Original Article

Segmentation and classification of lungs CT-scan for detecting COVID-19 abnormalities by deep learning technique: U-Net model

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Abstract

Background: Artificial intelligence (AI) techniques have been ascertained useful in the analysis and description of infectious areas in radiological images promptly. Our aim in this study was to design a web-based application for detecting and labeling infected tissues on CT (computed tomography) lung images of patients based on the deep learning (DL) method as a type of AI. **Materials and Methods:** The U-Net architecture, one of the DL networks, is used as a hybrid model with pre-trained densely connected convolutional network 121 (DenseNet121) architecture for the segmentation process. The proposed model was constructed on 1031 persons' CT-scan images from Ibn Sina Hospital of Iran in 2021 and some publicly available datasets. The network was trained using 6000 slices, validated on 1000 slices images, and tested against the 150 slices. Accuracy, sensitivity, specificity, and area under the receiver operating characteristics (ROC) curve (AUC) were calculated to evaluate model performance. **Results:** The results indicate the acceptable ability of the U-Net-DenseNet121 model in detecting COVID-19 abnormality (accuracy = 0.88 and AUC = 0.96 for thresholds of 0.13 and accuracy = 0.88 and AUC = 0.90 for thresholds of 0.2). Based on this model, we developed the "Imaging-Tech" web-based application for use at hospitals and clinics to make our project's output more practical and attractive in the market. **Conclusion:** We designed a DL-based model for the segmentation of COVID-19 CT scan images and, based on this model, constructed a web-based application that, according to the results, is a reliable detector for infected tissue in lung CT-scans. The availability of such tools would aid in automating, prioritizing, fastening, and broadening the treatment of COVID-19 patients globally.

Keywords: Classification, COVID-19, deep learning, lungs CT-scan, segmentation, U-Net model

Introduction

Coronavirus disease 2019 (COVID-19) is a communicable infection caused by the severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2). The first positive patient was detected in Wuhan, China, in December 2019. The disease spread worldwide, leading to the COVID-19 pandemic, which had a tremendous impact on patients and healthcare systems worldwide. In the fight against this new disease, to ensure timely quarantine and treatment, there is an emergency need for rapid and effective screening tools to identify patients infected with COVID-19. At present, reverse transcription-polymerase chain reaction *Reverse transcription* PCR *(RT-PCR)* testing is the primary screening method for COVID-19 because it can detect

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ribonucleic acid (RNA) of (SARS-CoV-2) in sputum samples gathered from the upper respiratory tract. While the RT-PCR test is specific to COVID-19, its sensitivity varies depending on the method and time of sampling, and some studies have reported relatively low sensitivity to COVID-19. In addition, RT-PCR testing is a time-consuming process currently in high demand. This issue leads to possible delays in obtaining test results. Computed tomography (CT) imaging has been suggested as an alternative screening tool for COVID-19 infection due to its high sensitivity. It may be effective by PCR if used as a supplement to RT testing. In the early stages of the COVID-19 pandemic, CT imaging was widely used, especially in Asia.[1]

Designing a tool for semantically segmenting lung CT scans of COVID-19 patients would help to assess and quantify those abnormalities. This can be an effective solution in controlling the pandemic. The AI cloud software solution enables radiologists to accurately detect high-level abnormalities on medical images to improve decision-making time, prioritize urgent cases, and deliver improved patient treatment.

Recently, deep learning (DL) techniques, as a type of AI, have revealed favorable results in various disciplines, particularly in bioinformatics and medical image analysis. DL has evolved into a common technique for creating networks skillful in successfully modeling higher-order systems to perform human-like performance.[2-5] Today, numerous studies have been performed for COVID-19 detection using the DL method of medical images and showed noteworthy results.[1,6-8] Nevertheless, few studies for semantically segmenting medical images of COVID-19 patients were published recently.[3,6] So, in this study, we aimed to use DL methods to segment CT-scan images to diagnose COVID-19 disease by processing chest CT-scan images.

Furthermore, creating a web-based application for use at hospitals and clinics to make the output more practical and attractive in the market is important. In such an application, the user can upload the patient's CT information for evaluation by AL models and segment them for classification into three categories: non-COVID-19, suspected COVID-19, and infected with COVID-19 and prioritizing them has high importance.

