12	MedSeg	CT	http://medicalsegmentation.com/covid19
13	COVID-19 Chest X-ray Dataset Initiative	X-Ray	https://github.com/agchung/Figure1-COVID-chestxray-dataset
14	COVIDx [23]	X-Ray	https://github.com/lindawangg/COVID-Net
15	COVID-19 X rays	X-Ray	https://www.kaggle.com/andrewmvd/convid19-X-rays
16	COVID-19 Radiography Database	X-Ray	https://www.kaggle.com/tawsifurrahman/covid19-radiography-database
17	COVID-19 [24]	X-Ray	https://github.com/muhammedtalo/COVID-19

examination and detection of Covid-19 [20], and [21] as presented in Table I. Hemdan *et al.* [22] presented a comparison of seven deep learning architectures using a limited data set with 50 sample images containing 25 of positive (Covid-19) and 25 samples of healthy subjects. Wang and Wong [23] introduced convolutional neural network (CNN)-based architecture named COVID-net for X-Ray samples classification into Covid-19, normal, and pneumonia, using a data set consisting of 800 images. The reported overall accuracy is 92.4%, and sensitivity is 80%. Farooq and Hafeez [24] used the ResNet-50 model to classify X-Rays samples into infected, healthy, viral, and bacterial pneumonia. The reported results are better as compared to COVID-Net [23]. The overall accuracy is 96.23% with 100% sensitivity. The data set used by the authors contains 68 Covid-19 X-Rays of 45 Covid-19 subjects, 1203 healthy subjects, 660 subjects of Non-Covid-19 viral pneumonia, and 931 subjects of bacterial pneumonia. Apostolopoulos and Mpesiana [25] developed an automatic detection model employing transfer learning with neural networks utilizing X-Ray samples. Pereira *et al.* [26] performed the task of Covid-19 detection in X-Rays of the chest. The data set used in their work was created from different public data sets, comprising 1144 X-Rays, including 90 images of Covid-19, remaining are five different kinds of pneumonia and healthy type images.

To the best of our knowledge and according to [7] and [11], we provide a review of different deep learning and artificial intelligence methods used for classification of Covid-19. According to the survey, mostly researchers used classification-based methods, including Resnet-50, Resnet-101, DenseNet, VGG, Inception, InceptionResNet, Xception, AlexNet, and SqueezeNet for chest X-Ray images

TABLE II
DATA SET USED FOR TRAINING AND TESTING OF THE MODEL

S.No	Images	Non-Covid-19	Covid-19	Total
1	Training	5600	3200	8800
2	Testing	1400	800	2200
3	Total	7000	4000	11000

classification as depicted in Fig. 3. Some researchers also used segmentation-based models, including U-Net, 3-D U-Net, VB-Net, DeepLab, Dense-Net, and MiniSeg. Mostly researchers in the literature used pneumonia data set as Chest X-Ray sample images. The summary of various deep learning architectures used for Covid-19 classification and detection is provided in Fig. 3. To the best of our knowledge, Faster-RCNN with ResNet-101 has not been utilized for Covid-19 detection, although [27] utilizes Faster-RCNN for Covid-19 detection but using VGG as base network. Similarly, Ismail *et al.* [28] used Faster-RCNN but for pathological Chest X-Ray image analysis using a limited data set.

III. DATA SET

In the literature, for Covid-19 detection, researchers used various public data sets, including X-Ray and CT images, as shown in Table I. Among both types of medical images, the X-Ray images data sets are mostly used. Most of the researchers used COVID-chest X-Ray-data set [22], [29], [30]. Some practiced Kaggle RSNA Pneumonia detection data sets, such as [31], Covid-19 database, e.g., [32], Chest X-Rays (Pneumonia) [33] for training and evaluation of their models. The most common data set for Chest X-Ray-based Covid-19 research is also shown in Table I. In this work, we customized an X-Ray image data set collected from different available online data sources, as highlighted in Table II, the images contain X-Rays of Covid-19 abnormalities. From different online available sources, approximately 4000 samples of Covid-19 (positive) and 7000 samples of Non-Covid-19 (negative) are obtained, as presented in Table II.

