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Fully Automatic End-to-End Convolutional Neural Networks-Based Pancreatic Tumor Segmentation on CT Modality

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A B S T R A C T

The pancreas is one of the vital organs in the human body. Early diagnosis of a disease in the pancreas is critical. In this way, the effects of pancreas diseases, especially pancreatic cancer on the person are decreased. With this purpose, artificial intelligence-assisted pancreatic cancer segmentation was performed for early diagnosis in this paper. For this aim, several state-of-the-art segmentation networks, UNet, LinkNet, SegNet, SQ-Net, DABNet, EDANet, and ESNet were used in this study. In the comparative analysis, the best segmentation performance has been achieved by SQ-Net. SQ-Net has achieved a 0.917 dice score, 0.847 IoU score, 0.920 sensitivity, 1.000 specificity, 0.914 precision, and 0.999 accuracy. Considering these results, an artificial intelligence-based decision support system was created in the study.

1. Introduction

The pancreas is a critical importance for human life which is located in the abdominal region. The size and location of the pancreas is the variety from person to person [1]. Therefore, the detection of the pancreas in computed tomography (CT) and magnetic resonance imaging (MRI) modality requires time and effort [2]. Pancreatic cancer is the riskiest type of cancer after lung cancer and bronchial cancer. Therefore, early detection of pancreatic cancer is vital. CT and MRI techniques are used to detect the pancreas and several pancreas diseases. But, the CT technique is generally preferred and used [3]. Nevertheless, in the imaging process using the CT method, the detection of pancreas and pancreas diseases may become more difficult depending on the irregularity of the pancreas, the presence of many organs around it, and the health status of the person [4]. So, the detection process of pancreatic disease is a time-consuming and labor-intensive process.

In this study, state-of-the-art segmentation models UNet [5], LinkNet [6], SegNet [7], SQ-Net [8], DABNet [9], EDANet [10], and ESNet [11] were used with the purpose of pancreatic tumor segmentation. In accordance with this

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purpose, CT images of 91 patients were used. SQ-Net segmentation model achieved the best predictive segmentation performance in the comparative analysis. The 0.917 dice score, 0.847 IoU score, 0.920 sensitivity, 1.000 specificity, 0.914 precision, and 0.999 accuracy were achieved by the SQ-Net model.

The main contributions of this proposed paper are outlined as follows:

1. The state-of-the-art segmentation architecture designs in the literature were used and the obtained performances were compared. Thus, suggestions were made to other researchers for their studies.

2. Thanks to the comparative analysis of the state-of-the-art segmentation architecture designs' used, information about the blocks in the these designs' were obtained.

The rest of this paper is organized as; a literature survey of several segmentation studies for the pancreas and pancreatic tumor segmentation has been shown in Section 2. The utilized methodologies, data and preprocessing, information about used segmentation networks and details of the training phase of segmentation networks, and the used performance evaluation metrics have been presented in Section 3. The results obtained by the state-of-the-art segmentation networks have been demonstrated in Section 4. Concluding remarks have been presented in Section 5.

2. Related Works

Numerous scientific researchers have proposed that different segmentation networks can be used for the pancreas and pancreatic tumor segmentation.

