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Review and analysis of COVID-19 lung lesion segmentation technique and algorithms

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***Abstract*---**COVID-19 is a rapidly spreading disease over the world, yet hospital resources are limited. A recent COVID-19 study reveals that CT imaging can be used to detect disease progression and aid diagnosis, as well as to better understand the disease. Many new studies suggest that deep learning could be used to swiftly and effectively detect COVID-19 in chest CT scans. The problem of automatically segmenting the lungs in CT scans of individuals with confirmed or suspected COVID-19 is intriguing. CT chest scan images allow us to analyze and categorize COVID-19's normal and abnormal properties in a comprehensive way. Segmenting and detecting suspicious areas in the images is done by the platform, which then assesses these regions to get an accurate categorization. Deep learning models can benefit from broad receptive fields that can learn contextual information and COVID-19 infection-related features for more accurate segmentation results. Deep learning models. More than 1800 annotated CT slices were used to construct and evaluate LungINFseg. For this purpose, we tested LungINFseg against 13 current deep learning-based segmentation techniques.

***Keywords*---**COVID-19, lung disease, CT imaging.

Introduction

A new disease caused by SARS-CoV-2 has been plaguing the world since December 2019, causing asthma symptoms, respiratory failure, and potentially long-term lung changes in people of all ages. This sickness was initially recorded in Wuhan, Hubei Province, China, and quickly spread throughout the world. Shortness of breath, diarrhoea, coughing, sore throat, headaches, and fever are all frequent COVID-19 symptoms. Patients may have a loss of taste, nasal

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obstruction, loss of smell, pains, and fatigue. The World Health Organization (WHO) designated the new infectious disease caused by the virus Coronavirus Disease 2019 (COVID-19), In addition, the International Committee on Taxonomy of Viruses designated the coronavirus as SARS-CoV-2 (SARS (ICTV).

Ground glass opacity, crazy paving pattern, and consolidation have all been found in early-stage research investigations on coronavirus disease 2019 (COVID-19) patients' chest CT images (Pan et al., 2020; Revel et al., 2020). Despite the fact that various lesion forms are not specific to COVID19, their presence, location, and extent are linked to different stages of the illness and likely outcomes. The European Society of Radiology (ESR) and the European Society of Thoracic Imaging (ESTI) both agree that (ESTI) ,Early-stage illness is associated with ground-glass opacity with a predominant peripheral, basal, and subpleural location, whereas crazy paving pattern is related with more advanced disease, and consolidation is associated with a poorer prognosis in elderly patients (Revel et al., 2020; Salehi et al., 2020; Ye et al., 2020).

Due to the COVID-19 epidemic, the health-care system has recently faced significant hurdles in terms of maintaining an ever-increasing number of patients and accompanying costs. As a result, COVID-19's recent impact requires a mental shift in the health-care sector. The development of intelligent and autonomous health-care solutions is becoming increasingly dependent on current technology, such as artificial intelligence. Unlike other viruses, COVID-19's rapid dissemination allowed it to become a global pandemic in record time. Medical and health care systems are still investigating and analyzing this critical issue of rapid proliferation in order to have a better handle on it.Modellingg COVID-19's propagation in the fight against it is a top priority. A RTPCR test, which identifies viral RNA in sputum or a nasopharyngeal swab in real-time, is the most often used diagnostic test. However, these tests involve a human connection, have a poor positive rate at the early stages of infection, and may take as long as 6 hours to provide results. When long-term lockdowns are lifted, extensive testing should be carried out to ensure that the pandemic does not recur.

