EMITTER International Journal of Engineering Technology
Vol. 10, No. 2, December 2022, pp. 320~337
DOI : 10.24003/emitter.v10i2.709

3D Visualization for Lung Surface Images of Covid-19 Patients based on U-Net CNN Segmentation

FX Ferdinandus[1,3], Esther Irawati Setiawan[3], Eko Mulyanto Yuniarno[1,2], Mauridhi Hery Purnomo[1,2,4]

[1]Department of Electrical Engineering, Institut Teknologi Sepuluh Nopember, Surabaya-Indonesia
[2]Department of Computer Engineering, Institut Teknologi Sepuluh Nopember, Surabaya-Indonesia
[3]Department of Informatics, Institut Sains dan Teknologi Terpadu Surabaya, Surabaya-Indonesia
[4]University Center of Excellence on Artificial Intelligence for Healthcare and Society (UCE AIHeS) Surabaya, Indonesia
Correspondence Author: hery@ee.its.ac.id

Received September 10, 2022; Revised October 11, 2022; Accepted November 13, 2022

Abstract

The Covid-19 infection challenges medical staff to make rapid diagnoses of patients. In just a few days, the Covid-19 virus infection could affect the performance of the lungs. On the other hand, semantic segmentation using the Convolutional Neural Network (CNN) on Lung CT-scan images had attracted the attention of researchers for several years, even before the Covid-19 pandemic. Ground Glass Opacity (GGO), in the form of white patches caused by Covid-19 infection, is detected inside the patient's lung area and occasionally at the edge of the lung, but no research has specifically paid attention to the edges of the lungs. This study proposes to display a 3D visualization of the lung surface of Covid-19 patients based on CT-scan image segmentation using U-Net architecture with a training dataset from typical lung images. Then the resulting CNN model is used to segment the lungs of Covid-19 patients. The segmentation results are selected as some slices to be reconstructed into a 3D lung shape and displayed in 3D animation. Visualizing the results of this segmentation can help medical staff diagnose the lungs of Covid-19 patients, especially on the surface of the lungs of patients with GGO at the edges. From the lung segmentation experiment results on ten patients in the Zenodo dataset, we have a Mean-IoU score = of 76.86%, while the visualization results show that 7 out of 10 patients (70%) have eroded lung surfaces. It can be seen clearly through 3D visualization.

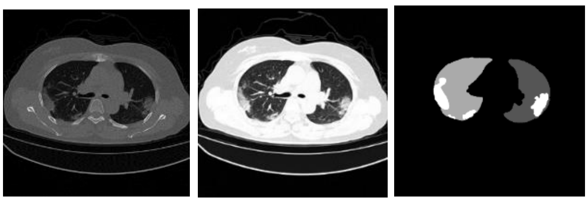
Keywords: Covid-19, CT-scan, Deep Learning, Lung segmentation, U-Net

1. INTRODUCTION

The World Health Organization (WHO) officially declared Covid-19 infection a global pandemic on Wednesday, March 11, 2020. Covid-19 has infected more than 126,000 people in 123 countries from Asia, Europe, the US, and South Africa in less than three months. Many patients with Covid-19 require hospital treatment with pain problems, especially in the respiratory tract. Medical staff at the hospital carry out a variety of tests as an initial diagnosis to ascertain whether the patient is declared positive for the Covid-19 virus, including using Rapid Antibody tests (through the blood), Antigen Swabs (Rapid Antigen Test), and PCR, if necessary. If the patient has been declared positive, in the advanced diagnosis phase, the medical personnel at the hospital will need to examine the severity of the Covid-19 virus infection. Special examinations of Covid-19 patients can be carried out by observing the patient's lungs through a CT-Scan or X-Ray examination. Examination through CT-Scan is relatively expensive compared to X-Ray, but it has the advantage of more precise image visualization for higher examination accuracy. Furthermore, X-Ray is only able to produce 2D visualization forms.

Examination results via CT-Scan can be saved in the Dicom format (Digital Imaging and Communications in Medicine) or NII (Neuroimaging Informatics Technology Initiative) format [1]. It is a 3D volume that can be observed through a 2D view with a choice of slicing the Sagittal, Coronal, and Axial dimensions. We chose to observe the Axial dimension because it is less restricted by the presence of bone surrounding the lungs. Thus, it will be more optimal in image processing, particularly for segmenting Covid-19 infected regions and visualization.

One of the issues that concern Covid-19 patients is the presentation of X-ray or CT-Scan results, which show parts of the lungs that turn white in a matter of days. This condition is called Ground Glass Opacity (GGO). GGO is an abnormal condition of the lungs characterized by white or gray areas on X-ray or CT-scan. Typically, the lungs will be black on an image, indicating that the lungs are soft tissue. In the case of Covid-19, an X-Ray or CT-Scan of the lungs show a white or a gray area. It reveals that the lung tissue in Covid-19 patients undergoes tissue compaction, as shown in figure 1.



(a) (b) (c)

Figure 1. Slice image on a CT-Scan file of one of the patients with COVID-19 using the Axial dimension. (a) GGO appears in several lung areas in the form of a white-gray mist, (b) Image after brightness, (c) Lung and Infection Mask on the dataset.

Currently, there is much research on various aspects of the Covid-19 pandemic. It is getting the attention of many researchers worldwide to contribute to preventing and dealing with the impact of this pandemic. In Artificial Intelligence, especially Deep Learning, the segmentation process for the lungs and Covid-19 infection in the lungs are exciting topics to study [2]. One of the architectures recommended by various researchers in segmentation techniques based on CNN is using the U-Net architecture that employs the Semantic Segmentation approach.

As a principle, segmentation is a process of getting the desired area from an image with various backgrounds. For example, face segmentation from a photo aims to get the face separated from the photo's background. Similarly, segmentation in medical images aims to obtain certain areas such as the lung, heart, brain, and bone.

