Automated Segmentation of COVID-19 Lesion from Lung CT Images Using U-Net Architecture

Seifedine Kadry[1](✉), Fadi Al-Turjman[2], and V. Rajinikanth[3]

[1] Faculty of Applied Computing and Technology, Noroff University College, Kristiansand, Norway

[2] Artificial Intelligence Department, Research Center for AI and IoT, Near East University, Nicosia, Mersin 10, Turkey

[3] Department of Electronics and Instrumentation Engineering, St. Joseph's College of Engineering, Chennai, India

Abstract. Pneumonia caused by the novel Coronavirus Disease (COVID-19) is emerged as a global threat and considerably affected a large population globally irrespective of their age, race, and gender. Due to its rapidity and the infection rate, the World Health Organization (WHO) declared this disease as a pandemic. The proposed research work aims to develop an automated COVID-19 lesion segmentation system using the Convolutional Neural Network (CNN) architecture called the U-Net. The traditional U-Net scheme is employed to examine the COVID-19 infection present in the lung CT images. This scheme is implemented on the benchmark COVID-19 images existing in the literature (300 images) and the segmentation performance of the U-Net is confirmed by computing the essential performance measures using a relative assessment among the extracted lesion and the Ground-Truth (GT). The overall result attained with the proposed study confirms that, the U-Net scheme helps to get the better values for the performance values, such as Jaccard (>86%), Dice (>92%) and segmentation accuracy (>95%).

Keywords: COVID-19 · Lung CT images · U-Net scheme · Segmentation · Performance validation

1 Introduction

Assessment of the disease in vital internal organ is very crucial and to assess the disease, considerable methodologies are followed including the bio-signal assisted procedures and bio-image assisted technique. The information existing in the bio-image based methodology is large compared to the signal based technique; and hence most of the diseases in the internal organs are widely assessed using the bio-image based methodologies. Due to its significance, a considerable number of bio-image modalities are developed and utilized to assess the disease in vital internal organs [1–3].

Lung is one of the vital internal organ; responsible to exchange the air between the atmosphere and other body sections. The disease in lung will severely affect the air

S. Paiva et al. (Eds.): SmartCity360° 2020, LNICST 372, pp. 20–30, 2021.
https://doi.org/10.1007/978-3-030-76063-2_2

exchange and this may cause very complicated situation, including the death. The abnormality in lung arises in various situations and pneumonia is one of the major causes of the lung abnormality and may cause very severe heath problem among the children (age $<$ 5 years) and elderly people (age $>$ 65 years). In humans, the pneumonia is caused due to a variety of reasons ranging from the climatic conditions to the virus/bacterium [4]. From the recent literature, it can be noted that, the infection due to COVID-19 causes a severe pneumonia in elderly people and the unrecognized and untreated COVID-19 will lead to death [5, 6].

From the literature, it can be noted that the COVID-19 infection is discovered only in December 2019, in China and due to the outbreak, the infection reached and affected almost all humans in the globe [7]. Even though a considerable number of precautionary measures are followed, the infection rate and the death rates are gradually rising till the date. The pneumonia due to the COVID-19 is discovered with; (i) RT-PCR test and (ii) Lung image assisted detection procedures [8–10]. The RT-PCR is a clinical trial, in which the samples collected from the infected patient is evaluated and confirmed with the possibility of the COVID-19 infection. When the RT-PCR test result is positive, then the patient is allowed to undergo the bio-medical imaging procedure using the imaging modality; Chest Radiograph (X-Ray) or the lung CT. From the earlier literature, it can be noted that, the assessment of the COVID-19 lesion with the lung CT is quite straight forward compared to the chest X-Ray [11, 12]. Hence, in most of the research works, the assessment of the lung CT is widely adopted compared to the chest X-Ray.

Due to its clinical significance, a considerable number of lung CT image examinations is proposed and implemented in the literature to detect the COVID-19 infection using the two-dimensional (2D) image slice of the chosen dimension. Every approach is implemented either a segmentation technique or a classification technique with the help of a chosen image examination technique. In the proposed research work, the examination of the COVID-19 lesion is assessed using the lung CT scan slices of the benchmark image dataset using a chosen segmentation technique.