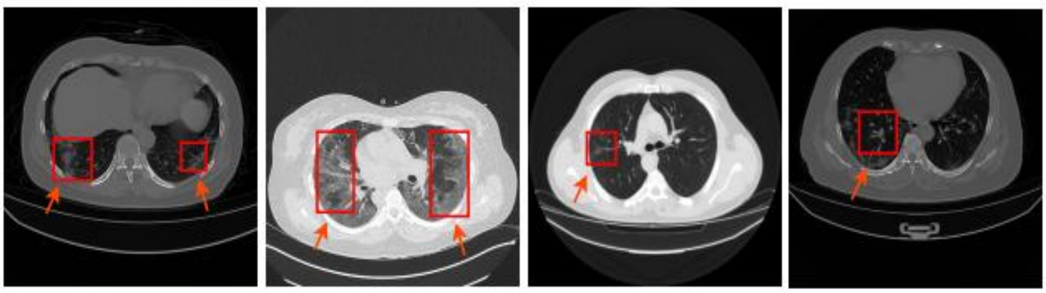

Figure 1. CT images in the chest show four distinct cases of COVID-19 (COVID-19 infection is highlighted by red boxes)

It is challenging for radiologists to analyze all CT images to identify COVID-19's important imaging characteristics because of the vast number of infections that occur every day. In order to accurately segment COVID-19 infection in chest CT scans at the lung level, automated procedures are needed. Figure 1 displays the results of four COVID19 chest CT scans. In COVID-19 CT images, ground-glass and consolidations can be seen. The accuracy of automated lobe segmentation systems can be hampered by these artefacts and pathological alterations. The radiologist can use computer-aided diagnostic (CAD) technologies to identify the COVID-19 infection in lung CT images. CAD technologies are needed to train less experienced radiologists on a new disease, COVID-19. To accurately divide the infected lung area from a CT scan, CAD technologies are essential.

The most frequent approaches to enhance the depth of a CNN's receptive field are to perform pooling operations, increase the size of filters, and increase the depth of the network. When the network or filter size or depth is expanded, the computational cost rises rapidly, and pooling processes cause data loss. Dilated convolution can be used to extend the receptive fields of CNNs without incurring any computational costs by adding zeros to the filters. COVID-19 infection in CT scans of the lungs can be segmented using the deep learning-based LungINFseg algorithm, is available to address the concerns stated above. For the RFA module, we introduce the receptive field-aware (RFA).which may widen a segmentation model's receptive field and boost the model's learning ability without sacrificing information.

Review of Literature

Vivek Kumar Singh, Vi To overcome the issues raised above, COVID-19 infection may be segmented from lung CT images using LungINFseg, a deep learning-based approach It is possible to increase a segmentation model's receptive field and its ability to learn without compromising any information by using the receptive-field aware (RFA) module. Receptive field expansion (RFA) is made up of COVID-19-related layers of convolution, dilated group convolution, frequency domain information acquired by discrete wavelet transform (DWT), Attention mechanisms that improve COVID-19-related properties are included.

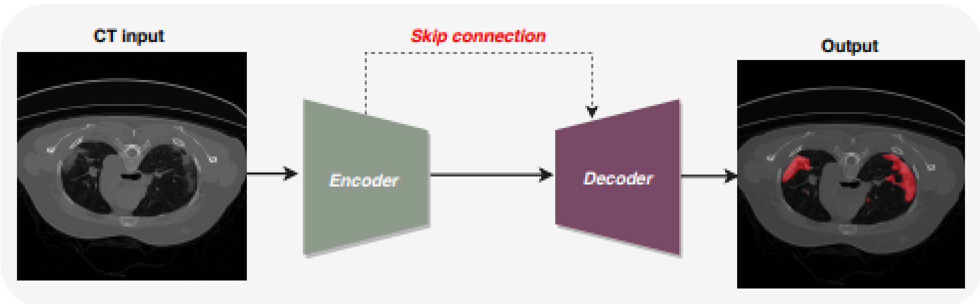

Figure 2.1. Framework of proposed LungINFseg

The suggested LungINFseg model's framework, which includes encoder and decoder networks, is shown in Figure 2.1. LungINFseg takes CT scans as input and generates binary masks that show diseased areas. A decoder block receives the encoder block's characteristics to maintain the spatial information in the encoder block.

Tilborghs Sofie (2020) CT chest scans from confirmed or probable COVID-19 patients present an intriguing challenge in terms of automatically segmenting abnormalities in the lungs. Deep learning algorithms, which include both open-source and in-house techniques, are evaluated using a dataset from many centres. Combining diverse strategies increases overall test set performance, according to the mean Dice scores of 0.982, 0.724, and 0.470 for binary lesion segmentation, multi-class lesion segmentation, and lung segmentation, respectively. There was a mean absolute volume error of 91.3 ml in the segmentation of binary lesions.