Medical image processing has been a widely used approach with the semantic segmentation method in recent years. The purpose of semantic segmentation [3]–[5] is to label each pixel in an image to the class it represents. The prediction will be made for each pixel in the image. This kind of prediction is called dense prediction. Each pixel will be classified into a specific class. If there are objects in the same class and separate locations, the pixel will still be labeled according to the predicted class. The U-Net architecture is a development of the Convolutional Neural Network, introduced in 2015 by Olaf Ronneberger et al. [6] and has been successfully used to segment Biomedical images. This architecture is proven to have excellent and fast performance in segmenting even though it uses little data training. From its development until now, U-Net has been widely used in image segmentation research in various medical fields because training data is difficult to obtain in the medical field. Much research on Covid-19 infection has been done, but no one has paid attention to the lung's surface area.

This study aims to segment the lungs of Covid-19 to determine the shape of the lung surface. Segmentation will use Deep Learning with a semantic segmentation approach using U-NET architecture[7]. The segmentation results will take some slices that can be represented to be stacked into a 3D lung shape and visualized using 3D animation. The contribution of this research is the visualization of the surface shape of the patient's lungs due to Covid-19 infection based on the semantic segmentation results of CNN's U-Net architecture.

This study begins with supporting previous research, then moves on to lung segmentation using U-NET, continued by preparation of data used for training and testing, experiments and results, and finally, discussion and conclusions.

2. RELATED WORKS

Segmentation on medical images has been used for a long time and is very helpful in diagnosing disease in patients, whether using conventional methods, machine learning, or deep learning. One of the exciting research areas is segmentation in the lung area, where the results can be used for the next stage, such as detecting and segmenting the lung area that is infected due to various lung diseases (pulmonary) such as tuberculosis, tumors, cancer, and Covid-19 [8]–[11]. Many studies have used CNN to segment the patient's lungs.

Alexander Kalinov et al. [12] segmented the lungs using CNN Encoder-Decoder based on X-Ray images. Suguna G.C et al. [13] using Machine Learning for detecting Covid-19. Others include using U-Net CNN to segment the patient's lungs based on CT-Scan or X-Ray images. Some use CT-Scan based on Axial dimensions as in Brahim et al. [14]. Some use X-Ray with Coronal dimensions as in Ching et al. [15]. Humera et al. [16] also used CT-Scan images with Axial dimensions. Many studies mention that the results of using U-Net are excellent for lung segmentation.

U-Net has a little difference from CNN in doing segmentation. The segmentation of the lung area received attention from Humera et al. [17] by comparing the segmentation using CNN and U-Net. Bressem K. et al [18] using 3D U-Net for segmentation of Covid-19. The results of this comparison state that U-Net is proven to make better improvements compared to segmentation using CNN.

Research in Radiology to determine GGO in Covid-19 patients has also attracted the attention of researchers, such as previous works conducted by E. Martinez Chamorro et al [19] and Diletta Cozzi et al [20]. Diagnostics were performed on X-Ray and CT-scan images to determine the infection classification in the lung area and review to GGO.

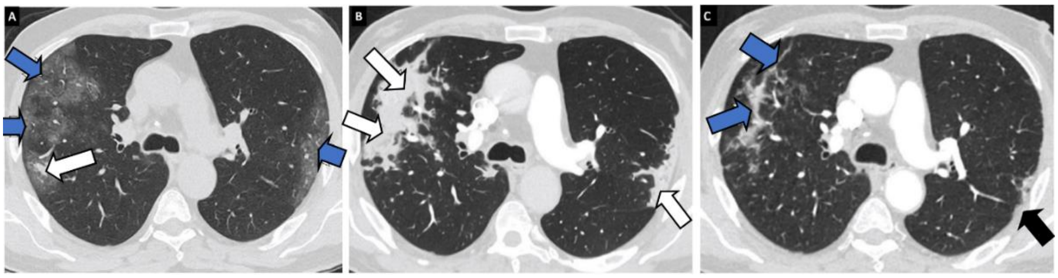
Some researchers have used Deep Learning to segment the lungs of Covid-19 patients where the architectures used are FCNN and U-NET. In his research, Athanasios et al. [21] segmented the Covid-19 infection in the lung area of Covid-19 patients using U-Net architecture and FCN-8s. The results were that U-Net was smoother than FCN-8s. Tongxue Zhou et al. [22] tried to produce a model based on U-Net with a spatial and channel attention module. The results are slightly better than the state-of-the-art model.

Evaluation metrics to state that the segmentation results are similar to ground-truth are the IoU and Dice scores. Some researchers use the IoU score, and some use the Dice Score IoU states that the similarity of the segmentation is based on the Intersection value divided by the Union value. In contrast, the Dice score states that 2x the Intersection value is divided by the sum of the image's two areas. These two metrics are almost similar and are widely used in various segmentation evaluations.

3. ORIGINALITY

First, we constructed a CNN model for lung segmentation using our parameters and training datasets. The resulting model can segment the lungs of CT images of Covid-19 patients. The training was carried out using a dataset from Kaggle[23], while the testing used a Covid-19 patient dataset from Zenodo[24]. The Zenodo dataset is processed by slicing from the resulting CT-scan (3D) into 2D images, and then we perform the enhancement process. For some training parameters, we try to find parameters that can produce a CNN model suitable for lung segmentation and visualization purposes.

