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Research Article

Analysis of the Effects of Segmentation Networks and Loss Functions in Ischemic Stroke Lesion Segmentation

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Abstract

Stroke was the cause of one out of every six deaths from cerebrovascular disease in 2020. A stroke occurs in the United States (US) every 40 seconds. Every 3.5 minutes, people die of a stroke. More than total 795,000 stroke cases occur yearly in the US. This study aims to detect the ischemic stroke lesion that occurs in the brain. The Ischemic Stroke Lesion Segmentation (ISLES) 2017 data set, which includes 82 Magnetic Resonance images of 43 patients, was used. The UNet, Attention UNet, Residual UNet, Attention Residual UNet, and Residual UNet++ segmentation networks were tested. Moreover, Cross Entropy, Dice, IoU, Tversky, Focal Tversky, and their compound forms were analyzed. The IoU loss function tested on Attention UNet achieved the best performance with the dice score of 0.766, the IoU score of 0.621, the sensitivity of 0.730, the specificity of 0.997, the precision of 0.805, and the accuracy of 0.993.

Keywords: Stroke, Segmentation, Artificial intelligence, Machine learning, Deep learning.

İskemik İnme Lezyon Segmentasyonunda Segmentasyon Ağlarının ve Kayıp Fonksiyonlarının Etkilerinin Analizi

Öz

2020'de serebrovasküler hastalıklardan her altı ölümden birinin nedeni inmeydi. Amerika Birleşik Devletleri'nde (ABD) her 40 saniyede bir inme vakası görülmektedir. Her 3.5 dakikada bir insan inmeden hayatını kaybetmektedir. ABD'de yılda toplamda 795.000'den fazla inme vakası meydana gelmektedir. Bu çalışma, beyinde oluşan iskemik inme lezyonunu tespit etmeyi amaçlamaktadır. 43 hastanın 82 Manyetik Rezonans görüntüsünü içeren İskemik İnme Lezyon Segmentasyonu (ISLES) 2017 veri seti kullanıldı. UNet, Attention UNet, Residual UNet, Attention Residual UNet ve Residual UNet++ segmentasyon ağları test edilmiştir. Ayrıca Cross Entropy, Dice, IoU, Tversky, Focal Tversky ve bunların bileşik formları incelenmiştir. Attention UNet üzerinde test edilen IoU kayıp fonksiyonu 0.766 Zar skoru, 0.621 IoU skoru, 0.730 duyarlılık, 0.997 özgüllük, 0.805 kesinlik ve 0.993 doğruluk ile en iyi performansı elde etmiştir.

Anahtar Kelimeler: İnme, Segmentasyon, Yapay zeka, Makine öğrenmesi, Derin öğrenme.

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1. Introduction

Ischemic stroke is the most prevalent cerebrovascular disease. Non-invasive imaging is used to diagnose ischemic stroke. An ischemic stroke results in infarction of the affected brain tissue when there is a disruption in the cerebral blood supply (Centers for Disease Control and Prevention, 2020). Diagnosis of ischemic stroke is difficult and time consuming. In the medical field, error tolerance should be very low, and it is vital that these diseases are detected in their early stages (Tsao et al., 2022). The error rates of healthcare professionals can be decreased and diseases can be detected at an early stage by creating pixel-based classification algorithms, namely segmentation algorihms, with high accuracy rate. A diagnosis tool for detection of diseases is Magnetic Resonance Imaging (MRI) scans. Ischemic stroke lesion segmentation task is technically demanding due to the appearance, location, and shape of lesions, dynamic development of lesions, medical inconsistencies, and insufficient data sets. Besides the technical difficulties, diagnostic results are based on personal, visual observation of neurologists under different conditions. As a result, all these conditions are taken into account, this medical segmentation process is complex.

The aim of this project is to ıschemic stroke lesion segmentation. Therefore, state-of-the-art segmentation networks, such as UNet, Attention UNet, Residual UNet, Attention Residual UNet, and Residual UNet++ were implemented on Ischemic Stroke Lesion Segmentation (ISLES) 2017 data set. In addition, well-known and widely used loss functions such as Cross Entropy (CE), Dice, IoU, Tversky, Focal Tversky, and their compound forms were analyzed. In the comparative analysis, the IoU loss function tested on Attention UNet achieved the best predictive performance with the dice of 0.766, IoU of 0.621, the sensitivity of 0.730, specificity of 0.997, the precision of 0.805, and accuracy of 0.993. Consequently, an artificial intelligence-based computer-aided diagnosis (CAD) system was proposed for ischemic stroke lesion segmentation.

