COVID Pneumonia Severity Detection of Chest CT-Scan Images based on Robust Semantic Segmentation

BAYAN ALSAAIDAH
Department of Computer Science,
Al-Balqa Applied University,
JORDAN

Abstract: - Image segmentation has steadily grown especially for clinical usage and disease recognition in radiological research. This procedure, aimed at acquiring quantitative measurements, strives to distinguish regions or objects of interest from adjacent body tissues. To be more specific, it entails measuring the area and volume of segmented structures to extract more refined diagnostic information. The main hurdles encountered by segmentation algorithms originate from challenges like variations in intensity, artifacts, and the close juxtaposition of diverse soft tissues in the grayscale. In this paper, a robust semantic segmentation is proposed to specify the infected regions of lung images and consider the severity degree of the pneumonia caused by COVID-19 disease. The proposed model provides an accurate diagnosis of the chest CT scan image with satisfied performance with 93% accuracy and the second most important metric which is the Jaccard Index with 0.746±0.09 shows higher prediction performance than most existing systems in the literature.

Key-Words: - CT-Scan, Chest images, COVID-19, Segmentation, Severity, Pneumonia.

Received: September 9, 2023. Revised: February 17, 2024. Accepted: March 19, 2024. Published: May 28, 2024.

1 Introduction

Since 2019, COVID-19 has caused a global emergency of the public health, [1] and over the whole world. Coronavirus (COVID) is an infectious disease that hits the lung cells and spreads rapidly from animals and easily among humans, [2].

The COVID-19 pandemic has prompted unheard-of hazards to public fitness, the worldwide economic system, and so on [3]. In this extreme situation, fast control of the spread of COVID-19 is especially crucial. Detection of the infected cells indicates the degree of severity of this infection.

In order to stop the COVID-19 virus from spreading, early diagnosis is essential. Chest computed tomography (CT) imaging is easier to use in a clinical context and provides more sensitive COVID-19 screening than RT-PCR, [4]. Additionally, the research community has been paying more and more attention to CT imaging, [5], with efforts being made to investigate the pathological alterations caused by COVID-19 from a radiological perspective.

Conventional manual or semi-automatic segmentation methods take a lot of time and need the assistance of medical professionals. Furthermore, there is a tendency for the segmentation results to favor the expertise of the expert. Thus, in a clinical situation, automatic segmentation of lung infections is highly desired. Considerable efforts have been made in this direction, [6].

In order to determine the source, location, and severity of the illness, patients with pneumonia or breathing problems according to an infection of the respiratory tract should receive treatment at hospitals where they were subjected to a variety of diagnostic procedures, including laboratory and non-laboratory tests.

The laboratory tests include common procedures such as CBC test, pleural effusion, and blood gas analysis tests, [7], which needs hospital and laboratory procedures. On the other side, non-laboratory testing consists of computer-aided imagery analysis methods used for CT scans or digital chest radiography, which are used to examine the lung regions.

The benefit of a CT scan, a non-destructive scanning method, it offers a highly detailed picture of the lung's fine tissues, bone, and blood vessels, [7]. Cost-effective, widely available, rapid frequent scanning process, ideal spatial resolution with contemporary multi-slice scanners, and high sensitivity present the most significant advantages of CT imaging. The drawbacks consist of Poorer soft tissue contrast in comparison to radiation exposure from MRIs and X-rays, [8].

Image segmentation has generally gained importance in radiological and medical research for diagnosis purposes. Segmentation attempts to isolate interest areas or objects from the other parts of the image so that quantitative measurements can be taken. More accurately, quantifying segmented structures' volume and area to obtain more diagnostic information. The main challenges in using segmentation algorithms are proximity, artifacts, and intensity heterogeneity in the grey scale of different soft tissues.

Numerous methods have been used to segment the lung, including hybrid, rule-based, atlas-based, manual, and machine learning-based approaches, [9], [10], [11]. It is tedious work and takes a long time to segment data manually, especially when the health system is overburdened.

Integrating AI with medical expertise can assist the healthcare system by offering automated COVID-19 diagnosis solutions capable of handling numerous cases more quickly. Additionally, utilizing AI in COVID-19 diagnosis can decrease the need for human involvement, thereby enhancing social distancing measures crucial for limiting the spread of infection, [12]. Deep learning has been actively used recently to segment COVID-19 lung infections using different network architectures including U-Net which is the most popular in a lot of works ,[13], [14], [15], [16].