Derin et al. [12] aimed to automatically segmentation of pancreas. In this study, different segmentation networks, such as U-Net, Attention U-Net, Residual U-Net, Attention Residual U-Net, and Residual U-Net++ were utilized. The NIH-CT82 data set was used in this study. The data set includes CT images from 82 patients. Residual U-Net achieved the best predictive with a 0.903 dice score, 0.823 IoU score, 0.898 sensitivity, 1.000 specificity, 0.908 precision, and 0.999 accuracy. Roth et al. [13] aimed to pancreas segmentation in CT images. In this study, the hierarchical coarse-to-fine classification of local image regions method was used. The data set includes CT images of 82 patients. This method achieved a 68% ± 10% average dice score in the testing phase. Li et al. [14] aimed to pancreas segmentation in CT images. In this study, a multiscale attention-dense residual U-Net network (MAD-UNET) was proposed. The data set includes 82 abdominal-enhanced CT scan from the NIH-CT82 data set and 281 CT scans from the MICCAI data set. In this proposed approach, the MAD-UNET achieved an 86.10 ± 3.52% and 88.50% ± 3.70 mean dice scores for NIH-CT82 and MICCAI data sets, respectively. Zhao et al. [15] aimed to fully automate pancreas segmentation in CT images. In this study, a two-stage method was proposed. In the first stage, a U-Net was trained with the purpose of the presumed pancreas was removed in the 3D volume. In the second stage, another 3D U-Net was trained for the removed pancreas. The NIH-CT82 data set was used for also these two stages. The 3D U-Net model achieved an 85.99% mean dice score. Kurnaz et al. [16] aimed to pancreas segmentation in CT images. In this study, the U-Net segmentation network was used. The data set includes CT images of 82 patients. In this proposed approach, the U-Net achieved a 0.78 dice score and a 0.66 Jaccard similarity score.

3. Methodology

The utilized methodologies in the paper are presented under the subtitles of data set and preprocessing, segmentation networks, and performance evaluation metrics.

3.1. Data set and preprocessing

In this paper, the pancreatic tumor dataset [17], which is publicly available and includes a total of 91 CT images, was used. Details of the preprocessing steps are; (i) 3D CT images were sliced into 2D images, and as a result total of 14611 2D images were obtained. (ii) 14611 2D images were clipped by using Hounsfield unit (HU) values. HU values are set to a range of from -100 to 240-pixel values. (iii) Images in the data set were normalized by using the min-max normalization technique. (iv) If the maximum pixel value is zero in the masks, those masks and images of masks were removed from the data set. Consequently, 1310 2D images have remained in the data set. (v) 90% of 1310 images were used in the training phase of segmentation models, while 10% of 1310 images were used in the validation process of segmentation models.

3.2. Segmentation networks

In this study, well-known segmentation networks such as UNet [5], LinkNet [6], SegNet [7], SQ-Net [8], DABNet [9], EDANet [10], and ESNet [11] were used for pancreatic tumor segmentation. Details of the training phase of segmentation models are; (i) Loss function is a compound form of cross entropy and dice loss functions. (ii) Optimizer is RMSprop with a learning rate of 1e-5, weight decay of 1e-8, and momentum of 0.9. (iii) The learning rate hyperparameter was linearly reduced to 1e-8. (iv) Epoch and batch size are set as 50 and 2, respectively. The effects of these hyperparameters on segmentation tasks carried out by using CT and MRI modalities have been demonstrated in previous studies in the literature [18-20].

3.3. Performance evaluation metrics

Widely used performance evaluation metrics in the segmentation problems which are accuracy, precision, sensitivity, specificity, dice, and IoU were utilized in the comparison of the predictive performance of segmentation models in this paper. The mathematical calculations of these performance evaluation metrics are shown in Equations 1, 2, 3, 4, 5, and 6.

$$Accuracy= \frac{TP+TN}{TP+FP+TN+FN} \tag{1}$$

$$Precision= \frac{TP}{TP+FP} \tag{2}$$

$$Sensitivity= \frac{TP}{TP+FN} \tag{3}$$

$$Specificity= \frac{TN}{TN+FP} \tag{4}$$

$$Dice= \frac{2*TP}{2*TP+FP+FN} \tag{5}$$

$$IoU= \frac{TP}{TP+FP+FN} \tag{6}$$

True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN) refer to the number of correctly classified positive classes, the number of correctly classified negative classes, the number of incorrectly classified positive classes, and the number of the incorrectly classified negative class, respectively. In this context, classes indicate pixel-based classes.

