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Original Article

Artificial Intelligence Applied to COVID-19 Lung Infection Segmentation from CT Images

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Abstract *- COVID-19 poses an exceptional health crisis to the world. Given its enormous effect on human health, it is imperative to provide a quick and efficient diagnosis to mitigate the pressure healthcare systems face. Numerous imaging methods, such as computed tomography (CT), are employed to diagnose COVID-19. This research paper introduces an approach for the automated segmentation of lung infections caused by COVID-19 in CT images. To achieve this objective, utilizing deep convolutional neural networks is suggested to study the most widely used architectures in the medical imaging field that rely on encoder/decoder models. Adopting an artificial intelligence data collection called the COVID-19 CT Segmentation Dataset; the suggested model is executed in areas framework in Python. Afterwards, models description, training with data augmentation, validation, and predictions are provided. Finally, the results are contrasted with existing labelled data. The trained model is tested with new images. Compared to manual expert segmentation, prediction results generated values of 0.884, 0.755, and 0.982 for metrics area under the ROC curve, Dice similarity, and accuracy, respectively. Ultimately, a summary is presented for future work, including integrating the suggested model within a consistent framework in medical image processing for clinical is given.*

Keywords *- COVID-19, Deep Learning, Convolutional Neural Network, Image Segmentation, Chest CT Scan*.

1. Introduction

COVID-19 was declared a pandemic by the World Health Organization on March 12, 2020, representing an immediate danger to humanity [1]. The COVID-19 (Coronavirus Disease 2019) pandemic was first identified in the city of Wuhan, located in the Hubei Province of China, during the last month of 2019 [2]. It is the result of a variety of intense acute respiratory syndrome called coronavirus "Severe Acute Respiratory Syndrome: SARS-CoV".

It has turned everyday life upside down for people around the world due to the huge number of cases and deaths it caused [3]. Initially, most people who become infected with COVID-19 have mild to moderate symptoms and do not require specific medical intervention, eventually recovering on their own. However, soon after, the disease spread very rapidly.

To date, as of May 6, 2023, more than 687 million coronavirus cases due to COVID-19 have been detected worldwide, of which about a quarter are registered in the United States only [4]. Figure 1 shows a chart of the top 20 countries in the world with the highest number of confirmed COVID-19 cases.

Timely detection of COVID-19 is vital not just to start treatment quickly but also to isolate patients and enable effective monitoring by public health authorities. Numerous methods and resources are employed for detecting and identifying COVID-19 disease, including Chest Computer tomography CT images [5]. Chest CT is a type of non-invasive imaging technique that offers a further understanding of the structural and pathophysiological characteristics of the lungs, ultimately leading to an enhanced comprehension of disease variability. This method has demonstrated utility in screening for lung cancer [6].

