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Segmentation And Analysis Of Covid-19 Chest Ct Scan Images Using The Methods Of Deep Learning

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Abstract: The corona virus disease is an infectious disease which primarily affects lungs of human body. Medical imaging using computed tomography (CT) plays an important role in the global fight in COVID-19. In present days deep learning techniques is useful for diagnose lung affected by covid-19 patients. HRCT images provide good analysis of segmentation of CT images. This process is based on segmentation of medical images in line with convolution neural networks which utilizes augmentation of data, evaluation pre-processing and segmentation of image analysis. Using u-net architecture this paper highlights an approach for lunch images of CT segmentation. The result shoes a comparative lung image of covid-19 patient and non covid-19 patient using U-net Architecture lung augmentation.

Keywords: deep learning; computed tomography images; data augmentation; COVID-19.

1. INTRODUCTION

The impact of COVID-19 is life-threatening and results in a decline in all aspects of life. Pathological changes are exhibited on chest CT of COVID-19 patients essentials. For faster screening of COVID-19 computed tomography (CT) tool is effective in clinical practices. Nevertheless, it is labour intensive and time consuming task if manual screening of COVID-19 from CT images is considered. This is mainly because of doctors involvement in finding the lesions from volumetric chest CT scans. With the help of image segmentation and deep learning paradigms, artificial intelligence has proven to be fruitful in development in the recent times of a well-known subfield [3]. To detect severe health conditions various approaches of neural network are utilized such as detection of lung cancer. It is beyond what we think in deep learning. There is an involvement of selecting, extracting and creating new structures in deep learning techniques. In the field of medical, deep learning has shown a significant presence in medical imaging with a proven good development [4]. As a result, medical images can be segmented automatically. For satisfactory medical image segmentation, U-Net [7] is most preferred encoder-decoder deep network architecture. To improve the performance of different organs segmentations some variants of U-Net [8-9] are proposed. However, it is observed that in segmentation of other medical images U-Net models perform very satisfactorily. U-Net could obtain excellent results if hundreds of labeled training samples are present. The paper is organized such that the section II has the image data set description. And the section III has the details of the proposed methodology. In section IV results of analysing the images. Finally Section V includes the conclusion of this paper.

2. DATA SET DESCRIPTION

For classifying of COVID-19 patients, for this research, CT scan images of different hospitals were collected [18]. In this dataset, 482 chest CT images are gathered from one of the hospitals. With respect to this dataset, among the 482 data, 252 were positive cases and 230 were negative cases. COVID-19 is identified and the effected lesions of the lungs are segmented by implementing deep learning methods. For lung feature extraction in CT images traditional U-Net architecture is implied by [19]. By utilizing two publicly available datasets the data used in this study is compiled. The first data set utilized was presented by [10]. In the first data set, total of 320 chest CT images were recorded. Of which, 259 chest CT images were of SARS, ARDS (pneumonia cases) and MERS. The chest CT scan images are collected and extracted from various hospitals. The images are majorly used for training (80%) and testing the system (20%). Out of 2606 images, 260 images were of COVID positive patients, whereas the other images were related to other diseases such as SARS/MERS/ SARS-Cov-2/ARDS/without chest disease.

3. METHODOLOGY

The main is established on segmentation of medical images with Convolution Neural Networks (CNN) model. For evaluation and straightforward training the model utilizes extensive augmentation of data, pre-processing and batch creation. The model uses extensive augmentation of data, pre-processing and batch creation for straightforward training and evaluation of medical image segmentation. The following main steps are outlined for the implementation of the image segmentation pipeline of COVID-19 CTs and are further explained in Fig 1.

1. Collected HRCT scan images
2. Different pre-processing techniques.
3. Thorough data augmentation.
4. Implementation of standard U-net (training)
5. Training And Testing of image.
6. Analyzing and evaluate the results