He goes by the name RaminRanjbarzadeh (2021) A substantial epidemic of the disease has occurred in both men and women since the COVID-19 pandemic began .Detecting lung infections and their borders from medical imaging can have a significant impact on COVID-19. Using lung CT scan images is one of the simplest techniques to diagnose patients. Detecting and segmenting diseased tissues from CT slices is difficult because of similar neighbouring tissues, fuzzy borders, and unpredictability. To get around these problems, we've developed a convolutional neural network with two paths. (CNN)

Table 1. All the benchmarked algorithms and their segmentation tasks described here

Method	Lung segmentation	Binary lesion segmentation	Multiclass lesion segmentation
JoHof (Hofmanninger et al., 2020)[11,16]	✓		
DMLu	✓		
DMLo	✓		
CTA (Chen et al., 2020) [12]	✓	✓	
CovidENet (Chassagnon et al., 2020) [13]		✓	
2DS		✓	
InfNet (Fan et al., 2020) [14]		✓	✓
DMmc			✓
2DRnx			✓
WASS	✓	✓	✓
UNWM	✓	✓	✓
MAJ	✓	✓	✓

for identifying and categorizing COVID-19 infection from CT images using global and local variables extracted from the images. Each pixel in the picture is divided into healthy and diseased tissues. In Figure 2.2, you can see our algorithm.

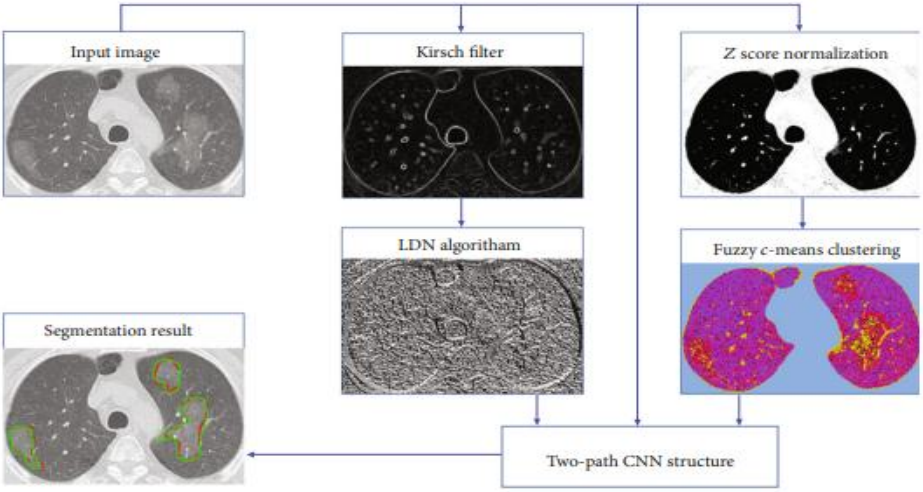

Figure 2.2: The suggested pipeline for segmenting diseased tissues is depicted in this diagram.Hussein Kaheel(2021) By studying CT chest scan pictures, we present a platform that encompasses investigation of COVID-19's normal and abnormal properties in various levels of detail. Segmenting and detecting suspicious areas in the images is done by the platform, which then assesses these regions to get the accurate categorization. After selecting the most appropriate module for our research, we additionally incorporate AI techniques. Finally, we compare our architecture's efficacy to that of other solutions described in the literature. According to the findings, the recommended architecture is 95 percent accurate.

Daryl L. X. Fung(2021), COVID-19 diagnosis should be made as quickly as possible. Two-stage deep learning approach is proposed to identify COVID-19 lesions (consolidation and ground-glass opacity) from chest CT images. Computer vision techniques such as generative adversarial picture inpainting, focus loss, and lookahead optimization are included in the proposed deep learning model The model's performance was evaluated using two real-world datasets and compared to previous comparable attempts. To better understand the clinical and biological origins of the projected lesion segments, we extract specific characteristics from the predicted lung lesions. As part of statistical mediation analysis, their impacts on the link between COVID-19 severity, underlying diseases, and age are assessed.