Due to the COVID-19 pandemic, we decided to develop a web-based application to detect the abnormalities of this disease in high priority by using a DL algorithm. Thus, this project aimed to design a web-based application by using the U-Net model as a DL algorithm to diagnose COVID-19 disease by processing chest CT-scan images.

Material and Method

Our constructed web-based "Imaging-Tech" application for detecting COVID-19 abnormalities in lung CT-scan works by incorporating the AL algorithm into data and imaging results instantly when the software detects the image. The machine learning (ML) capability detects abnormalities between the new image and a normal scan and identifies potential abnormalities or infections. The algorithm then sorts these abnormal cases in ascending order of their level of urgency and the critical need for attention. A trained radiologist then reviews the scans, prioritizing the cases that the algorithm has labeled as most critical. The present study with the fallowing ethical code (IR.MUBABOL.HRI.REC.1400.093) done to develop this application and divided into four categories.

Data, DL algorithm, software (web application), and digital marketing and website.

We have explained each of these steps in the next sections:

The datasets

Images of the primary dataset used in this study are a collection from the Ibn Sina Hospital in Tehran, Iran, in 2021. This dataset includes two categories: abnormal chest (COVID-19) and normal chest, consisting of 1031 persons' CT-scan images, each of which contains an average of three chest CT-scan images from neck to abdomen in Digital Imaging and Communications in Medicine (DICOM) format. The larger series has an average of 300 to 400 slices.

Due to the limited number of cases in this dataset, it is necessary to train the models on public datasets and test the results on these datasets since, in solutions based on ML and AI, the abundance of data will improve the performance of algorithms; therefore, we used some public datasets for model construction.[7-14]

Available public datasets are in png, jpg, tiff, and nii formats. We first defined the different forms and then converted them to DICOM using Python libraries. They are usually labeled as two classes (healthy and sick person). In some cases, the initial and final images do not contain useful information due to the small size of the lungs (these images are called closed pulmonary images), and testing the trained models on them will cause errors. To solve this challenge, the images in each folder were first converted to nii format. Each of these nii files was then converted back to png format, and the initial and final 15% of each sequence were removed. In this way, closed pulmonary images were removed.

Furthermore, in most existing datasets, abnormal cases are more than healthy cases. In neural network training, this increases the chance of the experimental sample belonging to a specific class. To solve this problem, combining multiple datasets and creating a balanced dataset solution has been considered. Then, a balanced dataset is created using the downsampling method.

According to previous studies, COVID-19 cases that have very few COVID-19 slices can affect teaching the model negatively. Because the training of our model was slice level, in all databases, the cases of COVID-19 were divided according to the number of available COVID-19 slices into several categories: 1–10, 11–20, 21–30, 31–40, and more than 40 slices.

Therefore, to train the model, COVID-19 cases with ≥30 COVID-19 slices were used, and closed lung images were deleted. Given all of these preprocessors, 6,000 slices were used for model training (2302 COVID-19 samples and 22302 healthy samples), 1,000 slices were used for validation (621 COVID-19 samples and 621 healthy samples), and 150 slices were used for testing. Test data was balanced according to the healthy (75 cases) and COVID-19 lung (75 cases). It is important to note that only slices with abnormalities are used for training in abnormal cases, but all slides are considered to find the threshold.

The U-Net-Densely Connected Convolutional Network 121 (DenseNet121) model

Segmentation tasks can be defined in two ways: preprocessing and diagnosis of disease progression. In preprocessing, the pulmonary lobes are separated from the background. By giving a three-dimensional input, we received the output of the segmented pulmonary as output, which can be seen in Figure 1. Using this preprocessing, that is, pulmonary segmentation, the segmented pulmonary can be given to the pre-trained network along with the raw CT-scan slice.