Second, based on the Radiology journal on the diagnosis in Covid-19 patients as shown in Figure 2, in the first phase, about ten days after the onset of symptoms, GGO areas on the lungs are observed in many patients. The second phase occurs approximately 15 days after the first CT scan when there is a solid concentration of GGO known as consolidation. In the third phase, about 32 days after the first CT scan, there will be a thickening of the infection area that can stick to the walls of the lung area (Black arrow). Our second originality, based on that report, is our approach to paying special attention to infections at the surface of the lungs. Until now, no study has paid attention to Covid-19 infection in the periphery of the patient's lungs. We will segment the patient's lung area at the initial stage to produce a lung shape whose edges are eroded due to Covid-19 infection. After the segmentation process is complete, the results will be stacked to be reconstructed into 3D form and processed with a rotation angle of every 5 degrees to 72 frames to create a 3D animation. The results will reveal the shape of the lungs that are eroded by Covid-19 infection.



(a) (b) (c)

Figure 2. Progression of COVID-19 pneumonia in a 56-year-old woman. Axial chest computed tomography (CT) image 1 mm thick at the carina level. (a) Ten days after the onset of symptoms. Peripheral ground glass, bilateral opacities (blue arrow) and small consolidations formed in the posterior segment of the right upper lobe (white arrow). (b) A CT scan 15 days after the first. Development of ground-glass opacity for consolidation (white arrow). (c) A CT scan 32 days following the first. Partial resorption of consolidation (blue arrow) and focal pleural thickening in the apicoposterior segment of the left upper lobe (black arrow).

4. SYSTEM DESIGN: LUNG SEGMENTATION AND VISUALIZATION

The approach used in this study is depicted in Figure 3 Methodology. There are four main steps, which are as follows:
1. Prepare images for CNN model training and segmentation.
2. Training and Testing of the CNN model
3. Image Segmentation
4. Visualization of segmentation results.

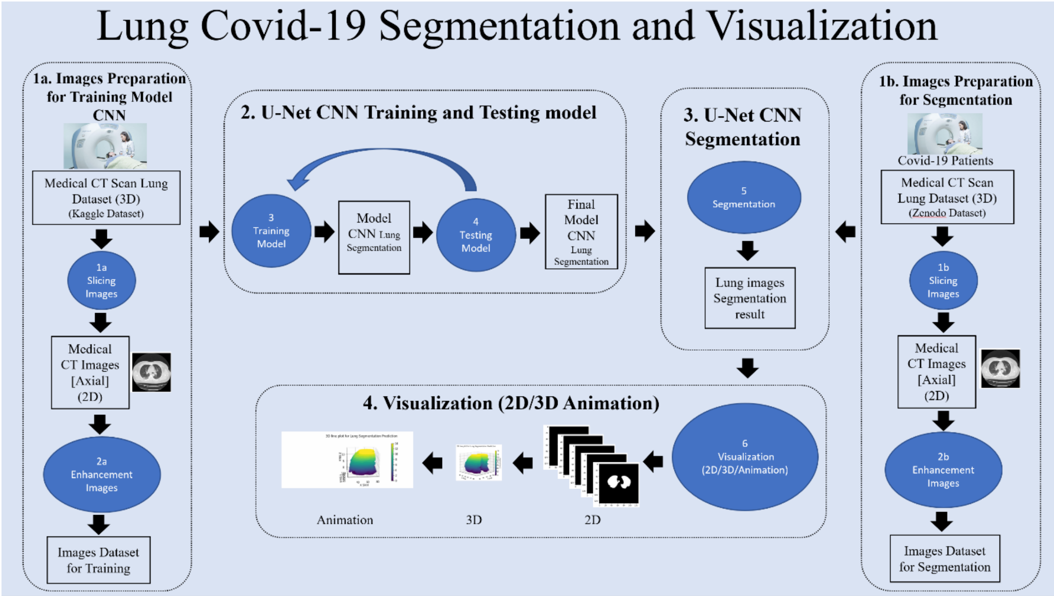
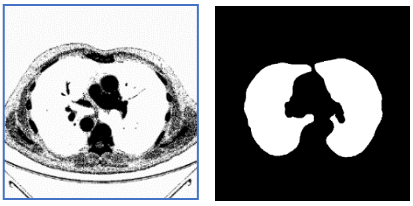


Figure 3. Methodology, there are four main steps in this work.

Dataset and Preprocessing

There are two datasets in our experiment

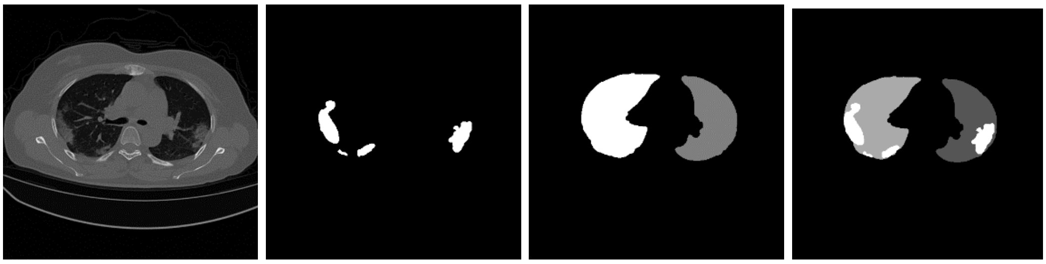
1. Kaggle Lung Dataset
   Four sets of NII files are comprised of Lung CT-scan and Lung masks, which are then sliced into 267 2D images in .png format with dimensions of 512 x 512 pixels. This dataset will be used as training and validation data for CNN models generated using U-Net architecture. Figure 4 shows an example of an image.



(a) (b)

Figure 4. Example of image slicing (a) CT-Scan image from the Kaggle Lung Dataset,
(b) the lung masks.

2. Zenodo Covid-19 Dataset
   The ten sets of NII files consist of a Lung CT-Scan image, an Infection mask, a Lung mask, and Lung and Infection Mask. This dataset comes from Covid-19 patients whom radiologists have confirmed. Slicing will be carried out from this dataset, and the results will be used as testing data for the U-Net model to produce a segmentation of the lung area. An example of an image is shown in Figure 5



(a) (b) (c) (d)

Figure 5. Example slicing image and mask from Zenodo Dataset, (a) CT-Scan image from
Zenodo Dataset, (b). Infections, (c) Lung mask, (d) Lung and Infection mask.

