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Research Article

Pancreas Segmentation Using U-Net Based Segmentation Networks in CT Modality: A Comparative Analysis

Alperen Derin[1], Caglar Gurkan[2,*], Abdulkadir Budak[3] and Hakan Karatas[4]

[1] Department of Computer Engineering, Faculty of Computer and Information Science, Sakarya University, Sakarya (ORCID: 0000-0002-2276-0591), alperenderinn@gmail.com
[2*] Department of Electrical and Electronics Engineering, Graduate School of Science, Eskisehir Technical University, Eskisehir, (ORCID: 0000-0002-4652-3363), caglargurkan@eskisehir.edu.tr
[2*] Department of Artificial Intelligence and Image Processing, Akgun Computer Inc., Ankara (ORCID: 0000-0002-4652-3363), caglar.gurkan@akgun.com.tr
[3] Department of Artificial Intelligence and Image Processing, Akgun Computer Inc., Ankara (ORCID: 0000-0002-0328-6783), kadir.budak@akgun.com.tr
[4] Department of Artificial Intelligence and Image Processing, Akgun Computer Inc., Ankara (ORCID: 0000-0002-9497-5444), hakan.karatas@akgun.com.tr

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Abstract

The pancreas is one of the small size organs in the abdomen. Moreover, anatomical differences make it difficult to detect the pancreas. This project aims to automatically segmentation of pancreas. For this purpose, NIH-CT82 data set, which includes CT images from 82 patients was used. U-Net which is state-of-the-art model and its different versions, namely Attention U-Net, Residual U-Net, Attention Residual U-Net, and Residual U-Net++ were tested. Best predict performance was achieved by Residual U-Net with the dice of 0.903, IoU of 0.823, sensitivity of 0.898, specificity of 1.000, precision of 0.908, and accuracy of 0.999. Consequently, an artificial intelligence (AI) supported decision support system was created for pancreas segmentation.

Keywords: Pancreas, Segmentation, Deep learning, U-Net, Residual U-Net++.

CT Modalitesinde U-Net Tabanlı Segmentasyon Ağlarını Kullanarak Pankreas Segmentasyonu: Karşılaştırmalı Bir Analiz

Öz

Pankreas, karın içindeki küçük boyutlu organlardan biridir. Ayrıca anatomik farklılıklar, pankreasın tespit edilmesini oldukça zorlaştırmaktadır. Bu proje pankreasın otomatik olarak segmentasyonunu amaçlamaktadır. Bu amaçla 82 hastanın bilgisayarlı tomografi (BT) görüntülerini içeren NIH-CT82 veri seti kullanılmıştır. Son teknoloji bir model olan U-Net ve farklı versiyonları olan Attention U-Net, Residual U-Net, Attention Residual U-Net ve Residual U-Net++ test edilmiştir. En iyi tahmin performansı, 0.903 zar skoru, 0.823 IoU, 0.898 duyarlılık, 1.000 özgülüllük, 0.908 kesinlik ve 0.999 doğruluk ile Residual U-Net tarafından elde edilmiştir. Sonuç olarak pankreas segmentasyonu için yapay zeka (YZ) destekli bir karar destek sistemi oluşturulmuştur.

Anahtar Kelimeler: Pankreas, Segmentasyon, Derin öğrenme, U-Net, Residual U-Net++.

[*] Corresponding Author: caglar.gurkan@akgun.com.tr

1. Introduction

In 2020, 60,430 new patients and 48,220 deaths dependent to pancreatic cancer have been reported in the United States. Pancreatic Cancer is the riskiest type of cancer after the Lung Cancer, Bronchial Cancer and Colorectal Cancer. It is conjectural that 111,500 patients will die from pancreatic cancer in the 28 countries of the European Union (EU) by 2025. In 2018, while the incidence of Pancreatic Cancer was 458,918 in the world, it was observed that the number of deaths was 432,242 and deaths constituted approximately 94.2% of new patients. Pancreatic cancer is the 7th prominent reason of cancer death all around the world. According to Global Cancer Statistics a total of 495,773 new patients and 466,003 deaths related to pancreatic cancer have been reported worldwide in 2020, it is almost as much as the incidence rate. The number of pancreatic cancer patients has increased by 1% every year from 2000 to 2020 (Hu et al., 2021).

