COVID-19 Detection Using Deep Learning Based Medical Image Segmentation

Sanika Walvekar(✉) and Swati Shinde

PCCOE, Pune, India
sanikawalwekar@gmail.com

Abstract. COVID-19 is a rapidly spreading illness around the globe, yet healthcare resources are limited. Timely screening of people who may have had COVID-19 is critical in reducing the virus's spread considering the lack of an effective treatment or medication. COVID-19 patients should be diagnosed as well as isolated as early as possible to avoid the infection from spreading and levelling the pandemic arc. To detect COVID-19, chest ultrasound tomography seems to be an option to the RT-PCR assay. The Ultrasound of the lung is a very precise, quick, relatively reliable surgical assay that can be used in conjunction with the RT PCR (Reverse Transcription Polymerase Chain Reaction) assay. Differential diagnosis is difficult due to large differences in structure, shape, and position of illnesses. The efficiency of conventional neural learning-based Computed tomography scans feature extraction is limited by discontinuous ground-glass and acquisitions, as well as clinical alterations. Deep learning-based techniques, primarily Convolutional Neural Networks (CNN), had successfully proved remarkable therapeutic outcomes. Moreover, CNNs are unable to capture complex features amongst images examples, necessitating the use of huge databases. In this paper semantic segmentation method is used. The semantic segmentation architecture U-Net is applied on COVID-19 CT images as well as another method is suggested based on prior semantic segmentation. The accuracy of U-Net is 87% and by using pre-trained U-Net with convolution layers gives accuracy of 89.07%.

Keywords: U-Net · COVID-19 · Deep learning · CT

1 Introduction

From its very appearance in late 2019, this current spread of the new coronavirus illness has caused the unanticipated worldwide calamity. The COVID-19 epidemic that resulted is transforming our communities and human livelihoods in several aspects, with over half a million fatalities to date. Despite the worldwide effort to keep the infection from spreading quickly, hundreds of new infections are recorded on a routine basis across the globe, raising fears of a huge second wave of the epidemic. As a result, timely screening of COVID-19 is critical in assisting medical and public officials in designing optimal network deployments and interrupting the recurrence process [1].

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Timely screening of COVID-19 illness is critical to save many lives but also safeguarding medical professionals considering the lack of vaccination or medication. RT-PCR (reverse transcription-polymerase chain reaction) is among the benchmark COVID-19 diagnostic procedures; nevertheless, this RT-PCR assay has tedious work and has poor susceptibility [2]. Furthermore, in all nations, RT-PCR screening capability is insufficient, as well as the essential things in hospitals are restricted, judging by the amount of probable illnesses.

It's worth noting that chest CT scan, a non-invasive, clinical screening technique for infection, has indeed been utilised to enhance RT-PCR analysis regarding COVID-19 detection [3]. Moreover, because of sample bias, degradation, or virus alterations in the COVID-19 sequence, a significant erroneous alarm frequency is common. Medical imaging is also a viable primary investigation. Unless the potential individuals display signs only after primary test, multiple studies advocate administering a lung computed tomography (CT) imaging as a recall test [4]. If suspicious individuals display signs following a false RT-PCR result, numerous case represents using a chest computerised tomography (CT) scan as a supplementary diagnostic [5]. In Wuhan, China, for example, 59% of 1014 COVID-19 cases received valid RT-PCR readings while 88% reported positive Diagnostic tests. Furthermore, these CT scans had a 97% responsiveness amongst those affirmative RT-PCR findings. As a result, Diagnostic tests are more accurate than RT-PCR at detecting COVID-19. Furthermore, CT radiographs of the lungs can reveal early malignancies or being utilised by doctors to identify patients. In the case of COVID-19 cases, physicians must do specific functions:

Detection and grading of seriousness. The goal of diagnosis is to find COVID-19 sufferers and other individuals because then that they can be isolated as soon as feasible. Hospital professionals can use intensity assessment to identify individuals who will necessitate medical attention. All jobs necessitate a significant amount of analysis competence on the part of doctors [6]. As a result, creating machine learning based methods that are particular to COVID-19 detection and intensity measurement would provide a quick, effective, and trustworthy alternative clinical treatment options. With the growing population who require a COVID-19 test, hospitals are dealing with a severe schedule, which is affecting their potential to cure and evaluate COVID-19 patients appropriately.