In addition, a noise-robust framework was presented for COVID-19 pneumonia lesion segmentation, utilizing a mean absolute error loss in addition to a noise-robust Dice loss. Deep learning models require a substantial quantity of labeled training data, which is difficult to ensure for the segmentation of COVID-19 infections, particularly in the early stages of the illness. The outcomes of this study demonstrated that the COPLE-Net outperformed the most advanced CNNs in medical image segmentation, and the suggested LNR-Dice outperformed existing noise-robust loss functions, [17].

Authors in [18], proposed a segmentation algorithm for lung infection known as LobeNet with the goal of predicting the regions of the left and right lungs in the event of consolidations and diffuse abnormalities. A Dice coefficient of 0.985 was found to be the average for the model evaluation performance of LobeNet on 87 patients.

One of the most popular image segmentation architectures is the U-Net architecture, which was used for COVID-19 lung segmentation in different studies such as 3D U-Net for lung areas segmentation combined with a cross-validation scheme which is applied to avoid any expected overfitting, [19]. The proposed study results indicate that the proposed deep learning algorithms performed satisfactorily, based on the false-positive and the false-negative ratios compared with the other published results in the literature.

The obtained segmentation performance was 0.956 and 0.761 for normal and infected. A similar analysis was carried out by [20] where the Dice Similarity Coefficient (DSC), sensitivity, and specificity were 0.950, 0.920, and 0.875. According to [21], SegNet and U-Net exceeded 90% accuracy.

Researchers in [22], demonstrated the usefulness of an automated tool for measuring and segmenting COVID-19 lung infections using chest CT scan data utilizing a combination of parametric stitching algorithms, linear and logarithmic. The proposed methodology Dice, Sensitivity, Specificity, and Precision were 0.714, 0.733, 0.994, and 0.739 respectively.

COVID-19 was automatically detected using the segmented CT slices by [23] using the Infection Segmentation Deep Network (Inf-Net). To increase COVID-19 prediction sensitivity, authors in [24] created a dual-branch network that combined segmentation and classification for defective areas of CT chest images. A highly accurate CT image segmentation network (COVID-SegNet) was presented by [25] to segment COVID-19 lesions. Enhanced features were combined with several scales which is known as COVID-SegNet. To segment infected regions from CT images and identify COVID-19, authors in [26] developed a CNN model called Anam-Net with fewer parameters which is simpler than U-Net.

This study looked into the automated lung segmentation from chest CT images for COVID-19 cases using deep learning. For normal and COVID-19 datasets, the suggested method produced very promising results, with DSC 0.980. Accurate diagnosis of COVID-19 patients with measurable values such as severity based on defected area will be facilitated by dependable lung segmentation, which will also help with lesion segmentation, [27].

A novel, two-stage cross-domain transfer learning framework was proposed by [28] to accurately segment lung infections of lung CT-scan images. The proposed framework is divided into two main innovations: a new transfer learning with two stages and an effective deep learning model for infection segmentation called nCoVSegNet. In particular, nCoVSegNet aims to address the problems associated with poor contrast at boundaries and high variance of the infected tissues by conducting efficient infection segmentation while utilizing large receptive fields and attention-aware feature fusion.

Due to the severe abnormalities of the infected lung, it becomes difficult to distinguish between the lung cells and the chest bone. This is especially evident when comparing them to normal patients. The accurate diagnosis and monitoring of COVID-19 pneumonia infection in CT-scan images acquiring a substantial set of high-quality annotations proves challenging. Addressing this challenge, we suggest a new noise-robust framework designed to learn from more easily attainable, albeit noisy, training labels for the segmentation task.

2 Materials

CT scans show great potential for offering precise, rapid, and cost-effective screening and testing for COVID-19. CT-based methods for COVID-19 prediction have primarily used different methods to extract features and combine them, while in chest X-ray research, only a few studies have used transfer learning for classifying CT images, [29]. The COVID-19 dataset employed in this study was sourced from [30] and has been confirmed by a senior radiologist in Tongji Hospital, Wuhan, China, encompassing a comprehensive collection of 216 patients. Data were diligently gathered over a period spanning from January to April 2020 to capture the evolving dynamics of the COVID-19 pandemic, ensuring a representative snapshot during the study duration as shown in Figure 1. Various data types were included in the dataset, covering COVID CT, Non-COVID CT, data split, and Clinical information (such as patient ID, patient information, and others).