The rest of this paper is organized as: Section 2 presents literature survey of several approaches for ischemic stroke lesion segmentation. Section 3 presents the utilized methodologies. Section 4 presents the results obtained by the segmentation models and loss functions. Section 5 presents concluding remarks.

2. Related Works

Numerous scientific researchers have proposed that different segmentation methods can be used for ischemic stroke lesion segmentation.

Seifedine et al. (Kadry et al., 2021) aimed the perform UNet Supported Segmentation of Ischemic-Stroke-Lesion using Brain MRI images. In this study, the ISLES2015 database which includes 500 MRI slices of 20 patients were studied. A pre-trained UNet was employed to extract the ISL from the selected test image. The model achieved the IoU score of 90%, the dice score of 95%, the accuracy of 98%.

Hyunkwang et al. (Shin et al., 2022) aimed for an automated segmentation of chronic stroke lesions using efficient UNet (e-UNet) architecture. A deep convolution-based e-block is included in the proposed e- UNet for the purpose of the efficiently minimize trainable parameters. By collecting global features between the encoder and decoder, with a global-feature attention block (GA-block) was increased the segmentation performance. When compared to UNet, the suggested e- UNet was reduced the number of trainable parameters by 3.75 times. The Anatomical Tracings of Lesions After Stroke (ATLAS) data set was used to evaluate the performance of e- UNet. The ATLAS data set includes 8694 images. The e- UNet model achieved the dice score of 59.2%, and the IoU score of 45.5%.

Samrand et al. (Khezrpour et al., 2022) aimed to perform automatic segmentation of brain stroke lesions from MR flair scans using the Enhanced UNet framework. In this study, the fluid-attenuated inversion recovery (FLAIR) modality was used. A deep supervised UNet architecture design that includes of five parallel layers was used. The ISLES 2015 data set was used. The model achieved the dice score of 0.89.

Sourodip et al. (Soltanpour et al., 2021) aimed to improve automatic ischemic stroke lesion segmentation on CTP (Computer Tomography Perfusion) maps using the deep neural networks. ISLES 2018 dataset was used in this study. In this paper, a novel deep learning-based network, called MutiRes UNet for segmentation of ischemic stroke lesions was proposed. Contra-lateral and corresponding Tmax images to enrich the input CTP maps was used in this network. The network achieved the dice score of 68%, IoU of 57.13%, and the mean absolute volume error of 22.62.

Yanglan et al. (Ou et al., 2021) aimed to segmentation of stroke lesions using the diffusion-weighted images (DWI). In this study, 2.5D approach was considered due to the volumetric nature and interslice discontinuities of images. In this paper, a novel deep learning-based network, called LambdaUNet was proposed. The network extends UNet by replacing convolutional layers with the proposed Lambda+ layers.Lambda+ layers have been used to transform both the intra-slice and inter-slice context around a pixel into linear functions called lambdas that are then applied to the pixel to produce informative 2.5D features. A novel clinical data set was prepared and used. LambdaUNet outperformed the 2D UNet and 3D UNet.

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 study, ISLES 2017 data set was used. This data set includes 82 MRI data of 43 patients. MRI data is 16 bits. Therefore, 16-bit MR images were converted to 8-bit images. If there is no label on the mask of the relevant image, these images were deleted. Later, MR images were normalized by using the min-max normalization method. All images and masks were used in the training and testing of the segmentation models as 128 by 128 pixels. %90 of the MR images were used in the training stage, while %10 were used in the testing stage.

3.2. Segmentation Networks

In this study, state-of-the-art segmentation networks UNet (Ronneberger et al., 2015), Attention UNet (Oktay et al., 2018), Residual UNet (Z. Zhang et al., 2018), Attention Residual UNet (Chen et al., 2020), and Residual UNet++ (Jha et al., 2019) were used.

Details of the training phase for segmentation models are shown below:

- Stochastic gradient descent (SGD) optimization algorithm was used with a learning rate of 1e-3, weight decay of 0.0005, and momentum of 0.9.
- If the predictive performance of segmentation models is not an improvement for along the 30 epochs, the learning rate was multiplied by 0.1.
- Batch size and epoch value were chosen as 100 and 2, respectively.
- The used Integrated Development Environment (IDE) is Spyder.
- The used programming language and framework are Python and PyTorch, respectively.
- NVIDIA GeForce RTX 3060 graphics card was used in the experiment.