4. Results and Discussion

Table 1 represents the results obtained by using segmentation models. The 0.880 dice score, 0.786 IoU score, 0.855 sensitivity, 1.000 specificity, 0.907 precision, and 0.999 accuracy were achieved by the U-Net model. The training time of the U-Net model is 13574 seconds. The 0.909 dice score, 0.834 IoU score, 0.907 sensitivity, 1.000 specificity, 0.912 precision, and 0.999 accuracy were achieved by the LinkNet model. The training time of the LinkNet model is 5688 seconds. The 0.883 dice score, 0.791 IoU score, 0.862 sensitivity, 1.000 specificity, 0.906 precision, and 0.999 accuracy were achieved by the SegNet model. The training time of the SegNet model is 10702 seconds. The 0.917 dice score, 0.847 IoU score, 0.920 sensitivity, 1.000 specificity, 0.914 precision, and 0.999 accuracy were achieved by the SQ-Net model. The training time of the SQ-Net model is 7825 seconds. The 0.904 dice score, 0.825 IoU score, 0.892 sensitivity, 1.000 specificity, 0.917 precision, and 0.999 accuracy were achieved by the DABNet model. The training time of the DABNet model is 6691 seconds. The 0.901 dice score, 0.820 IoU score, 0.904 sensitivity, 1.000 specificity, 0.898 precision, and 0.999 accuracy were achieved by the EDANet model. The training time of the EDANet model is 9213 seconds. The 0.888 dice score, 0.798 IoU score, 0.889 sensitivity, 1.000 specificity, 0.887 precision, and 0.999 accuracy were achieved by the ESNet model. The training time of the ESNet model is 6551 seconds.

The comparative analysis is shown below:

- The best three predictive performances were achieved by SQ-Net, LinkNet, and DABNet, respectively.
- UNet achieved the worst predictive performance.
- LinkNet has the shortest training time.
- UNet has the longest training time.

Dice score, IoU score, sensitivity, specificity, precision, accuracy, and training time of segmentation networks results obtained by segmentation models are shown in Figure 1 with the purpose of model performance comparison. The predictive segmentation results of the SQ-Net model on the three of sample images in the validation data set are shown in Figure 2.

Table 1. Results obtained by segmentation models

Models	Dice	IoU	Sensitivity	Specificity	Precision	Accuracy	Training Times (seconds)
UNet	0.880	0.786	0.855	1.000	0.907	0.999	13574
LinkNet	0.909	0.834	0.907	1.000	0.912	0.999	5688
SegNet	0.883	0.791	0.862	1.000	0.906	0.999	10702
SQ-Net	**0.917**	**0.847**	**0.920**	**1.000**	**0.914**	**0.999**	**7825**
DABNet	0.904	0.825	0.892	1.000	0.917	0.999	6691
EDANet	0.901	0.820	0.904	1.000	0.898	0.999	9213
ESNet	0.888	0.798	0.889	1.000	0.887	0.999	6551

* The highest performance obtained by among to segmentation models has been indicated by bold.