In total, the dataset comprises 349 images, each representing a distinct case of COVID-19, providing a robust foundation for statistical analysis and model development. Prior to analysis, the dataset underwent preprocessing steps, addressing challenges such as missing values and standardization of formats. Key features encompass patient demographics, comorbidities, symptom onset dates, and regional attributes, offering a comprehensive view of the COVID-19 cases under consideration.

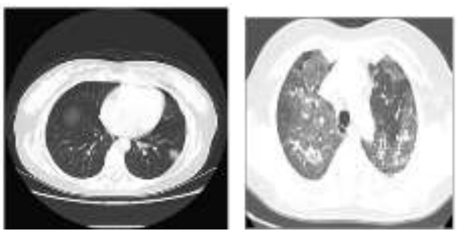

Fig. 1: Examples of lung CT images with COVID-19

Ethical considerations were rigorously observed, with all patient data anonymized, and the study protocol received approval from the Tongji Hospital, Wuhan, China. Acknowledging potential limitations, the dataset may be subject to reporting biases, variations in testing rates, and incomplete demographic information in certain cases. For machine learning model development, the dataset was randomly partitioned into training (80%), validation (10%), and test (10%) sets.

3 Method

Semantic segmentation of lung images involves classifying each pixel in the image into predefined categories, such as normal lung tissue, abnormalities, or specific structures. In this work, a semantic segmentation procedure is used to segment the infected tissues and then identify the severity degree based on the size of the segmented area. Figure 2 shows the general structure of the proposed methodology.

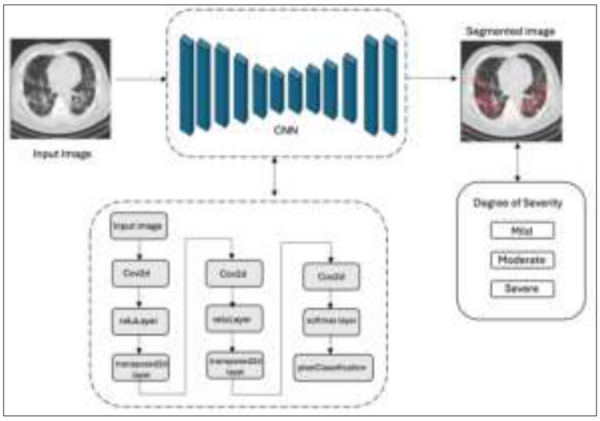

Fig. 2: General structure of the system

Semantic segmentation is a computer vision task that involves classifying each pixel in an image into a category. Unlike classification, which assigns a single label to the entire image, semantic segmentation labels each pixel with a corresponding class label. This technique is commonly used in various applications, such as object recognition, medical image analysis, and image editing.

Semantic segmentation is typically performed using deep learning models, especially convolutional neural networks (CNNs). These models learn to map input images to pixel-wise class labels through a process called convolution, where the network learns features at different spatial hierarchies.

The output of a semantic segmentation model is a segmented image, where each pixel is assigned a color corresponding to its predicted class. This can be useful in various applications. For example, in autonomous driving, semantic segmentation can help a vehicle understand the layout of the road and identify obstacles and pedestrians. In medical imaging, it can help in the detection and analysis of tumors or other abnormalities in scans.

The training set of CT images is labeled using the image labeler toolbox to label each pixel of the image where every pixel in an image is given a label by semantic segmentation. Only the infected cells are labeled in order to compute the infected area to identify the severity degree of pneumonia.

The input images with their labels are provided to the convolution neural network based on dilated convolutions. U-Net, [31], is an important deep-learning network with a broad range of applications that was primarily created for comprehending and classifying medical images. Semantic segmentation is a further application for this sort of network, which goes by the name U-Net due to its U-shaped encoder and decoder.

The U-Net encoder and decoder layers, respectively, carry out up-sampling and down sampling. The accompanying decoding layer receives the full feature map from the encoder. By combining the transferred feature map and the up-sampled feature map, the final feature map is generated. The U-Net architecture used in this study is shown in Figure 3 which shows the multi-channel feature map, the number of channels, and their size.