In the proposed work, the COVID-19 infection is assessed using the lung CT images with the help of the Convolutional Neural Network (CNN) and the well-known CNN based segmentation technique called the U-Net is then employed to extract and evaluate the pneumonia infection from the chosen lung CT scan slices. The methodology implemented in the proposed work is as follows; (i) Collection of the 3D lung CT from the benchmark dataset, (ii) 3D to 2D conversion and resizing the 2D slices into images with dimension $572 \times 572 \times 1$ pixels, (iii) Implementation of the pre-trained U-Net architecture to extract the COVID-19 lesion, and (iv) Executing a comparative assessment among the extracted lung lesion and the GT and computing the performance measures to validate the performance of the U-Net scheme.

In the proposed work, 300 numbers of images are collected from the benchmark datasets [13, 14] available for the research purpose and the essential performance measures are computed to confirm the superiority of the proposed technique. The proposed technique is implemented using the MATLAB software and the segmentation binary image is then considered to confirm the superiority of the proposed technique based on the computed values of the Jaccard, Dice and segmentation Accuracy. The experimental result with the proposed research confirms that, proposed technique helped to achieve a better result on the considered lung CT images and extracts the COVID-19 infection with better segmentation accuracy.

The main contribution of the research work includes:

- Implementing U-Net to segment the COVID-19 lesion
- Considering the clinical-grade lung CT images for the experimental investigation
- Improved overall accuracy (>96%) is achieved

The remaining section of this paper is arranged as follows; Sect. 2 presents the context, Sect. 3 discusses the methodology implemented and Sect. 4 and 5 shows the results of the proposed work and the conclusion respectively.

2 Context

In recent days, due to its clinical importance, a number of lungs CT based COVID-19 evaluation proposals are discussed by the researchers with (i) Segmentation methods, (ii) Machine-Learning (ML) techniques and (iii) Deep-Learning (DL) approaches. The earlier works also substantiate that the lung CT assisted evaluation will offer a better diagnosis compared to the chest X-ray. Table 1 summarizes few earlier research works implemented with the lung CT to detect the COVID-19 lesion.

Table 1. Summary of COVID-19 infection assessment with lung CT scan slices

Reference	Implemented assessment technique
Ahuja et al. [8]	This research implemented a detailed comparative studies on well known DL schemes to examine the COVID-19 lesion using lung CT images. The proposed ResNet18 helped to attain a better classification accuracy (>98%) on the considered image dataset
Dey et al. [9]	This work proposed a ML scheme by combining the morphological segmentation and classification methods. In this work, the implemented segmentation offered an accuracy of >91% and the K-Nearest Neighbor (KNN) classifier helped to achieve a classification accuracy of >87%
Rajinikanth et al. [10]	Implementation of Otsu's thresholding based enhancement and watershed based segmentation is executed on the benchmark lung CT images and this work helped to propose a methodology to identify the COVID-19 infection rate
Kadry et al. [11]	This work implemented a ML scheme to examine the COVID-19 infection using the lung CT images and the Support Vector Machine (SVM) classifier helped to get a classification accuracy of >89%
Fan et al. [12]	This work proposed a novel segmentation scheme called the Inf-Net to segment the COVID-19 lesion from the lung CT images and achieved better segmentation accuracy on the considered images

(*continued*)

Table 1. (*continued*)

Reference	Implemented assessment technique
Ardakani et al. [15]	Development of a clinical computer-aided diagnosis system (COVIDiag) is proposed in this work. The developed COVIDiag is tested and validated on 612 patient's lung CT images and this system helped to attain an accuracy of $>91\%$
Ardakani et al. [16]	This work implemented a detailed comparative study among ten DL schemes existing in the literature. In this work, 1020 lung CT images collected from 108 patients are evaluated and assessed
Chen et al. [17]	This work implemented a novel U-Net architecture to segment the COVID-19 lesions from the lung Ct images and the proposed scheme helped to attain a overall accuracy of 89%
Zhou et al. [18]	U-Net attenuation mechanism based segmentation is employed to extract the COVID-19 lesion from the lung CT images and this work helped to get a Dice score of 83.1%
Müller et al. [19]	Implementation of 3D U-Net is discussed in this work to segment the COVID-19 lesion from the lung CT images
Shi et al. [20]	This work presented a detailed review on the various artificial intelligence techniques employed during the collection, segmentation and classification of the lung images for the COVID-19 examination
Shoeibi et al. [21]	A detailed review on various DL system assisted COVID-19 lesion detection and forecasting using lung CT images are clearly presented and discussed

