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A simplified U-net model for Covid-19 CT image segmentation

Haitao Zhan

Computer Science Department, Beijing University of Technology, China

zhanhaitao@emails.bjut.edu.cn

Abstract. The ongoing COVID-19 pandemic has highlighted the importance of accurate and efficient medical image analysis to aid in the diagnosis and treatment of patients. In particular, the segmentation of COVID-19 medical images has become a critical task to identify regions of interest, such as the infected lung areas, and to track disease progression. Traditional image segmentation methods have been widely used in medical image analysis. However, these methods are often challenged by the complex and diverse nature of COVID-19 images, as well as the limited availability of data. In this paper, we propose a simplified version of the U-Net that eliminates redundant crop operations. This simplification reduces computational complexity and memory usage, and enables the model to learn from larger input images, resulting in better performance. We evaluate the performance of our simplified U-Net model on a public COVID-19 dataset and demonstrate that our model achieves state-of-the-art results while using fewer computational resources.

Keywords: Covid-19, image segmentation, U-net, deep learning, CT image.

1. Introduction

The COVID-19 pandemic has created an unparalleled global health crisis, profoundly impacting millions of lives and resulting in an alarming number of fatalities across the world [1]. The novel coronavirus SARS-CoV-2 primarily assails the respiratory system, causing severe pneumonia, acute respiratory distress syndrome, and in extreme cases, organ failure and death. The rapid transmission and high morbidity of the virus have placed immense strain on healthcare systems, necessitating the development of accurate diagnostic tools and efficient treatment protocols.

Computed tomography (CT) imaging has emerged as an indispensable diagnostic tool for COVID-19, owing to its exceptional sensitivity and capacity to detect early-stage lung abnormalities [2,3]. The ability to swiftly identify and assess the severity of lung lesions is crucial in determining appropriate treatment strategies and monitoring patient progress. However, manual segmentation of COVID-19 lung lesions in CT images poses a labour-intensive and time-consuming challenge, which is compounded by the sheer volume of CT scans that healthcare professionals must analyse daily. Moreover, the intricate nature of the disease, typified by diffuse lung opacities, consolidations, and ground-glass opacities, further complicates manual segmentation efforts.

Given the dire consequences of the COVID-19 pandemic and the critical role that CT imaging plays in diagnosis and treatment, the development of automated segmentation methods becomes indispensable for accurately and efficiently delineating COVID-19 lung lesions in CT images. Deep learning-based

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approaches have demonstrated immense promise in this domain, as they possess the ability to discern complex image features and perform segmentation tasks with remarkable precision and effectiveness. In this paper, we introduce a simplified U-Net model tailored specifically for the segmentation of COVID-19 lung lesions in CT images.

2. Previous works

Segmentation of CT images is a challenging task that involves separating the region of interest (ROI) from the background in medical images. Traditional machine learning methods, such as SVM and RF, have been applied to this task for a long time, and several studies have investigated their effectiveness in COVID-19 lung lesion segmentation [4,5]. In addition to SVM and RF, which have been widely used for medical image segmentation, other traditional machine learning methods, such as Otsu thresholding, watershed transformation, and superpixel segmentation, have also been investigated for COVID-19 lung lesion segmentation [6–8].

SVM is a popular method for image segmentation that uses a hyperplane to separate the ROI from the background in feature space [4]. However, SVM requires handcrafted feature extraction, which can be time-consuming and may not capture all the important information in the images. Furthermore, the effectiveness of SVM depends heavily on the choice of features, which can be difficult to determine in practice.

RF is another commonly used method for image segmentation that uses an ensemble of decision trees to classify pixels in the image [5]. RF does not require feature extraction, and can learn the features directly from the image. However, RF also has limitations in COVID-19 lung lesion segmentation due to the complex nature of the disease and the variability of the lesions.

Otsu thresholding is a simple and effective method for image segmentation that uses a threshold value to separate the foreground and background regions in an image [6,9]. This method is based on the assumption that the intensity values of the pixels in the foreground and background regions follow different statistical distributions. However, Otsu thresholding may not be effective for COVID-19 lung lesion segmentation due to the high variability of the lesions and the presence of noise in the images.

Watershed transformation is another commonly used method for image segmentation that treats the image as a topographic map and separates the regions based on the local minima and maxima of the image [7,10]. This method can be effective for segmenting objects with well-defined boundaries, but may not be suitable for COVID-19 lung lesion segmentation due to the diffuse nature of the lesions.

