Software system to predict the infection in COVID-19 patients using deep learning and web of things

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Abstract
Since the end of 2019, computed tomography (CT) images have been used as an important substitute for the time-consuming Reverse Transcriptase polymerase chain reaction (RT-PCR) test; a new coronavirus 2019 (COVID-19) disease has been detected and has quickly spread through many countries across the world. Medical imaging such as computed tomography provides great potential due to growing skepticism toward the sensitivity of RT-PCR as a screening tool. For this purpose, automated image segmentation is highly desired for a clinical decision aid and disease monitoring. However, there is limited publicly accessible COVID-19 image knowledge, leading to the overfitting of conventional approaches. To address this issue, the present paper focuses on data augmentation techniques to create synthetic data. Further, a framework has been proposed using WoT and traditional U-Net with EfficientNet B0 to segment the COVID Radiopedia and Medseg datasets automatically. The framework achieves an F-score of 0.96, which is best among state-of-the-art methods. The performance of the proposed framework also computed using Sensitivity, Specificity, and Dice-coefficient, achieves 84.5%, 93.9%, and 65.0%, respectively. Finally, the proposed work is validated using three quality of service (QoS) parameters such as server latency, response time, and network latency which improves the performance by 8%, 7%, and 10%, respectively.

KEYWORDS
COVID-19, deep learning, EfficientNet B0, SARS-CoV-2, segmentation, U-net, WoT

1 INTRODUCTION

In December 2019, a disease named the novel coronavirus 2019 (COVID-19) has erupted in Wuhan city of China and caused due to severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2). It has spread widely across the world, causing primary concern. It has widely spread worldwide, which has led to a major concern. In many nations, a large number of COVID-19 patients have overcome healthcare systems. As a result, providing a reliable automated tool for defining and quantifying contaminated lung regions would be extremely useful. Reverse transcription-polymerase (RT-PCR) chain reaction is a typical diagnostic tool for detecting nucleotides in nasopharyngeal, oropharyngeal, tracheal aspirates, bronchoalveolar. The survey of the latest reports was reviewed that the RT-PCR sensitivity for detecting
COVID-19 is adequate, which is due to the specimen stability, consistency, and insufficient viral content. Various researchers have suggested the diagnosis of COVID-19 CT-scans and X-ray scans. These tools are critical in treating patients who have been diagnosed with the virus or who are suspected of being infected. It is worth remembering that CT or X-ray findings are common in the absence of clinical suspicion, as many other diseases could display the same pattern. The CT scan of the thoracic is the imaging modality of choice for COVID-19 management. The diagnosis of COVID-19 thoracic CT scan is high, and it is considered a primary tool for detection purposes. This scan of the patient is capturing Chest X-ray, which is further detected for the radiation detectors which is converted into high-resolution images. There are specific patterns to look for in a chest CT scan that manifest themselves in different ways. Three irregularities identify the results with 100% confidence for COVID-19 in thoracic CT images: Pleural Effusion, ground-glass opacity (GGO), and Consolidation. The tools are developed for quantifying these irregularities, which are required to segment the lung images of COVID-19. It is pertinent to mention that the analysis and evaluation of the medical images are time-consuming and manual tasks that the experts and practitioners perform. Even though the resolution of the scans is improved and the different slices resulted in achieving higher accuracy and sensitivity. With the rapid development of artificial intelligence (AI), deep learning (DL) technology and the Internet of Things (IoT) have been extremely useful in medical imaging because of the representation of the beneficial features. The workload has also augmented due to these developments. Furthermore, inclusive development has a major impact on medical image annotations. Medical image segmentation (MIS) helps to simplify the recognition and labeling of regions of interest (ROI), for example, organs including the lungs or anomalies including lesions and tumor. Latest studies have shown that methods based on neural networks for segmentation of medical images have strong prediction capabilities and perform similarly to radiologists. Image segmentation can assist radiologists in detection, disease path tracking, reducing time-consuming examination procedures, and improving accuracy by automatically highlighting the ROIs and suspicious features. However, ample annotated medical imaging data are required to train reliable and robust models. Since manual annotation is time-consuming, labor-intensive, and involves professional radiologists, publicly accessible data are likely to be limited. Because of the lack of data, current data-hungry models are often over-fitted. Large enough medical imaging databases, particularly for COVID-19, are currently unavailable. With the help of DL, complex problems can be solved easily. In this article, the main goal is to design a reliable framework to segment the images of infection of COVID-19 patients that can be trained on dataset of small size.

Moreover, IoT also plays a vital role in analyzing image data. An intelligent network can be created with IoT for a health monitoring system by connecting multiple devices. The IoT is a set of physical devices or objects equipped with sensors, electronics, networking devices, and actuators which allow objects to share information with the users, manufacturers, users, and other connected devices. But it is not virtually possible to create a global system of devices communicating with each other. Usually, low-level sensors such as motion and temperature sensors transmit data using low-level protocols such as Zigbee, Bluetooth Low Energy, 6LoWPAN, and so forth, not compatible with the Internet. To overcome this problem, WoT is introduced to systematize communication protocols among various cloud platforms and smart devices over the Internet. The WoT enhances the IoT by integrating intelligent things into the web architecture. Therefore, we proposed a WoT-based COVID framework for the detection of infection present in the lungs of the COVID patient. Moreover, the performance of WoT can be validated using Quality of Service (QoS) parameters. Any technology that manages the data traffic to lessen the network delay, jitter, and packet loss is called as QoS. QoS handles and monitors network capacity by allotting resources to various kinds of data. The data come in the form of chunks. Without QoS, the chunks of data get disorganized and as a result network clogging takes place which leads to shutting down of network. Henceforth, QoS is required for the smooth working of the network. The QoS is measured using various parameters including response time, latency, network bandwidth and jitter.