Computed Tomography (CT) and Magnetic Resonance Imaging (MRI) modalities are generally used to diagnose pancreatic diseases (Chaudhary & Bano, 2011). The CT modality is frequently used for determination of pancreatic diseases. However, pancreas have a small size is one of the most minor organs in the abdominal region(Liu et al., 2022). Additionally, it is arduous to distinguish the borders of the pancreas on CT images due to its irregular shape, anatomical variations among individuals (weight, height, fat ratio, etc.), gender, age and having many different organs around it. Despite all this, the effective use of CT imaging techniques is an important tool for determining the pancreatic cancer diagnosis at the early stages.

The detection of pancreatic diseases is a time-consuming process for healthcare professionals. Therefore, artificial intelligence (AI)-supported algorithms such as segmentation, object detection, and image classification have been developed. Moreover, the percentage of error tolerance in the healthcare field should be quite low. Therefore, high-sensitivity methods are needed when predicting the medical images. For this, while it is necessary to examined images on a pixel-based classification algorithms are needed. For this reason, segmentation algorithms are frequently used in medical images. Thanks to these AI supported algorithms, the percentage of mistake of healthcare professionals can be reduced and the disease can be diagnosed at an early stage.

The aim of this paper is to pancreas segmentation which is located in the abdomen. For this reason, U-Net, Attention U-Net, Residual U-Net, Attention Residual U-Net, and Residual U-Net++ segmentation models were used in the study. CT images were used to train and test of these models. The used data set includes images of 82 patients. Residual U-Net++ segmentation model was achieved the best performance in the comparative analysis. The Residual U-Net++ segmentation model achieved the dice of 0.903, IoU of 0.823, sensitivity of 0.898, specificity of 1.000, precision of 0.908, and accuray of 0.999.

The rest of this paper is organised as: Section 2 presents literature survey of several approaches for pancreas segmentation. Section 3 presents the utilized methodologies, including data pre-processing techniques, details of segmentation networks, and computational details of performance evaluation metrics. Section 4 presents the results obtained by the segmentation models. Concluding remarks are presented in Section 5.

2. Related Works

In this section, the studies providing the analysis of the pancreas segmentation were pointed out with the indication on research using deep learning-based segmentation models for pancreas segmentation.

Zhang et al.(D. Zhang et al., 2021) aimed to perform pancreas segmentation using CT images. The used data set consists of CT images of 82 patients. A novel segmentation network, called DCNN was proposed. The segmentation accuracy was analyzed with the dice similarity coefficient (DSC). DSC of 84.90% was achieved in pancreas segmentation.

Dogan et al. (Dogan et al., 2021) aimed to perform pancreas segmentation using CT images. The used data set consists of CT images of 82 patients. A novel segmentation network was proposed. The segmentation network includes of two parts, namely Mask R-CNN and 3D U-Net. DSC of 86.15% was achieved in pancreas segmentation.

Liu et al. (Liu et al., 2022) aimed to perform pancreas segmentation using CT images. In this study, the NIH data set which is consist of number of patients of 82 was used. A novel segmentation network, called ROI-VGGU-Net was proposed. The segmentation network aims dynamic extraction of pancreatic ROI and classification of pancreatic ROI with end-to-end deep learning method such as transfer learning. ROI-VGGU-Net segmentation network was achieved DSC of 85.4% ± 1.6%.

Yan and Defu(Yan & Zhang, 2021) aimed to segmentation of the pancreas using abdominal CT images. The NIH data set was used in this study. 2.5D U-Net with an attention mechanism, which contains 2D and 3D convolutional layers was used. The segmentation network was achieved DSC of 86.61±3.47%.

Li et al. (Li et al., 2021) aimed to segmentation of the pancreas using abdominal CT images. The NIH data set was used in this study. Multilevel Pyramidal Pooling Residual U-Net was used. While the DSC score of 81.36% was achieved by using ADR-U-Net, the highest DSC score of 82.77% was achieved when MLPP module was added to U-Net.

Cai et al. (Cai et al., 2017) aimed to segmentation of the pancreas by using CT and MRI modalities. The NIH data set was used for CT modality while UFL-MRI-79 data set was used for MRI modality. The UFL-MRI-79 data set consists of MRI images of 79 patients. A novel segmentation network, called Convolutional/Recurrent Neural Network Architecture was proposed for the pancreas segmentation. DSC scores of 82. 4±6.7% and 80. 5±6.70% were achieved in the NIH-CT82 and MRI-79 data sets, respectively.

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

NIH-CT82 data set was prepared by The National Institutes of Health Clinical Center. This data set consists of 82 abdominal CT scans. CT scans includes 53 male and 27 female patients (Roth et al., 2015).