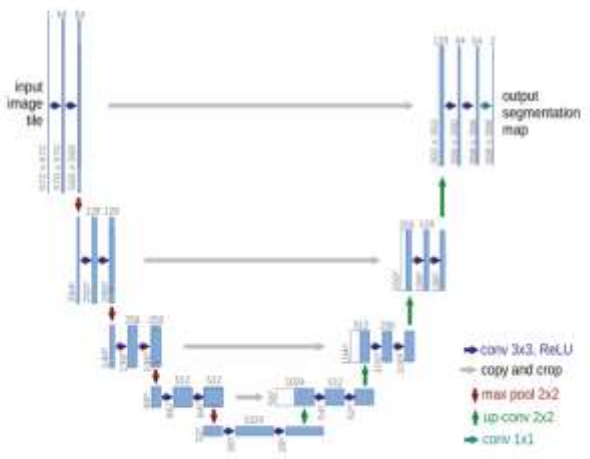

Fig. 3: U-net architecture, [29]

In this type of network, softmax layer comprises with the encoder and the decoder which are carried out repeatedly. ReLU activation, and 2x2 max-pooling2D are used two times in this network. The U-Net encoder down sampling process results in low-resolution feature maps, which may be improved to full-resolution feature maps by the U-Net decoder upsampling process.

Ten convolutional-2D layers with 3x3 filters, and four maxPooling2D layers with 2x2 windows are included in the U-Net encoder. ReLU (Rectified Linear Units) activations are also present. A ReLU layer applies each convolutional layer's output, element-by-element, to the function f (x) = max (0, x). By downsampling the input by a factor of two, the max-pooling process may be used to provide translation invariance for tiny spatial changes. Eight convolutional 2D layers with 3x3 filters and another ReLU, four convolutional 2D-transpose layers with 3x3 filters followed by one convolutional 2D layer with 1x1 filter which make up U-Net's decoder. For pixel-wise categorization, the decoder ends with a softmax layer.

In U-Net, the upsampling is provided by a concatenation of the convolutional 2D-transpose layer and convolutional 2D layers. The appropriately clipped feature map from the decoder is concatenated to create the upsampling layer. The last 1x1 convolutional-2D layer assigns the necessary number of classes to each 32-component feature vector.

The soft-max classifier that can be trained receives a high-dimensional representation of all features that are provided by the decoder output. This soft-max approach classifies each pixel independently. For pixel-wise classification, the decoder's high-dimensional dense feature maps are sent to the softmax layer.

Softmax layer creates probabilities for every class and classifies each pixel independently. The predicted segmentation corresponds to the class that has the highest probability at each pixel as shown below:

$$p_k(x) = \exp\big(a_k(x)\big) / (\sum_{k'=1}^{K} \exp(a_{k'}(x)))$$

Where $a_k(x)$ indicates the activation in feature channel k, and x is the pixel location inside the image.

After identifying the infected and the non-infected cells in the image, a simple calculation is carried out to recognize the severity degree of the lung pneumonia infection where the severity degree is recognizedrecognized into three levels: mild, moderate, and severe.

4 Results and Discussion

In order to evaluate the proposed segmentation and severity recognition model, several metrics have been measured such as accuracy, sensitivity, specificity, and dice coefficient (F). Besides the most important metric for segmentation is the Jaccard Index or the Mean Intersection-Over-Union (mIOU).

The following equations (1-6) present the metrics formulas that have been used for model evaluation:

$$Accuracy = \frac{TP + TN}{TN + TP + FN + FP} \quad (1)$$

$$Sensitivity = \frac{TP}{TP + FN} \quad (2)$$

$$Precision = \frac{TP}{TP + FP} \quad (3)$$

$$Specificity = \frac{TN}{TN + FP} \quad (4)$$

$$F1 = \frac{2TP}{2TP + FP + FN} \quad (5)$$

$$IOU = \frac{TP}{TP + FP + FN} \quad (6)$$

Where TP: True Positive, TN: True Negative, FP: False Positive, FN: False Negative. Table 1 summarizes the evaluation metrics of the proposed model.

Table 1. Evaluation metrics of the proposed model

Metric	Proposed segmentation model
Accuracy	0.926±0.00
Sensitivity	0.919±0.13
Specificity	0.938±0.15
Precision	0.842±0.08
F1	0.839±0.12
IOU	0.746±0.09

As shown in Table 1, the proposed segmentation shows a high performance for detecting the infected cells to recognise the level of the COVID-19 infection. The proposed model in [30] shows performance using U-Net 0.678, 0.836, 0.265, and 0.308 of Sensitivity, Specificity, Precision, and IOU respectively. The higher result of the proposed method may relate to the pre steps before training the model including clearing images, using high quality images, and tuning the network parameters.

