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IMPROVING NEURAL NETWORK METHODS FOR RECOGNIZING LUNG LESIONS WITH CORONAVIRUS INFECTION

IN THIS WORK MATHEMATICAL MULTILAYER IMAGES SEGMENTATION MODEL-BASED LUNG LESIONS RECOGNITION METHODS FOR MULTILAYER IMAGES SEGMENTATION WERE DEVELOPED. WE ANALYSED COVID-19 DIAGNOSIS METHODS, DEVELOPED LUNG DAMAGE PERCENTAGE DETERMINING SOFTWARE AND GAVE DATASET PREPARING STAGES DESCRIPTION

The study proposed in this paper considers the problem of lung damage percentage determining in patients with coronavirus infection. As initial data, the dataset with three-dimensional computed tomography images of the lungs of patients affected by COVID 19 was used [1]. Each image in the dataset has a lung mask and a lesion mask. Required:

1. Lungs region determination
2. Coronavirus pneumonia foci determination
3. The number of layers affected by the infection and lung damage volume calculation

The original images have weak intensity contrast and need conversion for better visual representation. To do this, we use Contrast Limited Adaptive histogram equalization [13]. CLAHE limits the gain by clipping the histogram to a predetermined value before computing the neighborhood distribution function (Figure 5). This limits its slope and hence the transform function. The clipping boundary depends on the normalization of the histogram and therefore on the size of the neighborhood area. It is advantageous not to discard that part of the histogram that exceeds the cutoff limit, but to redistribute it equally among all cells of the histogram. As a result of the redistribution, some histogram bins will again exceed the clipping limit, resulting in a larger effective clip limit.

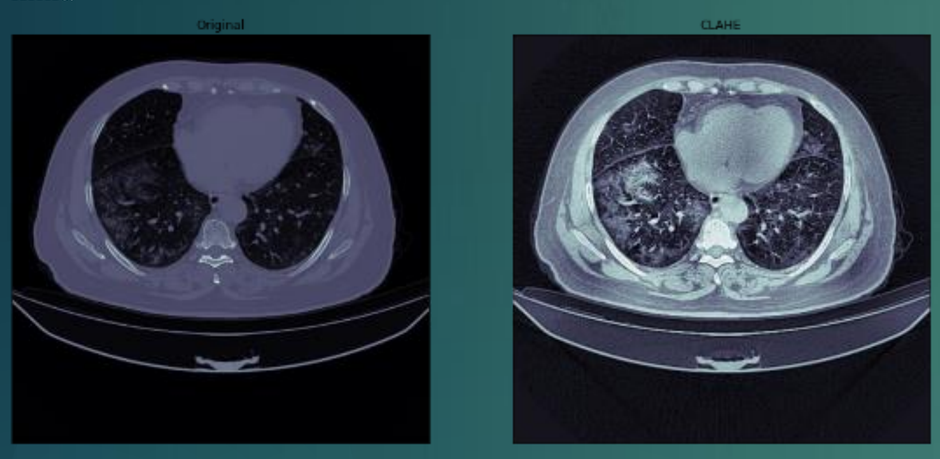

Fig 1. CT slice image before and after contrast enhancement

We apply preprocessing techniques to all images slices of each of the volumes. Also 20% of the volume from the beginning and from the end should be cut off, since these sections are of little information and are of no practical value for the model training. To load cropped volumes, we need a new image reader feature. Using this function, we will read the images of volumes. It also worth bearing in mind that readable images should be subject to scaling to reduce the amount of consumed RAM and reduce the number of model weights, and as a result, speed up its training and operation. The implementation of image scaling is performed to the size of 256\times256 pixels and is represented by the .resize() method.

