IFERP

ISSN (Online) 2394-6849

International Journal of Engineering Research in Electronics and Communication Engineering (IJERECE)

Vol 11, Issue 11, November 2024

Review of Segmentation Techniques in Coronavirus Disease-2019 Computer Tomography Images

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Abstract*— Coronavirus (COVID-19) has been widely transmitting around worldwide since December 2019 and this sudden outbreak has affected the normal life cycle and caused many casualties. Computed Tomography (CT) has an important role in diagnosing the disease in the field of healthcare and therefore CT imaging models are developed and deployed for efficient diagnosis. COVID-19 detection and segmentation models are developed using Deep learning and machine learning methods and are still in research. This paper addresses the insights obtained from several research articles focusing on various learning approaches, and their advantages, with the datasets used in the methods for segmentation and identification of COVID-19 CT data. The limitations of existing methods that need to be overcome with the aid of detection and segmentation procedures are discusses. To enhance the accuracy and efficiency, the models still have some clinical implications, complexity, limited data, need advanced algorithms, and so on which needs to be improved in further research. This study provides good insight for conducting more efficient identification and segmentation analysis of COVID-19 images.

***Index Terms*— Deep learning, Lung segmentation, COVID-19, Transfer learning, Computed Tomography.**

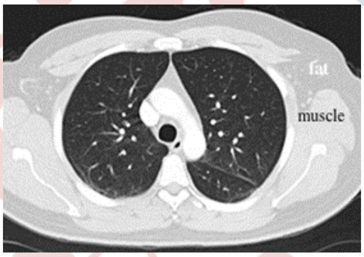
I. INTRODUCTION

COVID-19 has been predominantly transmitted around the world changing the lives of billions of people and causes severe pneumonia that can lead to death [2]. SARS-CoV-2 and novel coronavirus (nCoV) are infectious diseases caused by a new virus that was first transmitted in December 2019 leading to an outbreak in successive months. Respiratory sickness is caused with signs like cold, fever, and critical cases feels difficult to breathe and there is no specifically approved treatment for this virus so far [5]. The virus takes approximately 14 days to reveal its signs. The common examination for identifying COVID-19 is Reverse transcription-polymerase Chain Reaction (RT-PCR) but due to their high cost, most of the hospitals and countries do not provide enough of these tests to their patients [6]. Therefore, to lessen the spread of this threat, rapid and accurate testing is extremely important with prompt recognition and patient quarantine [8]. Because of the insufficient testing kits, and delayed testing cycles, CT can be applied in the initial screening process instead of RT-PCR [7]. However, without experienced radiologists, analyzing CT images is a great concern in remote areas and so a computer-based tool is needed to improve the performance for dealing with many patients [14]. To support rapid diagnosis of medical imaging-based COVID-19, efforts are made for creating artificial intelligence (AI) models [9]. However only using machine learning methods such as traditional statistical learning methods or image processing techniques, it is a challenge to model the right computer-aided technique for dealing with the complex features of pneumonia lesions [15]. Most of these models neglect the direct clinical stage assessment while focusing on the quantitative measurement for lesion regions, only a few models incorporated the knowledge of discrimination and feature extraction process [12]. However, most of the machine learning tasks only. optimize a single criterion or solve a single task which limits their potential to learn and represent all necessary information present in the datasets effectively. Multi-task learning models have been introduced to overcome the limitation, which can learn or optimize multiple cost functions simultaneously [19]. Recent research revealed that the deep convolutional neural networks (CNNs) could surpass medical experts' performance in various image detection tasks such as brain tumor detection, lung pathology screening, skin lesion classification, and breast cancer detection. Bio-medical image analysis has become an important domain for the identification of COVID-19, and various research has been conducted for the detection using DL analysis. Hence, it is reasonable to implement severity prediction and lung lobe segmentation together [20]. The survey aims to interpret the segmentation methods used in COVID-19 CT images. In this survey, 25 research articles were analyzed mainly focusing on the methodology, limitations, datasets used, and their results using various Deep learning (DL) and machine learning (ML) approaches such as ResNet, U-Net, CHS-Net, SegNet, and so on, their limitations, and datasets in COVID-19 CT images. This survey provides insight into the segmentation methods and provides an overview for the researchers to overcome the research gaps in the existing approaches and to develop more efficient and sustainable models in the future.