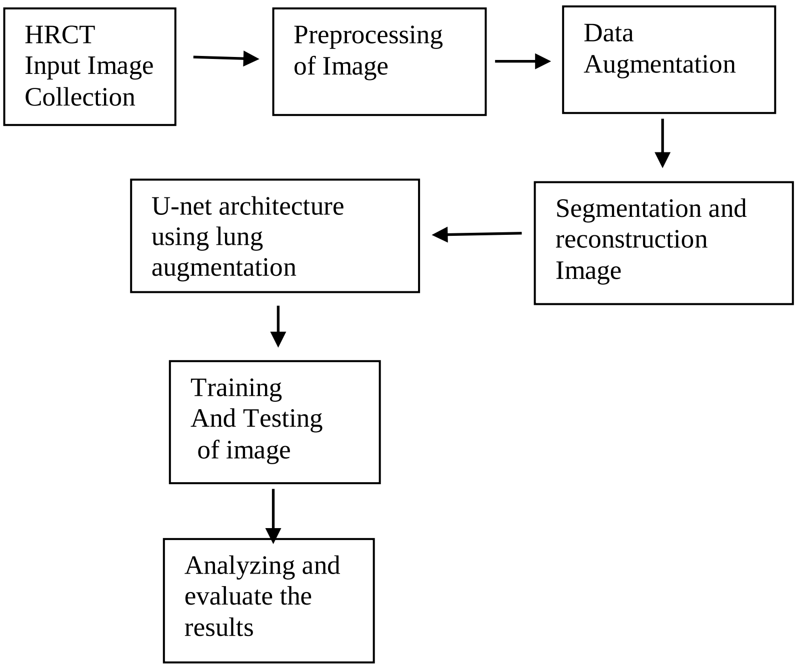

Fig.1. Block diagram of implantation of lung segmentation on the COVID CT images.

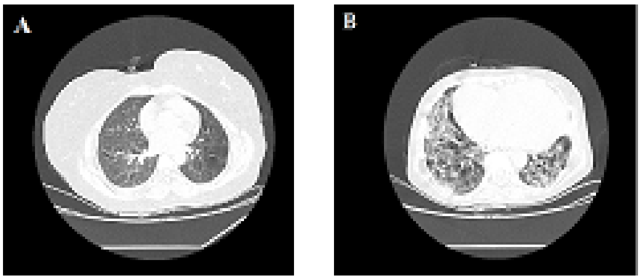

Fig.2. Images displays chest CT scanned images (COVID and non-COVID images)

3.1 HRCT Data Set Collection

Publicly available dataset consists of background CT scans, infection and lung masks. 20 CT volumes are consisted in each class.CT scans from the datasets are collected from various organizations like Radient licensed software. The dataset is verified and labeled by the radiologists. Even though there is a limitation in the dataset, however, there was an outstanding standard dataset in the method of annotation contribution. Pathological and normal regions were contained in the entire lung mask.

Table I: Images in CT scan Datasets.

Data set		Normal images	COVID-19 Positive
CT-scan	Training set	520	500
	Validation set	345	292
	Total	765	792

Table I shows data images in CT scan datasets, in this data sets two sets are used training sets and validation sets. Training sets used to normal images and COVID-19 positive. In normal images are 520 and validation 345 total 765 images and COVID-19 positive 500 are training set images and 292 are validation sets total is 792 images.

3.2 Preprocessing of image

For the purpose of identification of pattern multiple preprocessing techniques are implied on the data to avoid the over fitting. On the entire dataset resizing of the image process is implied. To ensure the accomplishment of the signal's dynamic intensity standardization of imaging data is important. Thus, scaling of the image data and normalization is also important. To a range of grayscale images are normalized. Cropping is used to crop the regions of interest since images contain no information in black space and thus they take unnecessary convolutions. The exact area of interest is extracted by cropping the rectangle which contains both the lungs and by applying the contours.

3.3 Data Augmentation

There is a possibility in the field of machine learning for artificial growth in the training of data under data augmentation techniques. As the amount of neat labeled and well trained data is less the above technique is important in medical imaging. To avoid the over fitting in limited datasets appropriate variants of the required pattern are established. Thus,

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augmentation techniques like shifting, scaling etc can be applied.

3.4 Segmentation and reconstruction Image

In processing and analysis of the COVID-19 image segmentation is a step which is essential in order to quantify and assess. It outlines the region of interest such as lung, pulmonary segments, lobes and infection lesions or regions in the CT or X-ray images. For diagnosis and other applications segmented regions could be further used to extract self learned features and or handcrafted features. Works which are in relation to segmentation on COVID-19 and the applications involved are summarized in the following subsection.