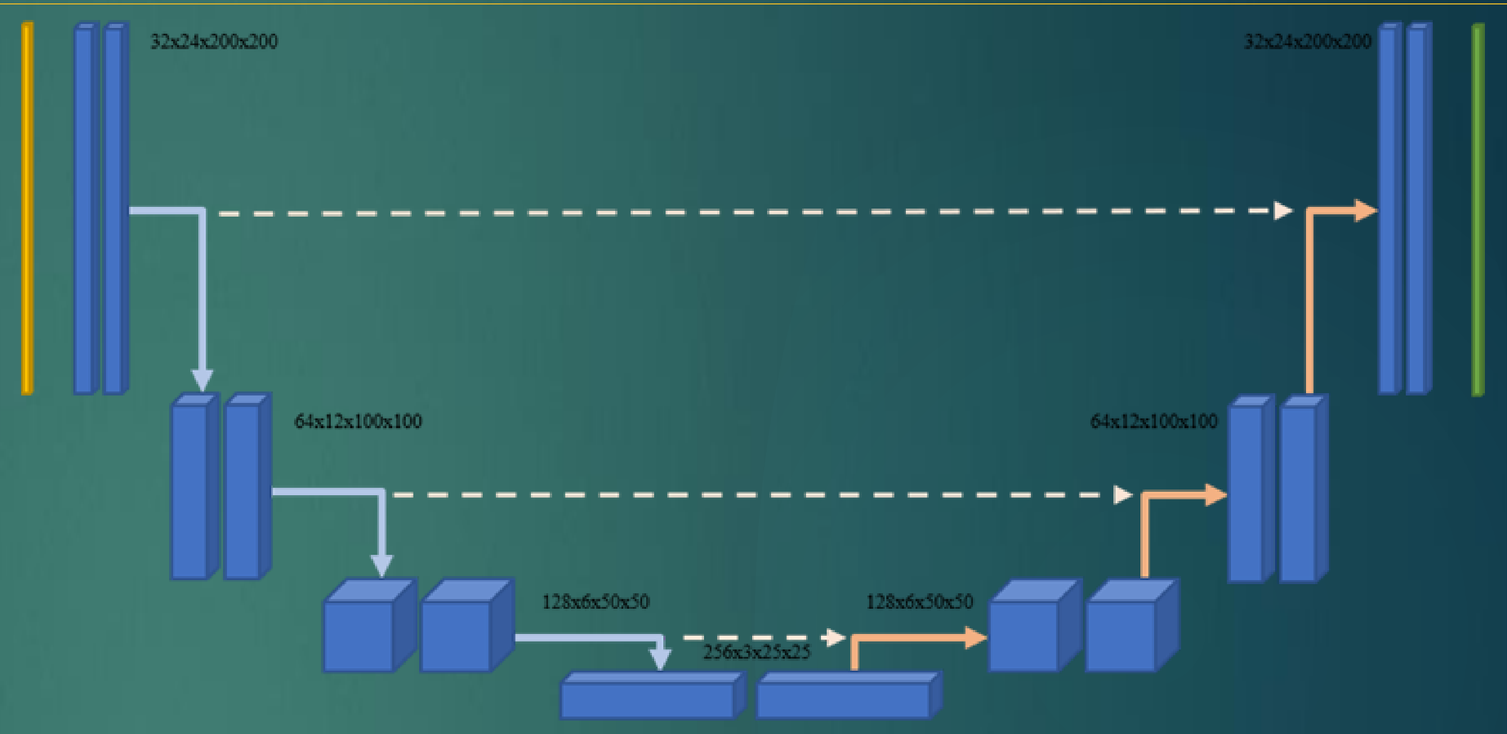

Fig 2. U-Net convolutional network architecture

The main tool for solving the problem are neural networks (NN). U-Net is a convolutional neural network designed for biomedical image segmentation [12]. The architecture consists of two parts.

1. Left - encoding. Used to extract feature maps. Represents a typical convolutional network consisting of successive convolutions, each of which passes through the ReLU activation layer. During contraction, the amount of spatial information is reduced and the amount of information about important features is increased.

2. Right - decoding. Used for precise localization. In this part, the feature and space information is combined using a sequence of unwrapping and merging layers with high-resolution features obtained from the respective layers of the tightening part.

An important feature of U-Net is that it contains a huge number of feature channels on the right side, which allows the network to propagate contextual information to higher resolution layers. As a result, the expanding part becomes more or less symmetrical to the contracting part, bringing the same U-shape (Fig. 4). The network uses only the valid part of each convolution without using fully connected layers. In order to predict pixels in the image boundary region, the missing context is extrapolated by mirroring the input image. This tiling strategy is important for applying the network to large images, because if not, the resolution will be limited by GPU memory.

To check the performance of the models on a test sample we run them on the CT image with random index. Then we compare the original masks with the ones predicted by models (Fig. 12). To calculate the volume of the lesion, it is better to use a direct comparison of two masks for their intersection and return the percentage of matching pixels to the sum of all pixels of the lung mask with maximum intensity. We calculate the metrics for 211 samples from the test sample in order to evaluate the effectiveness of the chosen technique. From the obtained results, it can be seen that the metrics for segmentation of the lungs are somewhat better than the segmentation of the affected areas (which is explained by a larger sample of training samples with labeling of the lungs). In general, the network shows high accuracy results for the selected metrics.