A. Diagnosis of COVID19 from CT Images

Alveoli are harmed by Covid 19 directly, which affects the lungs (tiny air sacs). The purpose of the alveolus is to supply the blood vessels with oxygen. The red blood cells receive their oxygen from these blood veins or capillaries (Red blood cells). Ultimately, the red blood cells (RBCs) supply oxygen to every single organ in the body. Additionally, the internal organs' inability to operate properly due to a lack of oxygen causes a deficiency in the body. The inclusion criteria for diagnosis of COVID 19 included: 1. Pharyngeal swabs tested positive for SARS-CoV-2 by RT-PCR. 2. Individuals admitted for isolation or therapy. 3. C-Reactive Protein Level in Blood Test May Indicate COVID-19 Risk. 4. a thin-section CT scan of the chest that reveals any pneumonia symptoms.

Serial CT examinations may be beneficial for tracking the progression of the disease and ensuring prompt therapy because COVID-19 exhibited recognizable CT characteristics during the course of the disease. Patchy ground glass opacities (GGOs), with a predominately peripheral distribution under the pleura and along the bronchovascular bundles, are the distinguishing feature of COVID-19. These GGOs may merge into dense, consolidative lesions. The number of lesions may develop quickly as the disease worsens and spread to central regions, more frequently affecting the left lower lobe than the right upper/middle and right lobes. The following characteristics of CT findings were examined: location, distribution, size, and type. Location related to the various lobes and involved segments. The lung's outer third was described as peripheral, the interior two-thirds as central, or both as peripheral and central. The lung pulmonary window had dimensions of 1500 Hounsfield units (HU) in breadth and -700 HU in level.



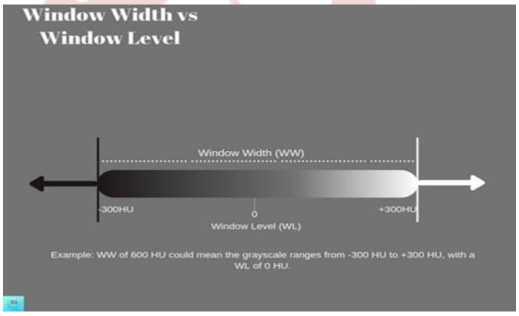


Fig. 1.1 Window Width Vs Window Level

The CT grading approach suggested by Camiciottoli was used to determine the severity of pulmonary fibrosis. There were two components to the scoring system: one for the type of lesion and the other for the extent of the lesions. The maximum score was 30. Groundglass opacities, linear opacities, interlobular septal thickening, reticulation, honeycombing, and bronchiectasis were the different types of lesions, and they were given scores of 1, 2, 3, 4, and 5, accordingly. Whether a lesion type was identified in 1, 3, 4, 9, or more than 9 lung segments—which were rated as 1, 2, and 3, respectively—determined how extensive it was. India categorizes the severity score into three categories: mild (score < 7), moderate (score 7 to 18), and severe (score >18).

II. TAXONOMY OF RELATED WORK

The taxonomy diagram represents the COVID-19 CT image segmentation utilizing various learning approaches such as Transfer learning, Deep learning, Multi-task learning, and other techniques, which are shown in Figure 1.

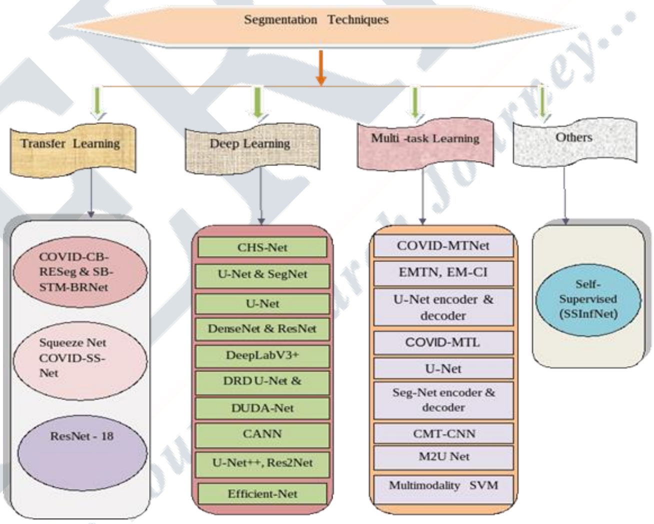


Figure. 1 Taxonomy diagram of Segmentation techniques

III. TRANSFER LEARNING METHODS

Saddam Hussain Khan, et al, [13] implemented Channel boosted deep segmentation (COVID-CB-RESeg), Squeeze and boosted dilated split transform merge (SB-STM-BRNet) which detected even small changes and analyzed COVID-19 infection. The model made use of the textural variations and homogenous regions in images that helped to differentiate the infected regions from healthy regions. However, the dataset was not augmented which reduced the efficacy and reliability.