IV. METHODOLOGY

In this work, an IoT-based deep learning framework is presented for Covid-19 detection. The overall framework is shown in Fig. 4; the medical sensors/X-Ray machines collected radiogram images of subjects—the collected data set is given to the model in order to detect the Non-Covid-19 and Covid-19 X-Ray samples. For the validation of the model, results are further referred to a medical expert for opinions. As discussed in the literature, utilizing X-Ray images, different deep learning-based architectures are utilized for Covid-19 detection. In this work, for detection purposes, Faster-RCNN [12] along with ResNet-101 [13] architecture is used. In recent years, it has shown remarkable performance for various classification and detection applications. It utilizes the same traditional network for region proposal generation and detection. The model's output includes a bounding box (containing detected X-Rays as Non-Covid-19 or Covid-19).
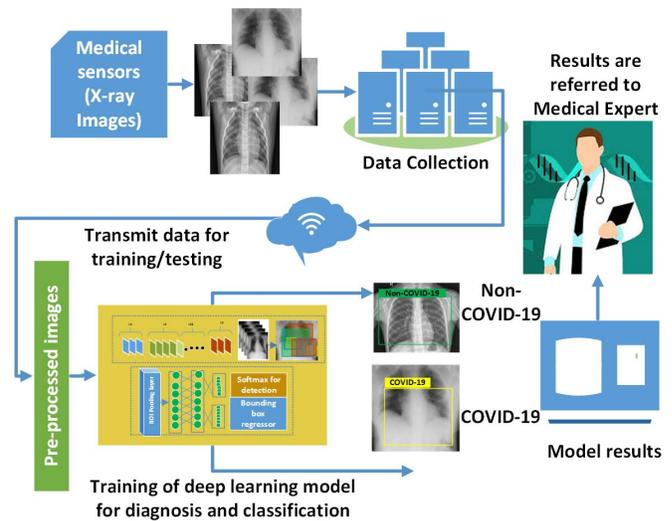

Fig. 4. IoT-based deep learning framework for early assessment of Covid-19.

The detection results can help the medical expert or radiologist reduce the working pressure and might be beneficial for pandemic control. The detail of the deep learning-based detection model consisting of Faster-RCNN with ResNet-101 is provided in the following section.

A. Detection of Covid-19 Using Faster-RCNN With ResNet-101

The deep learning-based architectures are utilized broadly over traditional machine learning-based techniques because it does not require either traditional feature extraction-based methods or any specific segmentation techniques. In this work, Faster-RCNN [12] is employed for Covid-19 detection utilizing X-Ray sample images of the chest, as depicted in Fig. 5. It is also known as a two-stage detection model as it essentially has two stages; the initial stage provides region anchors using region proposal network (RPN). The second stage is employed for X-Ray images classification using bounding boxes and detected regions' information.

In the literature, [27] also utilizes Faster-RCNN for Covid-19 detection but using VGG as a base network with a limited data set. While in this work, for backbone architecture ResNet-101 [13] is used. ResNet utilizes skip connection (or shortcut connection), allows a deeper network to match the input from the previous layer to the subsequent layer without transforming the input. Traditional deep learning models like VGG-Net normally have Conv layers for classification tasks, instead of fully connected (FC) layers, without any skip/shortcut connection named as plain networks. In that case, when layers are increased or the plain network becomes deeper, vanishing/exploding gradients occur. To resolve the vanishing/exploding gradients, a skip/shortcut connection is added. (for details, readers are referred to [13]). The process shown in Fig. 5 is mainly based on three steps.