Mohamed AbdElaziz, 2021; Mohamed AbdElaziz, 2022; Mohamed AbdElaziz The suggested image segmentation approach relies on the use of a generalized extreme value (GEV) distribution to improve density peaks clustering (DPC). The DPC is a faster and more stable clustering approach than previous methods. However, without visualization, determining the ideal number of clustering centres is challenging. Because of this, GEV is used to determine the appropriate threshold value for identifying the optimal number of cluster centres, which greatly enhances the segmentation process.

A series of twelve COVID-19 CT images is used to test the suggested model. It was also compared to classic kmeans and DPC methods, and it outperformed them on numerous metrics, including PSNR, SSIM, and Entropy. In the Arab world, Adel Oulefki is a well-known figure (2021) These photos will be used to develop and evaluate an automated method for identifying COVID-19 Lung Infection. More efficient and flexible than existing segmentation algorithms like GraphCut, our end-to-end learning method for CT image segmentation with picture augmentation. Medical Image Segmentation (MIS), and Watershed, according to extensive computer simulations. More than 275 positive COVID-19 CT scans were used in experiments, as well as additional data from the El-BAYANE Center for Radiology and Medical Imaging in Cairo. There is a significant improvement in the mean values for accuracy and sensitivity compared to the methods described above, with F-measure values of 0.98, precision values of 0.57, and specificity values of 0.99, all of which are better than the methods described above. This method is more reliable, accurate, and straightforward than the previous one.

Lu Huang (2020), Between January 1 and February 3, 2020, 19 individuals who received a chest CT were evaluated retrospectively. Patients were given one of four levels of severity based on their initial clinical, laboratory, and CT findings: mild, moderate, severe, or critical. Automatic quantification of the CT lung opacification percentages of the entire lung and five lobes was done using commercial deep learning software.The four clinical kinds were also evaluated in terms of longitudinal changes in the CT quantitative measure.

The name of AdnanSaood (2021) SegNet and U-NET are two well-known deep learning networks that can be used for image tissue classification. In contrast to SegNet, U-NET focuses on medical segmentation. binary and multi-class segments were utilized to identify infected lung tissue and identify the type of infection present in the lungs. To train each network, each network is provided with 72 data photographs, which are then validated and tested using 10 images. For the outcomes, several statistical scores are produced and summarized. The name of TaherehJavaheri (2021) Covid-19, a highly contagious and difficult-to-treat Coronavirus Disease, merged in the United States in 2019. The earlier identification of Covid-19 is vital in order to limit the development of the disease and its related deaths. Covid-19 detection in both outpatient

and inpatient settings is currently based on reverse transcriptase-polymerase chain reaction (RT-PCR) (RT-PCR). Even though the RT-PCR approach is a time-saving method, its detection accuracy is just 70–75 percent. Computed tomography (CT) imaging is another approved method. CT imaging has a much better sensitivity (80–98 percent) than MRI (70 percent), although the accuracy is similar. An open-source system, CovidCTNet, was developed to improve CT imaging detection accuracy by using a set of deep learning algorithms to effectively identify Covid-19 from CAP and other lung illnesses.

Table 2: Comparison of segmentation results of infected tissue using our model to the findings of three recently disclosed structures quantitatively. For example, these metrics include RVD (relative volume difference), ASD (average surface distance) and MSD (mean surface distance) (MSD)

Approach	ASD (mm)	VOE(%)	RVD(%)	MSD(mm)	RMS(mm)
DenseNet201[19]	5:4±0:3	11:4±7:3	−4:2±5:9	23:6±7:1	5:9±0:4