N.B. Prakash, et al, [25] presented the COVID-19 Super pixel SqueezNet (COVID-SSNet) framework for enhancing image diagnostic values for improved output which segmented the infected regions and localized them for precise detection. The model performed superpixel segmentation of activation maps that extracted the areas that carried the image traits and constructed an extend of lung X-ray inputs with the extracted regions. However, the segmentation of infections from other regions was limited and the model increased computational complexity.

Sakshi Ahuja, et al, [12] introduced Residual Network (ResNet 18), a deep transfer learning approach with a here-phase methodology that classified the slices into non-COVID and COVID. The three-phase detection model improved the accuracy and detection in terms of data augmentation, localization of abnormality, and identification utilizing the pre-trained CNN. The model detected COVID-19 infections in the images of lung rapidly and accurately but the model was not implemented on a wider set of COVID positive CT scans.

IV. DEEP LEARNING METHODS

Narendar Singh Punn and Sonali Agarwal, [1] implemented a Hierarchial Segmentation network (CHS-Net), an automated Deep Learning method that worked as a semantic segmenter and identified infected regions in the medical images using two cascaded residual attention models. The Segmentation loss function employed to train the method known as dice loss and binary cross entropy loss that penalized fake negative and positive detections. However, the technique had some limitations such as the inaccurate segmentation results and the architecture needed to be tuned with other DL components.

Adnan saood and Iyad Hatem [2] proposed two DL methods, a Convolutional neural network U-Net and Segmentation network (Seg-Net) that classified and segmented lung tissues with the highest mean accuracy. To discriminate both healthy and infected lung tissue, both networks were exploited as multi-class segmenters and binary segmenters that learned the type of infection. Seg-Net classified infected and non-infected regions but the image size in the dataset was small.

Athanasios Voulodimos , et al [4] modeled U-Net that segmented the affected areas in the input images helped in the better detection of positive cases. The network structures are reconfigured and the framework trusted the input data while ignoring the existing information. Results indicate improved segmentation accuracy while utilizing the validation outputs of various classifiers however it was implemented on a single DL model.

Yazan Qiblawey, et al [9] presented DenseNet and ResNet, a cascaded system for segmenting the lung, localizing, quantifying, and detecting infections from CT images that reliably localized infected regions of various sizes and shapes even considering smaller infected regions discriminated the levels of severity. The model achieved detection performance with high sensitivity and specificity. However, the model exhibited poor segmentation performance and needed further improvements.

Hasan Polat [15] implemented DeepLabV3+, a redesigned convolutional neural network (CNN) that applied three different tasks for segmentation and evaluation. The first task represented binary segmentation, the second one represented multi-class segmentation, and the third task represented a separate class for each lesion segmentation. The average Dice similarity coefficient (DSC) results demonstrated robust performance in detection. However, modifications were needed on the various parameters of DeepLabV3+.

Dilation, Residual and Dense block (DRD U-Net), and combined Wasserstein Generative adversial network (WGAN) were presented at [22] Luoyu Lian, et al, partitioned lung infections that improved the ability to reuse the feature and segment the target with smaller samples. The WGAN model effectively solved the issue of multi-classification differentiating COVID-19 cases, normal subjects, and pneumonia cases but had a low accuracy in data classification.

Feng Xie [24] implemented Double U shaped dilated attention network (DUDA-Net), a lesion partitioning network that focused on better quantitative information which strengthened the segmentation ability in subtle regions. The model was depending on U-Net backbone and to obtain the lung areas, a coarse segmentation network was created, for the precise segmentation, the network's segmentation ability was improved by the dilated convolutional attention (DCA), but DUDA-Net had a higher complexity in computation.