The training and testing process uses a dataset with the following preparations according as shown in figure 6,

1. The size of all images from the dataset is reduced from 512x512 pixels to 256 x 256 pixels. We chose this size to ensure that the training process is not long, and the segmentation quality is still good.
2. In the training process, the input image from the dataset is not modified. In the testing process, the brightness of the input image is adjusted with a Binary Threshold value = 60. Then the Invert process is carried out using the Binary Not operation.

(a) (b) (c)

Figure 6. (a) Original image (b) Brightness image (c) Invert image.

U-Net Architecture and Configurations

We employ the U-Net architecture proposed by Olaf Ronneberger et al. This architecture has a symmetrical shape on the left and right, with the left side being the image input and contracting process, while the right side is the expansive process and the output, as shown in Figure 7. The two stages of this process form the letter U. The contracting process consists of steps repeated in 5 layers, starting with an image input. A convolution process is performed at each layer twice with a 3x3 kernel, and the Relu activation function is followed by a max-pooling operation (stride=2). The expansive process also consists of 5 layers wherein each layer, the number of feature maps will be reduced, and the image dimensions will be enlarged using convolution transpose (2x2 kernel and stride = 2). After merging with feature map due to contracting side crop, two times convolution kernel (3x3) and Relu activation function, the last convolution 1x1 with Sigmoid activation will produce the image as output segmentation. It should be noted that the merging process with the crop results is required to restore the loss of pixels from the border in each convolution process in the contracting stage.

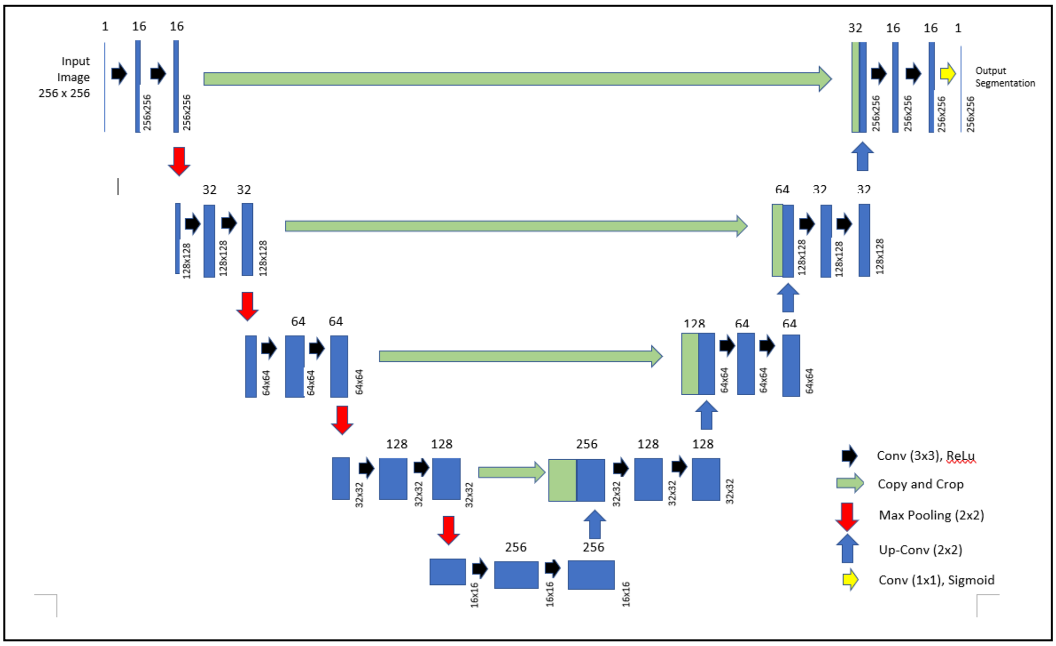


Figure 7. U-Net Architecture for training our CNN model.

Training Configuration

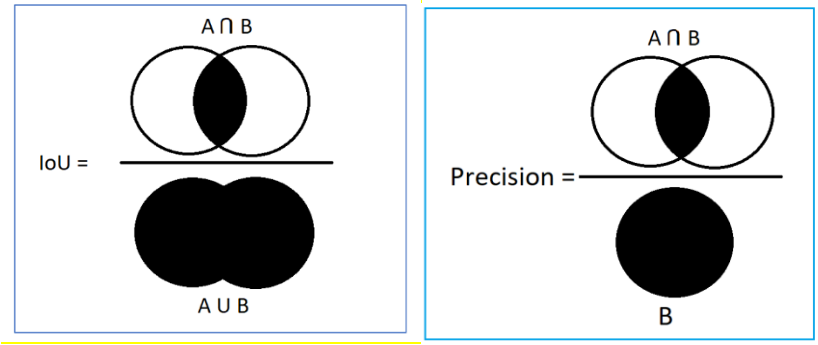
In the training process, the following parameters are used:
Optimizer = Adam, Loss = Binary cross entropy, Metric = Keras Mean IoU, Epoch = 50 with early stopper patience=5. The training model was built using an Intel® Core™ i7-1051OU CPU @ 1.8 GHz 2.30 GHz, 16-GB RAM without GPU under the Microsoft Windows operating systems

Evaluation Metrics

For evaluation metrics, we use two types of metrics [25]. The first metric for segmentation evaluation is the Intersection over Union (IoU). The second metric is Precision for predicting the volume of erosion on the lung surface due to Covid-19 infection.