The major contribution of this research is the use of DL for the detection of abnormalities available in the lungs. We proposed to combine the effectiveness of Efficient backbone b0 as an encoder with pre-trained image net weights for high-level feature extraction along with UNet decoder to segment the abnormalities present in CT scans of COVID-19 patients. The presented research is implemented and tested in the Python, and the relevant COVID-19 CT Scan images are gathered from the two datasets: Medseg dataset and Radiopaedia dataset. This dataset is present on the client-side. A call to restful application peripheral interface (API) is made, which will connect to the Google Collab server and transfer the data. The dataset is then processed using a trained UNet model placed on the server and return four segmented masks to the client.
1.1 Motivation and our contributions

Various state-of-the-art techniques such as DL and WoT has been explored to their full extent, and from the survey, it has been analyzed that the prediction of infection of COVID-19 patients is a challenging task. The existing work push toward the creation of an automatic tool to predict the lung infection present in COVID-19 patients using DL. Additionally, a smart monitoring system is required which will keep track of the COVID-19 patients. But, in IoT different applications are used for storing, processing, and accessing the information from the cloud. Therefore, instead of using different applications, a common dashboard can be used which will keep track of all the applications remotely. This can be possible only with the help of web-of-things. Motivated by the successful applications of WoT and techniques of deep learning, we have applied an Efficient UNet B0 backbone to segmentation the affected regions in COVID CT scans. To avoid overfitting, the data augmentation approach is used for reliable and Efficient performance and validated the proposed framework using WoT to estimate the performance of QoS parameters like Network Latency, Server Latency, and Network Bandwidth as compared to existing techniques. Several open challenges have been emphasized, which need to be addressed while implementing the framework using DL and WoT.

The key contributions of the paper are:

- A novel DL framework is proposed based on the basic architecture of UNet, which gives the expediency of Efficient Net B0 as an encoder and UNet decoder to reconstruct the segmentation map.
- The proposed framework achieves an F-score of 96.0%, Sensitivity 84.5%, Specificity 93.9, and Dice coefficient 68.2%, respectively.
- To check the robustness of the model, the results of the presented framework are evaluated on two benchmark datasets, Medseg and Radiopedia, of chest CT images.
- The proposed framework is validated using WoT in terms of QoS parameters such as server latency, network latency, and response time.

1.2 Article organization

The following is a summary of the paper which is as follows. The related work is presented in Section 2, followed by the deep learning in Section 2.1 and the WoT description in Section 2.2. Section 3 presents the background and preliminary of the present work. Section 4 discusses the proposed work using U-Net with EfficientNet B0 combined with WoT applications. Further, the experimental results and the evaluation parameters using both DL and QoS are described in Section 5. Finally, the conclusion, and future scope are discussed in Section 6.

2 RELATED WORK

2.1 Deep learning (DL)

A sub-analysis was performed by Hyungjin Kim et al. to evaluate CT scans of chest and the diagnosis of RT-PCR efficiency metrics and predictive values. From the experiment it was found that the specificity and sensitivity values were 37%, and 94% individually. Positive predictive performance of RT-PCR is 10 times that of CT scans, which are having a low prevalence in countries. Predictive performance varies from 99% to 99.9% when both methods are used. Jin et al. created an artificial intelligence system for the real time analysis of CT images to detect the infection features. Sample of 1136 cases (723 COVID-19 positive cases) having variety of lung infections was used and the experiment was performed which gives specificity and sensitivity of 0.922 and 0.974, respectively. Additionally, for faster prediction or analysis, the programme automatically highlighted all lesion regions. Caruso et al. compared CT accuracy to RT-PCR in COVID-19 patients in Rome. Between March 4th and March 19th, 2020, a comprehensive survey on the victims which are suspected with COVID-19 contamination. Further, respiration problems were also published based on the study of the victims. The study looked at 158 people who had symptoms like dyspnea, fever, lymphocytopenia, cough, elevated C-reactive protein, and elevated lactate dehydrogenase. The patients who were affected and conducted a chest CT scan with vascular signs and extreme CT motion artifacts were included in the analysis. The precision,
accuracy, and sensitivity of CT scans were 56%, 72%, and 97% respectively, meaning that doctors would be able to thoroughly identify the infection in patients using CT. Lin Li et al.\textsuperscript{35} used AI to identify radiological findings in chest CT scans from six Chinese hospitals.\textsuperscript{36} The development of a DL model called CovNet was used to extract the graphical features from 3D CT scans. The dataset comprises 4356 CT scans of the chest from 3322 patients. The performance was evaluated using area under curve (AUC) with 95%, responsiveness with 93%, and specificity with 97%, which were used to test the efficiency of the model. According to Hang et al.,\textsuperscript{37} the association between clinical lab and RT-PCR findings, including CT features,\textsuperscript{38} is inconclusive. They attempted to investigate this correlation in greater depth, especially patients who are recovered. The 52 COVID patients in this sample were hospitalized who were discharged after two periods of consecutively negative RT-PCR results. After negative RT-PCR tests, c-reactive protein levels fell dramatically relative to admission levels. Also, the number of lymphocytes were increased. In contrast, CT scans of the chest showed substantially improved oxidative exudation, except for two patients who had made substantial progress toward recovery. After the discharge, the 2-week follow up was considered for seven patients, with two patients who were progressed toward rehabilitation had good RT-PCR results again. Two patients out of seven showed new GGO, which is a clinical finding.\textsuperscript{39} A patient X-ray of the chest was captured and experienced COVID-19 symptoms.\textsuperscript{40} The most common abnormality is GGO in which some parts of the lungs are captured as a hazy shade of gray with little markings of white blood vessel. It is also important to note that chest X-rays are not very sensitive to COVID-19 and often yield false negatives. COVID-19 Lung Infection Automatic Chest CT Image Segmentation Using 3D U-Net for Smaller Datasets. Attention mechanisms are often integrated into classic U-Net architectures such as Inf-Net from Fan et al.\textsuperscript{40} or MiniSeg from Qiu et al.\textsuperscript{41} The creation of a benchmark model with a 3D U-Net by Ma et al.\textsuperscript{42,43} is particularly noteworthy since the researchers have provided high level of reliability through a publicly accessible dataset.\textsuperscript{42,43}