1) First, ResNet-101 CNN architecture is used for feature extraction and generation of convolution feature maps.
2) In the second step, using the sliding window strategy, k anchor boxes are produced. These anchor boxes are
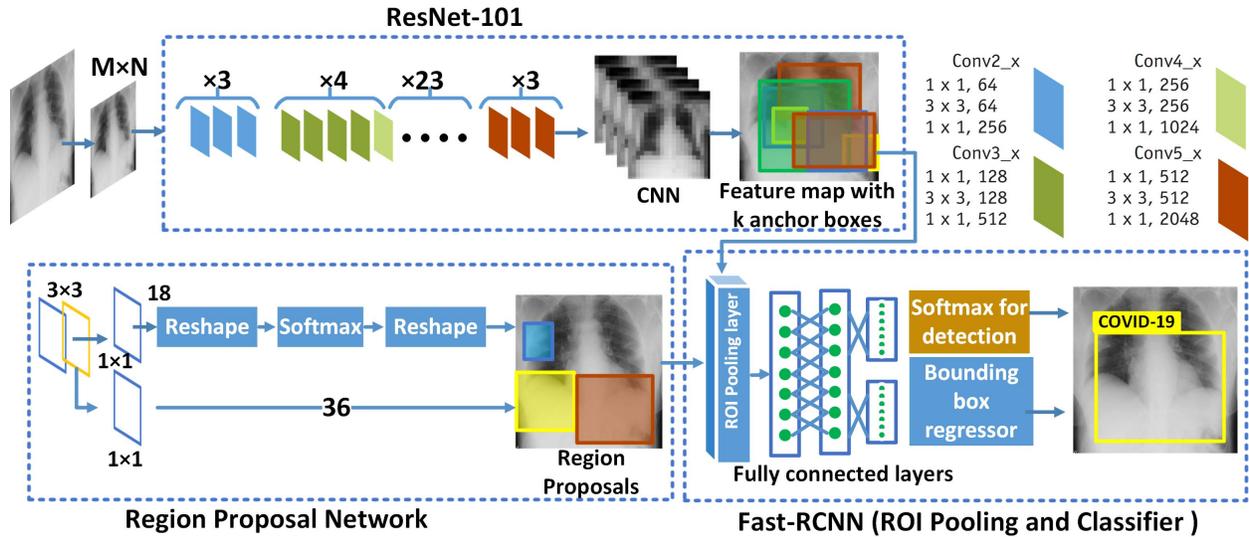
Fig. 5. Using Faster-RCNN [12] with ResNet-101 [13] architecture as backbone for detection of Covid-19.

further refined to define the exact region of interest, as shown in Fig. 5 using RPN, which is finally given to the Fast R-CNN for bounding box regression and classification.

3) In the final step, a small network is used to refined anchors, and the loss function is determined, selecting the best anchor regions.

In Fig. 5, it can be seen that X-Rays sample images of the chest are fed into the conventional layers that produce feature maps. For feature extraction, ResNet-101-based CNN architecture is used. For anchor selection, the anchors are subdivided into two classes (positive and negative). To determine where the anchor regions overlapped with ground-truth bounding boxes, the Intersection over the Union method (IoU) is used, and the overlap ratio is defined. The IoU overlap ratio is given as [12]

$$IoU = \frac{\text{Bounding Box (anchor)} \cap \text{GT}}{\text{Bounding Box (anchor)} \cap \text{GT}}. \quad (1)$$

After selecting anchor regions, the loss function is calculated at the end of the RPN. A network is utilized for detection of X-Ray samples as Non-Covid-19 or Covid-19. The regression function is employed to define the predicted bounding box positions. The loss function is defined to measure the regression and classification loss [12] as

$$L(\{p_i\}, \{t_i\}) = \frac{1}{N_{cls}} \sum_i L_{cls}(p_i, p_i^*)$$

$$+ \lambda \frac{1}{N_{reg}} \sum_i p_i^* L_{reg}(t_i, t_i^*). \quad (2)$$

In (2), L_{cls} represents classification loss, and L_{reg} shows regression loss. The normalization coefficients are represented with N_{cls} and N_{reg}, and the weight parameter between two losses is shown with λ. i is applied as an anchor index, and predicted probability Covid-19 is represented as p_i. The ground truth for Covid-19 classification is p_i^*, and if the value
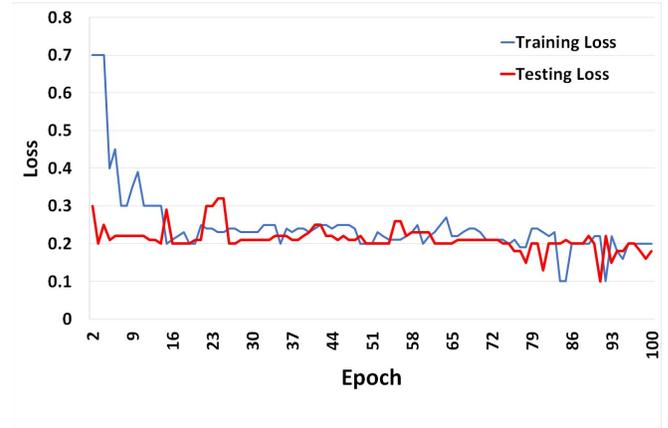

Fig. 6. Training and testing loss of faster-RCNN with Reset-101.