The metric used in the segmentation evaluation is the Intersection over Union (IoU) score, as shown in figure 8(a), where A is the predicted segmentation image, and B is the ground-truth image (B). IoU is an Intersection area divided by a Union area. Each slice from the patient will be scored, and the average IoU score (Mean-IoU Score) from one patient will be calculated. The range of IoU values is 0-100%, a value of 0 indicates different, and a value of 100% indicates the same. The values between them indicate the level of similarity. All values will be averaged again for all patients used as testing data to obtain the final value.

To predict the volume of erosion on the lung surface due to Covid-19 infection, we used the Precision metric as shown in figure 8(b), where A is the predicted segmentation image, and B is the ground-truth image (B). Precision is the Intersection area divided by the ground-truth area.



(a) (b)

Figure 8. Evaluation metric (a) IoU metric (b) Precision metric

5. EXPERIMENT AND DISCUSSION

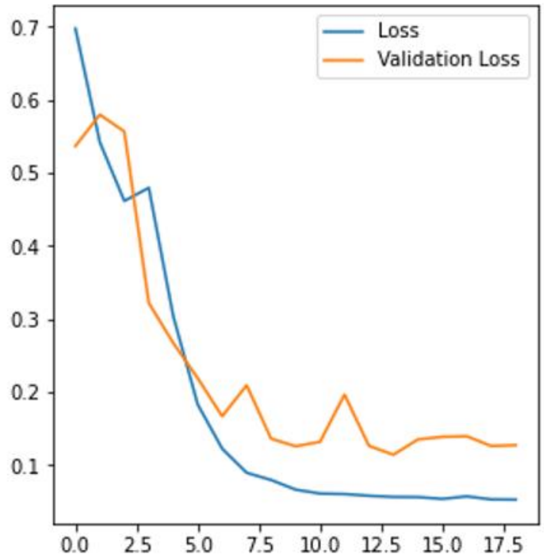
After determining the CNN model and its configuration, the U-Net training is executed,

```
concatenate_3 (Concatenate)  (None, 256, 256, 32) 0    conv2d_transpose_3[0][0]
conv2d_1[0][0]
__________________________________________________________________________
conv2d_16 (Conv2D)        (None, 256, 256, 16) 4624      concatenate_3[0][0]
__________________________________________________________________________
dropout_8 (Dropout)         (None, 256, 256, 16) 0          conv2d_16[0][0]
__________________________________________________________________________
conv2d_17 (Conv2D)         (None, 256, 256, 16) 2320      dropout_8[0][0]
__________________________________________________________________________
conv2d_18 (Conv2D)         (None, 256, 256, 1)  17         conv2d_17[0][0]
==========================================================================
Total params: 1,941,105
Trainable params: 1,941,105
Non-trainable params: 0
```

(a)

```
Epoch 19/50
15/15 [==============================] - ETA: 0s - loss: 0.0487 -
mean_io_u: 0.3758
Epoch 00019: val_loss did not improve from 0.13783
15/15 [==============================] - 77s 5s/step - loss: 0.0487 -
mean_io_u: 0.3758 - val_loss: 0.2072 - val_mean_io_u: 0.3741
Epoch 00019: early stopping
```

(b)



(c)

Figure 9. (a) CNN model (b) End of the training process (c) Loss and Validation-Loss Chart

Figure 10. Preprocessing results from patient-10 (image-11 to image-22)

The training is carried out with early stopping based on the condition that if, within five epochs, there is no change in the value of the validation loss. Validation was assessed based on the mean-IoU Keras value. According to figure 9 in the experiment, the training carried out stopped at the 19th epoch, with the best val-loss score = 0.13783 (loss = 0.0487, mean-IoU = 0.3758, val_loss = 0.2072, val_mean-IoU = 0.3741).

We slice the Kaggle Lung dataset NII file into 267 images with the dimensions 256x256 pixels and then preprocess them into images ready to be used in the U-Net training model. After our training produced the CNN model for segmentation, we used the Zenodo dataset for lung segmentation, which consisted of 10 datasets of patients who were confirmed to have Covid-19. The result of segmentation on U-Net has a float type value between 0.0 - 1.0, and the Binary Threshold is carried out with a value of 0.5. Figure 10 depicts the preprocessing results.

Figure 11 shows a collection of segmented images after completing the segmentation process. It demonstrates that the shape of the lungs is not smooth because there are erosions on some of the edges of the lung as the effect of covid-19 infection.

Figure 11. Lung Segmentation result from patient-10 (image-11 to image-22)

The stacking technique is carried out on the images sequentially into a shape such as a 3D plot from the collection of images in Figure 11. Figure 12 depicts the results of 3D visualization.

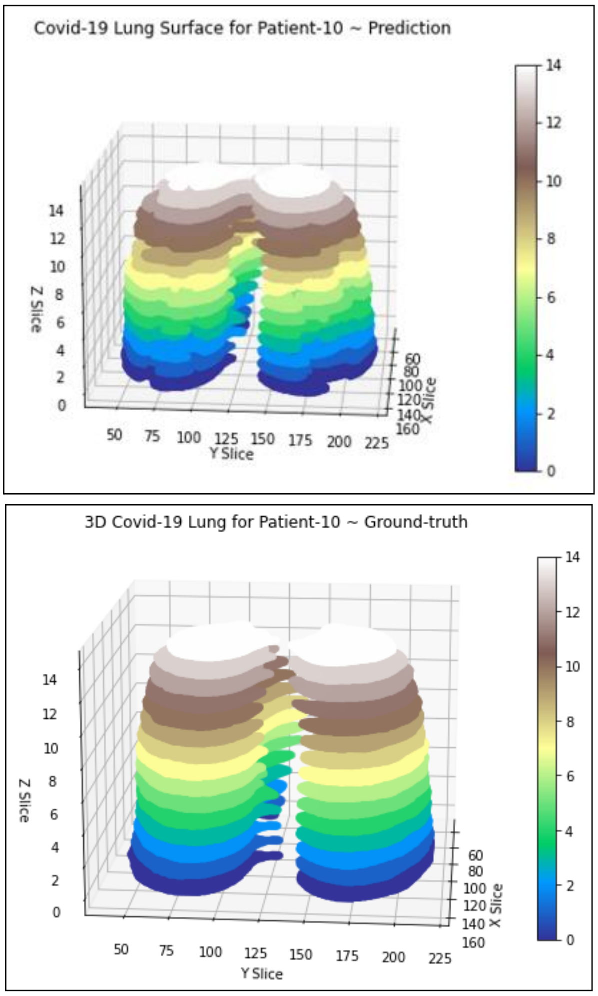


Figure 12. Visualization (Plot-3D) from patient-10. (a) Prediction infection Covid-19
(b) Ground-truth without Covid-19 infection