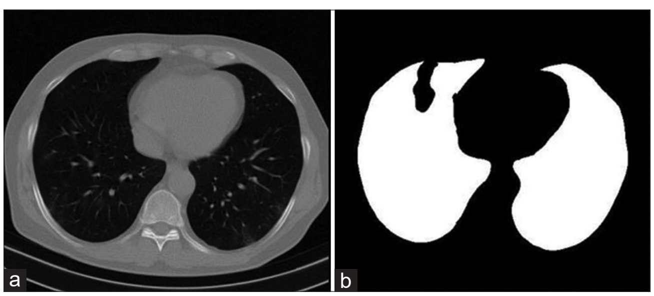

Figure 1: (a) CT-scan without preprocessing, (b) CT-scan after preprocessing. CT = computed tomography

In diagnosing the rate of disease progression, the range of infection is segmented, which can be detected according to the ratio of the area of infection to the pulmonary area. After considering the appropriate threshold level, the issue of classifying patients into two classes of healthy or sick people can also be evaluated after the segmentation process.

DL methods have a valuable role in the analysis and segmentation of infectious areas in radiological images. Several types of segmentation have been used to preprocess the training of some models. Medical images, such as CT-scans, have different backgrounds. Because we want to consider the model of features inside the lungs, in other words, focus on the lungs, we use pulmonary segmentation as preprocessing rather than the background removed from CT-scan slices. Pulmonary slicing is a method that uses an encoder-decoder network to batch CT-scan slices and returns the sliced slices as output. One of the most famous encoder-decoder is the U-Net network as an overall process of semantically segmenting images. This method aims to design a network that extracts segments through subsequent convolutions and employs that data to make a segmentation map as an output.[15] The structure of the U-Net network is presented in Figure 2. Also, the training and evaluation steps of the U-Net model are presented in Figure 3. With this U-Net architecture, the segmentation of images of sizes 512 × 512 can be computed with a modern graphics processing unit (GPU) within small amounts of time. In this study, the U-Net architecture, one of the supervised DL networks, is used as a hybrid model with DenseNet121 architecture as the pre-trained model for pulmonary segmentation.

DenseNet (Dense Convolutional Network) is an architecture that concentrates on creating DL networks to proceed even deeper, while simultaneously making them more efficient to train, by employing shorter connections between the layers.[16]

