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Convolutional Neural Networks for MRI-Based Brain Tumor Segmentation: A Comparative Analysis of State-of-the-Art Segmentation Networks

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A B S T R A C T

The prevalence of brain tumor is quite high. Brain tumor causes critical diseases. Also, brain tumor causes a variety of symptoms in most people. This study aims to segmentation of the tumor in the brain. For this purpose, state-of-art architectures, such as UNet, Attention UNet, Residual UNet, Attention Residual UNet, Residual UNet++, Inception UNet, LinkNet, and SegNet were used for segmentation. 592 magnetic resonance (MR) images were utilized in the training and testing of segmentation architectures. In the comparative analysis, Attention UNet achieved the best predictive performance with a 0.886 dice score, 0.795 IoU score, 0.881 sensitivity, 0.993 specificity, 0.891 precision, and 0.986 accuracy.

1. Introduction

The brain tumor is one of the most common, critical, and deadliest diseases worldwide. A brain tumor is a name given to the combination of a group of aberrant cells expanding in or around the brain [1]. The brain tumor is divided into two parts benign and malignant. The National Brain Tumor Foundation (NBTF) [2] reported that, according to its studies in welfare countries, the number of patients with brain tumors has nearly tripled in the last 30 years. Early diagnosis of a brain tumor is vital. Brain and brain tumors can be clearly seen in magnetic resonance imaging (MRI). However, when detailed analysis is required to make a diagnosis, the tumor area should be clearly shown with the details. It provides great help in determining the tumor region by segmentation. In addition, computer-aided diagnosis (CAD) systems show radiologists the location of the tumor and the area where it has spread. Therefore, it is needed by radiologists.

In this study, segmentation of the brain tumor was performed. The proposed segmentation method provides quantitative information by showing small areas that are likely to be overlooked. Also, automatic segmentation

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provides great convenience to radiologists. The state-of-the-art segmentation networks, such as UNet [3], Attention UNet [4], Residual UNet [5], Attention Residual UNet [6], Residual UNet++ [7], Inception UNet [8], LinkNet [9] and SegNet [10] were utilized for automatic segmentation of brain tumor. In the general analysis, Attention UNet achieved the best predictive segmentation performance with a 0.886 dice score, 0.795 IoU score, 0.881 sensitivity, 0.993 specificity, 0.891 precision, and 0.986 accuracy. Consequently, an artificial intelligence-based CAD system was developed.

The rest of this paper is organized as follows. In Section 2, related research based on segmentation for the brain and brain diseases has been reported. In Section 3, the utilized methodologies have been detailed. In Section 4, obtained results have been discussed. In Section 5, concluding remarks have been reported.

2. Related Works

Numerous scientific researchers have proposed that different segmentation methods can be used for brain and brain tumor segmentation.

Bayram et al. [11] aimed to the analysis of effects of loss functions on skull stripping and brain segmentation. In this study, different loss functions, such as Cross Entropy, Dice, IoU, Tversky, Focal Tversky, and their compound forms were utilized. The Brain Tumor Progression data set, which is publicly available was used. The data set includes 329 MR images of 20 patients. In the comparative analysis, the compound loss function of Cross-Entropy and Dice loss functions obtained the best predictive segmentation result with a 0.976 dice score, 0.964 IoU score, 0.972 sensitivity, 0.985 specificity, 0.960 precision, and 0.981 accuracy.

Bayram et al. [12] aimed to the analysis of effects of segmentation networks and loss functions on ischemic stroke lesion segmentation. In this study, several segmentation networks, UNet, Attention UNet, Residual UNet, Attention Residual UNet, and Residual UNet++ and different loss functions Cross Entropy, Dice, IoU, Tversky, Focal Tversky, and their compound forms were utilized. The Ischemic Stroke Lesion Segmentation (ISLES) data set was used in this study. ISLES data set includes 82 MR images of 43 patients. In the comparative analysis, Attention U-Net obtained the best predictive segmentation performance with a 0.766 dice score, 0.621 IoU score, 0.730 sensitivity, 0.997 specificity, 0.805 precision, and 0.993 accuracy.

Karakaya et al. [13] aimed to classification and segmentation of Alzheimer's disease. For the classification of Alzheimer's disease, 7 different state-of-the-art classification models, DenseNet121, EfficientNet, GoogLeNet, MobileNet version 3, ResNet101, ResNext101, and ShuffleNet were used. For the segmentation of Alzheimer's disease, the U-Net model was used. In this study, 2 different data sets were used for classification and segmentation tasks. In the classification task, The GoogLeNet model obtained the best predictive classification performance with a 0.9467 accuracy, 0.9474 sensitivity, 0.9811 specificity, and 0.9467 F1-score. In the segmentation task, the U-Net model obtained a 0.874 dice score, 0.776 IoU score, 0.868 sensitivity, 0.999 specificity, 0.879 precision, and 0.999 accuracy.