Superpixel segmentation is a method for partitioning an image into small, homogeneous regions called superpixels [11,12]. This method can be used to reduce the complexity of the image and improve the accuracy of subsequent segmentation tasks. However, superpixel segmentation may not be well-suited for COVID-19 lung lesion segmentation due to the variability of the lesions and the need for accurate segmentation of individual pixels.

Conventional machine learning approaches have consistently underperformed when confronted with CT image segmentation tasks that necessitate outstanding accuracy and efficiency. Traditional techniques, such as support vector machines, decision trees, and k-means clustering, generally require significant efforts in parameter tuning and feature engineering. This labor-intensive process consumes valuable time and resources and can result in models that are ill-equipped to generalize effectively to unseen data, potentially compromising their applicability in real-world clinical settings. Furthermore, traditional methods often struggle to handle the inherent complexity and variability of medical images, which can manifest in a multitude of forms, such as noise, artifacts, and anatomical variations. This inability to effectively manage the intricacies of medical images frequently leads to suboptimal segmentation outcomes, which, in turn, can undermine the reliability of subsequent analyses and diagnostic decisions. Additionally, traditional machine learning methods frequently suffer from the curse of dimensionality, as they are challenged by high-dimensional data typically encountered in medical imaging applications. This limitation can exacerbate the difficulties associated with parameter tuning and feature engineering, ultimately hampering the model's performance and robustness.

In the context of COVID-19 lung lesion segmentation, these shortcomings of traditional methods become particularly concerning. Accurate and timely segmentation of lung lesions is crucial for informing clinical decisions, such as patient triage, treatment planning, and monitoring disease progression. Consequently, the limitations of conventional machine learning techniques necessitate the exploration of alternative, more advanced methodologies capable of overcoming these challenges.

3. Deep learning and CT image segmentation

Deep learning-based approaches have emerged as a powerful alternative to traditional machine learning techniques for CT image segmentation tasks. Deep learning methods, such as convolutional neural networks (CNNs) and U-Nets, have demonstrated an exceptional capacity to learn intricate image features and hierarchies automatically. This ability allows them to extract relevant information without the need for manual feature engineering, enabling more efficient adaptation to new and diverse data.

Moreover, deep learning models are inherently designed to manage high-dimensional data, making them well-suited for the complexities of medical imaging. These models can effectively process large-scale datasets, which are common in medical imaging applications, and exploit the wealth of information contained within to enhance their performance and robustness. As a result, deep learning-based methods can more effectively cope with the inherent complexity and variability of medical images, leading to improved segmentation outcomes. Another advantage of deep learning models is their capacity to incorporate and leverage transfer learning, which allows the models to be pretrained on vast amounts of data and fine-tuned on specific tasks. This characteristic can further enhance the models' accuracy and generalizability, outperforming traditional methods in both regards.

Therefore, deep learning-based approaches offer significant advantages over conventional machine learning techniques for CT image segmentation tasks, particularly in the critical context of COVID-19 lung lesion analysis. The innate capacity of deep learning models to learn complex image features, handle high-dimensional data, and adapt to diverse data sources make them a promising solution for accurately and efficiently segmenting lung lesions, ultimately supporting more informed clinical decisions and improved patient outcomes.

4. Dataset

The database utilized in this study is from the Kaggle COVID-19 CT Images Segmen-tation competition, with the original data sourced from medicalsegmentation.com. The dataset was compiled by two radiologists from Oslo, who have extensive experience in collecting and segmenting CT images.