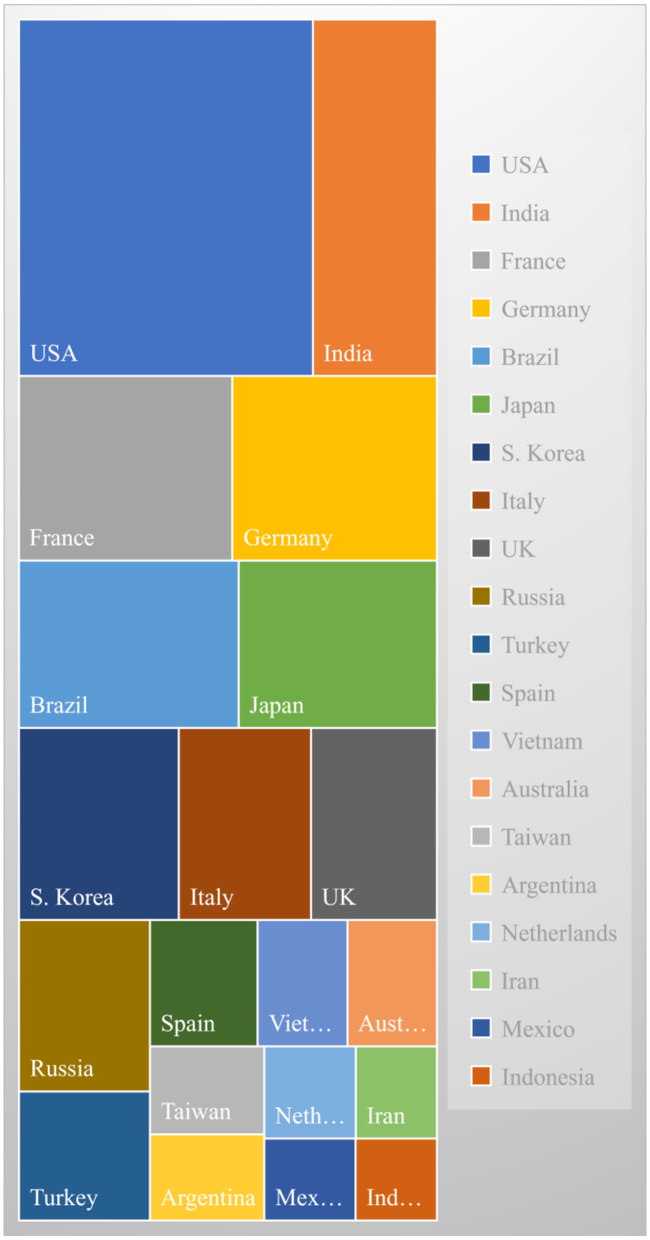


Fig. 1 Tree map displaying the 20 countries with the largest number of confirmed COVID-19 cases globally

CT images of the chest in COVID-19 patients demonstrate atypical manifestations, with Figure 2 displaying the characteristic visual features of COVID-19 on CT scans [7]. However, to automatically segment sections of COVID-19 abnormal symptoms in chest CT images. It uses an image segmentation process that allows the user to split the image into multiple segments or parts. In general, this initial step represents a crucial aspect of analysing image content for various purposes. Numerous image segmentation techniques may be employed to achieve this objective, including color-based methods, pixel value-based techniques, and deep convolutional neural networks. In this article, Convolutional Neural Networks (CNNs) for image segmentation have captured our interest.

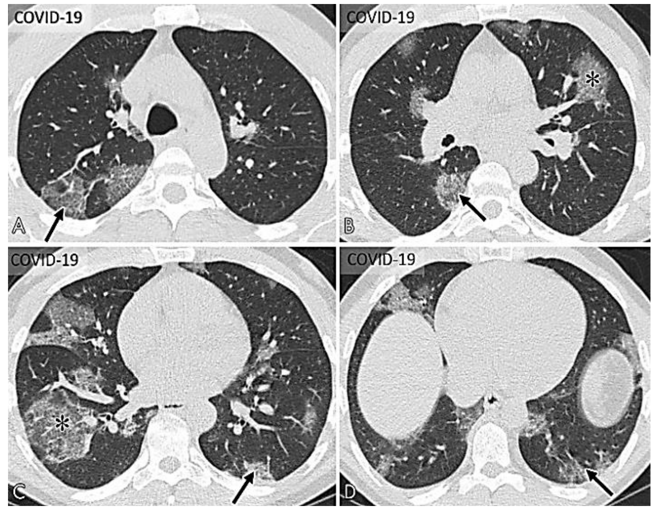


Fig. 2 COVID-19 typical chest CT imaging features [7]

Ardakani et al. suggested a detailed review of methods for COVID-19 diagnosis using CNNs techniques and lung segmentation [8]. In another review, Shoeibi et al. provide an overview of research that examines the utilization of Deep Learning (DL) methodologies for detecting COVID-19 and segmenting lungs [9]. They also discuss the prediction of COVID-19 incidence rates across various world regions. Lecun et al. developed CNNs using error gradients and achieved excellent results in diverse pattern recognition tasks [10,11]. They have become the norm for numerous computer vision assignments, including image classification, object detection [12,13], and image segmentation [14–16]. In a review article [16], Everingham et al. provide a concise summary of the most notable DL techniques used in computer vision tasks, including CNNs, Deep Boltzmann Machines, Deep Belief Networks, and Stacked Denoising Autoencoders. Additionally, the authors provide a concise overview of each technique's historical background, structure, advantages, and drawbacks. Furthermore, it provides detailed explanations of how these techniques can be applied to a range of computer vision tasks, including but not limited to object detection, facial recognition, activity and action recognition, and estimation of human poses, among other tasks.