2.2 Internet of Things (IoT)

IoT plays an important role in the detection of COVID-19 infected patients. Mohammed et al.\textsuperscript{44} proposed a framework for detecting COVID-19 from thermal images captured using a smart helmet. Real-time data were collected using a smart helmet-mounted with the thermal imaging system. Along with that, the face recognition system was also embedded on the smart helmet. The system detects the temperature of the patient and will call the health inspector in case of high temperature. The complete information of the patient, including the face and global positioning system location, was sent to the officer. The result proved that the proposed framework works well and can help in stopping the spread of coronavirus. Abdulkareem et al.\textsuperscript{31} presented a machine learning (ML) and IoT architecture for diagnosing COVID-19 in smart hospitals. X-Ray and CT scans of patients were captured remotely by the technician through a live streaming of the video images and passed to pre-processing stage to remove the not allowed (NA) values from the dataset. The pre-processed data were then trained on three ML models, comprising Naive Bayes (NB), Random Forest (RF), and Support Vector Machine (SVM).\textsuperscript{45} Additionally, the results were also compared with specific existing methods, and it is proved that the presented ML and IoT framework gives best sensitivity, accuracy, AUC, precision, and F-score value of 93%, 93%, 88%, 94%, 88%, and 92% respectively. Imran Ahmed\textsuperscript{46} used Faster Regions with Convolutional Neural Network (FasterRCNN) with ResNet-101 to diagnose the COVID-19\textsuperscript{47} patients using chest X-Ray images. A sample of data was captured with sensors and was passed on featuring extraction techniques to extract important features. The features were extracted and further passed to FasterRCNN for the classification of the data into infected and healthy samples. The experiment was performed, and it was evident from the results that the proposed framework works efficiently with 98% accuracy.

El-Rashidy et al.\textsuperscript{48} presented a fog computing framework consisting of three layers (patient layer, cloud layer, and hospital layer) to detect COVID-19 infections. X-Ray images were collected using wearable sensors and which was shown in the patient layer. After that, storage and data transmission issues were solved in the cloud layer, then passed to the hospital layer. In the hospital layer, a deep learning model CNN\textsuperscript{49} and transfer learning was applied to the dataset, which accurately classifies the images in COVID and non-COVID samples 97.95% and 98.85%, respectively. Deepak Gupta et al.\textsuperscript{50} proposed an IoT that enables a depthwise separable convolutional neural network (DWS-CNN) with a Deep support vector machine (DSVM) for the identification and classification of binary class and multi-class of COVID-19 patients. IoT devices and cloud sensors were used to collect the dataset and passed to Gaussian Filtering (GF) stage to remove the noise from the images. Then DWS-CNN feature extraction technique was employed to extract the important features. Finally, the DSVM was used for classifying the patients into COVID and non-COVID. The whole framework was tested on X-Ray
images of the chest dataset, and performance was calculated. The results based on the experimentation were proved that the proposed framework is superior with 98.54% and 99.06% accuracy on binary class and multi-class classification, simultaneously.