Table 1 confirms the availability of a considerable number of the image segmentation techniques to extract and evaluate the COVID-19 lesion using the lung CT images [20, 21]. Further, the CNN schemes, such as the U-Net architecture is also widely employed in the literature to extract and evaluate the COVID-19 lesion with better accuracy. The proposed research work in this paper also employed a traditional U-Net scheme to examine the lung CT images. The proposed technique is implemented using MATLAB software and the attained result (binary segmentation) is then considered to assess the performance of the proposed technique with the help of a comparative assessment with the existing Ground-Truth (GT) images.

3 Methodology

This section presents the methodology implemented in the proposed research work. Figure 1 depicts the various stages available in the proposed segmentation scheme.

The various phases existing in the proposed CT examination scheme is depicted in Fig. 1. Initially, the essential lung CT images (3D) are collected from the benchmark dataset. Assessment of 3D image needs major computation effort and hence, the 3D to 2D conversion is then executed using the ITK-Snap tool [22, 23]. The extracted 2D slices are then resized into $572 \times 572 \times 1$ pixels and the resized images are then considered to train

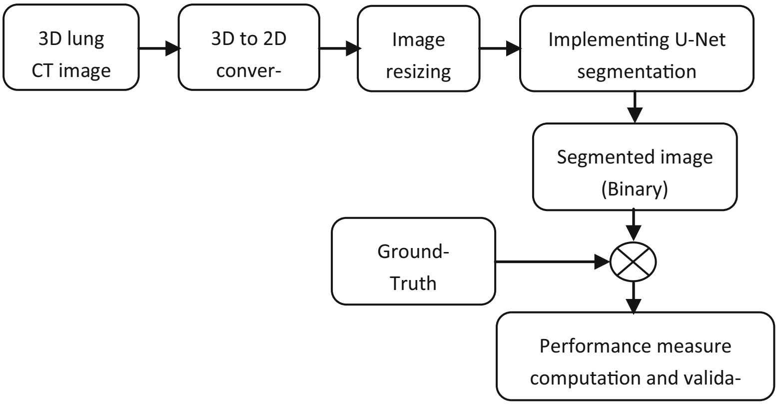


Fig. 1. Various phases involved in the proposed COVID-19 lesion segmentation system

and test the CNN based U-Net segmentation architecture. Initially, the U-Net scheme is trained with the original and augmented CT images and this procedure is repeated till the CNN trains completely to identify the COVID-19 lesion in the considered test image. The segmentation performance of the considered U-Net scheme is then confirmed based on a comparative assessment performed between the extracted COVID-19 lesion and the GT. During this comparison, essential image performance measures are computed and based on these values, the performance of the proposed technique is validated. The main need for the proposed approach is to extract the COVID-19 lesion automatically with improved accuracy. Based on the lesion dimension, the doctor can plan and implement the treatment to cure the infection.

3.1 Lung CT Image Collection

Due to its significance, a number of clinical grade lung CT images (healthy/COVID-19 class) are made available to the researchers. In this work, the COVID-19 class lung CT images available in [13, 14] is considered for the assessment. This dataset is one of the commonly adopted CT image dataset, since it has the clinical grade images collected from the real patients. Further, this database is available with the associated Ground-Truth provided by the image experts. Most of the benchmark lung CT images are available in 3D form and the assessment of the 3D images are quite complex compared to the 2D class. Hence, initially, ITK-snap tool is used to extract the 2D slice (Axial view) from the considered 3D images and the extracted 2D slices are resized into $572 \times 572 \times 1$. All the considered images are available along with the GT and 2D image of the GT (Axial view) is also extracted and resized into $388 \times 388 \times 1$. In the GT is a binary image in which the COVD-19 infection is assigned with a value of "1" and the background is assigned with a value of "0".