Weaklysuperviseddeeplearning[20]	5:1±0:4	11±7:3	7:8±10:3	21±6:6	5:5±0:7
Weaklysupervisedframework[21]	6:1±0:6	11:7±4:2	8:3±6:6	22:7±5:2	5:8±0:5
ProposedCNN	6:3±0:5	11:9±6:8	−5:8±3:5	21:3±6:1	5:7±0:4
ProposedCNN+LDN	5:1±0:1	8:3±4:7	6:5±4:1	15:4±4:8	4:7±0:2
ProposedCNN+fuzzy*c*-means	5:5:3±0:4	8:9±5:2	−6:9±7:3	16:5±4:9	5:2±0:5
ProposedCNN+fuzzy*c*-means+LDN	2:8±0:3	5:6±1:2	3:7±5:6	7:4±7:3	3:6±0:2

Comparative Study of Deep Learning Methods

For COVID-19, deep learning algorithms are being applied to chest CT scans in a fresh and fast-growing area of research CT scans from COVID-19 patients have been used in more than 90% of earlier research to train machine learning algorithms for automated diagnosis, which is the process of discriminating between participants with and without the condition (Shi et al., 2020; Dong et al., 2020).

Slice-by-slice lung segmentation may be taught to a 2D UNet utilizing a variety of datasets from diverse diseases, according to Hofmanninger and colleagues (2020). A git repository entry recently said that their approach might be used to data from COVID-19 chest CTs, even though it wasn't originally designed for this purpose. Patients with COVID-19 who had expected total lesion segmentation and other clinical features were able to predict short-term prognosis. Binary lesion segmentation algorithms are unable to distinguish among various categories of lesions when it comes to classification. COVID-19 development and severity are linked to the type of lesion in radiological literature (Revel et al., 2020).

Multiple-class COVID-19 lesion segmentation is supported. The goal of automatic multiclass COVID-19 lesion segmentation methods is to anticipate a mask for numerous classes of lesions at the same time. Each method helps to distinguish between different kinds of lesions. At the time of this writing, the most clinically significant types of lesions to diagnose and quantify are ground-glass opacity, consolidation, and crazy paving patterns.

Table 3. Covid-19 categorization methods using CT scans were compared

Author	Characteristics	Algorithm	Result (AUC, Sensitivity, Specificity)	# of evaluatedpatients (#of images)
Javaheri et al. [22]	Image preprocessing using U-net	BCDU-Net and Perlin noise exposure; CNN	91% , 92% , 99.9%	336 (16,751)
Bai et al.[23]	Lung segmentation based on HU	EfficientNet B4;CNN	86%,88% , 85%	1185 (132,582)
Mei et	Lung segmentation	ResNet-18;	91% ,	904 (unknown)

al.[24]	and clinical data were used to create a combined model.	CNN; SVM; Random Forest; MLP	83.3%, 81.8%	
Li et al.[25]	Image preprocessing using U-net	Resnet50; CNN	97%, 91% , 97%	3321 (4357)
Zhang et al.[26]	Lung segmentation and clinical data were used to create a combined model. U-net, DRUNET, FCN, SegNet and DeepLabv3-based lung segmentation	3D Resnet-18; CNN	96%, 91% , 86%	4153 (617,776)

Conclusion

A growing number of research propose employing deep learning to deliver quick and reliable COVID-19 assessment by chest CT. Using a multi-center dataset, we have provided the first systematic comparison of various deep learning techniques for CT segmentation. Comparative analysis of seven in-house and four open-source deep learning algorithms (Table 1). Lesion mask structure verified ground truth (GT) is required for the segmentation quality measures: the reference manual segmentation can only be provided by a medical practitioner. The imaging properties of COVID-19 lesions are equivalent to those of other types of pneumonia. We were unable to locate any cases of viral pneumonia for the sake of comparison because there was no scientific proof of the aetiology in each of these cases. In the future, we want to gather chest CT scans from diverse types of lesions across multiple institutions and countries in order to widen the validation of the technique. Medical image analysis is critical for identifying disorders, and there are some preliminary phases in the image analysis process that must be completed, such as image segmentation. Using segmentation algorithms in medical imaging, it is possible to identify and isolate the area of interest (ROI). In light of the COVID-19 epidemic, it is more critical than ever to identify efficient segmentation methodologies that can aid in the diagnosing process. Our suggested method's robustness and generalizability have been demonstrated through a series of sensitivity assessments. Additionally, the clinical implications of the computational GGO aspect of the study are explored.

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