In the 3D view, as seen in Figure 12, the surface of the Covid-19 patient's lungs is not smooth due to large quantities of GGO attached to the edges, whereas it should look smooth under normal conditions. The amount of GGO strongly influences the results of segmentation with rough edges conditions at the edges of the lung surface. Therefore, when segmentation is performed, erosion occurs on the lung surface. This condition does not affect all patients; GGO in large or small quantities may occur in the center of the patient's lungs so that it will not be visible on the surface.

Another factor is the preprocessing of the Zenodo dataset image prior to segmentation. We chose a threshold value of 60 (range value between 0-255) for the original image of the dataset when it is converted from a greyscale image into a bi-level image. If the value is less than 60, the GGO will be more apparent, followed by increased noise. This condition will affect the result of the 3D visualization. As seen in the segmentation results, segmentation noise can be found in Thus, we need to adjust the threshold value for better segmentation results and 3D visualization. As seen in the segmentation results, segmentation noise can be found in areas other than the lung area, such as the spinal area.

Table 1a. An example of the results of segmentation and visualization on the lung surface of the patient 1,3, and 6. The black circle on the 3D visualization shows the eroded surface of the lung. There is also noise in some visualizations, especially in lung patient-6.

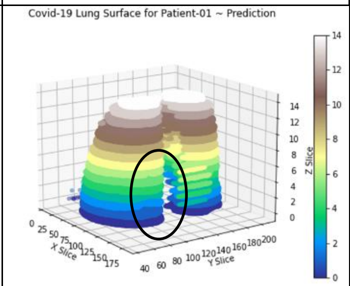
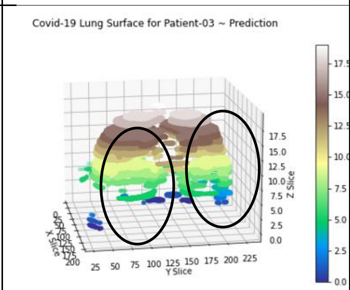
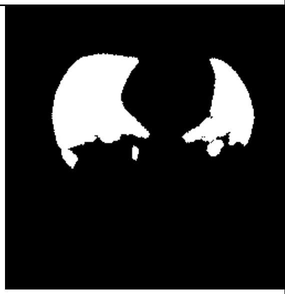
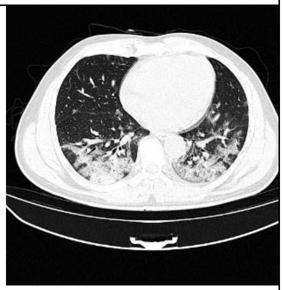
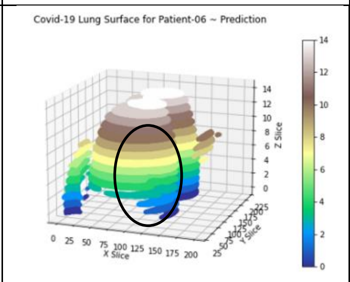
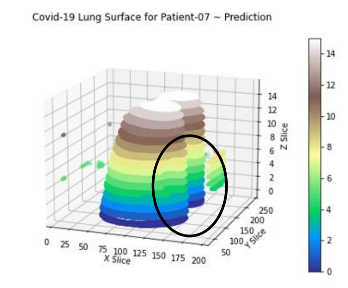
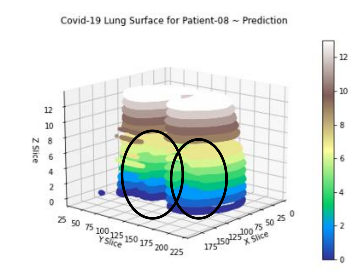
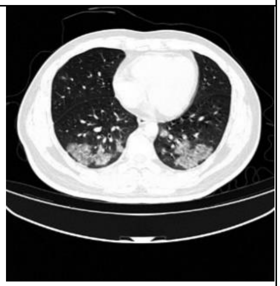
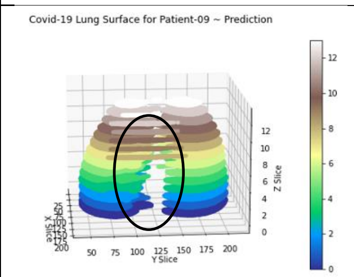
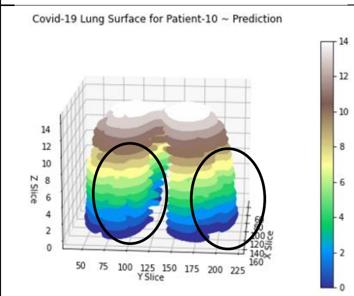
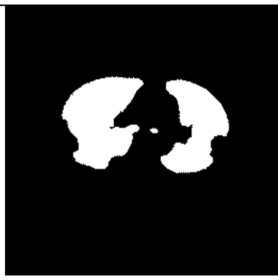
Patient #	3D Visualization	Segmentation result	CT Image
Patient -1			
Patient -3			
Patient -6			