CNNs use multiple layers of neurons named feature maps or channels in their convolution and subsampling layers. Each neuron in a feature map is linked to a small segment of the preceding layer, which is referred to as its receptive field. In the case of images, the feature map takes the form of a two-dimensional array or matrix of neurons. For other types of input data, such as audio data, a one-dimensional array is used, while for volume data, a three-dimensional array is utilized [17,18].

The remaining parts of the paper are structured as follows: In the subsequent section, a summary is provided on the use of CNNs for the purpose of image segmentation, which includes a discussion on image segmentation through CNNs and introduces some related works. Section 3, entitled Materials and Method, presents the description of the datasets, the processing equipment and the methodology proposed. The outcomes and discussions are included in Section 4, followed by the conclusion in Section 5, which suggests areas for future improvements.

2. Related works

2.1. Image Segmentation with deep CNNs

Utilizing a variety of approaches, image segmentation is employed to identify and isolate objects and contours in images. DL architecture represents the most advanced techniques for addressing image segmentation challenges. This section delineates some of the CNN architectures employed in DL for this purpose [8–11].

In image segmentation using CNN, image segments are fed as input to CNNs to label the pixels. In CNNs, images are not processed all at once. Instead, they are divided into smaller parts and scanned using filters consisting of a few pixels (such as 3x3 or 5x5) until all pixels in the image have been analysed. Ultimately, the entire image is mapped through this process [10].

Long et al. presented a Fully Convolutional Network (FCN) that builds upon the concept of CNNs. The approach involves substituting the fully connected CNN layer with a convolutional layer and incorporating an upsampling operation to achieve image segmentation for input images of any size [18]. A basic instance of FCN for semantic segmentation is depicted in Figure 3. FCNs can effectively acquire the ability to generate dense predictions for tasks that involve individual pixels, such as semantic segmentation.

An additional noteworthy architecture, called U-Net, utilizes CNNs and was specifically created for biomedical image segmentation. It has since become the most widely used architecture within the medical imaging field [19].

The network depicted in Figure 4 is based on an encoder-decoder architecture, with an Encoder responsible for extracting spatial features from the image and a Decoder tasked with constructing the segmentation map using the encoded features.

The Encoder follows a typical convolutional network structure, consisting of a series of two 3×3 convolution operations followed by a max-pooling operation using a 2×2 pooling size and stride. This sequence is repeated four times, with an increase in the number of filters in the convolutional layers after each down-sampling. Finally, the Encoder is connected to the Decoder via a sequence of two 3×3 convolution operations, followed by a single 1×1 convolution for outputting the segmentation map [20].

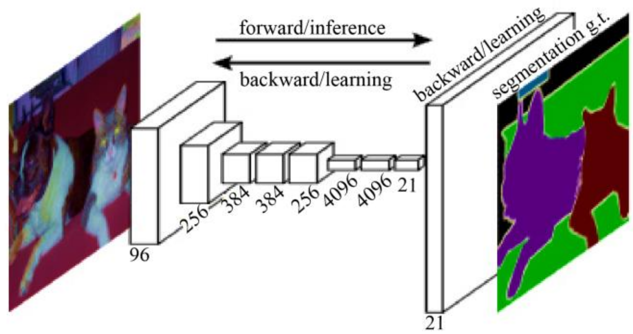


Fig. 3 Example of FCN for semantic segmentation [18]

Various convolutional network architectures, including AlexNet [13], GoogLeNet [22], VGGNet [23], and ResNet [24], have been presented as winners in the ImageNet competition in 2012, 2013, 2014, and 2016, respectively. Although there are additional convolutional network architectures beyond the scope of this text