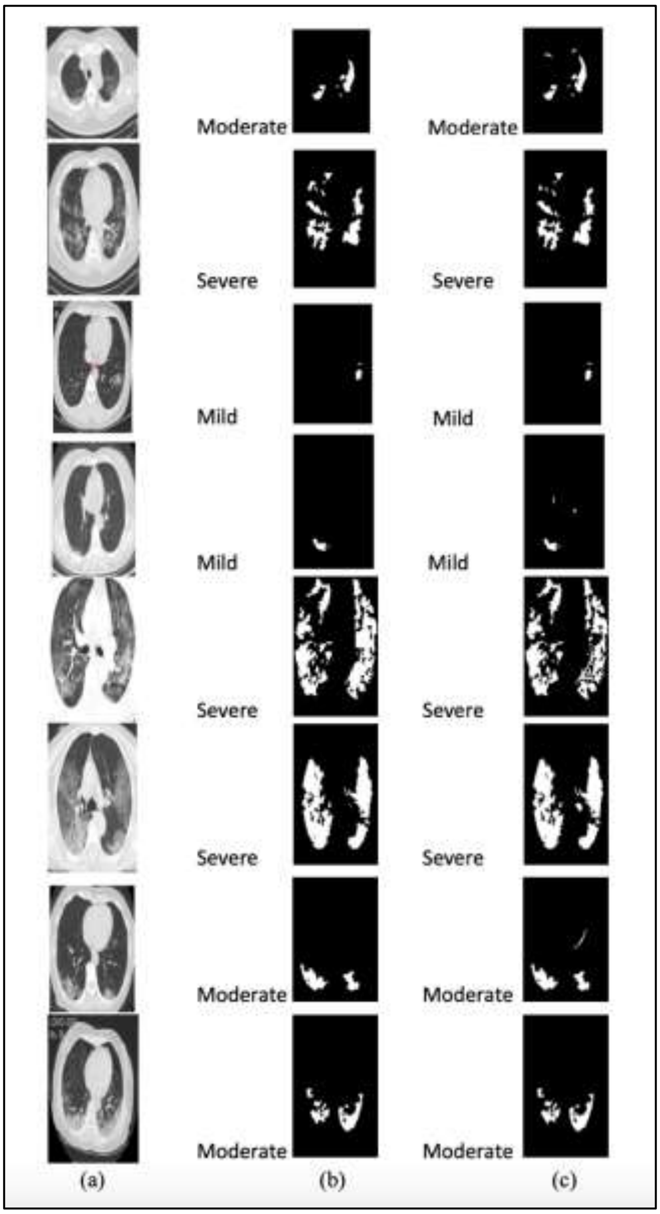

Fig. 4: Visual illustration of the proposed segmentation model (a): CT Image (b): Ground Truth (c): Segmentation and recognition result

Figure 4 shows some cases of lung infection recognition including the ground truth which has been recognized by an expert clinical biologist.

Figure 4 demonstrates a strong match between the ground truth and the proposed method result for infected lung tissue segmentation and recognition for COVID-19 CT-scan images testifying to the deep learning model's promising performance in infected cell detection and segmentation.

As shown in lung images there is a high similarity between the infected cells and the blood vessels, however, the model succeeded in recognizing using a robust deep learning network. Figure 4 depicts two cases where the model failed to accurately highlight the infected cells exactly as the ground truth which has not been affected by the severity degree of the diagnosis.

Due to the blood vessel and infection regions having comparable intensities, it is more difficult to accurately identify the infected cells, which makes the miss-segmentation more obvious in mild cases of COVID-19 patients.

Recently, an AI system aimed to develop and enhance an automatic intelligent system for classifying chest X-ray images to detect and identify the COVID-19 virus using machine learning into infected and normal, [32]. The concentration in this work is based on infected images only.