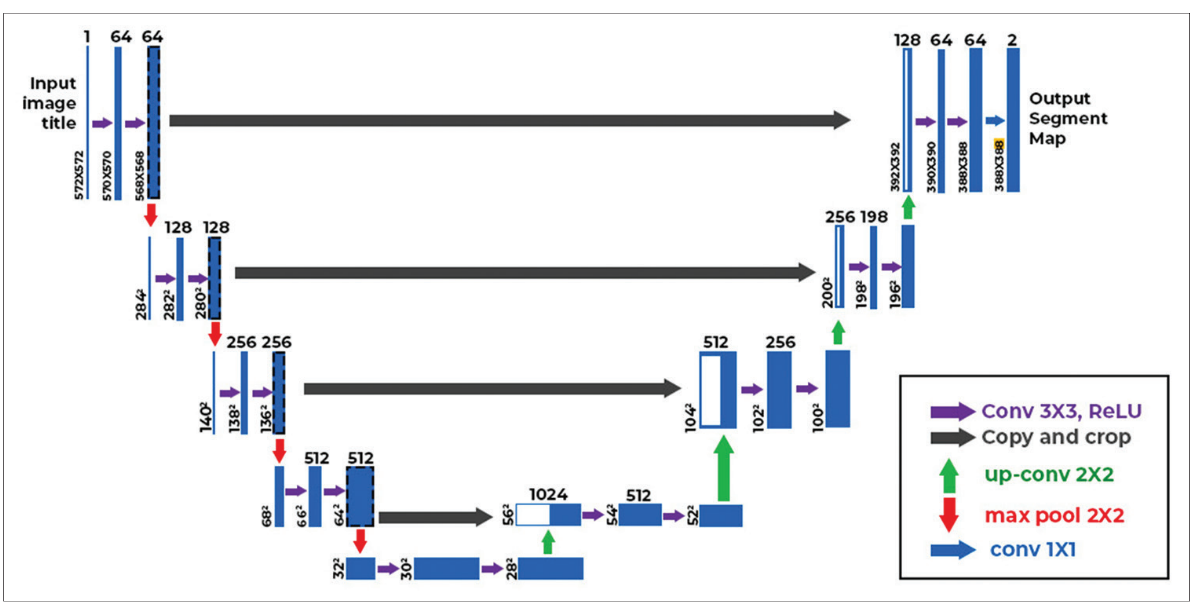

Figure 2: Structure of U-Net Model

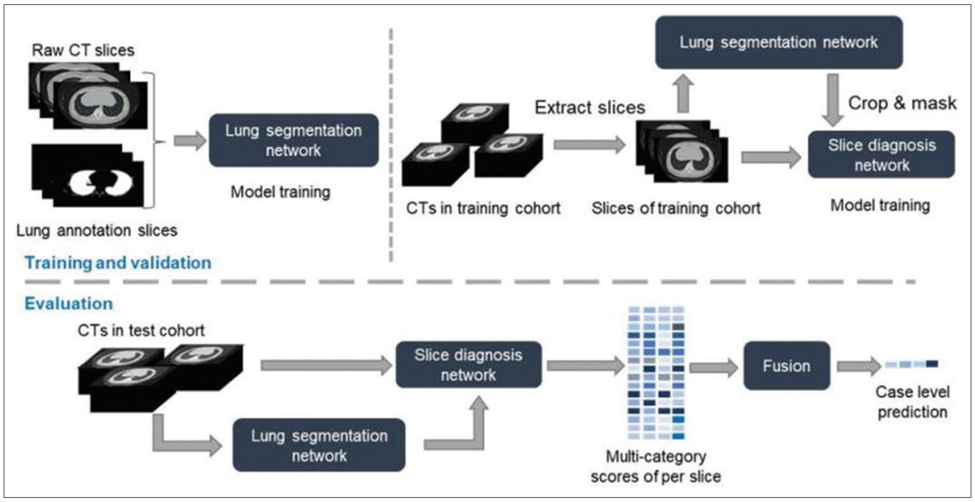

Figure 3: Training and evaluation process in the U-net model

Specifications of the presented U-Net model

In this study, the U-Net model with pre-trained DenseNet121 architecture for the segmentation process was used for pulmonary infection segmentation and measuring infected area percentage. U-Net produces a grey-scale segment image that needs a thresholding operation to achieve a final classification.

Because a case with mild abnormality with very few abnormal slices can be classified in the normal class, to reduce this misclassification error, two thresholds were calculated, and the data were divided into three classes: normal, abnormal, and suspicious. Also, closed lungs were removed during the threshold selection and testing phases.

The mean of the lowest infection rates and the mean of the medium infection rates are the parameters we chose as the thresholds. We used these thresholds to separate the three classes of healthy lungs and lungs with abnormalities and suspicious lungs.

Adjusting model parameters

To improve the model's performance, we repeated the process with various hyperparameter values, and values with the highest accuracy rate in validation data were selected as the final hyperparameter setting. The results of which are shown in Table 1.

Result

Model Performance

In this study, a model based on the U-Net model for the segmentation task was trained on 6000 slices, validated on 1000 slices, and tested on 150 slices. Two thresholds of 0.13 and 0.2 were selected to classify patients. If the amount of infection percentage was lower than 13%, it was considered as a healthy lung, more than 20% was COVID-19 affected, and between 13% and 20% was considered a suspected case. So, the constructed model input is all DICOM files related to one person, and its output is the label associated with the whole case (normal)/abnormal (COVID-19)/suspected. The overall accuracy of this model for threshold = 0.13 was 88.6%, and for threshold = 0.2 was 88.0%. The results of the model performance are presented in Table 2.

Software (Web Application): "Imaging-Tech" Application

Activities in the field of software product development

Developing a suitable software product for use at hospitals and clinics was put on the agenda to make our project's output more practical and attractive in the market. We have taken some actions to develop the software product of the startup plan, which are as follows:

Analyzing the requirements and identifying the main functions

Analyzing the requirements and identifying the main functions and use cases of the software product that investigates the patient's medical images to find abnormalities and prioritizing patients based on the number of abnormalities found in their medical images have been done.

Making a wireframe for our software product under the functions and requirements extracted in the previous stage

Figure 4 is the wireframe of the "Imaging-Tech" application. This wireframe is a low-fidelity design layout that serves three simple but exact purposes: (1) It presents the information that will be displayed on the page. (2) It gives an outline of the structure and layout of the page. (3) It conveys the overall direction and description of the user interface.