Ameni Kale et al. proposed a hybrid framework by integrating machine learning, cloud, fog, and IoT technologies to monitor and prognosis of the COVID-19 disease. The streaming dataset was collected from both medical and non-medical devices. X-ray machines and ultrasound machines were used for medical devices, and bracelet, smartwatch, and smart helmet were used for non-medical devices. Moreover, the hybrid framework was divided into two parts, that is, distributed batch-ML as a service (batch-MLaaS) for long-term decision making and was implemented on cloud, and distributed stream-MLaaS for short term decision making. The real-time symptom data were processed using stream-MLaaS, and the prediction is made in the fog environment. The six ML models comprising Logistic Regression, Adaptive Random Forest, Hoeffding Adaptive Tree, Extremely Fast Decision Tree, Naïve Bayes, and K-Nearest Neighbor were used for training purpose, and results were evaluated, which shows that the proposed framework works effectively with accuracy, root mean square estimation, precision, F-score, and execution time values of 68.23%, 56.22%, 76.43%, 77.29%, and 1.1 s, respectively. Kalle et al. presented the work in two folds. The first fold was a business process model (BPM). It focuses on notation extension, which is combined with an IoT to get the BPM activated. The architecture has acquired heterogeneous and non-heterogeneous IoT resources, resource measurements, QoS constraints. The second fold was presented a new IoT-fog architecture with the integration of cloud services. This architecture enables the intra and interlayer communication to improve the system reliability for processing IoT data. Hsu et al. proposed a cloud computing framework that is in integration with machine learning and the semantic web. A platform was also projected based on the linked data query, which delivers a graphical approach for the queries and Facebook fan pages to facilitate the end-user requirements.

### 2.3 Critical analysis

Table 1 shows the analysis and the comparison of proposed work using traditional methods. All of the above-mentioned research work has presented the COVID detection work using ML and DL models. None of the following existing frameworks has validated against the F-score parameter, and only four research works, including Mohammed et al., Imran Ahmed, Nora et al., and Deepak Gupta et al., have used IoT framework for COVID detection. There is no existing work present that has used WoT and Deep Learning simultaneously for COVID prediction. None of the authors has validated their results using three QoS parameters as network latency, server latency, and response time. Thus, the proposed framework uses an integrated WoT and Deep Learning framework to achieve better results.

| Work             | WoT | IoT | DL | Accuracy | Sensitivity | Specificity | F-score | Network latency | Response time | Server latency |
|------------------|-----|-----|----|----------|-------------|-------------|---------|----------------|---------------|----------------|
| Kim et al.       |     | ✓   |    | ✓        | ✓           | ✓           |         |                |               |                |
| Jin et al.       |     | ✓   |    | ✓        | ✓           | ✓           |         |                |               |                |
| Caruso et al.    |     | ✓   | ✓  | ✓        | ✓           | ✓           |         |                |               |                |
| Li et al.        |     | ✓   |    |          | ✓           | ✓           |         |                |               |                |
| Mohammed et al.  |     | ✓   |    | ✓        |             | ✓           |         |                |               |                |
| Imran Ahmed      |     | ✓   | ✓  | ✓        |             | ✓           |         |                |               |                |
| Nora et al.      |     | ✓   | ✓  | ✓        |             | ✓           |         |                |               |                |
| Deepak Gupta et al. |     | ✓   | ✓  | ✓        |             | ✓           |         |                |               |                |
| Proposed work    | ✓   | ✓   | ✓  | ✓        | ✓           | µ           | ✓       | ✓              | ✓             | ✓              |

Note: WoT is web of things, IoT is the Internet of Things, and DL is Deep Learning.
3 | BACKGROUND AND PRELIMINARIES

3.1 | Deep learning models

Deep learning is used to identify patterns in data, extract features, and create intermediate representations in several domains. Deep learning techniques first emerged in the 2000s, and they soon demonstrated their remarkable capabilities in image processing tasks. The powerful supervised machine and learning methods are available to employ various models that offer a better approximation to the human brain using sophisticated mechanisms compared with the basic neural networks. The use of a deep neural network model is suggested by the term “deep learning.” The neuron is inspired by the human brain analysis, the basic computational unit in neural networks. The input passed as the multiple signals, which are concatenated with linear weights and generate the output signals, further transmits the combined signals through non-linear operations. DL approaches have emerged as a primary option for the segmentation of images, especially medical images, due to their promising capabilities. Several deep learning-based methods for detecting the infection and viral pneumonia in chest CT images have been suggested. The present work is proposed using a UNet-based method for automating COVID-19 patient segmentation using CT scan images.

3.2 | UNet architecture

U-Net was first introduced by Ronneberger et al.\(^\text{55}\) using the principle of deconvolution, which is one of the most well-known systems for MIS. The innovative architecture of fully convolutional networks (FCN) is the cornerstone of this model. The proposed structure has two analysis and synthesis directions. An upsampling layer is followed by a deconvolution layer in the synthesis path, which is also known as the expansion phase. The most significant feature of U-Net is the ability to create shortcut networks among equal-resolution layers in the analysis and expansion paths. The deconvolution layers depend on these connections for high-resolution functionality. The encoder is constructed in the manner of a convolutional network. Two $3 \times 3$ convolution operation accompanied by a $2 \times 2$ max-pooling operations and a stride of $2$ were involved in the architecture. The process is repeated $22$ times, including various filters in the convolution layers and doubling after each downsampling. A two $3 \times 3$ convolution operations are connected by encoder and decoder paths. The decoder, on the other side, uses a $2 \times 2$ transposed convolution operation to up-sample the function map,\(^\text{56}\) halving the number of feature channels. After that, a series of two $3 \times 3$ convolution operations is conducted once more. These two convolutional and upsampling sequences are repeated four times, each time the number of filters are halved, just as it is with the encoder. Finally, the final segmentation map is generated using a $1 \times 1$ convolution operation. All convolutional layers Rectified Linear Unit (ReLU) as the activation function.\(^\text{55}\) But the final convolutional layer uses a Sigmoid activation function. The U-Net architecture added skip connections which is the most innovative feature. Throughout all four stages, the output of the convolutional layer is transferred to the Decoder prior to the pooling process of the encoder. The output of the upsampling process is then concatenated with the feature maps, and the resultant feature map is propagated to subsequent layers. The network will use these skip connections to recover spatial data that has been lost due to pooling operations.\(^\text{56}\) Figure 1 shows the architecture of U-net.