Saba et al. [14] aimed to detection of brain tumors using a MRI database. In this study, the Grab cut method was used for the accurate segmentation of lesions. The VGG-19 model was used as the transfer learning method. The 0.99, 1.00, and 0.99 dice scores were obtained on BRATS 2015, 2016, and 2017 datasets, respectively.

Zhang et al. [15] aimed to segmentation of the brain tumor using a MRI database. In this study, the Attention Gate Residual U-Net segmentation network was trained and tested on images from the BraTS database. Attention Gate Residual U-Net obtained the 0.876, 0.772, and 0.720 dice scores for the whole tumor, core tumor, and enhancing tumor segmentation, respectively.

Aboelenein et al. [16] aimed to segmentation of the brain tumor using a MRI database. In this study, a Hybrid Two-Track U-Net (HTTU-Net) architecture design was proposed. The design was trained and tested on BRATS 2018 dataset. HTTU-Net obtained 0.865, 0.808, and 0.745 mean dice scores for the whole tumor region, core region, enhancement region, respectively. Moreover, 0.883, 0.895, and 0.815 median scores were obtained for the whole tumor region, core region, enhancement region, respectively.

Zhou et al. [17] aimed to segmentation of the brain tumor using a MRI database. For this purpose, BRATS 2018 dataset was used in this paper. In this study, an efficient 3D residual neural network (ERV-Net) architecture design was proposed. ERV-Net obtained 81.8%, 91.21%, and %86.62 dice scores for the enhancing tumor, whole tumor and tumor core, respectively. In addition, 2.70 mm, 3.88 mm and 6.79 mm Hausdorff distance were obtained by ERV-Net for the enhancing tumor, whole tumor and tumor core, respectively.

Thaha et al. [18] aimed to segmentation of the brain tumor using an MRI database. For this purpose, BRATS 2015 dataset was used in this paper. In this study, an Enhanced Convolutional Neural Networks (ECNN) was proposed. Also, BAT loss function optimization algorithm was used. ECNN obtained 87% precision, 90% recall, and %92 accuracy results.

Li et al. [19] aimed to segmentation of the brain tumor using a MRI database. For this purpose, BRATS 2015 and 2017 datasets were used in this paper. In this study, a novel end-to-end brain tumor segmentation method was proposed. In BRATS 2015 dataset, the proposed method obtained 0.890, 0.733, and 0.726 dice scores for the complete, core, and enhancing tumor regions, respectively. In BRATS 2017 dataset, the proposed method obtained 0.876, 0.763, and 0.642 dice scores for the complete, core, and enhancing tumor regions, 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

The Brain Tumor data set [20], which is publicly available and contains a total of 642 MR images, was utilized in this study. 50 of 642 MR images, were utilized for testing, while the remaining images were utilized for training and validation. The training and validation MR image rate is 90% and 10%, respectively. In the data set, since the images, and masks of the images are different sizes, firstly, all images and masks of the images were resized as 256 by 256 pixels. Subsequently, images were normalized by using the min-max normalization method.

3.2. Segmentation networks

In this study, the state-of-the-art segmentation networks such as UNet [3], Attention UNet [4], Residual UNet [5], Attention Residual UNet [6], Residual UNet++ [7], Inception UNet [8], LinkNet [9] and SegNet [10] were implemented for brain tumor segmentation. In addition, the predictive performances of these networks have been demonstrated in the previous study [21].

The details of the training phase for segmentation models; loss function set as the compound form of the cross entropy and dice loss functions, optimizer set as RMSprop, batch size set to 8, and epoch value set to 100. The initial learning rate is set to 1e-5. But, if segmentation performance is not an improvement for during the 2 epochs, the learning rate was linearly decreased until 1e-8 by learning rate multiplied by 0.1 All experiments were implemented by using Pytorch framework and Google Colab integrated development environment (IDE) which has a NVIDIA Tesla T4 graphics card.