The preprocessing techniques are shown below:

- CT images were clipped with HU values of range of -100 and 240.
- 16-bit images were lossless converted to 8-bit images.
- Volumetric CT images were sliced into 2D images.
- If the maximum value is 0 in the masks, that masks and related images of masks were eliminated from the data set.
- Images were normalized with min-max normalization technique.
- 512 by 512 pixels images were resized to 256 by 256 pixels images. Cubic interpolation and exact nearest interpolation were used for images and masks, respectively.
- 90% of the images were used in training phase, while 10% were used in testing phase.

3.2. Segmentation Networks

In this study, U-Net (Ronneberger et al., 2015), a state-of-the-art segmentation network is considered. In this context, U-Net, Attention U-Net (Oktay et al., 2018), Residual U-Net (Z. Zhang et al., 2018), Attention Residual U-Net (Chen et al., 2020), and Residual U-Net++ (Jha et al., 2019) segmentation models were used. The attention mechanism was used because it achieves outperform in segmentation tasks.

In the training phase for segmentation models; loss function, optimizer, batch size, and epoch value were set as, the compound form of the cross entropy and dice loss functions, RMSprop, 2, and 20, respectively. Also, the initial learning rate was set as 1e-4. If performance of segmentation models is not improvement for during the 6 epochs, the learning rate was multiplied by 0.1.

PyTorch framework in Python programming language was used on Spyder Integrated Development Environment (IDE) in the experimental analysis procedure. NVIDIA GeForce RTX 3060 graphics card was used in training and testing procedures.

3.3. Performance Evulation Metrics

Accuracy, precision, sensitivity, specificity, dice, and IoU performance evaluation metrics were used to comparison the predictive performance of segmentation models. The formulations of performance evaluation metrics are shown in Equations 1, 2, 3, 4, 5, and 6.

True Positive (TP) refers to number of correctly classified positive class. True Negative (TN) refers to number of correctly classified negative class. False Positive (FP) refers to incorrectly classified positive class. False Negative (FN) refers to number of the incorrectly classified negative class.

Accuracy, precision, sensitivity, specificity, dice and IoU indicates the results of pixel-based classification.

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

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

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

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

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

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

4. Results and Discussion

Table 1 represents the results obtained by using segmentation models. The dice of 0.895, IoU of 0.809, sensitivity of 0.876, specificity of 1.000, precision of 0.914, and accuracy of 0.999 were achieved by U-Net model. The dice of 0.899, IoU of 0.816, sensitivity of 0.913, specificity of 0.999, precision of 0.885, and accuracy of 0.999 were achieved by Attention U-Net model. The dice of 0.899, IoU of 0.816, sensitivity of 0.903, specificity of 0.999, precision of 0.895, and accuracy of 0.999 were achieved by Residual U-Net model. The dice of 0.895, IoU of 0.810, sensitivity of 0.900, specificity of 0.999, precision of 0.890, and accuracy of 0.999 were achieved by Attention Residual U-Net model. The dice of 0.903, IoU of 0.823, sensitivity of 0.898, specificity of 1.000, precision of 0.908, and accuracy of 0.999 were achieved by Residual U-Net++ model.

Considering the overall experimental analysis, the attention mechanism significantly increased the sensitivity result. The Residual U-Net++ segmentation model has outperformed other segmentation models while the U-Net model has the lowest segmentation performance according to the results of dice and sensitivity.

Performance comparison of models is shown in Figure 2. The results obtained by Residual U-Net++ are given in Figure 3.

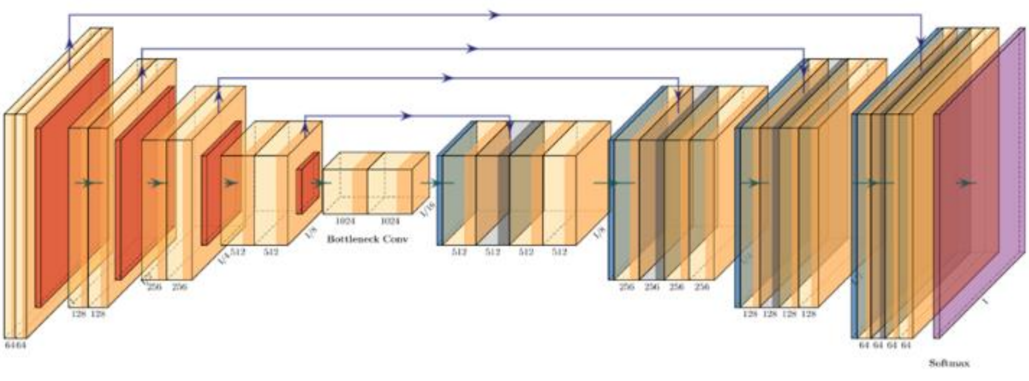

*Figure 1. U-Net architecture design (*Iqbal, H., 2018)