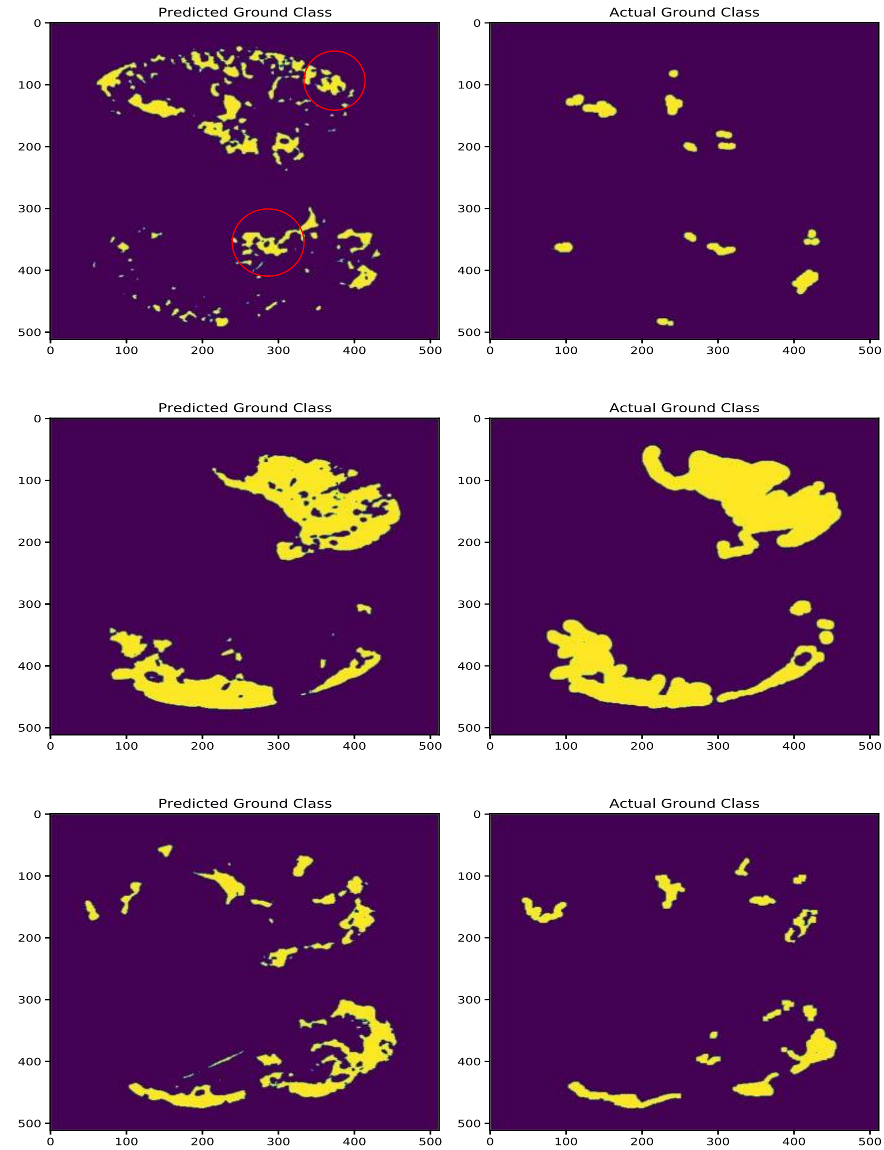
The dataset is divided into two parts: the Medseg part and the Radiopedia part. The Medseg portion contains 100 axial CT images from over 40 COVID-19 patients, which were converted from publicly accessible JPG images. The Radiopedia section includes nine segmented axial volumetric CT scans. The primary data used in this study is Medseg part, which consisting of 100 training images with a size of 512x512 pixels. We split this dataset into 5 test samples and 95 training samples. Covid-19 CT image segmentation contains four segmentation tasks, namely Mask for Ground Glass class, Mask for Consolidation class, Mask for Lungs Other class, Mask for Background Class. We have performed image segmentation for all four segmentation tasks, and only the segmented image for one of them is shown here.

5. Model

In this study, we developed an enhanced U-Net model with several improvements [13]. First, we streamlined the model by removing redundant crops, which not only reduced computational complexity but also improved efficiency [14,15]. Second, we simplified the model by decreasing the number of epochs, resulting in faster training while maintaining performance [16]. Third, we expanded the model's architecture by increasing the number of layers from the original four-layer model to a five-layer model. This enhancement allowed for additional convolution and pooling operations, which significantly improved the model's capability to capture and learn complex features in the data. Overall, these improvements not only make the model more efficient but also enhance its accuracy and effectiveness in segmenting medical images. We set batch size to 1, select 'adam' as the optimizer, and set the learning rate to 0.001 and epoch to 40.

6. Results

The comparative analysis presented in Figure.1 clearly demonstrates that the simplified U-Net model trained for 40 epochs achieves superior segmentation quality compared to the model trained for 100 epochs. In addition, our enhanced 5-layer model outperforms the original 4-layer model in terms of segmentation accuracy. As shown in the red circle in the Figure.1, the predicted image generated by the improved U-Net model exhibits clearer lesion pixels and more prominent lesion locations. This leads to a more comprehensive segmentation contour and a more complete segmentation area. Our results demonstrate that our proposed model significantly enhances the quality and accuracy of medical image segmentation, which can benefit clinicians in accurately diagnosing and treating patients.