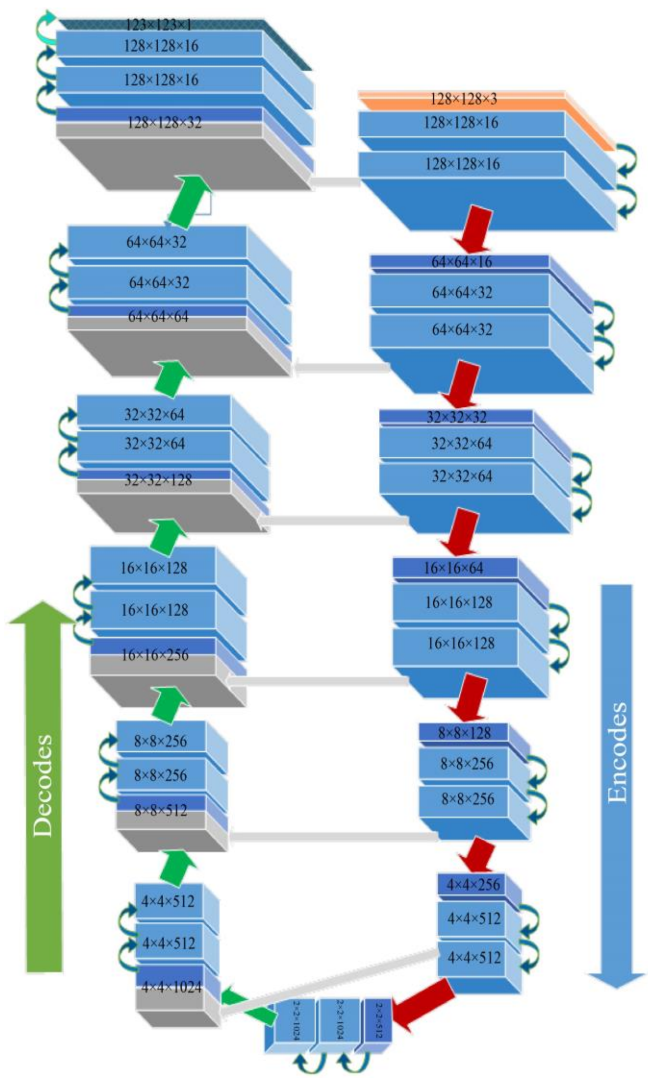


Fig. 4 Architecture of the Encoder-Decoder model used in this experiment [21]

2.2 Medical Imaging Works for COVID-19

In the context of the current epidemic, computed tomography (CT) is a significant medical imaging technique that is utilized as a vital tool in diagnosing COVID-19 pneumonia [21]. In this section, several studies related to COVID-19 lung segmentation from CT images are presented. Fan et al. introduce a new convolutional network model called Inf-Net for segmenting COVID-19 lung CT infections. Inf-Net consists of a parallel partial decoder that combines high-level features to produce a global map, an implicit reverse attention module, and an explicit edge-attention module to enhance the identification of infected regions. To address the lack of labeled COVID-19 data, the authors develop a semi-supervised segmentation framework that relies on a propagation strategy using only a small number of labeled images and mostly unlabeled data [25].

Zhou et al. propose an automated and machine diagnosis method capable of segmenting and quantifying areas of infection in CT scans [26]. A pre-processing technically was applied to datasets to integrate any CT scan in a standardized space for machine-diagnostic and to get more data; the authors suggest creating a COVID-19 simulator by modifying the dynamic changes observed in real patient data taken at various time intervals. The proposed algorithm allows to decompose of the 3D segmentation problem into three separate 2D that achieve a high performance demonstrated by calculating the recall and dice coefficient on the Harbin dataset; they obtain 0.783 and 0.776 as values.

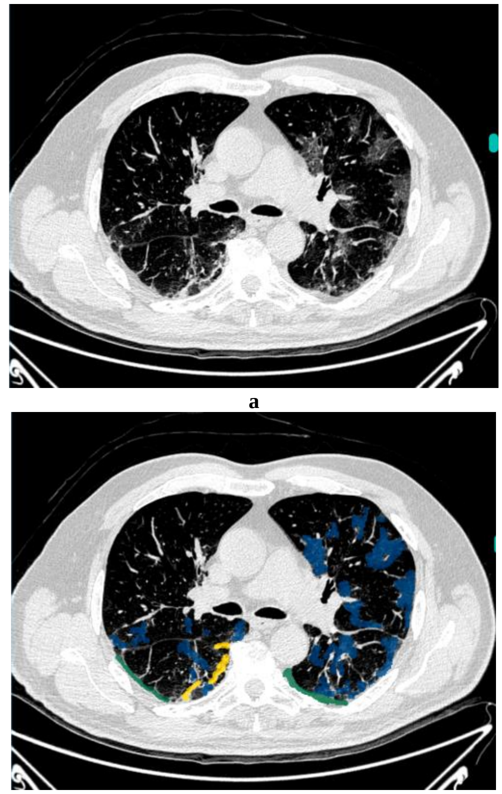
Wang et al. developed a cloud-based structure for efficient COVID-19 infection prediction [27]. They designed a deep learning model for the automated diagnosis of COVID-19 using chest CT scans and integrated it with a weakly supervised deep learning framework.