3.3 | Web of things

Web of things is an IoT’s web standard that allows communication between web-based applications and smart things. The thing definition is the main portion of the WoT specification. It involves a thing’s metadata and interfaces in a structured manner to allow the thing to interact in a heterogeneous environment with other things.\(^\text{57}\) The web of things is described in four layers and is shown in Figure 2.

**Layer 1—Access Layer:** The first layer is the access layer. This layer is used to access everything on the web by integrating the things on the web. The services are accessible by calling the restful APIs using HTTP protocol.\(^\text{58}\) These restful APIs will enhance communication with anything in the real world. The IoT devices\(^\text{59}\) can be easily mapped with the restful APIs and is shown in Figure 3.

**Layer 2—Find Layer:** The second layer is the find layer which will locate the devices so that the services can be used by the server. This layer is not only used by the HTTP clients but also can be easily findable and usable by the other
FIGURE 1  Diagrammatic view of the U-Net architecture

FIGURE 2  WoT architecture

FIGURE 3  Mapping of IoT devices with restful APIs

WoT applications. Search engines can be used to search for things and other WoT applications and automatically generate the interface to interact with things. JSON is used to interact with various applications.60

Layer 3—Share Layer: The third layer is the share layer in which the data are shared securely over the devices. Proper authentication is performed at this layer to connect the server using the OAuth web authentication mechanism. This mechanism is integrated into the restful API. These things are shared securely with the help of web browsers.60

Layer 4—Composition Layer: The final layer is the composition layer used to write the large scale requests.61 At this layer, the data and services are integrated into a system of web-related tools, including software and platforms.
4 | PROPOSED FRAMEWORK

In the proposed architecture, the WoT is implemented in cloud server model which is described below. In the Client–Server model, single or multiple clients can send or accept requests from a decentralized server. An interface is provided by the client device, which allows the users to interact with the server and to present the results provided by the server. On the other side, the server waits for the client’s request and return the result to them. In the proposed framework, the client–server architecture is implemented and is shown in Figure 4 below.

On the client-side, the image dataset of size 256*256*1 is taken from multiple clients and is converted into binary format to be easily processed by the machine. When we convert the dataset in binary form, then special characters are inserted between them, which cannot be processed by the restful APIs. Therefore, we convert them into base32 (b32) encoding. Then the base32 encoded data are passed to the server-side for processing. To connect to a server, we call to restful API using HTTP protocol, which will pass the dataset to the Google Collab server, our Graphics Processing Unit, bypassing all the layers of WoT architecture. First, in the access layer call is made to API using an HTTP protocol. Second, it will find the device to connect with, that is, Google Collab server. Then, authentication is made using an OAuth mechanism to transmit the data securely, and finally, a connection is made to process it. We first decode the encoded data on the server-side, which is then passed to the U-Net model for processing. The complete structure and processing of U-Net are explained in Section 4.1.1 below. The 256*256*1 size images are passed to a NumPy array (trained U-Net), which will return the size 256*256*4 after training. The trained model will return four masks as output, that is, the images are classified into four classes: glass, consolidation, lungs-other and glass, and consolidation. But there are significant rules which are to be followed by web-of-things. They do not understand the NumPy arrays. They only understand arrays. Therefore, we change them in JSON format in which the NumPy object is converted into list format. Once the JSON processing is complete, it is converted back to the NumPy object. The complete working of the UNet model, along with the data description, is described as below:

4.1 | Segmentation of COVID chest images

An automated and novel framework has been proposed to segment COVID-19 chest scans of the lung using UNet architecture with EfficientNet B0 as the backbone. The network will use these skip connections to recover spatial data that
has been lost due to pooling operations. This framework contains an underlying architecture called UNet, which has two paths, the encoder and the decoder. The encoder path uses Efficient Net B0 with encoder weights from the ImageNet to extract the relevant features, and the decoder path uses the UNet decoder. The complete framework is divided into different phases, which is expressed in Figure 5.

### 4.1.1 Data description

The present paper focuses on two datasets, namely Radiopedia and Medseg, of annotated volumetric CT images. Nine volumetric CT scans create the first collection of data. These CT scans’ format has been changed from JPG to Nifti. It also contains radiologist-created annotation masks, such as lung masks and COVID-19 masks. Twenty volumetric CT scans are used in the second dataset. The manual annotations of the right lung, left lung, and infections are labeled by the radiologists. The annotated masks of both the datasets are available with four channels 0—“ground glass,” 1—“consolidations,” 2—“lungs other,” 3—“background.”