Fig. 7. Training and testing accuracy of faster-RCNN with Reset-101.

of $p_i^* = 1$, then anchor relates to a positive class (Covid-19), and in the case of 0, the anchor belongs to a negative class (Non-Covid-19). t_i shows a predicted bounding box vector, while t_i^* represents ground truth. The RPN's chosen
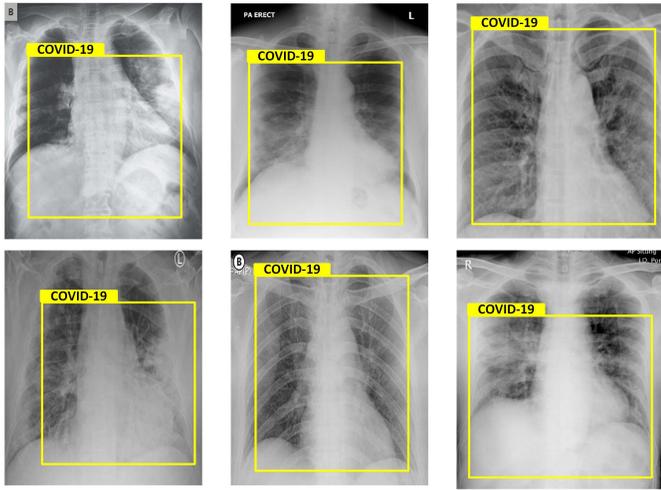
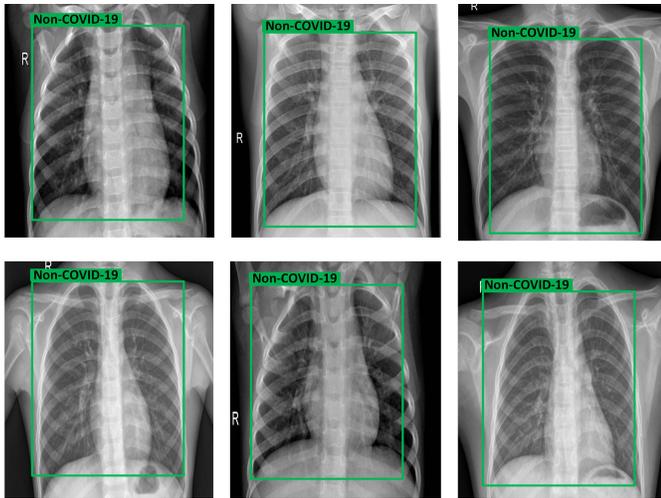Fig. 8.   Results of chest X-Rays, detected as Covid-19.

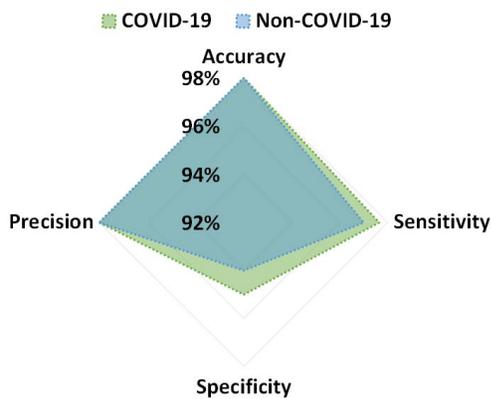Fig. 9.   Results of Chest X-Rays, detected as Non-Covid-19.