Development and manufacturing of software product according to the main functions of the software product, wireframe, and mockup

Using DL algorithms, the COVID-19 "Imaging-Tech" diagnostic system allows the diagnosis of the COVID-19

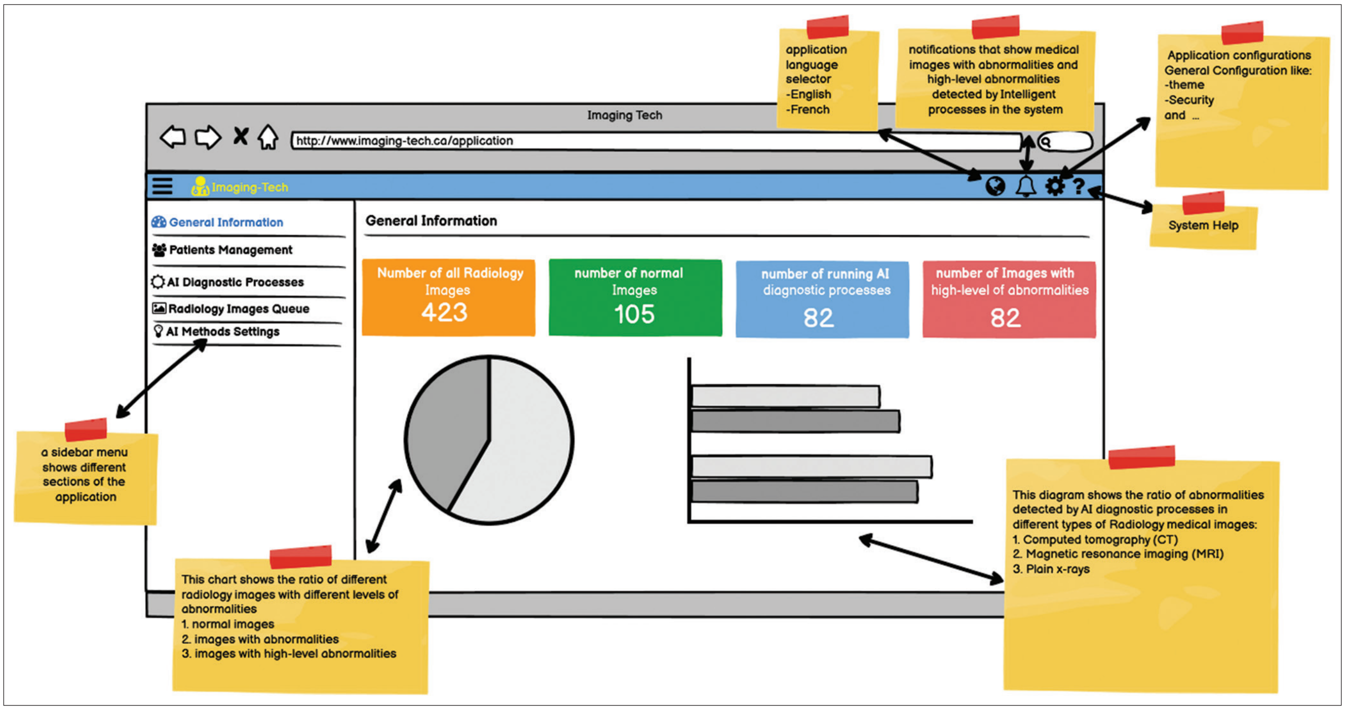

Figure 4: Imaging-Tech application's wireframe

Table 1: Adjust the model hyperparameters

Model	Size of image	Learning rate	Trainable parameters at time tune	Train accuracy	Validation accuracy
1	160×160	0.0001	17000000	80	77
2	160×160	0.001	17000000	92	76
3	160×160	0.001	90000000	85	76
4	64×64	0.001	90000000	79	67
5	200×200	0.001	17000000	94	81
6 (selected model)	512×512	0.001	17000000	97	86

Table 2: The results of the model performance

	Metrics of threshold=0.13	Metrics of threshold=0.2
Accuracy	0.886	0.880
Precision	0.837	0.860
F1 score	0.894	0.883
AUC	0.960	0.906
Sensitivity	0.960	0.906
Specificity	0.813	0.853

AUC=Area under the curve

disease by processing chest CT scans. In this system, the user uploads the patient's CT information. Then, this information is evaluated by AI models, during which the uploaded file is divided into three categories: non-COVID-19, suspected COVID-19, and infected with COVID-19. Slices that have a disease lesion are also marked. Finally, the machine prioritizes the uploaded information and evaluates and provides it to the physician [Figures 5 and 6].