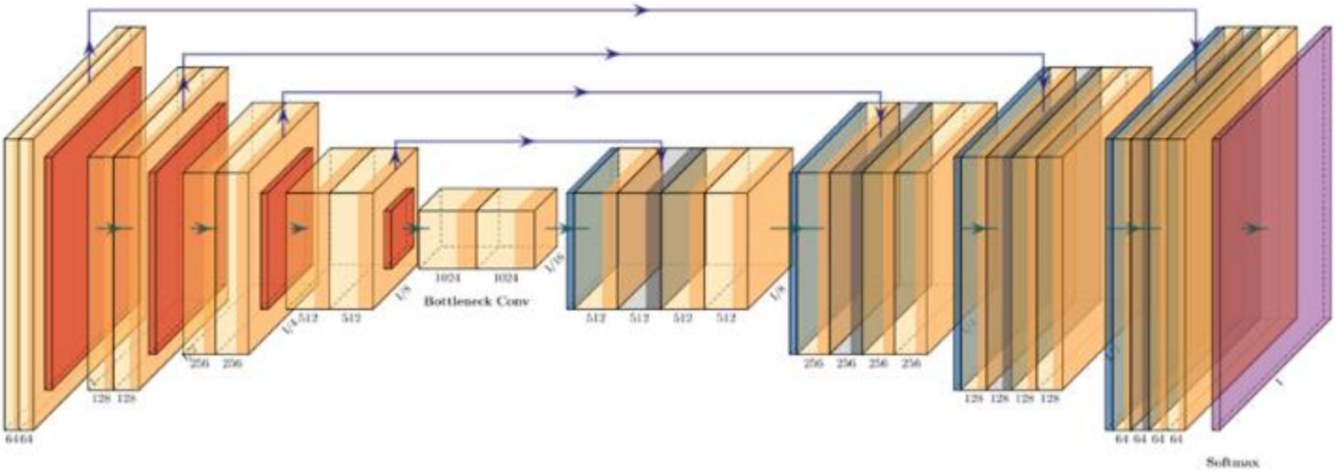

Figure 1. U-Net architecture design (HarisIqbal88/PlotNeuralNet: Latex Code for Making Neural Networks Diagrams, n.d.)

3.3. Performance Evaluation Metrics

The predictive performance of segmentation models and loss functions was analyzed by using performance evaluation metrics, such as accuracy, precision, sensitivity, specificity, dice, and IoU. Formulations of performance evaluation metrics are shown in Equations 1, 2, 3, 4, 5, and 6.

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

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

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

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

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

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

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

4. Results and Discussion

Table 1 shows the results obtained by using segmentation models. The dice score of 0.687, the IoU score of 0.523, the sensitivity of 0.604, the specificity of 0.998, the precision of 0.796, and the accuracy of 0.992 were achieved by the U-Net model. The dice score of 0.754, the IoU score of 0.605, the sensitivity of 0.720, the specificity of 0.997, the precision of 0.791, and the accuracy of 0.993 were achieved by the Attention U-Net model. The dice score of 0.490, the IoU score of 0.324, the sensitivity of 0.369, the specificity of 0.998, the precision of 0.727, and the accuracy of 0.998 were achieved by the Residual U-Net model. The dice score of 0.556, IoU score of 0.385, the sensitivity of 0.447, the specificity of 0.998, the precision of 0.736, and the accuracy of 0.989 were achieved by the Attention Residual U-Net model. The dice score of 0.615, the IoU score of 0.444, the sensitivity of 0.496, the specificity of 0.998, the precision of 0.807, and the accuracy of 0.991 were achieved by the Residual U-Net++ model.

In the general analysis carried out by taking into account the results obtained by segmentation models, the Attention UNet model achieved the highest predictive performance. The attention mechanism increased the segmentation performance. The Residual UNet model has the lowest predictive performance. Attention UNet model has been tested with different loss functions as it achieved the best segmentation performance.