Mouna Afif, et al, [6] presented a Context Aggregation Neural Network (CANN) that segmented and analyzed CT images and had three models. Attention mix model (AMM), Context fuse model (CFM), and a Residual convolutional model (RCM). The model detected the two main areas, consolidation area, and ground glass opacity in images with a better dice score and accuracy but the construction module was not fully automated so 3D screening results were not obtained.

Zhidan Li, et al [11] introduced U-Net++ and Res2Net for the fine examination of infection in 3D CT scans that segmented lung and lesions together, and the classification accuracy was improved by combining the clinical metadata. The model had sufficient data for segmentation but failed to exhibit a better progressive stage performance.

Efficient-Net was modeled at [23] Vinayakumar Ravi, et al, ensembled meta-classifier and DL feature fusion approach that extracted features from EfficientNet layers, and the dimensionality was reduced using principle component analysis (PCA) and merged the extracted features. The model exhibited higher accuracy and precision in classification but there was no interpretive rationale for selecting the Support vector machine (SVM), and random forest in the stack classifier for using in the initial process and considering logistic regression in the next level.

V. MULTI-TASK LEARNING (MTL)

Md Zahangir Alom, et al [5] designed COVID-MTNet that identified COVID-19 cases faster and more effectively using CT scans and X-ray, and also a quantitative analysis strategy was implemented that determined the percentage of infected regions in medical images. The model was efficient in

ISSN (Online) 2394-6849
International Journal of Engineering Research in Electronics and Communication Engineering (IJERECE)
Vol 11, Issue 11, November 2024

detecting and localizing the infected regions however the limited samples of affected subjects reduced the accuracy and robustness.

Minglei Li, et al [14] implemented EMTN, and EM-CI that diagnosed and segmented lesions in CT images simultaneously and the model learned task-related features with weights and provided excellent results with coordination between both tasks. EMTN also gave the patient status for the auxiliary diagnosis with the severity levels and lung infection rate but it required human oversight and more complete information for detection.

Shirin Kordnoori, et al, [17] introduced U-Net which automatically segmented and classified Covid-19 infection with lung CT scans. The framework included a common decoder, encoder, and a multi-layer perceptron that evaluated three data with the influence of image dimension on the results, resulting in high accuracy in both classification and segmentation. The model represented higher results than other models but the input images were not enhanced by the image enhancement algorithms.

COVID-MTL was presented at [20] by Guoqing Bao, et al, an end-to-end automated learning model that simultaneously detected infection along with the severity assessment through a random-weighted loss function. The model also identified high throughput features of lung images and was able to improve the workflow of diagnosis but the unsupervised approaches were not identified with lung imaging features.

Shirin Kordnoori, et al [18] modeled U-Net that addressed the segmentation and classification tasks for COVID-19 identification. The framework comprised a decoder, encoder, and a perceptron with multiple levels for representation, classification, and segmentation. Combination of median filter preprocessing and U-Net yielded impressive results with high accuracy but the evaluation was limited to specific datasets that reduced the general applicability of the findings to different populations.

Omar Elharrouss, et al [10] introduced SegNet, a decoder and encoder-based technique that segmented infections in the lung on input images, and multiple class of segmentation was performed using two-stream inputs that allowed reduction in the limitation of labeled data. The multiple-input network allowed the framework to study from various traits for improving the segmentation output but segmentation was performed on a limited amount of labeled data.

A contrastive multi-learning approach based on a Convolutional Neural network (CMT-CNN) was presented by Jinpeng Li, et al [16] that composed of two tasks, which differentiated COVID-19 infection from other types of lung diseases and the contrastive loss encouraged the local aggregation. The model also predicted invariant transformations and preserved the diffusing properties of data where unseen samples are generalized however, the model needed effective algorithms for long-tail data set problems.

Kelei He, et al [19] implemented a Multi-task Multi-instance deep network (M2UNet) that jointly performed multi-instance classification and segmentation of the lung lobes. Every input image was represented by a bag that dealt with critical problems. The severity was related to the local affected areas and the method exhibited higher accuracy than any other traditional techniques. However, the model needed independent testing data for the generalization of input images.