### 4.1.2 Data preprocessing and augmentation

Various preprocessing methods are applied to the datasets to simplify the pattern findings and achieve the desired features. Firstly, the images for both datasets are converted to grayscale ranges between 0 and 255. The histograms of the image data are found from Radiopedia and Medseg datasets, shown in Figure 6(A),(B). The histograms indicate the pixel distribution of intensity values of an image which measures the occurrence of each pixel for a given image. Based on these probability distributions, both datasets are sampled between training data and the validation data. For achieving the consistency of the intensities, scaling and standardization of imaging data is the most significant phase. Therefore, both the datasets are normalized using mean and standard deviation. The plots after the normalization of both the datasets are represented in Figure 6(C),(D). Before resizing the images, the original size of the image was 512×512, and the UNet architecture with Efficient Net B0 specifies the size should be 256×256, which is shown in Figure 5. Thus, the images are reduced to 256×256 to maintain the uniformity of the images used for training.

**Figure 5** Framework for segmentation of COVID chest images
Data augmentation is an essential way of minimizing the problem of overfitting while training the model. A limited amount of data (in the form of images) is available in the case of medical images, due to which data augmentation plays a very significant role. Moreover, the problem of overfitting is critical with a UNet-based model which is trained on a limited amount of datasets. Hence, present work applied data augmentation technique to generate huge amount of data for model training. To make the model more robust and to make the model cover different orientations of the input dataset, rotation, cropping, and horizontal flip are used. The small dataset comprising Radiopedia and Medseg transforms into an abundant and diverse dataset with variations by rotating, shearing, and translation of the images. The rotation is performed with a specified degree, such as $45^\circ$, $60^\circ$, $70^\circ$, the translation of images is performed within a range of $[-20, 20]$ and shearing operation within the range of $[-40, 40]$. The other transformation is flipping the images horizontally and vertically, which again turns to create synthetic data. The images have been augmented and shown in Figure 7.

4.1.3  EfficientNet B0 encoder

For MIS, the encoder–decoder network is one of the most widely used architectures. The encoder path entails a CNN encoder which is used to retrieve the relevant attributes from the image. It then reduces the features and downsamples the image to get the high-level information in the form of data. Traditional architectures information like ResNet, MobileNet, and InceptionNet, and so forth, is used to produce the final feature map by reducing the input resolution of the image. Whereas in the case of decoder path, it usually consists of a set of layers which is upsampling the feature maps of the encoder in getting spatial information. Instead of using the traditional encoder–decoder network such as UNet or UNet++, the present framework is focusing on EfficientNet B0, which is considered to be balanced network with depth, width, and resolution. The other significant contribution for designing the framework is that the encoder path speeded up the training process by using pre-trained ImageNet weights with a lesser number of parameters to achieve the best performance. The experimentation is completed with EfficientNet B0, and subsequent tests show that there is no requirement of using larger encoders such as EfficientNet B1 till B7. This B0 is a mobile-sized architecture with a smaller number of training parameters, that is, approximately 11 million parameters. The architecture consists of seven residual
blocks along with resolution and channels, which is represented in Table 2, and the architecture details are presented in Figure 8.

The overall structure is divided into nine processes, seven blocks are for Mobile inverted bottleneck convolution (MBConv), and the rest are for convolutional, pooling, and fully connected layers. Each MBConv block is shown with its filter size, number of channels and striding operations. MBConv block considers two inputs called data and its arguments. A block argument is a set of features such as input filters, output filters, expansion ratio, squeeze ratio, and so forth, is which to be used within an MBConv block.
4.1.4 UNet decoder

The second part of the architecture is the decoder path, which consists of a stack of convolutional, pooling, and activations layers to acquire the information in the image. The decoder path uses the output of the encoder, which gets expanded in this expansion or the decoder path. It essentially concatenates the feature maps from the contraction or encoder route with the high-level features and their spatial details through a series of upconvolutions and concatenation. The expansion path in traditional UNet architectures is almost similar to the contraction path. In the existing UNet architecture, the encoder has the conventional set of convolutional layers but the present work consisting EfficientNet B0 as an encoder, whereas the decoder path is the same as the traditional architecture. The proposed architecture, including both the paths such as Encoder and Decoder, is represented in Figure 9. The original input size of the image was 512 × 512 with convolutional operation Conv(3,(1,1)), which produces a three-dimensional feature map. The original size of the image is resized to 256 × 256 × 1, and the UNet backbone produces four masks. This detailed architecture also represents the number of levels, resolution, and number of channels. Bilinearly upsampling by a factor of two is used for upsampling the function map. This is further concatenated with the feature map to get the same spatial resolution. Then a 3 × 3 convolutional layers are used before the upsampling of the feature map by a sample of two. To get the segmentation map of the same size to input image, the process is iterated. The present framework with EfficientNet B0 as an encoder boosts the segmentation of lung CT images.

5 PERFORMANCE EVALUATION

The proposed framework has been trained on a network with an input size of 256 × 256 for 20 epochs. The backbone network called EfficientNet B0 has used ImageNet pre-trained weights in the encoder path. The training data consisting of a smaller number of images due to which leads to the model overfitting. Therefore, to increase the dataset, data augmentation is applied using various transformations like rotation, cropping, flipping, and so forth. Adam optimizer is used for model training with a 0.001 learning rate. The loss is considered as categorical cross-entropy. The proposed framework achieves the best results for both Radiopedia and Medseg datasets when compared with existing segmentation approaches. The experimental findings of the presented framework are described and computed using different performance metrics such as sensitivity, accuracy, specificity, and F-score. By definition, the higher values of all the parameters represent the better quality of segmentation. Table 3 shows the performance parameters along with their mathematical formula.