Table 1. Results obtained using segmentation models

Models	Dice	IoU	Sensitivity	Specificity	Precision	Accuracy
UNet	0.687	0.523	0.604	0.998	0.796	0.992
Attention UNet	0.754	0.605	0.720	0.997	0.791	0.993
Residual UNet	0.490	0.324	0.369	0.998	0.727	0.988
Attention Residual UNet	0.556	0.385	0.447	0.998	0.736	0.989
Residual UNet++	0.615	0.444	0.496	0.998	0.807	0.991

Table 2 shows the results obtained by testing several loss functions on the Attention UNet model. The dice score of 0.688, the IoU score of 0.524, the sensitivity of 0.597, the specificity of 0.998, the precision of 0.812, and the accuracy of 0.992 were achieved by the CE loss function. The dice score of 0.729, the IoU score of 0.573, the sensitivity of 0.659, specificity of 0. 998, the precision of 0.815, and accuracy of 0.993 were achieved by the Dice loss function. The dice score of 0.766, the IoU score of 0.621, the sensitivity of 0.730, the specificity of 0.997, the precision of 0.805, and the accuracy of 0.993 were achieved by the IoU loss function. The dice score of 0.745, the IoU score of 0.594, the sensitivity of 0.735, the specificity of 0.996, the precision of 0.756, and the accuracy of 0.992 were achieved by the Tversky loss function. The dice score of 0.718, the IoU score of 0.560, the sensitivity of 0.658, the specificity of 0.997, the precision of 0.789, and the accuracy of 0.992 were achieved by the Focal Tversky loss function. The dice score of 0.754, the IoU score of 0.605, the sensitivity of 0.720, the specificity of 0.997, the precision of 0.791, and the accuracy of 0.993 were achieved by the compound loss function of CE and Dice loss functions. The dice score of 0.752, IoU score of 0.603, the sensitivity of 0.715, the specificity of 0.997, the precision of 0.793, and the accuracy of 0.993 were achieved by the compound loss function of CE and IoU loss functions. The dice score of 0.760, the IoU score of 0.613, the sensitivity of 0.727, the specificity of 0.997, the precision of 0.797, and the accuracy of 0.993 were achieved by the compound loss function of CE and Tversky loss functions. The dice score of 0.765, IoU score of 0.619, the sensitivity of 0.733, the specificity of 0.997, the precision of 0.799, and the accuracy of 0.993 were achieved by the compound loss function of CE and Focal Tversky loss functions. The results obtained by using the IoU loss function with Attention UNet are given in Figure 2.

Table 2. Results were obtained by testing several loss functions on the Attention UNet model

Loss Functions	Dice	IoU	Sensitivity	Specificity	Precision	Accuracy
CE	0.688	0.524	0.597	0.998	0.812	0.992
Dice	0.729	0.573	0.659	0.998	0.815	0.993
IoU	0.766	0.621	0.730	0.997	0.805	0.993
Tversky	0.745	0.594	0.735	0.996	0.756	0.992
Focal Tversky	0.718	0.560	0.658	0.997	0.789	0.992
CE+Dice	0.754	0.605	0.720	0.997	0.791	0.993
CE+IoU	0.752	0.603	0.715	0.997	0.793	0.993
CE+Tversky	0.760	0.613	0.727	0.997	0.797	0.993
CE+Focal Tversky	0.765	0.619	0.733	0.997	0.799	0.993

In the general analysis was carried out by taking into account the results obtained by testing several loss functions on the Attention UNet model. The compound loss function of CE and IoU loss functions achieved the highest predictive performance. The CE loss function has the lowest predictive performance. The Dice loss function outperformed the Focal Tversky loss function but was worse than the Tversky. Alpha, beta, and gamma refer to the coefficient of the FN, the coefficient of the FP, and the exponential coefficient of the Tversky loss function, respectively. In the experimental procedure, the alpha and beta coefficients were chosen as 0.7 and 0.3 in Tversky and Focal Tversky loss functions, respectively. The gamma coefficient was chosen as 0.75 in the Focal Tversky loss function. Therefore, several different alpha, beta, and gamma coefficients can be tested for the Tversky and Focal Tversky loss functions.

In the comparative analysis, while the IoU loss function obtained the best predictive performance among the lean loss functions, the CE loss function obtained the worst predictive performance. While the compound loss function of CE and Focal Tversky loss functions obtained the best predictive performance among the compound loss functions, the compound loss function of CE and IoU loss functions obtained the worst predictive performance.