3.5 U-net architecture

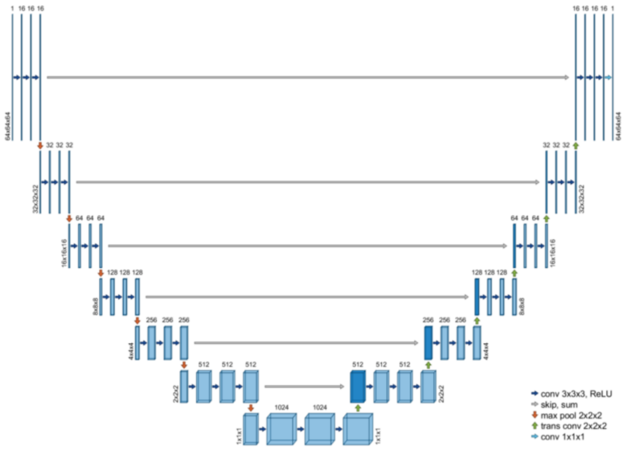

Fig 3. U-net architecture lung segmentation on COVID CT images.

Encoding and decoding layers is utilized in the U-net segmentation neural network model. The model also helps to skip the connection to avoid unnecessary convolutions. The encoder part receives the CT scan as the input. On the image several layers of convolutions, max-pooling, activations, and compression of data is implemented. The decoder part receives the earlier compressed data stored in latent space as an input. To decode the details transposed convolution is applied. Segmentation mask is introduced as an output. In U-Net architecture a feature of distinct is used. To transmit data to encoder and decoder of high reolution layers the skip connection feature is utilized Thus, production of tiny and accurate high resolution data in the system observed. This, however, is a significant difference between normal encoder decoder systems and U-Net. Standard U-Net architecture lung segmentation on images of COVID CT are illustrated in Fig.3.

3.6 Training and Testing

To separate train and test the data splitting function is used. Separate binary classifier is applied to avoid complete black masks. Slices up to 350 were present in 12 patients with no infection. From data augmentation and pre-processing more than 1,500 samples were collected. Standardized splitting of 80% was applied thus this resulted in slices of 1200 for the purpose of training and testing, approximately.

Table.II: Statistics of Data split

	Non COVID	COVID	Total
Train	55	42	97
Test	50	50	100
Validation	50	50	100

Using precision and recall on lung/infection segmentation, table II illustrates the representation of the analysed total CT scanned images. The subset includes 50 patient's CT scan taken by 256-CT. Radiologists visually confirmed that the subset in the data set has the highest signal to noise ratio (SNR).

3.7 Evaluation criteria

As the evaluation criteria, Precision, recall, accuracy, AUC score and F1 score. Out of all predictions accuracy is the total number of correct predictions. The depiction of the recall suggests that out of total and actual corona virus cases; how many patients are identified as the affected patients of corona virus? Whereas, from the total subjects predicted with the corona virus, amongst them how many patients are actually affected by the corona virus. Between precision and recall F1 score is harmonic mean. Area under the ROC curve is the AUC. Aggregated measure of performance is provided across all possible threshold classification by the AUC, Accuracy, recall, precision and F1-score respectively.

Accuracy: A ratio of the measured value or findings reflects the real or the original values.

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

Recall: A ratio of accurately categorized instances divided by instances of actual.

$$\text{Recall} = \frac{TN+FP}{TN+FP+TP} \quad (2)$$

Precision: is a ratio of accurate prediction of COVID-19over total pixels which are predicted as positive as COVID-19.

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

F1 score: Weighted average of Recall and precision is the F1 score. Hence, both false negative and false positive is taken into account by this score. However, F1 is more useful than the accuracy.

$$\text{Score} = \frac{\text{Precision+Recall}}{\text{Precision+Recall+Accuracy}} \quad (4)$$

4. RESULTS OF ANALYZING IMAGES

The trained model predicted the accuracy around 0.92 for infection and whereas 0.90 for segmentation of lung. Loss of 0.03 and 0.04 were observed for the infection and lung segmentation.