5 Conclusions

Segmentation is necessary for an accurate diagnosis and tracking of pneumonia lesions caused by COVID-19 in CT images. Although deep learning holds tremendous potential for automating this procedure, a substantial quantity of high-quality annotations is hard to come across. To overcome this challenge, a novel semantic segmentation and severity recognition framework is proposed to detect the severity level of COVID-19 after diagnosis of the infection. Overall, semantic segmentation is a powerful technique in computer vision that enables a detailed understanding of images at the pixel level, with numerous applications across different domains.

Adequate segmentation of the lungs is essential for determining the infected tissues and severity of COVID-19. Deep learning provides several types of networks that can be trained using labeled images in which the model detects the infected tissues to recognize the severity degree based on the infected area.

The proposed framework revealed encouraging findings in the segmentation of COVID-19 images of contaminated lung tissue. Nonetheless, there are some challenges related to this research that need to be addressed in further studies. One of these limitations is the nature of the CT-scan imaging which is carried out several times with several angles as slices, so in some slices, the image is recognized as mild, and in different slices for the same patient is recognized as moderate or severe. Moreover, to develop this work to be used in clinical practice the model should be integrated with another model that identifiesidentifies the image as infected or normal before using the proposed criteria to distinguish the level of the infection.

Acknowledgments:
Sincere gratitude to Dr. Haitham Azzam the head of the radiology department at Issra hospital in Jordan for his help in lung CT-scan image labeling and recognizing the severity level of the COVID-19 infection.

References:

[1] Lancet, T., 2020. *Emerging understandings of 2019-nCoV*. Lancet (London, England), 395(10221), p.311, DOI: 10.1016/S0140-6736(20)30186-0.

[2] Xu, J., Zhao, S., Teng, T., Abdalla, A.E., Zhu, W., Xie, L., Wang, Y. and Guo, X., 2020. Systematic comparison of two animal-to-human transmitted human coronaviruses: SARS-CoV-2 and SARS-CoV, *Viruses*, 12 (2), p.244, DOI: https://doi.org/10.3390/v12020244.

[3] Xiong, J., Lipsitz, O., Nasri, F., Lui, L.M., Gill, H., Phan, L., Chen-Li, D., Iacobucci, M., Ho, R., Majeed, A. and McIntyre, R.S., 2020. Impact of COVID-19 pandemic on mental health in the general population: A systematic review. *Journal of Affective Disorders*, 277, pp.55-64, https://doi.org/10.1016/j.jad.2020.08.001.

[4] Xie, X., Zhong, Z., Zhao, W., Zheng, C., Wang, F. and Liu, J., 2020. Chest CT for typical coronavirus disease 2019 (COVID-19) pneumonia: relationship to negative RT-PCR testing, *Radiology*, 296(2), pp. E41-E45, https://doi.org/10.1148/radiol.2020200343.

[5] Phelan, A.L., Katz, R. and Gostin, L.O., 2020. The novel coronavirus originating in Wuhan, China: challenges for global health governance. *Jama*, 323(8), pp.709-710, doi:10.1001/jama.2020.1097.

[6] Vaishya, R., Javaid, M., Khan, I.H. and Haleem, A., 2020. Artificial Intelligence (AI) applications for COVID-19 pandemic. *Diabetes & Metabolic Syndrome: Clinical Research & Reviews*, 14(4), pp.337-339, https://doi.org/10.1016/j.dsx.2020.04.012.

[7] Bhandary, A., Prabhu, G.A., Rajinikanth, V., Thanaraj, K.P., Satapathy, S.C., Robbins, D.E., Shasky, C., Zhang, Y.D., Tavares, J.M.R. and Raja, N.S.M., 2020. Deep-learning framework to detect lung abnormality–A study with chest X-Ray and lung CT scan images. *Pattern Recognition Letters*, 129, pp.271-278, https://doi.org/10.1016/j.patrec.2019.11.013.

Gu, Y., Kumar, V., Hall, L.O., Goldgof, D.B., Li, C.Y., Korn, R., Bendtsen, C., Velazquez, E.R., Dekker, A., Aerts, H. and Lambin, P., 2013. Automated delineation of lung tumors from CT images using a single click ensemble segmentation approach. *Pattern Recognition*, 46(3), pp.692-702, https://doi.org/10.1016/j.patcog.2012.10.005.

[8] Hofmanninger, J., Prayer, F., Pan, J., Röhrich, S., Prosch, H. and Langs, G., 2020. Automatic lung segmentation in routine imaging is primarily a data diversity problem, not a methodology problem. *European Radiology Experimental*, 4(1), pp.1-13, https://doi.org/10.1186/s41747-020-00173-2.