In this paper, Python is used to implement the proposed work with Tensorflow as the backend and Keras libraries were used to form the deep learning framework. The usefulness of the UNet-based presented framework is demonstrated with pretrained EfficientNet B0 backbone for the segmentation of the lungs containing COVID-19 infected regions. Currently, the available COVID-19 datasets are small and are without annotated imaging. The major problem is that the existing datasets may have incomplete information in annotations, leading to challenging task for models. Therefore, we have performed data augmentation using rotation, cropping, and horizontal flip to increase the dataset. An ADAM optimizer with a learning rate of 0.001 and the loss function is used as categorical_crossentropy. Additionally, cross validation is used with 80:20 ratios to validate the trained model and it is done using both the Radiopedia and Medseg datasets.
**FIGURE 9** The architecture or the workflow of the proposed framework

**TABLE 3** Performance parameters used

| S. no | Name     | Parameter                                                                 |
|-------|----------|---------------------------------------------------------------------------|
| 1     | Accuracy | \( \frac{(TP+TN)}{(FP+FN+TP+TN)} \)                                    |
| 2     | Sensitivity | \( \frac{TP}{(TP+FN)} \)                                           |
| 3     | Specificity | \( \frac{TN}{TN+FP} \)                                              |
| 4     | F-score | \( 2 \times \frac{(Precision \times Recall)}{(Precision+Recall)} = \frac{TP}{(TP+FP+FN)} \) |

Note: TP, true positives; TN, true negatives; FP, false-positive; FN, false-negatives, respectively.
The performance of the proposed framework is evaluated against the seven existing methods. The framework improved the sensitivity, specificity, and dice coefficient, compared with UNet,\textsuperscript{53} Attention-UNet,\textsuperscript{64} Gated UNet,\textsuperscript{65} Dense UNet,\textsuperscript{66} U-net++,\textsuperscript{67} Inf-Net, and UNet, respectively, which can be observed in Table 4. The presented framework achieves excellent results, with an increase of 15\% in sensitivity, 8\% in specificity, respectively. The framework gives a similar result in the dice coefficient comparable with Li et al.\textsuperscript{68} It has achieved a higher $F$-score than traditional methods, which is shown in Table 5. A higher value of $F$-score suggests good performance in the lung segmentation task. The results are stated in quantifiable way that deep neural network is reliable, which differentiates between the non-infected and the infected ones, which are the faulty portions of the lungs. A more detailed analysis of the proposed method is evaluated using $F$-score, which is represented in Figure 10.

The diagram represents the COVID-19 dataset using four classifications, namely glass, consolidation, lungs-other and glass, and consolidation. These curves represent the performance of the proposed framework for both testing and

| Reference         | Methods             | Sensitivity | Specificity | Dice coefficient |
|-------------------|---------------------|-------------|-------------|------------------|
| Ameni et al.\textsuperscript{53} | U-Net              | 0.534       | 0.858       | 0.439            |
| Oktay et al.\textsuperscript{64} | Attention-UNet    | 0.637       | 0.744       | 0.583            |
| Tuli et al.\textsuperscript{65} | Gated UNet        | 0.658       | 0.725       | 0.623            |
| Oktay et al.\textsuperscript{66} | Dense UNet        | 0.594       | 0.655       | 0.515            |
| Schlemper et al.\textsuperscript{67} | U-Net++         | 0.672       | 0.722       | 0.581            |
| Li et al.\textsuperscript{68} | Inf-Net           | 0.692       | 0.781       | 0.682            |
| Our method        | UNet-Efficient B0 | 0.845       | 0.939       | 0.650            |

| Reference | Methods             | $F$-score |
|-----------|---------------------|-----------|
| 53        | U-Net               | 0.897     |
| 64        | Attention-UNet      | 0.942     |
| Our method| UNet-EfficientNet  | 0.960     |

**TABLE 4** Results of the proposed framework in comparison with the existing methods

**TABLE 5** Comparison of the different model against a common metric using $F$-score

**FIGURE 10** Visual representation of the COVID-19 dataset using glass, consolidation, lung-other and glass, and consolidation classes
validation. With an increase in the number of epochs, the F-score is also increasing for four different classifications. The curves for all classification categories under testing and validation phase converge from 25th epoch onwards to stable which depicts the efficiency of the proposed framework.

The visual representation of the segmented image using the proposed method is represented in Figure 11. The figure illustrates the original image, masked image or the ground truth, and the segmented image. The segmented images are almost similar to the masked images, which show that the model performs the best and outperforms this baseline. The COVID-19 infected regions are much more intense, which is considered to be a challenging task.

| Original Image | Mask Image/Ground Truth | Segmented Image |
|----------------|------------------------|-----------------|
| ![Original Image](image1) | ![Mask Image](image2) | ![Segmented Image](image3) |
| ![Original Image](image4) | ![Mask Image](image5) | ![Segmented Image](image6) |
| ![Original Image](image7) | ![Mask Image](image8) | ![Segmented Image](image9) |
| ![Original Image](image10) | ![Mask Image](image11) | ![Segmented Image](image12) |

**FIGURE 11** CT scans of the original masks and the segmented image
The proposed framework efficiently performed great on the CT scans of the COVID-19 patients. The proposed framework focuses on the aid provided to the doctors and is considered a more accurate way to handle the diagnosis of COVID-19 data.