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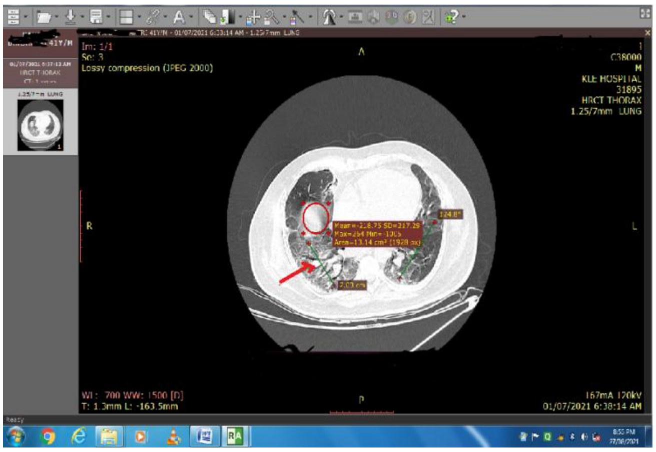

Fig. 4. Infection regions of patients for COVID-19 positive.

With reference to examples shown in Fig 4, it can be observed that the method utilized in this study constituently performed well with the account of segmentation results for different methods from the dataset. By the compared methods, infection regions are sometimes under or over segmented. The majority of the large infected regions can correctly be segmented by our method. It is embedded in the regions as indicated by blue arrows. During the training process in the collection of data testing accuracy, Recall, Precision, F1 Score are preferred and chosen as measurement of performance. Five pre-trained models were trained in the data collection.

Table III: Analyzing the total CT scan images

Length	11.85cm	
Eclipse	mean	357.34
	max	769
	min	24.88cm
Angle	50.0º	

Table III illustrates the reported performance of the methods of segmentation. The possible reasons are as follows: firstly, the referred dataset consists of different and mixed stage scans, of which are early-stage scenarios (83%), majorly. Because of the small infection and the scattered regions, the early stage of segmentation is much more challenging than the progressive and or the sever stage of the segmentation.

Table. IV: performances of measurement data

Train data	Accuracy (%)	F1-score (%)	AUC (%)
COVID-CT-349	79.5	76.0	90.1
COVID-CT-349 with lung mask	85.0	85.9	92.8

The above table IV illustrates and compares the current study with the previous work in terms of performance of measurement data to find accuracy and F1-score. Hence, we can further conduct a more in depth analysis on different methods.
The proposed method is tested analyses for 523 COVID-19 HRCT images in which 120

images are analyzed for positive and 60 images for negative images. With this technique achieved detection rate is 94% accuracy.

5. CONCLUSION

In this paper, segmentation of infected regions is developed and analyzed of COVID-19 CT images. An obstacle of a dataset which is limited is handled by utilizing and applying many pre-processing and data augmentation techniques. This provides good analysis of segmentation of CT images. The process in this paper is based on segmentation of medical images with the help of convolution neural networks model which utilizes augmentation of data, pre processing, evaluation and analysis of image segmentation.

6. REFERENCES

[1] Aravind Jadhav, Sanjay Pujari. “Efficient medical image segmentation of COVID-19 chest CT scan images analysis based on deep learning technique”. ‘International Conference On Emerging Trends In Science Engineering And Management (ICETSEM-2021), GM Institute of Technology Davangere, Karnataka, India held on 15th & 16th July 2021.Page no: 178

[2] Aravind Jadhav, Sanjay Pujari. “Radiological image Quality enhancement and analysis”. ‘IEEE International Conference on Advance in Information Technology (ICAIT-2019), Adichunhanagiri Institute of Technology Chikkamagaluru, 26th and 27th July 2019.Page no: 3119

[3] Aravind Jadhav, Sanjay Pujari. “Fuzzy Clustering Based Kidney Stones Analyses in Computed Tomography Images”. ‘IEEE International Conference on Innovations in Engineering, Technology and Sciences’ (ICIETS), NIE Institute of Technology Mysore,20th and 21st September 2018.

[4] Aravind Jadhav, Sanjay Pujari. “Resolution Enhancement of CT Images Based on Histogram Equalization”. ‘International Journal of Engineering and Advanced Technology (IJEAT)’ Volume-6 Issue- ICDSIP17, Page No.: 129-132, March 2017.

[5] A. Oulefki, S. Agaian, T. Trongtirakul, and A. Kassah Laouar, "Automatic COVID-19 Lung Infected Region Segmentation and Measurement Using CT-Scans Images,"(in eng), Pattern recognition,

[6] A. Amyar, R. Modzelewski, and S. Ruan, “Multi-task deep learning based ct imaging analysis for covid-19: Classification and segmentation,” medRxiv, 2020.