This necessitates the appropriate distinction of lay terms and non-COVID illnesses from COVID-19 patients in favour of focusing more attention on COVID-19 affected individuals. Utilizing deep learning-based classification techniques cases into COVID and non-COVID instances, practitioners may swiftly rule out non-COVID patients in the initial phase, allowing them to focus more energy and cost on COVID-19 situations [7]. Though RT-PCR is frequently utilised as a detection test for COVID-19 identification, CT imaging is generally employed as the principal prediction system in certain areas with a large proportion of COVID-19 instances.

As a result, there is an urgent need for improved deep learning-based analysis relies on CT scans to accelerate treatment. We present a completely reliable and faster deep learning-based technique to handle key challenges mentioned earlier.

2 Literature Survey

Numerous researchers employed Convolutional Neural Networks (CNNs) to compensate for user shortcomings in identifying COVID-19. CNNs are sufficient to remove unique characteristics from CT scans and x - ray, making them effective features in network activities [8]. Several research has used CNNs to diagnose COVID-19 instances through diagnostic data in this aspect. The researchers' approach emphasizes the importance of how CNN can be used to identify COVID-19, with CNN being already trained on the ImageNet Extracted features. The CR collection is therefore used for fine-tuning.

The reliability in discriminating between healthy, non-COVID-19 pneumonia, and COVID-19 infections patients was 93.3%. The authors [9] too have looked into the similar topic, but instead of using a neural network, they used a Support Vector Machine (SVM) to discover affirmative COVID-19 occurrences. Study findings demonstrate a 95.38% accuracy results, a 97.29% sensitivity, as well as a 93.47% specificity [10]. A further research presents a CNN-based approach for extracting additional alternative perspective of ultrasound images using complexity convolution layers with different deformation frequencies. They employed a pre-trained network on a collection of healthy, contagious, and bacterial influenza cases, proceeded by further fine-tuned layers on a dataset containing COVID-19 as well as other influenza sufferers, resulting in a higher performance of 90.2% [11].

X-Rays are easier to do and expose you to very little radioactivity compared to CT scans. The separate CR scan, on the other hand, doesn't even include features of respiratory illness and hence may not provide a perfect overview for lung assessment [12]. The CT scan, but in the other side, is a type of radiography that shows the inner anatomy including its lungs as well as contaminated regions. Computed tomography, similar CR scans, provide cross-sectional scans to construct a three-dimensional depiction of the organ [13]. As a result, there seems to be a lot of attention in using 2D and 3D CT imaging to detect COVID-19 infestation. A Long short-term memory (LSTM) model examined the first diagnostic data obtained by hospitalised sufferer (flu, coughing, problems inhaling, etc.) and combined everything with demographic variables (demographic characteristics), as well as derived descriptors from CT scans [14]. Furthermore, a predictive method was used to determine if the alleged individual had community-acquired pneumonia (CAP) or was otherwise healthy.

The lack of medical records is a disadvantage of user interfaces, primarily when a significant number of clinically suspected are pending to be confirmed. To reduce the dimensionality on all CT scans, employed a U-net [15] centred feature extraction to separate the lung areas, and then used these to fine-tune a ResNet50 network that had been pre-trained on object detection from the ImageNet database. Using Chest radiography, the abovementioned artificial intelligence approaches were confined to solely COVID-19 identification [16]. COVID-19 influenza testing, on the other hand, is critical for determining the sufferer's medication reconciliation options. Identification of COVID-19-related infections and fragmentation of lung regions, in specifically, is critical for effective treatment and check of influenza sufferers [17, 18]. Classification of the chest and regions, identification of the circulatory system, filtering away respiratory veins from the CT image, and identification of illness were the 4 components of the machine methodology. Breakpoints and area growth were used to divide the disease. It's worth noting that perhaps the approach fails to account for pneumonic zones that are close in size to the vasculature [19].

3 Methodology

3.1 Dataset

An open database by Ma et al., that comprises 20 labelled COVID-19 CT scans slices, is included in this work. The Corona cases Initiative and Radiopaedia provided these Diagnostic tests, which had been licenced through CC BY-NC-SA [20]. Every CT scan were initially annotated by novice evaluators, secondly revised with two physicians with five years of knowledge, but then checked by experienced physicians with more than 10 years of knowledge. Considering the limited data, the labelling approach resulted in a significant database of the highest standard. All dataset images were 512 $\times$ 512 pixels (Coronacases Initiative) or 630 $\times$ 630 pixels (Radiopaedia), including an average of 176 samples. Backdrop, lung right, lung left and COVID19 disease had all been indicated upon CT scans. Sample dataset images of chest CT are shown in Fig. 1.