Subsystems

The COVID-19 diagnostic system consists of several subsystems, which are as follows.

Labeling system

This system has been developed for collecting basic information to train AI models. The chest CT scan images are uploaded to this system and labeled by radiologists. After that, the Information prepared by this labeling system is used as input to the models for training.

AI system

This system receives the required information, like CT images of the patient from the physicians' system, and after processing the data, sends the obtained results to the physicians' system.

Technologies used in AI

Python: Python is an interpreted high-level, general-purpose programming language. Its design philosophy emphasizes code readability with its use of significant indentation. Its language constructs, as well as its object-oriented approach, aim to help programmers write clear, logical code for small and large-scale projects.

NumPy: NumPy is a library for the Python programming language, adding support for large, multi-dimensional arrays

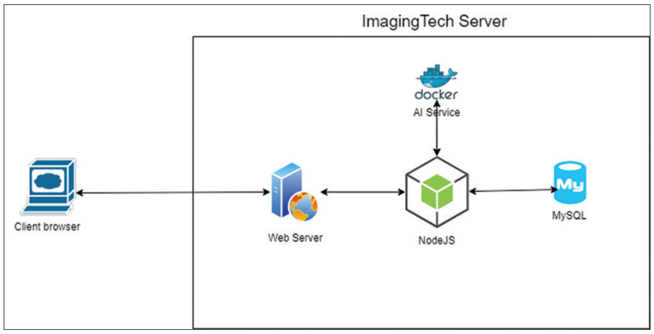

Figure 5: General system diagram

and matrices, along with an extensive collection of high-level mathematical functions to operate on these arrays.

TensorFlow: TensorFlow is a free and open-source software library for ML and AI. It can be used across a range of tasks but focuses on the training and inference of deep neural networks.

Keras: Keras is an open-source software library that provides a Python interface for artificial neural networks. Keras acts as an interface for the TensorFlow library. Up until version 2.3, Keras supported multiple backends, including TensorFlow, Microsoft Cognitive Toolkit, Theano, and PlaidML.

Doctors' system

The patients' information (chest CT-scan images) is loaded into this system and then sent to the AI system. After that, the results are prepared by the AI system. The obtained results are in the doctor's system. By referring to this system, the physician can access the list of prioritized patients according to the number of abnormalities found in their CT-scan images.

Digital Marketing and Website

Access information to doctors' system

The doctor's system is a web-based software that can be accessed through the following link. http://app.imaging-tech.ca

Technologies used in doctors' web applications

- React JS: React is a free and open-source front-end JavaScript library for building user interfaces or UI components. It is maintained by Facebook and a community of individual developers and companies. React can be used as a base in developing single-page or mobile applications.
- Next JS: Next.js is an open-source development framework built on top of Next. js is a React framework that enables several extra features, including server-side rendering. React is a JavaScript library that is traditionally used to build web applications rendered in the client's browser with JavaScript.
- Node.JS: Node.js is an open-source, cross-platform, backend JavaScript runtime environment that runs on the V8 engine and executes JavaScript code outside a web browser.
- MySQL: is an open-source relational database management system.