Layer=4, Epoch=100
(a)

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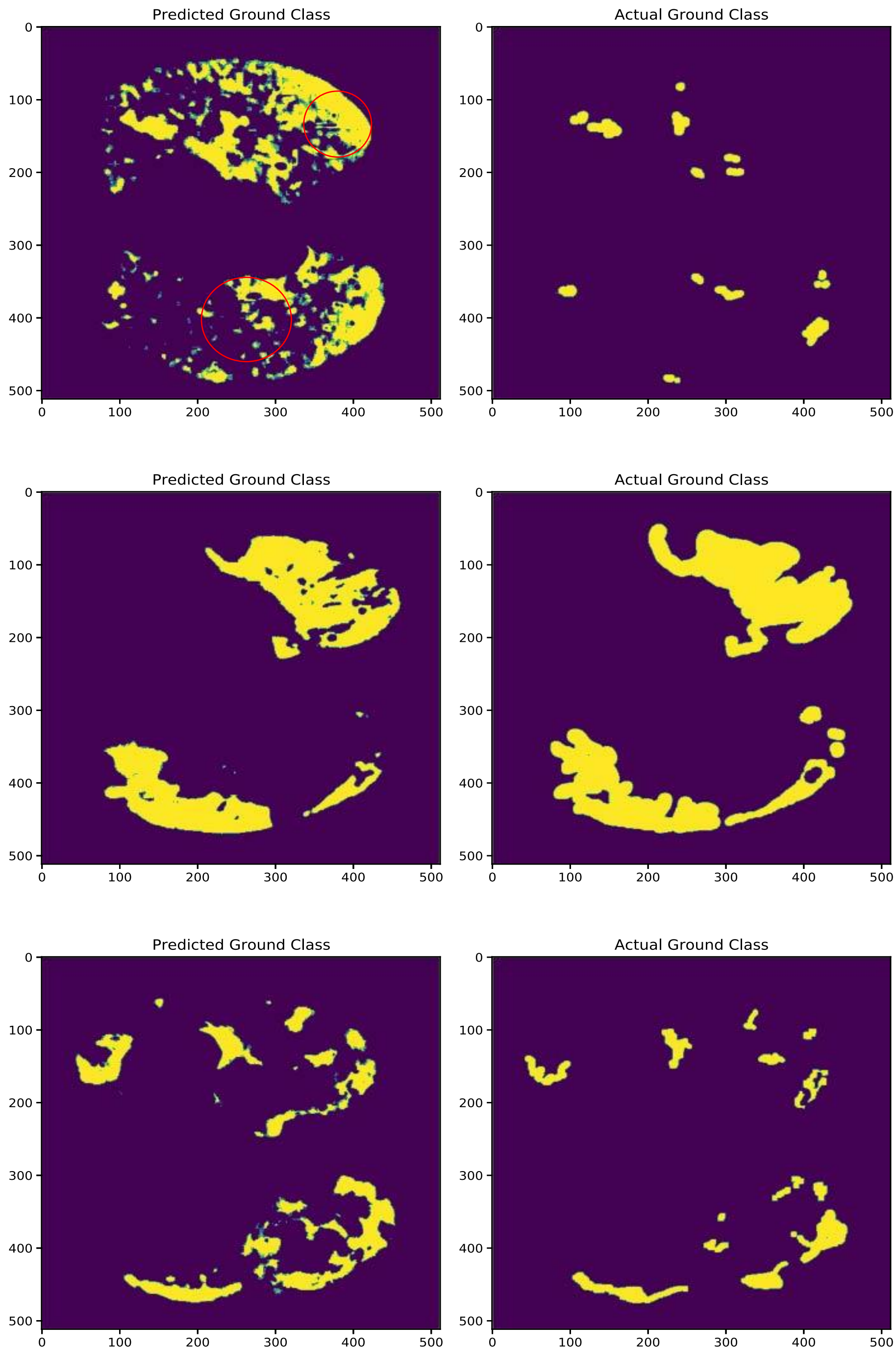