Fig. 1. Sample chest CT images from dataset

3.2 Methodology I

1. **Network model for U-Net segmentation**

   Pre-processing - We used multiple prepping approaches on the database to make the pattern identification and training procedure for the network easier. These feature vectors throughout the data were adjusted then transferred to intensity values in the 0–255 spectrum. For the feature extraction, all image got downsized to 256 $\times$ 256 pixels. Image signal intensity variations can have a significant impact upon this training phase and the effectiveness of networks. Scaling and standardising spectral information is advised for establishing fluctuating intensity spectrum uniformity [21]. As a result, the Corona cases Initiative CT scans were also adjusted to grayscale spectrum. Following that, all values subsequently normalised using the z-score method.

Data augmentation - The goal of data augmentation would be to intentionally expand the proportion of input images by creating additional data of realistic variants of the target structure. Spatial augmentation through replicating, scaling, elastic deformations and rotation were the 3 kinds of enhancements used. Color enhancements through intensity and brightness techniques [22–24].

Neural Network - Among the most important components of a healthcare segmentation process is the convolutional neural network and its hyper parameters. Among the most important components of a healthcare segmentation process is the convolutional model and its parameters. Transposed computation would be used for encoding, and optimum pooling was used for decoding. At its greatest fidelity, the structure employed 32 extracted features, while at its minimum pixel density, it utilized 512. With the exception of up- and deconvolutions, which were performed with a kernel $2 \times 2 \times 2$ stride, other convolution layers were performed with a kernel size of $3 \times 3 \times 3$ in a stride of $1 \times 1 \times 1$. Figure 2 depicts the flow of typical network for unet segmentation. Model got the accuracy of 87%.

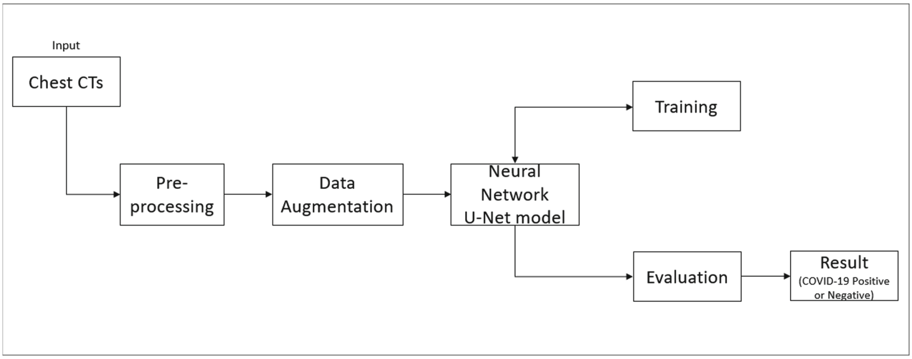

Fig. 2. Network architecture for semantic segmentation of CT images.

3.3 Methodology II

1. **Classification using U-Net model followed by convolution neural network**

For elimination of non-essential features and distortions from a CT scan, the already evaluated U-Net based chest area biomedical segmentation architecture was used. It is already trained for the COVID-19 data specially. The retrieved lung regions are returned by the system that will go into some standardization and scaling procedures. In order to aid generalizability but also proper fitting of the network, the outcomes would be standardised around 0 and 1. Figure 3 represents sample CT images of extracted lung region from pretrained U-Net.

Sections which do not contain identifiable lung tissue were discarded, while the others are retained for use in the architecture. As described in fig, our structure is begun with a sequence of convolutional layers, one max pooling layer and one batch-normalization layer. The Fig. 4 illustrates pipeline of proposed system. The final convolutional layer would then be designed to estimate whether the outcome is positive or negative for COVID-19. The proposed system got accuracy of 90.3%.