6 VALIDATION OF PROPOSED FRAMEWORK USING WOT

The proposed framework is validated against Deepak Gupta et al.\textsuperscript{50} using three QoS parameters including server latency, response time, and network latency. The main goal of the study is to lower the server latency, network latency, and response time. Table 6 shows the results of proposed framework.

(i) Server Latency: The time taken by the model to return the output on the server-side. While calculating the server latency, the time of three things is included. First, the decoding time followed by a model prediction time. The third is the JSON conversion time. The server latency for all eight images is calculated, and the result is shown in Table 6. The average latency is calculated, which is 0.11 secs. The calculated latency is compared with existing work\textsuperscript{50}, which is 8% lower.

(ii) Response Time: It is the time taken by the server to return the result to the client. Response time is also calculated for all images, and the average is considered as the final output, which is 8.080 s. This response time also includes the time of three things, that is, binary conversion, the encoding of the image, and call to the API. The proposed framework response time is 10% lower than the state-of-the-art-work\textsuperscript{50}.

(iii) Network Latency: Network latency is the measure of time taken by the data to reach its destination all over the network. The total network latency captured for all the images to transfer across the network is 1562 ms which is 7% lower than the existing work\textsuperscript{50}.

The experiment was performed in Chandigarh using Jio 4G operator. The signal rating and signal quality were good and average, respectively. The downloading speed and uploading speed were 1.77 and 1.25 mbps individually. There is no packet loss during the whole procedure. Along with that network jitter is also calculated, which is 379 ms. The jitter is caused due to network congestion while transferring the image dataset.

6.1 Discussion

We used the popular Deep Learning model UNet (Efficient net B0) to classify COVID-19 images based on the infection using WoT. The performance of the UNet is compared with the traditional work as shown in Table 4 using four performance parameters comprising accuracy, sensitivity, specificity, and F-score, and it shows an improvement of 5%, 15%, 8%, and 7%, respectively. Also, it is validated in WoT framework using three QoS parameters, including server latency, network latency, and response time\textsuperscript{68,69} which improves the performance by 8%, 7%, and 10%, respectively.

| Images | Server latency (s) | Response time (s) |
|--------|--------------------|-------------------|
| 1      | 0.5187             | 6.7575            |
| 2      | 0.1122             | 6.4154            |
| 3      | 0.1152             | 10.4085           |
| 4      | 0.1148             | 9.4751            |
| 5      | 0.4689             | 9.4532            |
| 6      | 0.1171             | 8.9572            |
| 7      | 0.1103             | 7.5563            |
| 8      | 0.1110             | 5.6180            |
CONCLUSIONS AND FUTURE WORK

With advancements in healthcare, WoT-based Deep Learning framework has appeared as one of the most effective approaches for predicting COVID-19 infections. Therefore, in this research, we have presented a WoT-based framework for detecting COVID-19 infections using chest CT scans. Further, a DL model such as UNet with EfficientNet B0 as the backbone is used for the segmentation of images. The designed framework will help the clinicians to automatically and accurately detect the infections in the COVID-19 patients. This automated framework also prioritize and widen the treatment of patients for future pandemics. The performance was evaluated in the form of performance parameters such as specificity, sensitivity, accuracy, and F-score. Finally, the presented approach is validated using WoT to estimate the performance of QoS parameters such as Network Latency, Server Latency, and response time as compared to the existing work. This research can be extended using a transfer learning approach for COVID-19 detections and can also work on clinical datasets in future studies. It is to mention that the present work can also be strengthened to work on different COVID-19 strains such as the SARS-CoV-2 Consortium on Genomics (INSACOG), N440K and E484Q, which are more infectious and dangerous than the original strain spread from Wuhan. Another objective for the research is to integrate the system with hardware components that can work on real-time applications. Furthermore, the web services in the proposed work are connected to web using a centralized approach. In future, fog computing can be integrated with WoT to connect the web services in distributed manner. By doing so, the network latency and response time can be reduced. Additionally, the software developer can be freed from maintaining a server and can be deployed as serverless framework which allows the services to execute in the form of functions. This service is known as Function-as-a-service (FaaS) and can be implemented using various cloud platforms and related services like AWS Lambda, Microsoft Azure, DynamoDB, and Google cloud. Serverless computing methods provide an easy way to decentralize computation by calling the web services remotely.

AUTHOR CONTRIBUTIONS

All authors discussed the results and contributed to the final manuscript. Ashima Singh proposed the software system/framework to predict infection in COVID-19 patients. The segmentation of lung CT images is implemented by Amrita. Arwinder Dhillon and Sahil Ahuja carried out the experiment on Google Collab. The diagrams, visualisation of results, and article formatting is done by Harpreet Vohra. Ashima Singh wrote the manuscript with Amrita Kaur and Arwinder Dhillon.

DATA AVAILABILITY STATEMENT

A significant amount of data is presented in this article. The remaining data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

ENDNOTE

*https://www.kaggle.com/c/covid-segmentation/data.

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