This framework enables the use of 3D CT volumes for COVID-19 classification and localization of lesions and then gives high accuracy achievements. The following section will provide details about the materials used in this study, including the datasets and method that allows us to COVID-19 Lung Infection Segmentation from CT Images.

3. Materials and Method

3.1. Dataset

To accomplish our goal, an available dataset called the COVID-19 CT segmentation dataset was utilized [28], which includes 100 axial CT images from over 40 COVID-19 patients. These images were obtained from openly accessible JPG images found in the Italian Society of Radiology [29]. The conversion process is detailed in the following blogpost: "COVID-19 radiology — data collection and preparation for Artificial Intelligence"[30]. To summarize, the radiologist segmented the images into three categories: ground-glass (mask value=1), consolidation (mask value=2), and pleural effusion (mask value =3).



a

b

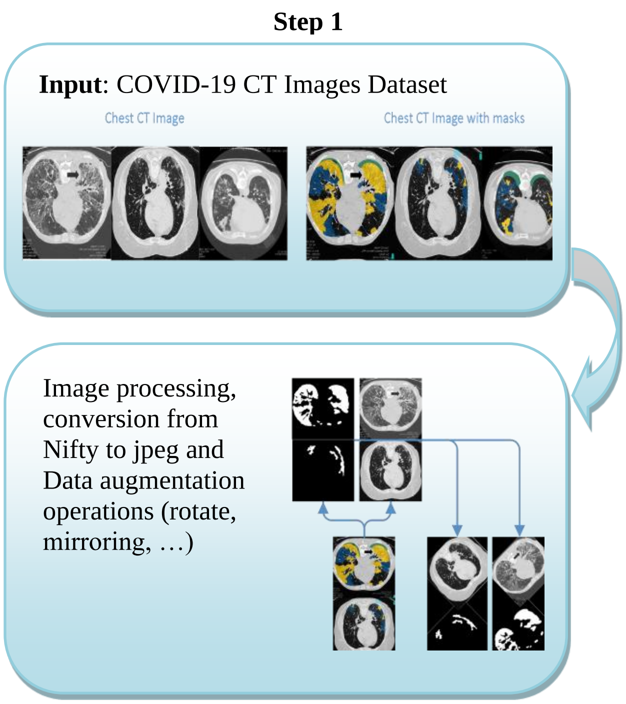
Fig. 5 One example from the dataset: (a) Example of COVID-19 CT axial slice. (b) Manuel radiologists segmented annotation Ground-glass opacities in blue (Mask), consolidation in yellow and pleural effusion in green [28]

Figure 5 displays an example image along with a manual segmentation of COVID-19 lung infection from CT scans.

3.2. Method

This section presents the proposed method based on deep CNNs for automatic COVID-19 Lung Infection Segmentation from CT Images. The model [31] was inspired by an encoder-decoder architecture initially used for optic disc segmentation in retinal images [31]. Among the medical imaging community, this architecture stands out as one of the most renowned and extensively utilized. A simple modification is implemented to the hyperparameters of the original model; in convolutional operations, the mode "same" instead of "valid" was used to keep the same dimension as input to output.

Data augmentation techniques were employed to enhance training performance, and the network underwent training for a mere 25 epochs. Concurrently, loss and accuracy were computed for each epoch. Following the completion of model training, the prediction process was applied to novel CT images in order to generate segmented predictions for COVID-19 lung infection. Finally, contour detection was applied to the mask. The result was drawled into the COVID-19 CT image. Figure 6 below summarizes the method for different steps.