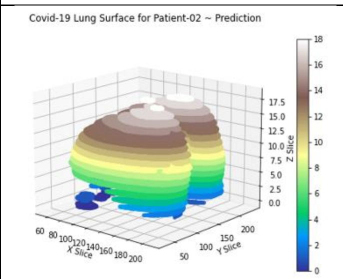
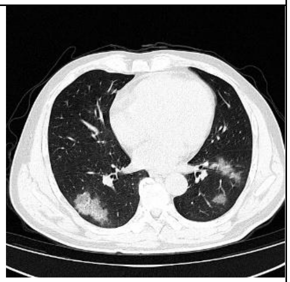
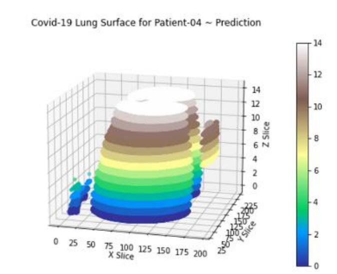
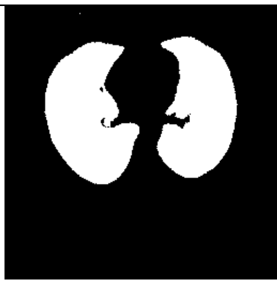
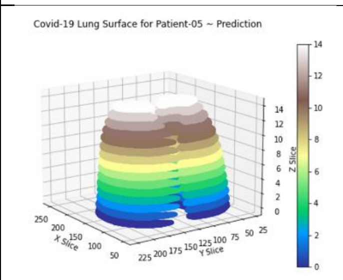
Table 1b. An example of the results of segmentation and visualization on the lung surface of the patient 7, 8 ,9, and 10. (Continued from table 1a)

Patient #	3D Visualization	Segmentation result	CT Image
Patient -7			
Patient -8			
Patient -9			
Patient -10			

Not all slices are used in the reconstruction of 3D lung formation. Only slicing in the middle part of the Lung is taken to provide a more concentrated visualization of the contour of the Lung's surface. On average, patients with severe COVID-19 had dense GGO at the periphery of the Lung. As indicated in table 1a and table 1b, 7 out of 10 patients in the Zenodo dataset had GGO at the periphery. Meanwhile, the other three patients only had a slight GGO, and it was not located at the periphery. Thus, it was not visible on the lungs' surface, as shown in table 2.

The metric evaluation of the average IoU segmentation results from 10 patients was 76.86%. This score is not very good for assessing lung segmentation typically. It is due to erosion at the edges of the lungs of each patient, which makes the Mean-IoU value not optimal. However, to visualize the surface of the lungs affected by Covid-19 infection, this score can be used as a reference for the magnitude of erosion and an estimate of the infection size at the periphery of the patient's lungs.

Table 2. Examples of segmentation and visualization results that do not appear to be eroded on the surface of the patient's lungs

Patient #	3D Visualization	Segmentation result	CT Image
Patient -2			
Patient -4			
Patient -5			

As previously explained, the Precision metric determines how precise the lung segmentation prediction is on the ground-truth image. In table 3, the results of the Precision metric calculations are given for each patient. From this value, it is obtained how much erosion is on the surface of the patient's lungs by calculating the difference (pixel) in the Precision metric value from 100% of the lung shape according to ground truth.

Table 3. Percentage Erosion Prediction for each patient

Patient#	Lung Segmentation Precision metric score for patient#	Lung Erosion prediction for patient#
1	95.18 %	4.82 %
2	94.16 %	5.84 %
3	74.74 %	25.26 %
4	98.49 %	1.51 %
5	94.24 %	5.76 %
6	92.25 %	7.75 %
7	96.23 %	3.77 %
8	90.20 %	9.80 %
9	89.86 %	10.14 %
10	85.97 %	14.03 %

6. CONCLUSION

Lung segmentation with a relatively minimal training dataset using U-Net CNN can produce the lung shape of COVID-19 patients. Due to an infection that causes GGO at most patients' periphery of the lungs, the segmentation results become eroded. However, by using the right image preprocessing technique, we can achieve good segmentation results. Moreover, reconstruction into 3D form by stacking some slices of segmentation results in the central part of the lungs, and displaying in 3D animation form, could successfully shape the condition of the lung surface of Covid-19 patients. The visualization on the surface of the lungs must be complemented by visualization of the infection inside the patient's lungs to complete the diagnosis.

Our research has three stages. The first stage of our research is lung segmentation, the second stage is a visualization of the surface of the lungs affected by Covid-19 infection, and the third stage is segmentation and visualization of Covid-19 infection. Our future work will use a surface 3D mesh shape to visualize the lung surface and infection in the patient's lungs, which will complement the study's results for diagnosing infected lungs by Covid-19

Acknowledgments

The authors would like to express special thanks to The University Center of Excellence on Artificial Intelligence for Healthcare and Society (UCE AIHeS), Institut Teknologi Sepuluh Nopember, for fully supporting this work.

REFERENCES

[1] **Nifty format**, [Online]. Available: http://nifty.nimh.nih.gov.

[2] W. Zhao, W. Jiang, and X. Qiu, **Deep learning for COVID-19 detection based on CT images**, *Sci Rep*, vol. 11, no. 1, Dec. 2021, doi: 10.1038/s41598-021-93832-2.

[3] Jeremy Jordan, **An Overview of Semantic Image Segmentation**, *https://www.jeremyjordan.me/semantic-segmentation*, May 21, 2018.

[4] X. Liu, Z. Deng, and Y. Yang, **Recent progress in semantic image segmentation,** *Artif Intell Rev*, vol. 52, no. 2, pp. 1089–1106, Aug. 2019, doi: 10.1007/s10462-018-9641-3.

[5] I. Ulku and E. Akagunduz, **A Survey on Deep Learning-based Architectures for Semantic Segmentation on 2D images**, Dec. 2019, doi: 10.1080/08839514.2022.2032924.