[9] Arabi, H. and Zaidi, H., 2017. Comparison of atlas-based techniques for whole-body bone segmentation. *Medical Image Analysis*, 36, pp.98-112, https://doi.org/10.1016/j.media.2016.11.003.

[10] Arabi, H. and Zaidi, H., 2016. Whole-body bone segmentation from MRI for PET/MRI attenuation correction using shape-based averaging. *Medical Physics*, 43(11), pp.5848-5861, https://doi.org/10.1118/1.4963809.

[11] Alsaaidah, B., Al-Hadidi, M.D.R., Al-Nsour, H., Masadeh, R. and AlZubi, N., 2022. Comprehensive survey of machine learning systems for COVID-19 detection. *Journal of Imaging*, 8(10), p.267, https://doi.org/10.3390/jimaging8100267.

[12] Zheng, C., Deng, X., Fu, Q., Zhou, Q., Feng, J., Ma, H., Liu, W. and Wang, X., 2020. *Deep learning-based detection for COVID-19 from chest CT using weak label*. MedRxiv, pp.2020-03, https://doi.org/10.1101/2020.03.12.20027185.

[13] Cao, Y., Xu, Z., Feng, J., Jin, C., Han, X., Wu, H. and Shi, H., 2020. Longitudinal assessment of COVID-19 using a deep learning–based quantitative CT pipeline: illustration of two cases. *Radiology: Cardiothoracic Imaging*, 2(2), p.e200082, https://doi.org/10.1148/ryct.2020200082.

[14] Jin, S., Wang, B., Xu, H., Luo, C., Wei, L., Zhao, W., Hou, X., Ma, W., Xu, Z., Zheng, Z. and Sun, W., 2020. *AI-assisted CT imaging analysis for COVID-19 screening: Building and deploying a medical AI system in four weeks*. MedRxiv, pp.2020-03, https://doi.org/10.1101/2020.03.19.20039354.

[15] Ronneberger, O., Fischer, P. and Brox, T., 2015. U-net: Convolutional networks for biomedical image segmentation. In Medical Image Computing and Computer-Assisted Intervention–MICCAI *2015: 18th International Conference*, Munich, Germany, October 5-9, 2015, Proceedings, Part III 18(pp. 234-241). Springer International Publishing. DOI: 10.1007/978-3-319-24574-4_28.

[16] Wang, G., Liu, X., Li, C., Xu, Z., Ruan, J., Zhu, H., Meng, T., Li, K., Huang, N. and Zhang, S., 2020. A noise-robust framework for automatic segmentation of COVID-19 pneumonia lesions from CT images. *IEEE Transactions on Medical Imaging*, 39(8), pp.2653-2663, DOI: 10.1109/TMI.2020.3000314.

[17] Gerard, S.E., Herrmann, J., Xin, Y., Martin, K.T., Rezoagli, E., Ippolito, D., Bellani, G., Cereda, M., Guo, J., Hoffman, E.A. and Kaczka, D.W., 2021. CT image segmentation for inflamed and fibrotic lungs using a multi-resolution convolutional neural network. *Scientific Reports*, 11(1), p.1455.

[18] Müller, D., Rey, I.S. and Kramer, F., 2020. Automated chest ct image segmentation of covid-19 lung infection based on 3d u-net. *Informatics in Medicine Unlocked*, (25) 2020, https://doi.org/10.1016/j.imu.2021.100681.

[19] Trivizakis, E., Tsiknakis, N., Vassalou, E.E., Papadakis, G.Z., Spandidos, D.A., Sarigiannis, D., Tsatsakis, A., Papanikolaou, N., Karantanas, A.H. and Marias, K., 2020. Advancing COVID-19 differentiation with a robust preprocessing and integration of multi-institutional open-repository computer tomography datasets for deep learning analysis. *Experimental and Therapeutic Medicine*, 20(5), https://doi.org/10.3892/etm.2020.9210.

[20] Saood, A. and Hatem, I., 2021. COVID-19 lung CT image segmentation using deep learning methods: U-Net versus SegNet. *BMC Medical Imaging*, 21(1), pp.1-10.