3.2 U-Net Segmentation

After preparing the essential test images (200 images from database 1 and 100 images from database 2) for the assessment, the traditional U-Net architecture is then employed to extract the COVID-19 infection with better accuracy. This work implements the U-Net architecture in MATLAB® environment using the workstation with the following specifications; Ryzen 5 quad core 2.1 GHz processor with 8 GB RAM and the implemented U-Net provides a segmentation result with a mean time of 107 ± 29 s.

Figure 2 shows the traditional U-Net architecture implemented in this research. The various stages of the scheme is clearly presented in this figure and from this scheme, it is clear that the input image given to this network is with a dimension of 572 × 572 × 1 and the output image is with a dimension of 388 × 388 × 1 pixels. To extract the essential information, this scheme implements both the down and the up convolution process and finally, it extracts the essential information from the image under study. In this work, the following initial parameters are assigned before training and testing the considered segmentation technique; number of iterations is assigned as 500, Number of Epochs are fixed as 50, the learning rate is assigned as 0.001. Initially, the considered images (original and augmented) are considered to test the segmentation performance of the U-Net and then all the considered original images are considered to test and validate the performance of the proposed scheme. The final outcome of the U-Net is a binary image with a dimension 388 × 388 × 1 pixels and the extracted binary image is then compared against its GT and the essential image performance measures are then computed.

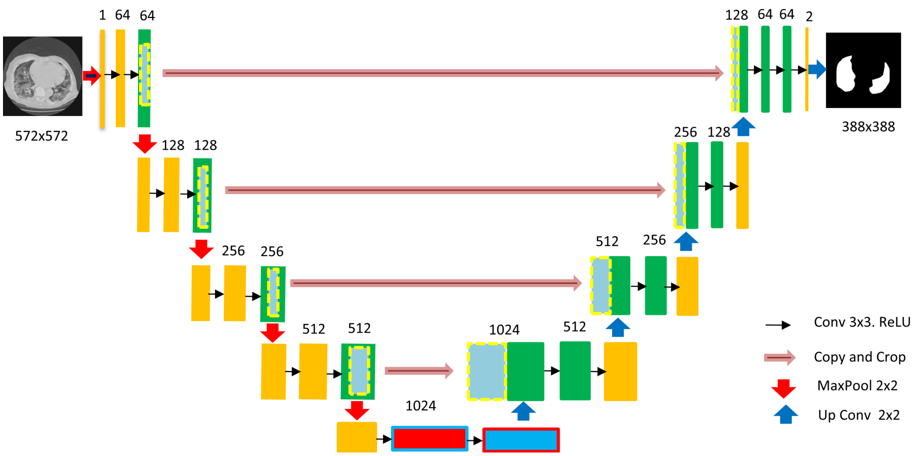


Fig. 2. Employed U-Net architecture considered to extract COVID-19 lesion

3.3 Performance Evaluation

The merit of any computer based image examination system is confirmed by computing the essential image performance measures. In this work, after extracting the COVD-19 lesion from the chosen test image, a comparison is then executed with the related GT and the essential performance measure is then computed.

The performance measures considered in this research is depicted in Eq. (1) to (6) [24–30]:

$$\text{Jaccard} = \frac{\text{GT} \cap \text{SI}}{\text{GT} \cup \text{SI}} \tag{1}$$

$$\text{Dice} = \frac{2|\text{GT} \cap \text{SI}|}{|\text{GT}| + |\text{SI}|} \tag{2}$$

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \tag{3}$$

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \tag{4}$$

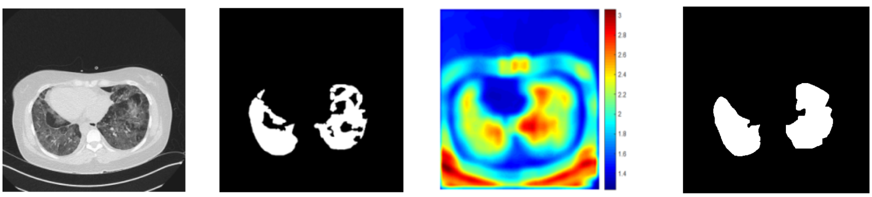
$$\text{Sensitivity} = \frac{\text{TP}}{\text{TP} + \text{FN}} \tag{5}$$

$$\text{Specificity} = \frac{\text{TN}}{\text{TN} + \text{FP}} \tag{6}$$

where GT is the ground-truth-image, SI is the segmented-image, TP, TN, FP and FN denotes true-positive, true-negative, false-positive and false-negative, respectively.