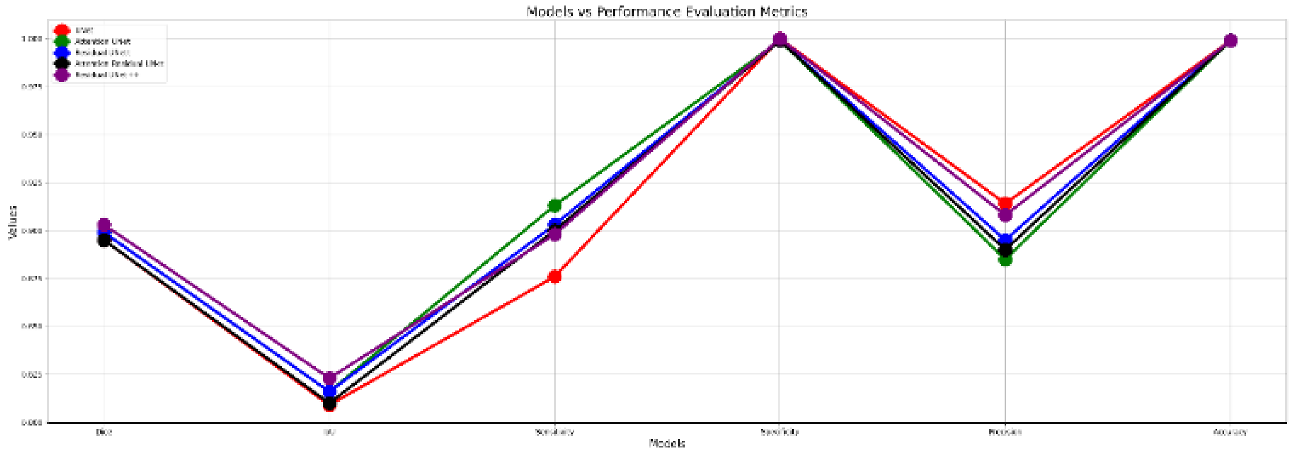

Figure 2. Performance comparison of models

Table 1. Results obtained using segmentation models

Models	Dice	IoU	Sensitivity	Specificity	Precision	Accuracy
U-Net	0.895	0.809	0.876	1.000	0.914	0.999
Attention U-Net	0.899	0.816	0.913	0.999	0.885	0.999
Residual U-Net	0.899	0.816	0.903	0.999	0.895	0.999
Attention Residual U-Net	0.895	0.810	0.900	0.999	0.890	0.999
Residual U-Net++	0.903	0.823	0.898	1.000	0.908	0.999

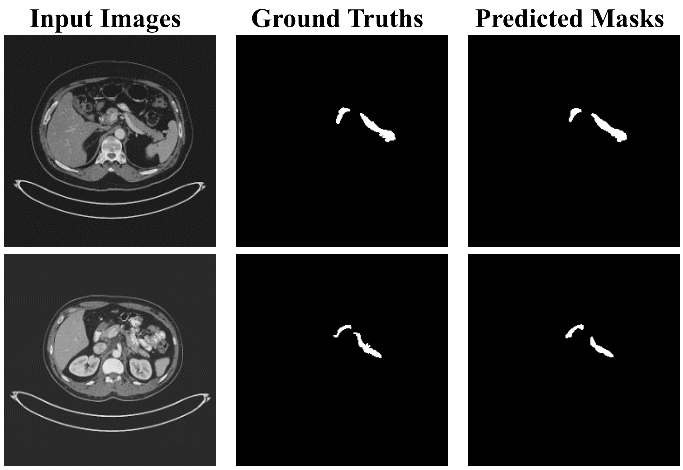

Figure 3. Results obtained by Residual U-Net++

5. Conclusion

In this study, several segmentation models were used to perform pancreas segmentation. It is attempted to present a suggestion to other researchers on the segmentation performances of the models by comparing U-Net, Attention U-Net, Residual U-Net, Attention Residual U-Net, and Residual U-Net++ networks. In comparative analysis, the attention mechanism increased the segmentation performance. The Residual U-Net++ segmentation model has outperformed other segmentation models with the dice of 0.903, IoU of 0.823, sensitivity of 0.898, specificity of 1.000, precision of 0.908, and accuracy of 0.999. As a result, with the help of the AI assisted decision support system, the workload of health employees can be reduced.

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