Multi-task multi-modality SVM was implemented by Rongyao Hu, et al, [21] to distinguish critical patients from the less affected patients and also predicted the transformation time from less affected to critical. A unified framework was analyzed that explored the High Dimension and Low Sample Size (HDLSS), the difference, and so on. Dealt with interpretability issues and HDLSS at the same time but the local infection changes were not accurately measured.

Overall analysis based on segmentation of COVID-19 CT images

Transfer Learning Method

The diagnosis framework was not extended for multi-class challenges such as bacterial and viral pneumonia, COVID-19, and other types of lung infections. At different stages of COVID-19, the model fluctuated in learning infectious patterns and failed to retain infected regions. COVID-SS-Net did not investigate any sign of infection in the areas segmented and also the combinations of appearances that happened in the CXR images. The important issue of COVID-19 management, severity analysis was not dealt in this method. The Residual network had more layers that increased the complexity and required a larger input image. Due to the large number of layers the time consumption was higher in the network.

Deep Learning Method

The model exhibited a low performance and also the architecture was not tuned with other DL components. The CHS-Net model was limited to specific applications and not applied to other approaches concerning biomedical image segmentation. Few-shot learning was used by the U-Net model but it was not combined with other deep learning methods or learning models such as the concept of transformers and had computational complexity. The DenseNet and ResNet models used different window levels for different datasets while the image features were not considered for all datasets and the segmentation process needed more improvements. The classification accuracy of the model needed improvements and had a low accuracy as well as the characteristics of the U-Net structures in the model were not enhanced. DUDA-Net had a complex structure that reduced the efficiency and segmentation and required more data for multi-category segmentation for COVID-19 lesions. The CANN model was not evaluated in real-world conditions and had a high time complexity. The accuracy of the system was lower and required different compression techniques for a lighter version. The performance of the model in the progressive stage was low and the categories were not balanced, so the stage-assessing datasets need to be extended. Low performance in segmenting the lesions of COVID-19 CT images. The Efficient-Net method did not evaluate the misclassification rate of real-time COVID-19 data and was limited in handling imbalanced datasets. Data imbalance approaches were needed to improve the performance of imbalance handling.

Multi-task Learning (MTL)

The model was trained on limited samples and needs to be tested with more data. The scarcity of labeled samples provided false positive detections as output and also the accuracy and robustness were low. The proposed model EMTN and EM-CI had limited labeled datasets and the interpretability of diagnosis methods was low. The model also required human oversight and was limited in clear complete information. The U-Net model did not utilize image enhancement algorithms that decreased the quality of the input while pre-processing the data. Complexity of the network was also higher and the performance effects of the algorithms were not highlighted. Chest CT scans were not utilized in the COVID-MTL model and the unsupervised diagnosis techniques along with the detected lung imaging features were not explored. The model's performance was low and needed cross-continental information for further validation. The U-Net model does not integrate other image processing algorithms or advanced DL techniques for classification and segmentation. Disease progression and treatment response were not evaluated; further new image processing algorithms were needed for enhanced performance. The model used limited data for training reduced the obtained results and also for multi-class segmentation the availability of labeled data was low. Computer vision features like structure and texture components were not used for the extraction process. The CMT-CNN method was not evaluated in localization under the weakly supervised settings and normal settings. The samples were limited and unevenly distributed for appropriate discrimination of pneumonia and effective algorithms were needed for solving long-tail dataset problems. The success and failure information of the lung CT image analysis and the PCR examination of the same patients were not evaluated in the self-supervised SSInfNet model.

VI. CONCLUSION

This study investigated different approaches such as MTL, ML, and DL implemented for identifying, classifying, and segmenting COVID-19 CT data. The research also analyzed various segmentation methods, datasets utilized, and computational sources. In this survey, the preprocessing techniques, lung segmentation, lesion segmentation, and feature extraction process were investigated. The complexity, limited samples of COVID-19-affected CT scans along with the requirement of enhanced algorithms were challenging for implementing the model. Image enhancement algorithms were not applied in the U-Net multi-task learning models. Moreover, ML and MTL have certain other limitations such as the overfitting or underfitting of data and high error susceptibility. Out of all the approaches, Deep learning methods exhibited higher accuracy, and precision in detection and segmentation. The future works will be focused on implementing enhanced algorithms and training the method on a larger dataset in real-world conditions as well as enhancing the precision of segmentation approaches.

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