[21] Oulefki, A., Agaian, S., Trongtirakul, T. and Laouar, A.K., 2021. Automatic COVID-19 lung infected region segmentation and measurement using CT-scans images. *Pattern Recognition*, 114, p.107747, https://doi.org/10.1016/j.patcog.2020.107747.

[22] Fan, D.P., Zhou, T., Ji, G.P., Zhou, Y., Chen, G., Fu, H., Shen, J. and Shao, L., 2020. Inf-net: Automatic covid-19 lung infection segmentation from ct images. *IEEE Transactions on Medical Imaging*, 39(8),

pp.2626-2637, DOI: 10.1109/TMI.2020.2996645.

[23] Gao, K., Su, J., Jiang, Z., Zeng, L.L., Feng, Z., Shen, H., Rong, P., Xu, X., Qin, J., Yang, Y. and Wang, W., 2021. Dual-branch combination network (DCN): Towards accurate diagnosis and lesion segmentation of COVID-19 using CT images. *Medical Image Analysis*, 67, p.101836, https://doi.org/10.1016/j.media.2020.101836.

[24] Yan, Q., Wang, B., Gong, D., Luo, C., Zhao, W., Shen, J., Ai, J., Shi, Q., Zhang, Y., Jin, S. and Zhang, L., 2021. COVID-19 chest CT image segmentation network by multi-scale fusion and enhancement operations. *IEEE Transactions on Big Data*, 7(1), pp.13-24, DOI: 10.1109/TBDATA.2021.3056564.

[25] Paluru, N., Dayal, A., Jenssen, H.B., Sakinis, T., Cenkeramaddi, L.R., Prakash, J. and Yalavarthy, P.K., 2021. Anam-Net: Anamorphic depth embedding-based lightweight CNN for segmentation of anomalies in COVID-19 chest CT images. *IEEE Transactions on Neural Networks and Learning Systems*, 32(3), pp.932-946, DOI: 10.1109/TNNLS.2021.3054746.

[26] Gholamiankhah, F., Mostafapour, S., Goushbolagh, N.A., Shojaerazavi, S., Layegh, P., Tabatabaei, S.M. and Arabi, H., 2021. *Automated lung segmentation from CT images of normal and COVID-19 pneumonia patients*. arXiv preprint arXiv:2104.02042, https://doi.org/10.48550/arXiv.2104.02042.

[27] Liu, J., Dong, B., Wang, S., Cui, H., Fan, D.P., Ma, J. and Chen, G., 2021. COVID-19 lung infection segmentation with a novel two-stage cross-domain transfer learning framework. *Medical Image Analysis*, 74, p.102205, https://doi.org/10.1016/j.media.2021.102205.

[28] Karthik, R., Menaka, R., Hariharan, M. and Kathiresan, G.S., 2022. Ai for COVID-19 detection from radiographs: Incisive analysis of state of the art techniques, key challenges and future directions. *IRBM*, 43(5), pp.486-510, https://doi.org/10.1016/j.irbm.2021.07.002.

[29] Zhao, J., Zhang, Y., He, X. and Xie, P., 2020. Covid-ct-dataset: a ct scan dataset about covid-19. arXiv preprint v(1) arXiv:2003.13865, 490(10.48550), https://arxiv.org/abs/2003.13865v1.

[30] Ronneberger, O., Fischer, P. and Brox, T., 2015. U-net: Convolutional networks for biomedical image segmentation. In *Medical Image Computing and Computer-Assisted Intervention-MICCAI 2015: 18th International Conference*, Munich, Germany, October 5-9, 2015, Proceedings, Part III 18(pp. 234-241). Springer International Publishing, https://doi.org/10.1007/978-3-319-24574-4_28.

[31] Alsaaidah, B., Mustafa, Z., Al-Hadidi, M.D.R. and Alharbi, L.A., 2023. Automated Identification and Categorization of COVID-19 via X-Ray Imagery Leveraging ROI Segmentation and CART Model. *Traitement du Signal*, 40(5), pp.2259-2265, https://doi.org/10.18280/ts.400543.

Contribution of Individual Authors to the Creation of a Scientific Article (Ghostwriting Policy)

Bayan Alsaaidah contributed the presented research, at all stages from the formulation of the problem to the final findings and solution.

Sources of Funding for Research Presented in a Scientific Article or Scientific Article Itself

No funding was received for conducting this study.

Conflict of Interest

The authors have no conflicts of interest to declare.