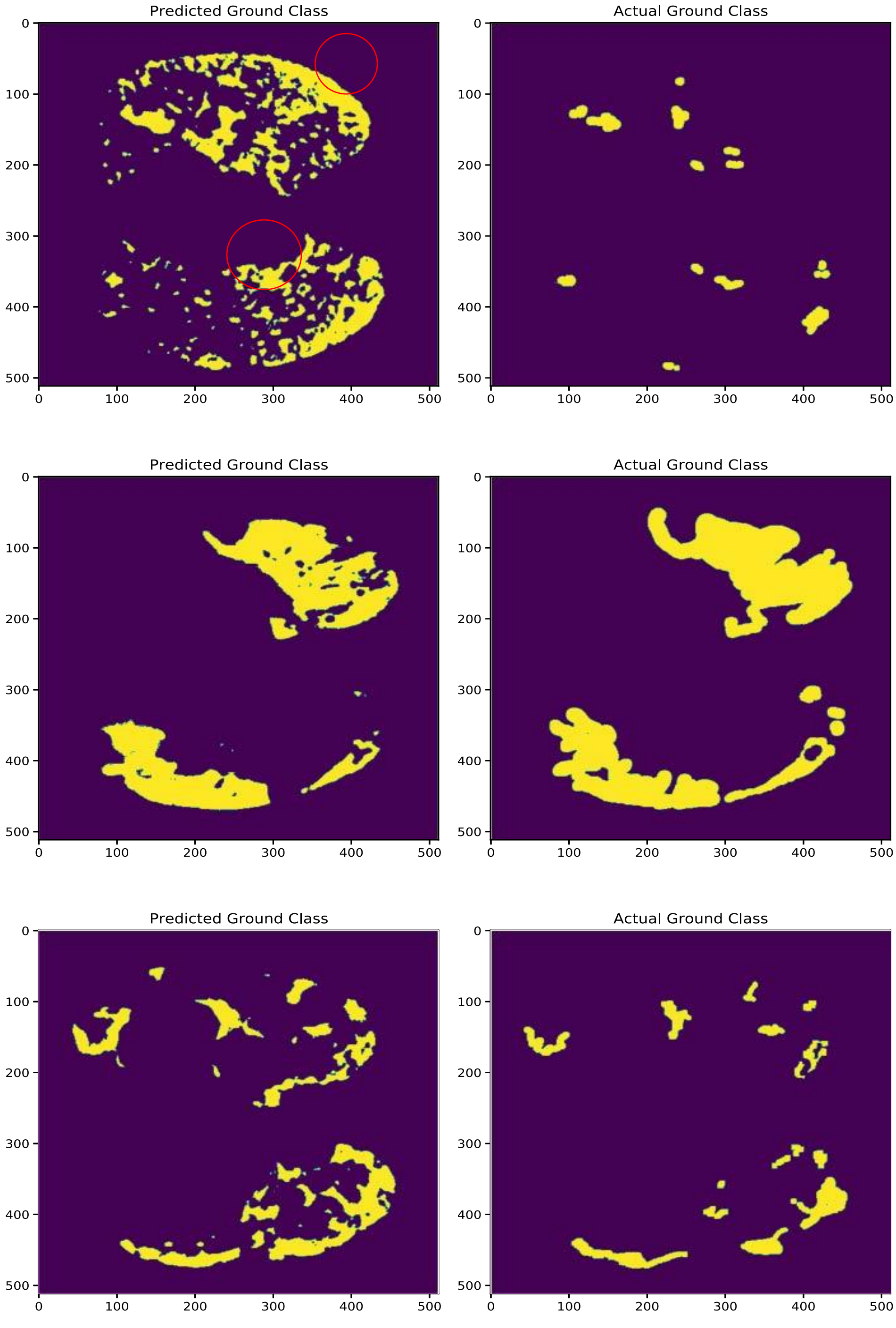
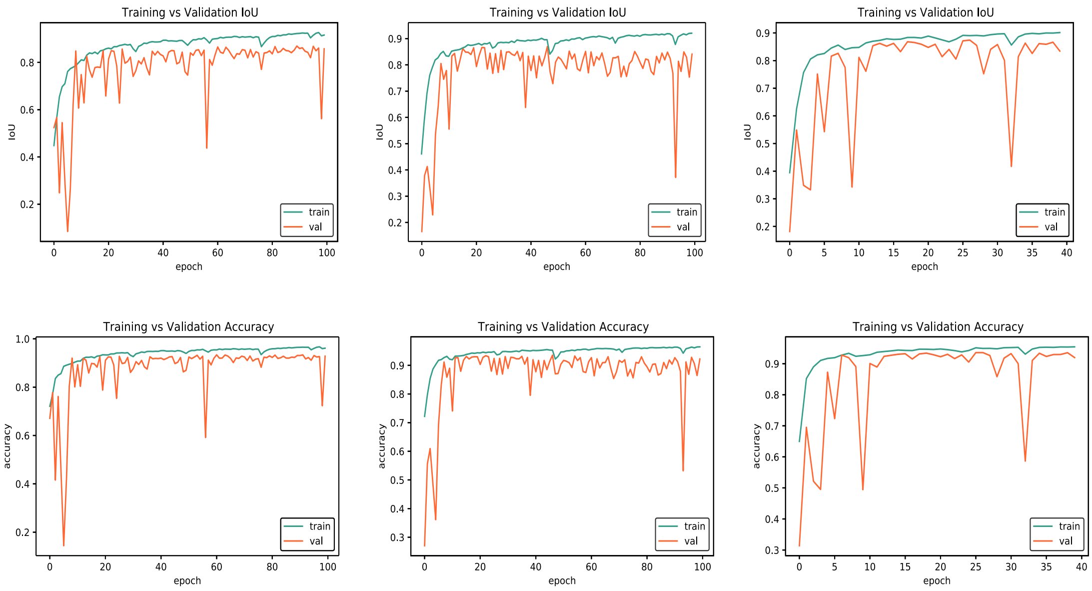