4 Result and Discussion

This section presents the experimental results and discussion attained in the proposed work. Initially the considered U-Net architecture is implemented on all the 300 images and the segmented COVID-19 lesion is then considered for the further assessment. Figure 3 presents a sample test image of the benchmark Database 1 and the corresponding result. Figure 3(a) and (b) depicts the test image and the binary GT. Figure 3(c) and (d) shows the saliency map and the binary SI respectively.



(a) Test image (b) Ground-truth (c) Saliency map (d) Extracted lesion

Fig. 3. Test image and various phase results attained using U-Net segmentation

Table 2 presents the outcome attained with the U-Net architecture for the test image depicted in Fig. 3(a). From this table, it can be noted that the accuracy will gradually rise when the number of iteration as well as the epoch rises and finally the U-Net produces the segmented image when the loss value equals to the assigned learning rate. Similar procedure is implemented on all other images of Database 1 [13] and Database 2 [14] considered in this study and the attained result are considered for further assessment.

Table 2. Sample results attained with the implemented U-Net scheme

Epoch	Iteration	Elapsed time (mm:ss)	Mini-batch		Learning rate
			Accuracy	Loss	
1	1	00:16	68.16%	3.1642	0.001
25	250	02.35	93.42%	0.6153	0.001
50	500	03.47	97.16%	0.0011	0.001

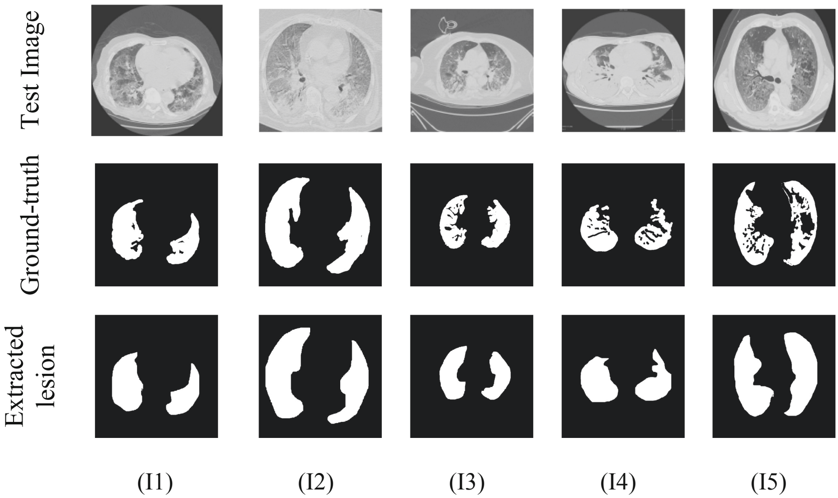


Fig. 4. Results attained with the sample test images of Database 2 [14]

Table 3. Preliminary image similarity measure

Image	TP	FP	TN	FN	Jaccard	Dice
I	6313	972	132938	528	0.8080	0.8938
I1	12333	339	127811	1304	0.8824	0.9375
I2	22392	635	108765	2060	0.8926	0.9432
I3	8284	304	132694	1381	0.8310	0.9077
I4	9519	243	128125	2130	0.8005	0.8892
I5	13796	761	113759	3546	0.7621	0.8650

Figure 4 depicts the sample test images, GT and extracted SI for the images of the database 2 and similar results are attained for all other test images. Tables 3 and 4 present the computed performance measures based on the comparison between the GT and SI. In these tables, the image I denotes the test image discussed in Fig. 3 and other images

Table 4. Essential similarity measure to confirm U-Net performance

Image	Accuracy	Precision	Sensitivity	Specificity
I	0.9893	0.8666	0.9228	0.9927
I1	0.9884	0.9732	0.9044	0.9974
I2	0.9799	0.9724	0.9158	0.9942
I3	0.9882	0.9646	0.8571	0.9977
I4	0.9831	0.9751	0.8172	0.9981
I5	0.9673	0.9477	0.7955	0.9934

are presented in Fig. 4. Table 3 and 4 confirms that, the performance measures, such as Jaccard, Dice and the segmentation accuracy is better for the considered images. Similarly, the performance measures for the images of database 1 and database 2 is separately compared as depicted in Fig. 5. This figure also confirms that, proposed CNN based segmentation technique works well on the considered lung CT images.