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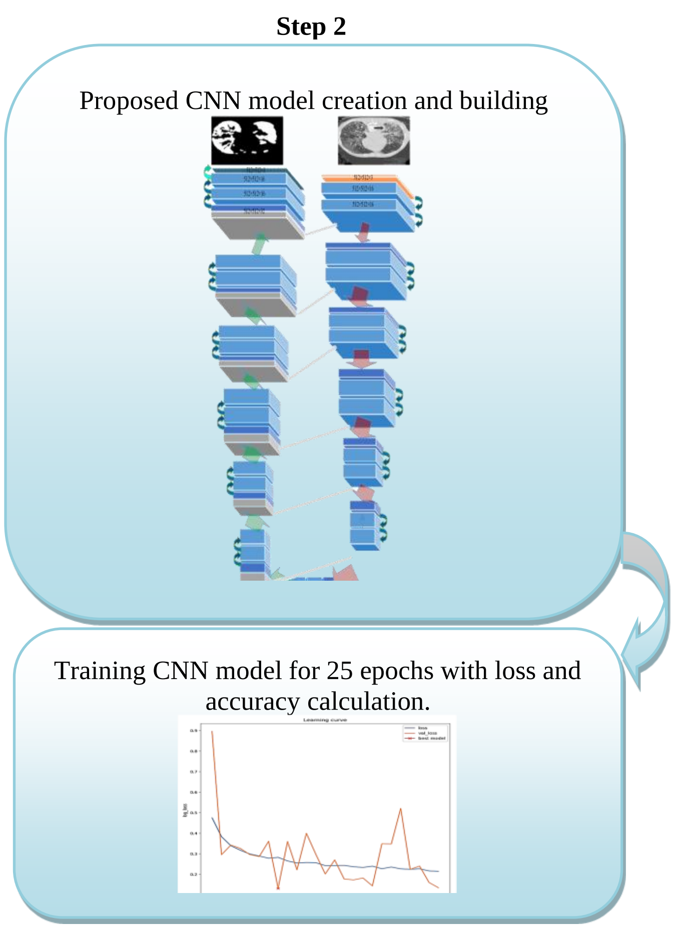

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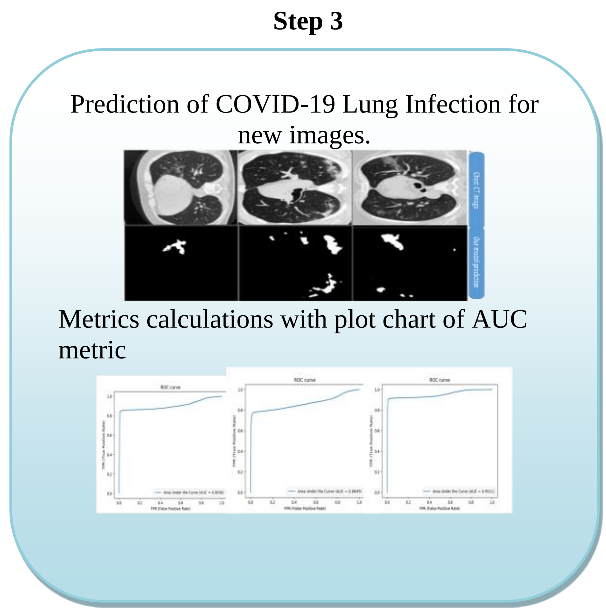

c

Fig. 6 Simplified follow charts of our proposed method: (a) Step 1 and (b) Step 2 and (c) Step 3

As shown in Figure 6, the method comprises three key steps; the first step consists of image processing. Firstly, the original images are converted from Nifty to jpeg images, and then data augmentation techniques, such as rotation and mirroring operations, are applied. After that, in step 2, the proposed network model was created and built using the keras framework and the model was trained for a total of 25 epochs. The historical loss and accuracy calculation was saved for plotting and analysis. Finally, the trained model was evaluated in step 3 by prediction operations for new CT images to get the segmentation of COVID-19 Lung Infection, and the performance of the trained model was evaluated by metrics calculation.