[6] O. Ronneberger, P. Fischer, and T. Brox, **U-net: Convolutional networks for biomedical image segmentation**, in *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, 2015, vol. 9351, pp. 234–241. doi: 10.1007/978-3-319-24574-4_28.

[7] F. Ferdinandus, E. Mulyanto Yuniarno, I. Ketut Eddy Purnama, and M. Hery Purnomo, **Covid-19 Lung Segmentation using U-Net CNN based on Computed Tomography Image**, *in 2022 IEEE 9th International Conference on Computational Intelligence and Virtual Environments for Measurement Systems and Applications (CIVEMSA),* June 2022.

[8] J. F. W. Chan *et al.*, **A familial cluster of pneumonia associated with the 2019 novel coronavirus indicating person-to-person transmission: a study of a family cluster**, *The Lancet*, vol. 395, no. 10223, pp. 514–523, Feb. 2020, doi: 10.1016/S0140-6736(20)30154-9.

[9] F. Shi *et al.*, **Review of Artificial Intelligence Techniques in Imaging Data Acquisition, Segmentation, and Diagnosis for COVID-19**, *IEEE Reviews in Biomedical Engineering*, vol. 14. Institute of Electrical and Electronics Engineers Inc., pp. 4–15, 2021. doi: 10.1109/RBME.2020.2987975.

[10] D. P. Fan *et al.*, **Inf-Net: Automatic COVID-19 Lung Infection Segmentation from CT Images**, *IEEE Trans Med Imaging*, vol. 39, no. 8, pp. 2626–2637, Aug. 2020, doi: 10.1109/TMI.2020.2996645.

[11] T. Karlita, E. M. Yuniarno, I. K. E. Purnama, and M. H. Purnomo, **Detection of COVID-19 on Chest X-Ray Images using Inverted Residuals Structure-Based Convolutional Neural Networks**, in *2020 3rd International Conference on Information and Communications Technology, ICOIACT 2020*, Nov. 2020, pp. 371–376. doi: 10.1109/ICOIACT50329.2020.9332153.

[12] A. Kalinovsky and V. Kovalev, **Lung Image Segmentation Using Deep Learning Methods and Convolutional Neural Networks**, 2016. [Online]. Available: http://imlab.grid.by/

[13] S. G. C, V. S. T, R. v Gowda, P. R. Udupa, and S. Reddy, **A Machine learning Classification approach for detection of Covid 19 using CT images**, *EMITTER International Journal of Engineering Technology*, vol. 10, no. 1, pp. 183–194, 2022, doi: 10.24003/emitter.v10i1.672.

[14] B. Ait Skourt, A. el Hassani, and A. Majda, **Lung CT image segmentation using deep neural networks,** in *Procedia Computer Science*, 2018, vol. 127, pp. 109–113. doi: 10.1016/j.procs.2018.01.104.

[15] T. Tolxdorff, T. M. Deserno Heinz Handels, and A. H. Maier Klaus Maier-Hein Christoph Palm Hrsg, **Bildverarbeitung für die Medizin 2020**, 2020. [Online]. Available: http://www.springer.com/series/2872

[16] Adhiparasakthi Engineering College. Department of Electronics and Communication Engineering, Institute of Electrical and Electronics Engineers. Madras Section, and Institute of Electrical and Electronics Engineers, *Proceedings of the 2018 IEEE International Conference on Communication and Signal Processing (ICCSP) : 3rd - 5th April 2018, Melmaruvathur, India.* 2018.

[17] H. Shaziya and K. Shyamala, **Pulmonary CT Images Segmentation using CNN and UNet Models of Deep Learning**, in *2020 IEEE Pune Section International Conference, PuneCon 2020*, Dec. 2020, pp. 195–201. doi: 10.1109/PuneCon50868.2020.9362463.

[18] K. K. Bressem, S. M. Niehues, B. Hamm, M. R. Makowski, J. L. Vahldiek, and L. C. Adams, **3D U-Net for segmentation of COVID-19 associated pulmonary infiltrates using transfer learning: State-of-the-art results on affordable hardware**, Jan. 2021, [Online]. Available: http://arxiv.org/abs/2101.09976

[19] E. Martínez Chamorro, A. Díez Tascón, L. Ibáñez Sanz, S. Ossaba Vélez, and S. Borruel Nacenta, **Radiologic diagnosis of patients with COVID-19**, *Radiología (English Edition)*, vol. 63, no. 1, pp. 56–73, Jan. 2021, doi: 10.1016/j.rxeng.2020.11.001.

[20] D. Cozzi *et al.*, **Ground-glass opacity (GGO): a review of the differential diagnosis in the era of COVID-19**, *Japanese Journal of Radiology*, vol. 39, no. 8. Springer Japan, pp. 721–732, Aug. 01, 2021. doi: 10.1007/s11604-021-01120-w.

[21] E. P. I. K. A. D. N. D. Athanasios Voulodimos, **Deep learning models for COVID-19 infected area segmentation in CT images**, vol. 6, 2021, doi: 10.1101/2020.05.08.20094664.

[22] T. Zhou, S. Canu, and S. Ruan, **Automatic COVID-19 CT segmentation using U-Net integrated spatial and channel attention mechanism**, *Int J Imaging Syst Technol*, vol. 31, no. 1, pp. 16–27, Mar. 2021, doi: 10.1002/ima.22527.

[23] K Scott Mader, **Kaggle Lung Dataset**, 2017.

[24] Ma Jun, et all, **Zenodo Lung Covid-19 Dataset**, *https://zenodo.org/record/3757476*, Apr. 20, 2020.

[25] Y. H. Nai *et al.*, **Comparison of metrics for the evaluation of medical segmentations using prostate MRI dataset**, *Comput Biol Med*, vol. 134, Jul. 2021, doi: 10.1016/j.compbiomed.2021.104497.