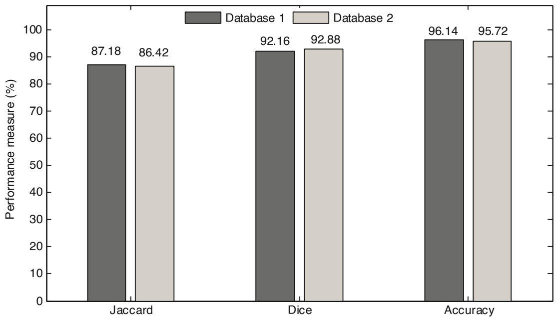


Fig. 5. Overall performance measures attained with U-Net segmentation

The experimental result of the proposed study confirmed that, the segmentation accuracy attained with the U-Net scheme is >95% and in future, the attained outcome can be compared with other traditional and CNN based segmentation techniques existing in the literature.

5 Conclusion

The proposed research work implemented a CNN supported segmentation to extract and evaluate the COVID-19 infection in lung CT images. The traditional U-Net scheme is employed to mine the COVID-19 lesion from the chosen test images. The proposed scheme help to process the images with $572 \times 572 \times 1$ pixels and after the processing, the implemented U-Net helps to offer a binary SI with a dimension of $388 \times 388 \times 1$ pixels. The procedure implemented on 300 test images offers a better overall performance measures, such as Jaccard (>86%), Dice (>92%) and Accuracy (>95%) is superior with the proposed automated segmentation technique. In future, a CNN classification can be included along with the U-Net in order to classify the lung CT images into normal/COVID-19 class. Further, the performance of U-Net can be improved using VGG16 architecture as the encoder section (VGG-Unet).

References

1. Khan, M.A., et al.: Computer-aided gastrointestinal diseases analysis from wireless capsule endoscopy: a framework of best features selection. IEEE Access **8**, 132850–132859 (2020)
2. Bakiya, A., Kamalanand, K., Rajinikanth, V., Nayak, R., Kadry, S.: Deep neural network assisted diagnosis of time-frequency transformed electromyograms. Multimedia Tools Appl. **79**(15–16), 11051–11067 (2018). https://doi.org/10.1007/s11042-018-6561-9
3. Fernandes, S.L., Rajinikanth, V., Kadry, S.: A hybrid framework to evaluate breast abnormality using infrared thermal images. IEEE Consum. Electron. Mag. **8**(5), 31–36 (2019)
4. Bhandary, A., et al.: Deep-learning framework to detect lung abnormality–a study with chest X-Ray and lung CT scan images. Pattern Recogn. Lett. **129**, 271–278 (2020)
5. Nishiura, H., et al.: Closed environments facilitate secondary transmission of coronavirus disease 2019 (COVID-19). *MedRxiv* (2020)
6. Satapathy, S.C., Hemanth, D.J., Kadry, S., Manogaran, G., Hannon, N.M., Rajinikanth, V.: Segmentation and evaluation of COVID-19 lesion from CT scan slices-a study with Kapur/Otsu function and cuckoo search algorithm (2020)
7. Zu, Z.Y., et al.: Coronavirus disease 2019 (COVID-19): a perspective from China. Radiology **96**, E15–E25 (2020)
8. Ahuja, S., Panigrahi, B., Dey, N., Rajinikanth, V., Gandhi, T.: Deep transfer learning-based automated detection of COVID-19 from lung CT scan slices. Appl. Intell. **51**(1), 571–585 (2020). https://doi.org/10.1007/s10489-020-01826-w
9. Dey, N., Rajinikanth, V., Fong, S., Kaiser, M., Mahmud, M.: Social group optimization–assisted Kapur's entropy and morphological segmentation for automated detection of COVID-19 infection from computed tomography images. Cogn. Comput. **12**(5), 1011–1023 (2020). https://doi.org/10.1007/s12559-020-09751-3
10. Rajinikanth, V., Dey, N., Raj, A.N.J., Hassanien, A.E., Santosh, K.C., Raja, N.: Harmony-search and Otsu based system for coronavirus disease (COVID-19) detection using lung CT scan images. arXiv preprint arXiv:2004.03431 (2020)
11. Kadry, S., Rajinikanth, V., Rho, S., Raja, N.S.M., Rao, V.S., Thanaraj, K.P.: Development of a machine-learning system to classify lung CT scan images into normal/COVID-19 class. arXiv preprint arXiv:2004.13122 (2020)
12. Fan, D.P., et al.: Inf-Net: automatic COVID-19 lung infection segmentation from CT images. IEEE Trans. Med. Imag. **39**(8), 2626–2637 (2020)
13. Database 1. https://zenodo.org/record/3757476#.X0Jztcgza6k
14. Database 2. https://medicalsegmentation.com/covid19/
15. Ardakani, A.A., Acharya, U.R., Habibollahi, S., Mohammadi, A.: COVIDiag: a clinical CAD system to diagnose COVID-19 pneumonia based on CT findings. Eur. Radiol. **31**(1), 121–130 (2020)
16. Ardakani, A.A., Kanafi, A.R., Acharya, U.R., Khadem, N., Mohammadi, A.: Application of deep learning technique to manage COVID-19 in routine clinical practice using CT images: results of 10 convolutional neural networks. Comput. Biol. Med. **121**, 103795 (2020)
17. Chen, X., Yao, L., Zhang, Y.: Residual attention U-Net for automated multi-class segmentation of COVID-19 chest CT images. arXiv preprint arXiv:2004.05645 (2020)