[7] T. Zhou, S. Canu, and S. Ruan, “An automatic covid-19 ct segmentation network using spatial and channel attention mechanism.” arXiv preprint arXiv:2004.06673, 2020.

[8] L. Perez, J. Wang, The Effectiveness of Data Augmentation in Image Classification using Deep Learning, (2017). http://arxiv.org/abs/1712.04621 (accessed July 23, 2019).

[9] Ronneberger, Olaf, Philipp Fischer, and Thomas Brox.

[10] "Unet:Convolutional networks for biomedical image segmentation."International Conference on Medical imag computing and computer-assisted intervention. Springer, Cham, 2015.

[11] C. Ye, W. Wang, S. Zhang, and K. Wang, “Multi-depth fusion network for whole-heart ct image segmentation,” IEEE Access, vol. 7, pp. 23 421–23 429, 2019.

[12] L. Huang, R. Han, T. Ai, P. Yu, H. Kang, Q. Tao, and L. Xia, "Serial quantitative chest ct assessment of covid-19: Deep-learning approach," Radiology:Cardiothoracic Imaging, vol. 2, no. 2, p. e200075, 2020.
[13] A. Amyar, R. Modzelewski, and S. Ruan, "Multi-task deep learning based ct imaging analysis for covid-19: Classification and segmentation," medRxiv, 2020.
[14] Y. Xiong, D. Sun, Y. Liu, Y. Fan, L. Zhao, X. Li, W. Zhu, Clinical and high-resolution CT features of the COVID-19 infection: comparison of the initial and follow-up changes, Invest. Radiol. 55 (6) (2020) 332–339.
[15] S.M. Lee, J.B. Seo, J. Yun, Y.-H. Cho, J. Vogel-Claussen, M.L. Schiebler, W. B. Gefter, E.J. Van Beek, J.M. Goo, K.S. Lee, Deep learning applications in chest radiography and computed tomography, J. Thorac. Imaging 34 (2) (2019) 75–85.
[16] W. Shi, X. Peng, T. Liu, Z. Cheng, H. Lu, S. Yang, J. Zhang, F. Li, M. Wang, X. Zhang, Deep Learning-based Quantitative Computed Tomography Model in Predicting the Severity of COVID-19: a Retrospective Study in 196 Patients, 2020.
[17] W. Shi, X. Peng, T. Liu, Z. Cheng, H. Lu, S. Yang, J. Zhang, F. Li, M. Wang, X. Zhang, Deep Learning-based Quantitative Computed Tomography Model in Predicting the Severity of COVID-19: a Retrospective Study in 196 Patients, 2020.
[18] Xiaowei Xu, Xiangao Jiang, Chunlian Ma, Peng Du, Xukun Li, Shuangzhi Lv, Liang Yu, Yanfei Chen, Junwei Su, Guanjing Lang, et al., "Deep learning system to screen coronavirus disease 2019 pneumonia," arXiv preprint arXiv:2002.09334, 2020.
[19] Xiaowei Xu, Xiangao Jiang, Chunlian Ma, Peng Du, Xukun Li, Shuangzhi Lv, Liang Yu, Yanfei Chen, Junwei Su, Guanjing Lang, et al., "Deep learning system to screen coronavirus disease 2019 pneumonia," arXiv preprint arXiv:2002.09334, 2020.
[20] Jinyu Zhao, Yichen Zhang, Xuehai He, and Pengtao Xie, "Covid-ct-dataset: A ct scan dataset about covid- 19," arXiv preprint arXiv:2003.13865, 2020.
[21] Ai T, Yang Z, Hou H, Zhan C, Chen C, Lv W, Tao Q, Sun Z, Xia L. Correlation of chest ct and rt-pcr testing in coronavirus disease 2019 (covid-19) in China: a report of 1014 cases. Radiology 2020:200642.
[22] Wang L, Wong A. Covid-net: a tailored deep convolutional neural network design for detection of covid-19 cases from chest radiography images. 2020. arXiv preprint arXiv:2003.09871.
[23] He X, Yang X, Zhang S, Zhao J, Zhang Y, Xing E, Xie P. Sample-efficient deep learning for covid-19 diagnosis based on ct scans. medRxiv; 2020.