Fig. 10.   Accuracy, sensitivity, precision, and specificity.
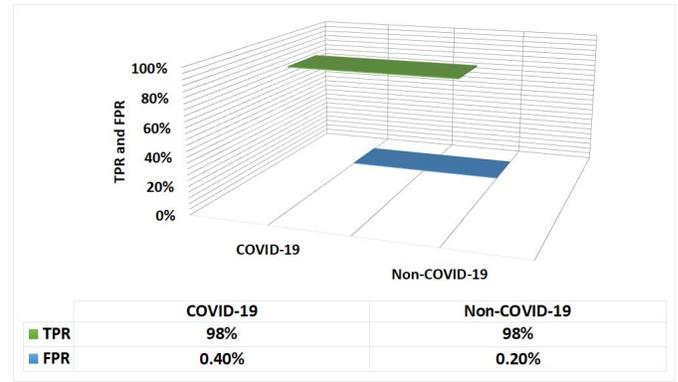

Fig. 11.   True positive rate and false positive rate.
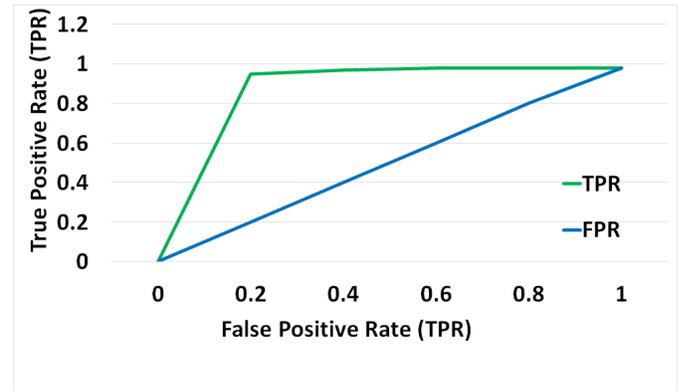
Fig. 12.   ROC curve of the model used for Covid-19 detection.
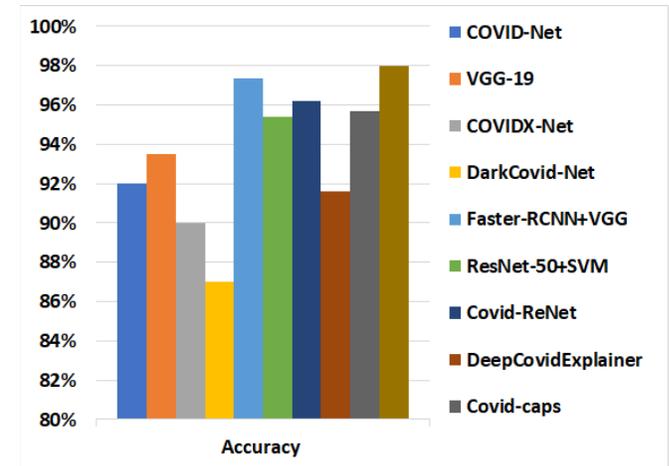
Fig. 13.   Comparison results with deep learning methods.

features are provided to the ROI pooling layer, which detects X-Ray image as Covid-19 or Non-Covid-19. For classification loss L_{cls} of Covid-19 or Non-Covid-19, a logarithmic loss is defined of two categories and provided as

$$L_{\mathrm{cls}}(\{p_i\}, \{p_i*\}) = -\log\left(p_i, p_i^*\right) + (1 - p_i*)(1 - p_i)]. \quad (3)$$

Using (4), the regression loss is given as [12]

$$L_{\mathrm{reg}}\left(\{t_i\}, \{t_i^*\}\right) = \mathrm{smooth}_{L_1}\left(t_i - t_i^*\right) \quad (4)$$

where $smooth_{L_1}$ is defined as [12]

$$\mathrm{smooth}_{L_1} = \begin{cases} 0.5x^2, & |x| < 1 \\ |x| - 0.5 = \text{others.} \end{cases} \quad (5)$$

The model outputs the X-Ray image of the chest with bounding box information containing (detected Covid-19 region), as shown in Fig. 5. A Tensorflow library is used for building and training of the model. The data set is randomly