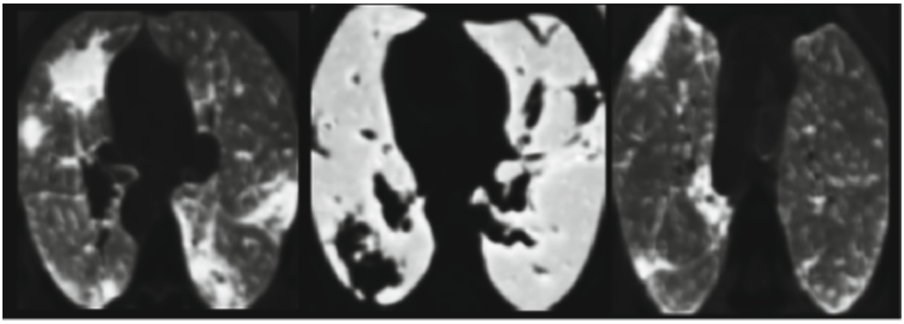

Fig. 3. Extracted lung region using pre-trained U-Net

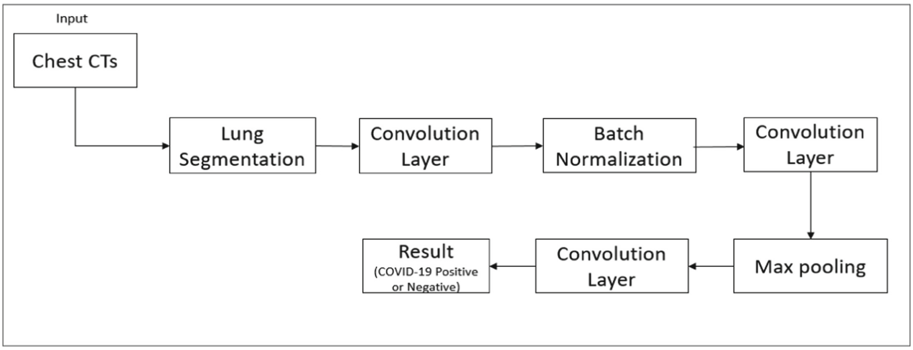

Fig. 4. Proposed system for classification of COVID-19.

4 Evaluation Results

For the COVID-19 identification process, statistical assessments of the suggested methodology are carried out. The identification activities are graded on a pixel-by-pixel basis, with the forefront (affected region) being the positive case and the backdrop being the negative case. The effectiveness being estimated by CT scan for the COVID-19 identification, wherein segments having COVID-19 illness denoted as the positive category and healthy segments were denoted the negative category.

The intersection over union (IOU), accuracy and dice similarity coefficients DSC were used to monitor the effectiveness of the network

Accuracy –

$$\text{Accuracy} = (\text{TP} + \text{TN})/(\text{TP} + \text{TN} + \text{FN} + \text{FP}) \tag{1}$$

In which the percentage of correct predictions cases among the remaining cases is called accuracy.

Where TP, TN, FP, FN are true positive, true negative, false positive and false negative respectively.

The critical distinction among IOU and DSC is that DSC includes twice value for TP than to IOU.

$$\text{Intersection over union (IoU)} = \text{TP}/(\text{TP} + \text{FP} + \text{FN}) \tag{2}$$

$$\text{Dice Similarity Coefficient (DSC)} = 2\text{TP}/(2\text{TP} + \text{FP} + \text{FN}) \tag{3}$$

where precision refers to the percentage of accurately categorized true positive CT findings across all confirmed cases.

$$\text{Precision} = \text{TP}/(\text{TP} + \text{FP}) \tag{4}$$

wherein sensitivity is the proportion of accurately projected confirmed cases in the true positive values, and specificity is the proportion of accurately classified confirmed samples in the negative class samples.

$$\text{Sensitivity} = \text{TP}/(\text{TP} + \text{FN}) \tag{5}$$

$$\text{Specificity} = \text{TN}/(\text{TN} + \text{FP}) \tag{6}$$

wherein F1 is the periodic mixture of precision plus sensitivity

$$\text{F1} - \text{score} = (2 * \text{TP})/(2 * \text{TP} + \text{FP} + \text{FN}) \tag{7}$$

5 Result and Discussion

The segregation of U-Net using CNN is remarkably compatible to ground truth, as can be depicted. Despite the fact that COVID-19 infections can have a significant impact on the lungs, the developed system was utilized to segregate the results accurately. The noise removal portion is based on a COVID-19 with regular cases database. In the related training phase, the Adam optimizer is employed including a baseline learning value of 1e-4, a batch size of 16, and four iterations (Table 1).

Table 1. Result of typical u-net segmentation and pre-trained u-net segmentation with CNN.

Evaluation metrics	U-Net (%)	Pre-trained U-Net with CNN (%)
Precision	83.09	85.65
Accuracy	87.77	89.07
Sensitivity/Recall	88.87	87.97
Specificity	85.06	87.43
F1-Score	83.97	82.89
Dice Score	89.11	91.73
IOU	89.05	86.09

6 Conclusion

We developed a comprehensive technique for COVID-19 identification from CT scans throughout this work. We explored various state-of-the-art classification models to determine the well trained accurate deep learning models. In summary for COVID 19 detection and classification Pre-trained U-Net with CNN outperformance U-Net. Accuracy of 87.77 and 89.07% achieved with U-Net and pre-trained U-Net respectively.

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