3.3. Data Augmentation

In order to achieve better performance for deep learning network models, a substantial dataset is necessary. Training models on more data can lead to development of more adept and skillful models, and augmentation techniques can further contribute to this process [1], [2]. It is also possible to create diverse variations of the images by applying transformations such as rotation, flip/mirroring, and other operations to the existing training data. This process generates new samples with the objective of enhancing the accuracy and effectiveness of classifiers. It has the potential to enhance the capability of well-fitted models to apply their learned to novel images effectively.

Deep learning frameworks typically offer pre-built data augmentation tools, and the Image Data Generator class was utilized in this study. This class is particularly useful for image processing tasks as it generates batches of tensor image data while applying real-time data augmentation techniques.

In the next section, the training strategy was presented for the proposed method based on deep CNN.

3.4. Training

The training procedure involves supplying images along with manually created expert segmentation maps as labeled data, which were then used to train the network. The goal is to get just one class of segmentation from CT Images; the Dice coefficient Equation 1 [32] was used as the losses function of the network.

$$\tau_{dice} = 1 - \frac{2|X \cap Y|}{|X| + |Y|} \quad (1)$$

Where X predicted segmentation, Y is the ground truth. The Adam was also used to optimize with default parameters in areas. For all convolutional and deconvolutional layers, the “Rule” Equation 2 is used as an activation function except for the final layer [33]. The sigmoid activation function is used in output layers to get the segmentation prediction of COVID-19 Lung Infection.

$$f(X_{i,j,c}) = max(w_c X_{i,j}, 0) \quad (2)$$

Where $X_{i,j}$ is the input pixel at index (i,j), and c is color channels that equal 1 in our case; when the value is less than 0, it becomes 0; otherwise, it keeps its value.

Nwankpa et al. define Sigmoid Eq. (3) activation function as [33]:

$$f(X) = \frac{1}{(1+exp(-X))} \quad (3)$$

Where X is the input and f is the activation function.

All Network weight was initialized randomly with Xavier normal initialize, also known as glorious normal initialize, with default parameters [34]. In the next section, the results were presented and discussed the performance of the proposed method compared to expert segmentation.

4. Results and Discussion

The proposed model is evaluated on the same COVID-19 CT segmentation dataset, and data augmentation operations and technics are applied to the dataset to get more samples. This dataset is divided into training data representing 80%, and validation data representing 20%. Samples are also retained for the test dataset that presents nearly 5% of the initial dataset for prediction, evaluation, and visual presentation.

The segmentation performance of the implemented model was evaluated by calculation of loss function and accuracy metric on 25 epochs size training. Figure 7 shows the line plot chart over the learning curve epochs with dice loss calculations for the training and validation stages.