Sample	IoU	Precision	Recall	F1
1	0.993285	0.99537	0.976142	0.980724
2	0.993305	0.99232	0.984129	0.988952
3	0.989315	0.993082	0.970711	0.985757
4	0.991378	0.973345	0.979637	0.987854
5	0.99325	0.991699	0.960892	0.977158
Mean	0.99561	0.99124	0.979286	0.985327

Table I. Lung Segmentation Metrics

Sample	IoU	Precision	Recall	F1
1	0.974118	0.813062	0.81845	0.813856
2	0.952856	0.814853	0.816293	0.81416
3	0.949292	0.811065	0.814245	0.81775
4	0.954491	0.812655	0.815083	0.814254
5	0.95757	0.814893	0.817255	0.813876
…	…	…	…	…
Mean	0.957495	0.812016	0.816361	0.814174

Table II. Segmentation Of Affected Areas Of The Lungs

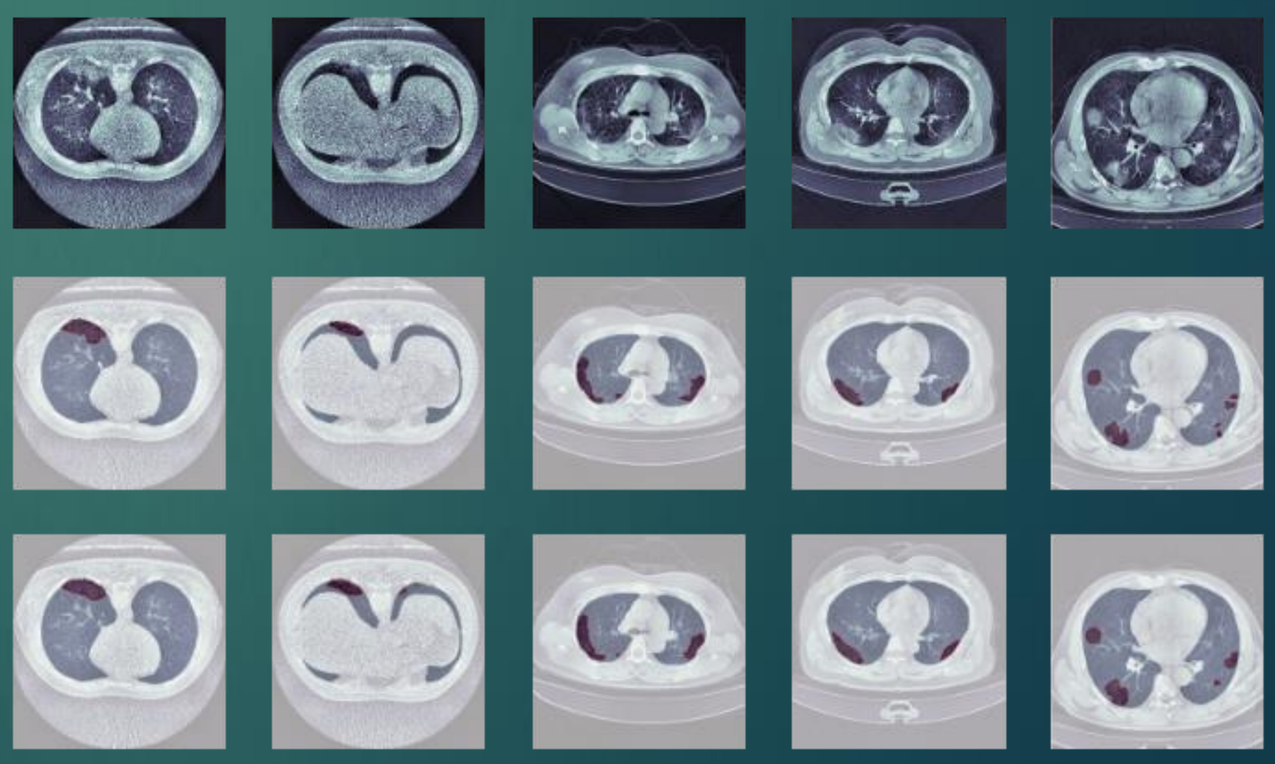

Fig 3. Comparison of original and predicted masks

Conclusion

From the obtained results, it can be seen that the metrics for segmentation of the lungs are somewhat better than the segmentation of the affected areas (which is explained by a larger sample of training samples with labeling of the lungs). In general, the network shows high accuracy results for the selected metrics. The neural network U-Net architecture has been successfully applied to the problem of computed tomography images lung segmentation. Combination of the mathematical multilayer images segmentation model with the CLAHE preprocessing algorithm increased the model's accuracy. This will speed up the diagnosis process and minimize the influence of the human factor in the work of radiologists.

[1] MosMedData, Chest CT Scans with COVID-19, Internet: https://mosmed.ai/datasets/covid19_1110/

[2] K. Zuiderveld, "Contrast Limited Adaptive Histogram Equalization", Academic Press Inc., 1994, pp. 474-485

[3] O. Ronneberger, P.Fischer, T.Brox, "U-Net: Convolutional Networks for Biomedical Image Segmentation", Medical Image Computing and Computer-Assisted Intervention – MICCAI 2015. Lecture Notes in Computer Science, vol 9351. Springer, Cham.