18. Zhou, T., Canu, S., Ruan, S.: An automatic COVID-19 CT segmentation based on U-Net with attention mechanism. arXiv preprint arXiv:2004.06673 (2020)
19. Müller, D., Rey, I.S., Kramer, F.: Automated chest CT image segmentation of COVID-19 lung infection based on 3D U-Net. arXiv preprint arXiv:2007.04774 (2020)
20. Shi, F., et al.: Review of artificial intelligence techniques in imaging data acquisition, segmentation and diagnosis for COVID-19. IEEE Rev. Biomed. Eng. **4**, 4–15 (2021)
21. Shoeibi, A., et al.: Automated detection and forecasting of COVID-19 using deep learning techniques: a review. arXiv preprint arXiv:2007.10785 (2020)
22. Yushkevich, P.A., Gao, Y., Gerig, G.: ITK-SNAP: an interactive tool for semi-automatic segmentation of multi-modality biomedical images. In: 2016 38th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), pp. 3342–3345. IEEE, August 2016
23. ITK-Snap. https://www.itksnap.org/pmwiki/pmwiki.php
24. Liu, X., Lin, C.C., Muhammad, K., Al-Turjman, F., Yuan, S.M.: Joint data hiding and compression scheme based on modified BTC and image inpainting. IEEE Access **7**, 116027–116037 (2019)
25. Al-Turjman, F.: AI-powered IoT for COVID-19 (2020)
26. Rahman, M.A., Zaman, N., Asyhari, A.T., Al-Turjman, F., Bhuiyan, M.Z.A., Zolkipli, M.F.: Data-driven dynamic clustering framework for mitigating the adverse economic impact of COVID-19 lockdown practices. Sustain. Cities Soc. **62**, 102372 (2020)
27. Ramchandani, A., Fan, C., Mostafavi, A.: DeepCOVIDNet: an interpretable deep learning model for predictive surveillance of COVID-19 using heterogeneous features and their interactions. arXiv preprint arXiv:2008.00115 (2020)
28. Nagasubramanian, G., Sankayya, M., Al-Turjman, F., Tsaramirsis, G.: Parkinson data analysis and prediction system using multi-variant stacked auto encoder. IEEE Access **8**, 127004–127013 (2020)
29. Stephan, T., Al-Turjman, F., Balusamy, B.: Energy and spectrum aware unequal clustering with deep learning based primary user classification in cognitive radio sensor networks. Int. J. Mach. Learn. Cybern. 1–34 (2020)
30. Rajinikanth, V., Joseph Raj, A.N., Thanaraj, K.P., Naik, G.R.: A customized VGG19 network with concatenation of deep and handcrafted features for brain tumor detection. Appl. Sci. **10**(10), 3429 (2020)