TABLE III
COMPARISON RESULTS WITH SOME DEEP LEARNING-BASED METHODS

S.No	Ref	Method	Image Type	Training	Testing	Accuracy
1	[23]	COVID-Net	Chest X Ray	258	100	92%
2	[25]	VGG-19	Chest X Ray	202	22	93.48%
3	[22]	COVIDX-Net	Chest X Ray	20	5	90%
4	[34]	DarkCovid-Net	Chest X ray	4500	1550	87.02%
5	[27]	Faster-RCNN+VGG	Chest X Ray	17749	1500	97.36%
6	[35]	ResNet50 + SVM	Chest X Ray	NA	NA	95.38%
7	[24]	Covid-ResNet	Chest X Ray	NA	NA	96.23%
8	[36]	DeepCovidExplainer	Chest X Ray	181	78	91.60%
9	[37]	Covid-caps	Chest X Ray	70	50	95.70%
10	Ours	Faster-RCNN+ResNet-101	Chest X ray	7000	4000	98%

split into 20% of the testing set and 80% of the training set. The detail of the testing and training set is already provided in Table II. The training set is utilized for learning, and the testing set is used for evaluation of the model.

V. EXPERIMENTAL RESULTS

The evaluation and visualization results of the above-explained model are elaborated in this section. The testing experiments are performed by utilizing X-Ray sample images. First, the observation of the model after training using chest X-ray samples has been discussed. The training, testing loss, and accuracy are presented in Figs. 6 and 7. It can be observed that the training and testing loss are decreasing steadily after every ten epoch, as shown in Fig. 6. From Fig. 7, it is noteworthy that training and testing accuracy rates raised significantly at the initial epoch because we practiced only specific class data as Covid-19 data.

The visualization results of a deep learning model are presented in Figs. 8 and 9. The testing results of X-Ray samples of the chest detected as Covid-19 is shown in Fig. 8. In all images, the model accurately recognizes the infection (white spots that contain pus and water). It can be seen that in some cases, the spread of the virus is severed, for which expert opinion is needed. Therefore, these results can be are further referred to a medical expert for further analysis and examination. Similarly, in Fig. 9, the healthy or Non-Covid-19 detected results are depicted. The deep learning model effectively classified both cases.

For evaluation purposes, different parameters have been utilized, including false-positive, true-positive, false-negative, and true-negative. To show the performance of the model, accuracy, precision, recall, true-positive rate (TPR), and false-positive rate (FPR) are estimated using these parameters. The precision, sensitivity, accuracy, and specificity results are visualized using Fig. 10. It can be seen that the accuracy of the model is 98% for both classes. The sensitivity is 98% and 97% while Specificity is 95 and 94% for Non-Covid-19 and Covid-19 images, respectively.

The TPR and FPR of the above-discussed model are depicted in Fig. 11; the model achieves TPR of 98%, while the FPR is 0.4%. The ROC curve is also plotted using TPR

versus FPR, as shown in Fig. 12. It can be noted that the model produces good results.

The accuracy results of the above-discussed model are also compared with different deep learning methods, as illustrated in Fig. 13. The comparison results are provided in Table III. For a fair comparison, the results presented in the table are the same as provided in the original work. Most of these methods are developed using limited data sets.

VI. CONCLUSION AND FUTURE DIRECTIONS

An IoT-based deep learning framework has been introduced for early assessment of Covid-19. The framework is capable of relieving medical experts/radiologists' working pressure by diagnosing infection in X-Rays of the chest and controlling the pandemic spread. A deep learning-based model, i.e., Faster-RCNN with ResNet-101, is applied for Covid-19 detection using online available data sets. The model uses RPN in order to produce region proposals and perform detection. For training and testing, a data set is customized from different available online data sources. We utilized a total of 7000 Non-Covid-19 and 4000 Covid-19 X-Ray sample mages. The model achieves a 98% detection accuracy. From experimental results, we believe that the system may assist medial expert/radiologist to support early assessment toward Covid-19. The accuracy results are also compared with some different deep learning-based approaches. Regrettably, due to the current public health emergency, the collection of the extensive data set for the training of the deep learning model is delicate. Although we used almost all freely available online data sets in this research, even then, a significant increase in data set is needed compared to the number of cases reported throughout the globe. Nevertheless, a pure IoT-based model is capable of generating a vast amount of data set. In the future, the framework might be developed using vast X-Ray images that might be further tuned with different backbone architectures.

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