3.3. Performance evaluation metrics

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

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

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

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

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

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

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

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

4. Results and Discussion

Table 1 represents the results obtained by using segmentation models. The 0.882 dice score, 0.789 IoU score, 0.888 sensitivity, 0.992 specificity, 0.877 precision, and 0.985 accuracy were achieved by the U-Net model. The 0.886 dice score, 0.795 IoU score, 0.881 sensitivity, 0.993 specificity, 0.891 precision, and 0.986 accuracy were achieved by the Attention U-Net model. The 0.836 dice score, 0.718 IoU score, 0.813 sensitivity, 0.991 specificity, 0.861 precision, and 0.980 accuracy were achieved by the Residual U-Net model. The 0.870 dice score, 0.769 IoU score, 0.859 sensitivity, 0.992 specificity, 0.881 precision, and 0.984 accuracy were achieved by the Attention Residual U-Net model. The 0.860 dice score, 0.754 IoU score, 0.856 sensitivity, 0.991 specificity, 0.863 precision, and 0.983 accuracy were achieved by the Residual U-Net++ model. The 0.860 dice score, 0.755 IoU score, 0.885 sensitivity, 0.989 specificity, 0.837 precision, and 0.982 accuracy were achieved by the Inception U-Net model. The 0.869 dice score, 0.768 IoU score, 0.870 sensitivity, 0.991 specificity, 0.868 precision, and 0.984 accuracy were achieved by the LinkNet model. The 0.879 dice score, 0.785 IoU score, 0.875 sensitivity, 0.992 specificity, 0.883 precision, and 0.985 accuracy were achieved by the SegNet model. The training times of UNet, Attention UNet, Residual UNet, Attention Residual UNet, Residual UNet++, Inception UNet, LinkNet, and SegNet models are 76, 89, 87, 113, 114, 109, 46, and 43 minutes, respectively.

The general and comparative analysis carried out by taking into account the results obtained by segmentation models and the training time of segmentation models are shown below:

- The Attention UNet model achieved the highest predictive performance while the Residual UNet model has the lowest predictive performance.
- The Segnet model has the shortest training time, while the Residual UNet++ model has the longest training time.
- The usability of the SegNet model is high when training time and segmentation performance are considered together.

Figure 1 shows the performance evaluation metrics results obtained by the segmentation models and the training times of these models. The segmentation performances of the Attention UNet model on the several samples in the test data set are shown in Figure 2.

Table 1. Results obtained by segmentation models

Models	Dice	IoU	Sensitivity	Specificity	Precision	Accuracy	Time
UNet	0.882	0.789	0.888	0.992	0.877	0.985	76 minutes
Attention UNet	**0.886**	**0.795**	**0.881**	**0.993**	**0.891**	**0.986**	**89 minutes**
Residual UNet	0.836	0.718	0.813	0.991	0.861	0.980	87 minutes
Attention Residual UNet	0.870	0.769	0.859	0.992	0.881	0.984	113 minutes
Residual UNet++	0.860	0.754	0.856	0.991	0.863	0.983	114 minutes
Inception UNet	0.860	0.755	0.885	0.989	0.837	0.982	109 minutes
LinkNet	0.869	0.768	0.870	0.991	0.868	0.984	46 minutes
SegNet	0.879	0.785	0.875	0.992	0.883	0.985	43 minutes