Layer=5, Epoch=100
(b)



Layer=5, Epoch=40
(c)

Figure 1. (a-c) Predicted ground class and Actual ground class of size 512x512 pixels generated by segmenting the image using different U-net models.



Layer=4 Epoch=100 Layer=5 Epoch=100 Layer=5 Epoch=40

Figure 2. IoU [17,18] line chart (top row) for training and validation and accuracy line chart (bottom row) for training and validation.

Based on Figure.2, it can be observed that the training accuracy of the four-layer model exhibits a consistent increasing trend after 100 epochs, while the validation accuracy shows multiple troughs with relatively small differences as the number of epochs increases. As for the five-layer model, its training accuracy also increases as the number of epochs increases, but the accuracy curve displays more fluctuations and more troughs in the first 100 epochs. The training accuracy of the five-layer model with 40 epochs is similar to that of the five-layer model with 100 epochs, but after 40 epochs, it starts to decrease and the validation accuracy has fewer valleys. The trends of training and validation changes for each model shown in the IoU images are consistent with those observed in the accuracy images, indicating that the five-layer model trained with 40 epochs performs better.

Despite the improvements made, the refined U-Net model still has some limitations. It has difficulty accurately segmenting certain CT images, which may be due to its limited ability to capture complex features in the data. In addition, the dataset used in this study is characterized by a small sample size, low data volume, and inadequate sample coverage, which may hinder comprehensive analysis. Furthermore, the quality of the segmented images could be further improved.

7. Conclusion

The enhanced U-Net model has significantly contributed to the segmentation of COVID-19 lung lesions in CT images, providing clearer segmentation results and making it easier to observe the location of the affected areas. This improvement is crucial for timely and accurate diagnosis, ultimately aiding in effective patient management.

Despite the notable successes of the proposed model, there remains considerable scope for further refinement and enhancement. In future research, several strategies can be explored to boost the model's performance and robustness, particularly in the context of CT image segmentation.

One promising avenue to consider is the implementation of data augmentation techniques. These methods can be employed to introduce image noise, artificially enlarge the dataset, and diversify the training data [19]. By exposing the model to a broader range of input variations, data augmentation can help improve the model's generalization capabilities and overall robustness, ultimately leading to more accurate segmentation outcomes.

Transfer learning is another powerful technique that could be leveraged to enhance the improved U-Net model [20–22]. By identifying and exploiting similarities between the source and target domains of various CT image segmentation tasks, transfer learning allows for the efficient reuse of knowledge gained from one domain to improve performance in another. This process involves quantifying the similarities between domains and employing learning strategies to maximize these similarities for the purpose of refining the U-Net model. The integration of transfer learning can significantly accelerate the model's training process and improve its ability to adapt to new and diverse datasets, thereby making it a valuable asset for CT image segmentation.

Another potential approach to consider is the incorporation of a convolutional network discriminator to evaluate the segmented images produced by the U-Net model. This discriminator can act as a quality control mechanism, assisting in the identification of the precise location of lesions and improving the overall accuracy of the segmentation process. The integration of a discriminator can also encourage the model to generate more realistic and high-quality segmentations, which may ultimately contribute to better diagnostic and prognostic outcomes.

By exploring and implementing these strategies, the improved U-Net model could become an even more indispensable tool in the diagnosis and management of COVID-19 and other diseases that require accurate CT image segmentation. The ongoing refinement of such models not only holds promise for enhancing the efficiency and accuracy of medical imaging analysis but also for improving patient care and outcomes in the face of complex and rapidly evolving health challenges.

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