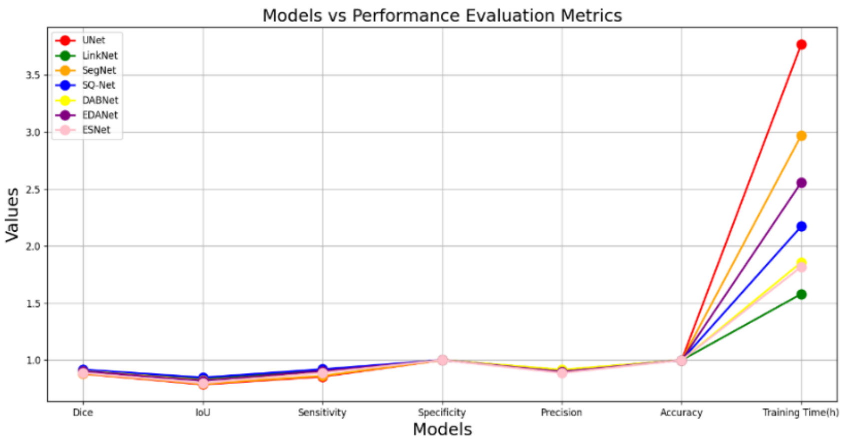

Figure 1. Model performance comparison

5. Conclusion

In this study, the segmentation architecture designs, such as UNet, LinkNet, SegNet, SQ-Net, DABNet, EDANet, and ESNet were used to perform pancreatic tumor segmentation. SQ-Net achieved the best segmentation performance with a 0.917 dice score, 0.847 IoU score, 0.920 sensitivity, 1.000 specificity, 0.914 precision, and 0.999 accuracy. In light of the achieved predictive results, an artificial intelligence (AI) assisted computer-aided diagnosis (CAD) system has been developed in this paper. With the use of the developed system can reduce the workload of health employees. In addition, thanks to this study, the process of pancreatic tumor diagnosis, which is a complex analysis process for healthcare professionals and radiologists, can be shortened. At the same time, since one of the areas is the health area where the risks should be the least, this study was carried out by using segmentation networks which is considering pixels-based processing of images. The main contribution of this study is the comparative analysis of segmentation networks. Thus, various information about segmentation networks was presented to other researchers. Future studies can be explained as; experimental studies will be carried out by using different segmentation models for the pancreatic tumor. The size of the data set will be increased. Other well-known loss functions will be used for pancreatic tumor segmentation.

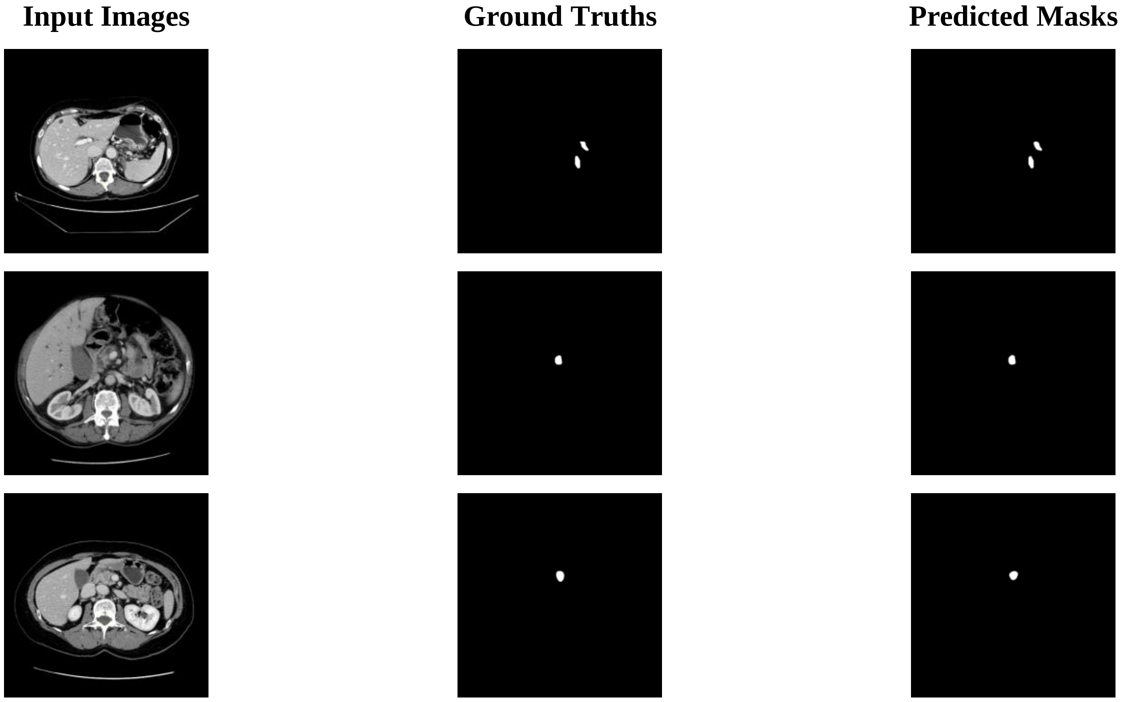

Figure 2. Segmentation results obtained by SQ-Net model

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