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

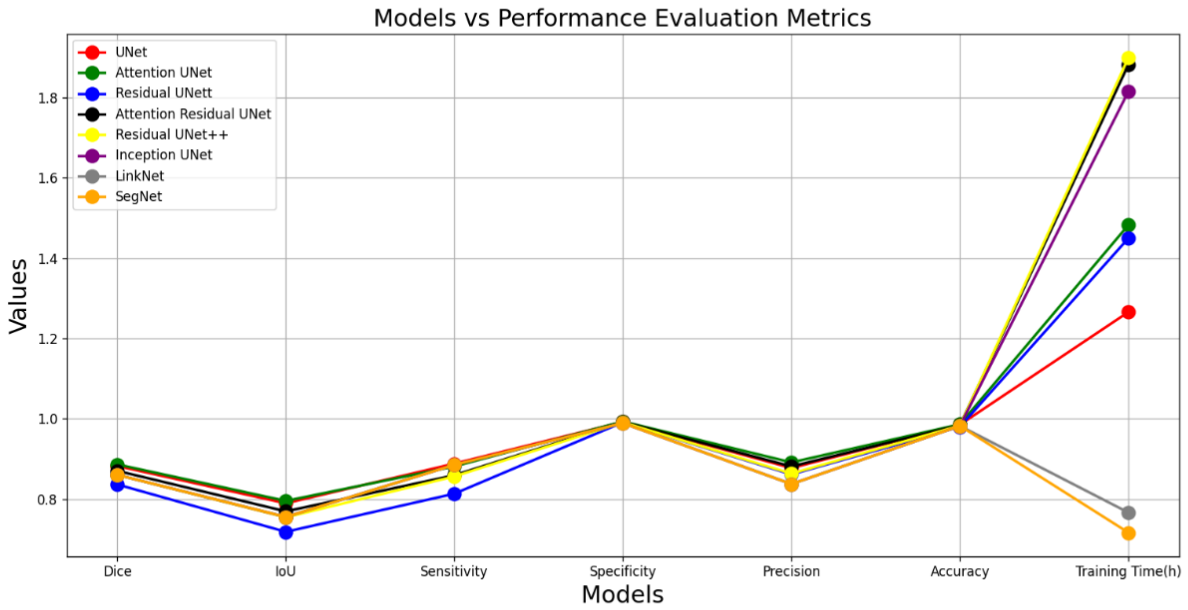

Figure 1. Model performance comparison

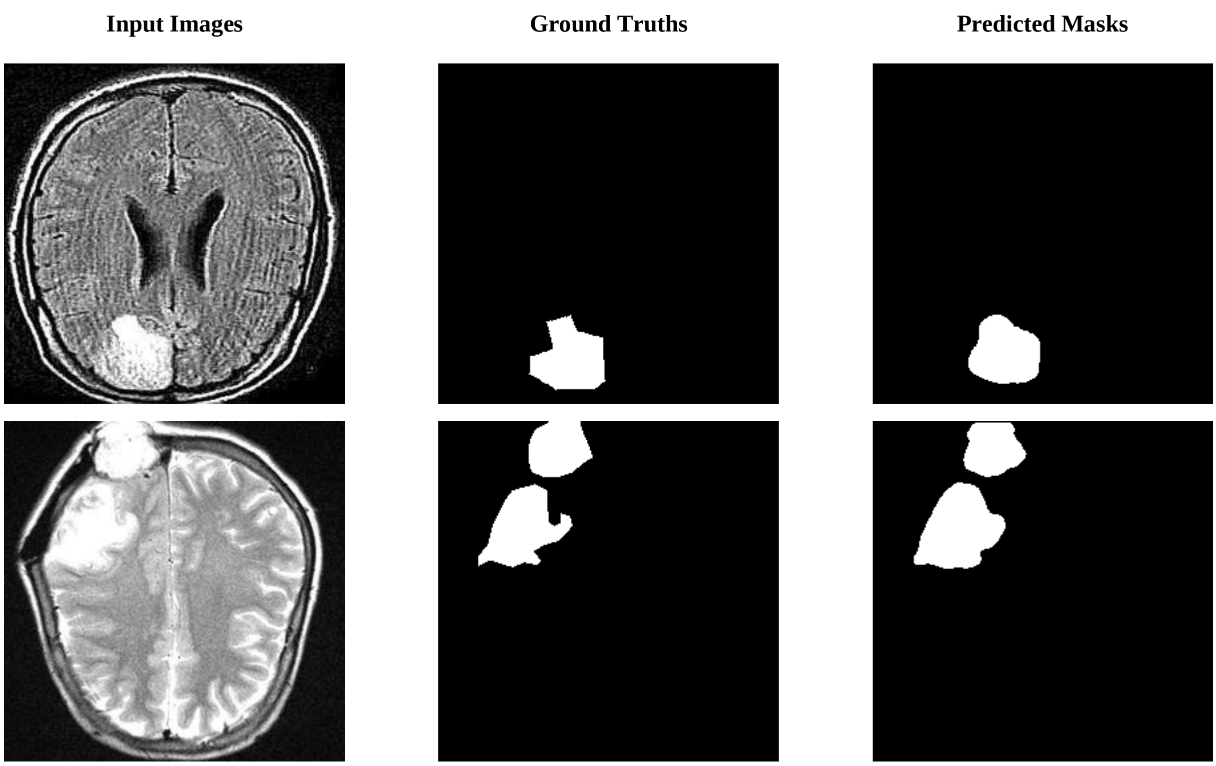

Figure 2. Results obtained by the attention UNet model

5. Conclusion

In this study, well-known segmentation architecture designs, such as Attention UNet, Residual UNet, Attention Residual UNet, Residual UNet++, Inception UNet, LinkNet, and Segnet were used to perform brain tumor segmentation. The best predictive segmentation performance among these well-known segmentation architecture designs was achieved by Attention UNet with a 0.886 dice score, 0.795 IoU score, 0.881 sensitivity, 0.993 specificity, 0.891 precision, and 0.986 accuracy. Considering these promising results, a decision support system has been developed for the early diagnosis of brain tumors. Another important point of this study is thanks to this comprehensive analysis, information about segmentation analysis was presented to the other researchers. In future studies, experiments will be conducted with different data sets. The size of the dataset will be increased. In addition, other state-of-the-art segmentation networks will be used.

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