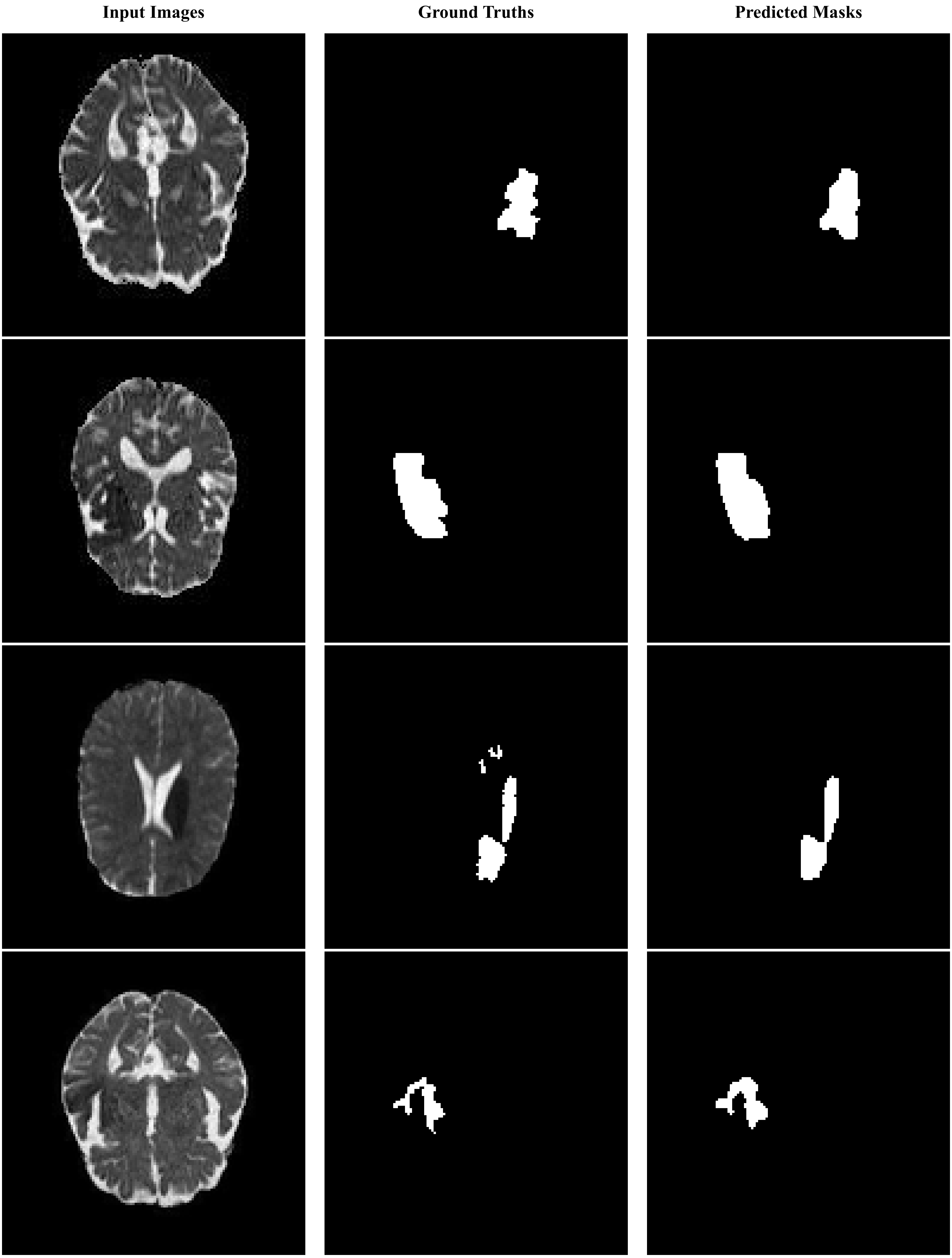

Figure 2. Results were obtained by using the IoU loss function with Attention UNet

5. Conclusion

In this study, the U-Net-based architecture designs, such as Attention UNet, Residual UNet, Attention Residual UNet, and Residual UNet++ were used to perform ıschemic stroke lesion segmentation. Moreover, the architecture designs were tested by using several loss functions widely used in segmentation tasks, such as CE, Dice, IoU, Tversky, Focal Tversky, and their compound form. The IoU loss function used in conjunction with Attention UNet achieved the best predictive performance with the dice score of 0.766, the IoU score of 0.621, the sensitivity of 0.730, the specificity of 0.997, the precision of 0.805, and the accuracy of 0.993. Consequently, a decision support system has been developed for ıschemic stroke lesion segmentation. It has been pointed out that the attention mechanism improves segmentation performance. Thanks to this comprehensive analysis, information about segmentation analysis was presented to the researchers. In future studies, experimental studies will be conducted using different alpha, beta, and gamma coefficients for Tversky and Focal Tversky loss functions. Experimental studies will be carried out with different data sets. Other well-known segmentation networks will be used in ıschemic stroke lesion segmentation.

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