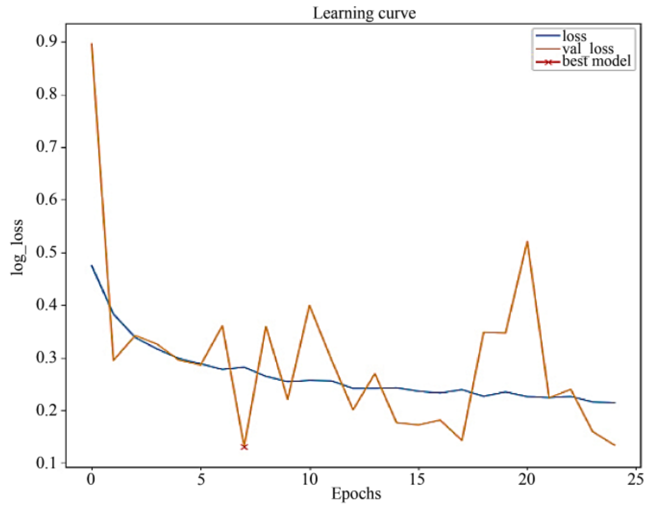

Fig. 7 Shows the plot chart

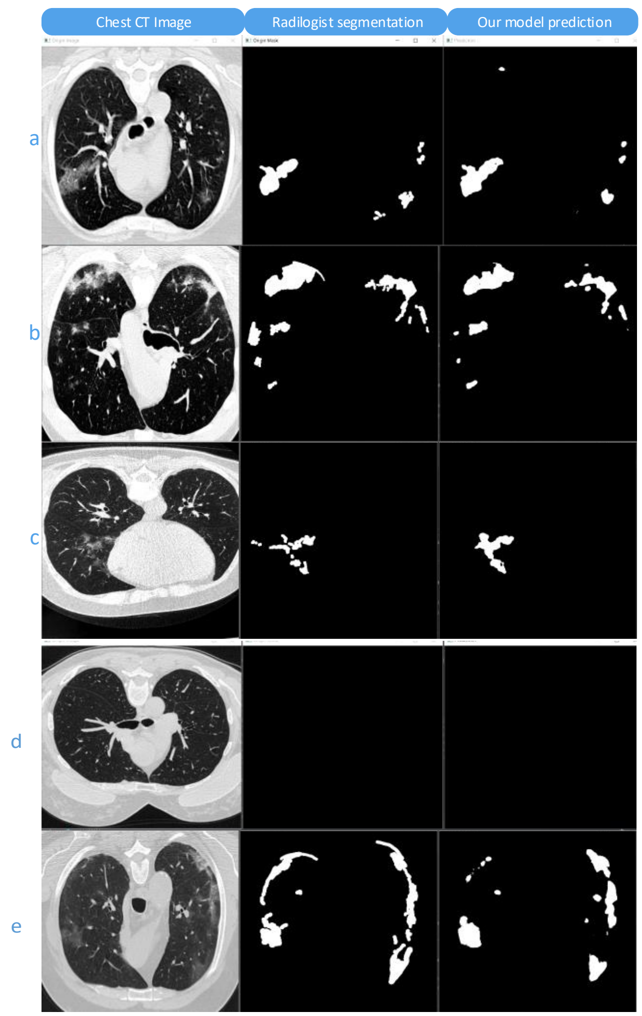

Fig. 8 Visual comparison of our COVID-19 Lung Infection Segmentation from CT Images results with a manual segmentation labeled from an expert

Once the model is trained and saved, a mask prediction is given for new images (five images in our case), and it is used for visual presentation and tested on new chest CT images. Figure 8 shows the prediction of the trained model on new CT images.

In order to measure the performance of this work, The following metrics are calculated for all tested images: Accuracy (ACC) Equation 4, Dice similarity (DICE) Equation 1 and Area under ROC curve (AUC) [35].

$$ACC = \frac{TP + TN}{TP + TN + FN + FP} \quad (4)$$

The proposed method has obtained promising results in the segmentation of infected regions, and the obtained results for Area under the ROC Curve, Dice similarity and Accuracy metrics are respectively the values 0.884, 0.755 and 0.982; it is also capable of knowing the absence of lung infection for non-COVID-19 patients.

The future work focuses on integrating COVID-19 lung infection segmentation and detection in a homogeneous framework for clinical purposes. In comparison with other works in the literature cited in section 2. In their Inf-Net model [25],

Fan et al. successfully achieved the identification of infected regions from chest CT slices, achieving dice coefficients of 0.579, 0.870, and 0.974, sensitivity, and specificity, respectively. Similarly, Zhou et al. attain in their model recall and dice coefficient values of 0.783 and 0.776, respectively [26].

Table 1. Metrics measurement on the COVID-19 CT segmentation dataset for five test set images

Image	AUC	DICE	ACC
Image-11	0.864	0.773	0.977
Image-18	0.951	0.834	0.991
Image-32	0.818	0.693	0.966
Image-82	0.903	0.719	0.992
Image-49	--	--	--

5. Conclusion

This paper introduces an automated approach that utilizes CNN for segmenting COVID-19 lung infections from CT images. Encoder-decoder architecture was proposed and implemented into Python in the keras framework. The proposed method uses the input data from the COVID-19 CT image dataset by applying a data augmentation technique. Finally, it can be concluded that the application of CNNs architecture for image segmentation applied to chest CT images confirms the performance of the proposed model based on the encoder-decoder architecture in the new image segmentation context.

Author Contributions

All authors contributed to the manuscript as conceptualization, methodology, software, validation, investigation, and supervision.

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