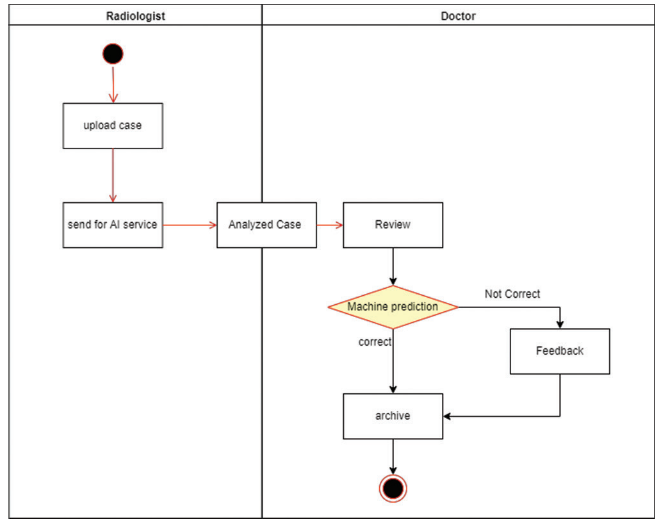

Figure 6: Activity diagram

Discussion

Using DL algorithms, the COVID-19 "Imaging-Tech" diagnostic system allows the diagnosis of the COVID-19 disease by processing chest CT scans. In this system, the user uploads the patient's CT information. Then, this information is evaluated by AI models, during which the uploaded file is divided into three categories: non-COVID-19, suspected COVID-19, and infected with COVID-19. Slices that have a disease lesion are also marked. Finally, the machine prioritizes the uploaded information and evaluates and provides it to the physician.

In this study, a AI-based model for COVID-19 segmentation from CT images was employed, and the results provided a piece of evidence for advantageous areas of research in AI-based for assessing COVID-19 CT-scan images and may assist the researcher in designing their own customized AI-based diagnostic instruments for effectively manage new variants of COVID-19 and its challenges.

We used U-Net architecture as the principal framework and enhanced the performance of the DenseNets network as the pre-trained model to enable the model to create more accurate segmentation maps. This study had a supervised nature, in which labeled COVID-19 cases had been used for training the model. The results show that our trained model had an acceptable accuracy rate for detecting COVID-19 abnormalities. We reported the model performance with different hyperparameter settings, which can be useful for a prospective study to know the influence of parameter setting on the model performance.

The results indicate the acceptable ability of the U-Net-DenseNet121 model in detecting COVID-19 abnormality (with 0.88 accuracies for both thresholds). Based on this model, we developed the "Imaging-Tech" web-based application for use at hospitals and clinics to make our project's output more practical and attractive in the market. One of the limitations of this study was the lack of samples to build the model. We used some public data in model construction steps to solve this problem.

Also, there was the problem of misclassification of cases with a mild infection in the normal class; we tried to reduce this error by setting two thresholds and considering a group as suspicious cases.

Comparing the results of the present study with similar studies indicates the acceptable efficiency and performance of our model for the segmentation and classification task of COVID-19 CT-scans images. Similar studies with other approaches, such as artificial neural networks and DL with different networks such as infection segmentation deep network (Inf-Net), segmentation network (*SegNet*), efficient spatial pyramid network (*ESPnet*), etc., have attempted to build a segmentation and classification model for lung CT-scan images. The results of these studies, along with our study, are more or less similar and indicate the ability of AI models to diagnose COVID-19 disease.[17-21] Studies with models with more traditional methods for segmentation and classification tasks have shown less efficiency.[22,23]

In one study, authors developed a DL-based system for multi-class diagnosis tasks on a large dataset with more than 10,000 CT volumes from COVID-19, influenza-A/B, nonviral community-acquired pneumonia (CAP), and non-pneumonia subjects. Area under the curve (AUC) of the developed deep convolutional neural network-based systems was higher than nine for various test datasets.[1]

In another study, the authors proposed the Visual Basic. Network Enabled Technologies (VB-NET) model (a DL-based segmentation system), which had Dice similarity coefficients of 91.6% between automatic and manual segmentations.[18]

Another study used the *Residual neural networks 50 (ResNet-50)* model for the classification of COVID-19. The AUC and sensitivity of this model were 0.95 and 0.96, respectively.[24]

A review of similar articles shows that the majority of classification and segmentation task was performed by Artificial Intelligence (AL) due to the ability of such models to detect the pattern of the data.

Conclusion

We designed a DL-based network (U-Net) for the segmentation of COVID-19 CT-scan images and, based on this model, constructed a web-based application that, according to the results, is a reliable detector for infected tissue in lung CT-scans. The availability of such a tool would aid in automating, prioritizing, fastening, and broadening the treatment of COVID-19 patients globally.

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Nil.

Conflicts of interest

There are no conflicts of interest.

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