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Comparative Study on Stroke Lesion Core Segmentation in CTP Images

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***Abstract*— Automatic segmentation of ischemic stroke using Computed Tomography Perfusion (CTP) images becomes an essential tool for quantification of the extension of stroke in early stages because of its availability, speed, and low cost. Inthis paper, we combined non-contrast CT scans which help in showing the core of the lesion along with CTP perfusion maps that show the abnormality of perfusion to enhance the core segmentation task. We utilized the performance of Unet, ResUnet, and ResUnet++ architectures on the ISLES 2018 dataset to usea single architecture for direct segmentation. Data augmentation helped in increasing the training data, overcoming overfitting issues, and teaching the neural network the properties of invari- ance and robustness. Unet with data augmentation achieved a dice coefficient equal to 0.65 while ResUnet++ achieved a dice coefficient equal to 0.55 without using data augmentation.**

Keywords—* *Stroke segmentation, Medical image analysis, Deep Learning, CNN

I. Introduction

As per World Health Organization (WHO) statistics, stroke is considered as the 2nd global cause of death, also the 3rd cause of disability. Every year, fifteen million people are affected by it; five million of them die, and another five million are disabled. Stroke is a fatal disease that happens when the blood supplying a portion of the brain stops. It leads to a part of the brain not getting the nutrition it needs and causes brain cells to die. Ischemic stroke and Hemorrhagic stroke are considered the two main types of stroke [1]. The first type happens due to an obstruction of a blood vessel supplying the brain. It is about 87 percent of all strokes. While the rupture of a weakened blood vessel leads to hemorrhagic stroke. The stroke lesion consists of two regions, the infarct core and penumbra. The infarct core is a tissue that can't be reversible. The penumbra, on the other hand, is a tissue that may be healed if the blood supply is quickly restored. The ability to locate and quantify the acute core or penumbra aids in determining the amount of tissue that can be restored using various treatments, allowing for more useful decisions. Brain imaging modalities such as Magnetic Resonance Images (MRI) and Computed Tomography (CT) are the most effective modalities used to assess and evaluate stroke lesions. Magnetic Resonance Images is highly sensitive to infarction's parenchymal changes. However, it cannot be used widely in the clinical setting due to its limitations in availability, time, and cost. Compared to MRI, CT scans are rapid, cost-effective, widely available, and clinicians use them as the first step for diagnosis of the acute ischemic stroke [2]. Computed Tomography Perfusion (CTP) determines brain's blood flow. In CTP imaging, the patient is injected with an intravenous contrast agent, followed by multiple scans as it spreads through the brain. CTP is useful to determine the abnormal perfusion areas; the infarct core and penumbra, whereas CT manages to show the core. So, the combination of them can help in providing informative data for automatic segmentation.

Furthermore, in literature, the usage of CTP is to diagnose acute stroke patients instead of using MRI that can help in reducing patient's time [3]. A series of recent studies have indi- cated that Convolutional Neural Network (CNN) has achieved significant success for different tasks in computer vision such as classification [4], detection [5], and segmentation. Also, CNN has proved its power and effectiveness in biomedical segmentation tasks. Criesan et al. [6] applied CNN to the problem of medical image segmentation, which can predict the pixel's label based on information in a separate square window around it. Later, the fully convolutional network (FCN) [7] is proposed, which can predict the image's pixel-label in a single step forward operation. UNet [8] is an FCN-based method for combining localization and context information using an encoder-decoder structure and skip-connections. Nielsen et al. [9] pioneered the CNN method for stroke segmentation using a simple deep encoder-decoder structure.

Recently, Deep Learning began to be applied to CT scans for stroke lesion segmentation such as in the 2018 edition of ISLES challenge [10]. The beginning of ISLES competition was in 2015. It allows a direct comparison of automated stroke imaging techniques. In 2018, the 1st public acute stroke dataset was released in the 4th version of the competition based on CT and CTP images. Song et al. [11], and P. Liu et al. proposed a framework to analyze CTP using Generative Adversarial Networks (GAN) [13]. They succeeded to achieve an average dice coefficient of 62.4%, 60.65% respectively. While Clerigues et al. [14] introduced in their research an automated tool using an asymmetrical encoder-decoder CNN for acute stroke segmentation on ISLES 2018 challenge dataset and obtained a Dice similarity coefficient of 49%. The proposed work by Chen et al. [15] achieved a dice coefficient equal to 48% by using the ensembling approach of multiple models.

In this work, we proposed a segmentation technique using a single network.

- Use non-contrast CT images concatenated with CTP perfusion maps.
- Compare the performance of three CNN architectures used popularly for semantic segmentation tasks on ISLES 2018 dataset, U-net, ResUnet [16], ResUnet++ [17].
- Examine the effect of using data augmentation and in- creasing the number of training samples regarding the three networks' performance.

II. Methods

A. Dataset

ISLES 2018 dataset is used for the purpose of training and testing the system [10]. This year's challenge offers CT, CTP scans and lesions drawn from DWI images acquired after CT. The provided dataset has ninety-four training images with masks and sixty-two without masks provided for testing. The images have the same resolution of 256 *256. In training, each case has seven modalities, which are non-contrast CT, the source of CTP data, and four CTP maps (CBF, CBV, MTT, and Tmax), and ground truth, OT.

B. Data Preprocessing

MTT, Tmax, CBV, and CBF maps are concatenated with the non-contrast CT scans during the training phase. Perfusion maps help in determining the perfusion abnormalities and non-contrast CT scans show the infarct core; this helps in determining the extension of the stroke. In addition, whenfeeding training samples, we perform data augmentation. Dataaugmentation is crucial when the training samples are limited. It teaches the model the properties of invariance and robustness and improves the segmentation task. In medical segmentation tasks, affine transformations are usedwidely to expand the training samples. Augmentation operations such as scaling, flipping, rotation, and adding Gaussian filters are used.

C. Architectures

a) *Unet:* Unet architecture proposed by [8] is a powerful CNN model for medical imaging applications. It has two paths:a contracting one and an expansive one like a U-shaped architecture. The first path is considered an encoder composed of repeated convolutional layers, which is followed by two layers; a rectified linear unit (ReLU) and a max-pooling layer. Main function of the encoder is to reduce the spatial informationand increase feature information. While the expensive pathis a decoder combines feature and spatial information by a series of deconvolution operations and concatenations of high-resolution encoder features. Fig. 1 illustrates the architecture of Unet.

b) *ResUnet:* ResUnet [16] is a modified architecture from U-Net that has shown latest results in road extraction. It is a semantic segmentation neural network that was constructed by integrating the strengths of U-Net and residual neural networks. Fig. 2 illustrates the architecture of the network.The advantages of this combination are that residual units will make training the network much easier. Furthermore, skip connections inside the residual unit and between low and high levels of the network will solve the degradation problem and promote information propagation. That would succeed in designing a network with fewer parameters and obtain better results in semantic segmentation.

c) *ResUnet++ [17] :* It is a modified network of ReSUnet. The main advantage is adding residual units, squeeze and excitation block [18], Atrous Spatial Pyramidal Pooling (ASPP) [19], and attention block [20]. The residual unit mainly contains batch normalization layer, ReLU, and convolutional layers which help in decreasing the parameters and enhancing the model performance. The squeeze and excitation block can help in increasing the network sensitivity in relevant features and removing unnecessary ones. ASSP is a link between the contracting and expensive paths. Its function is capturing multi-scale information at different scales and controlling the receptive field. The attention block has been used widely in natural language processing. It can determine which parts of the network need attention and help in reducing the computational of the encoding and boosts the results.

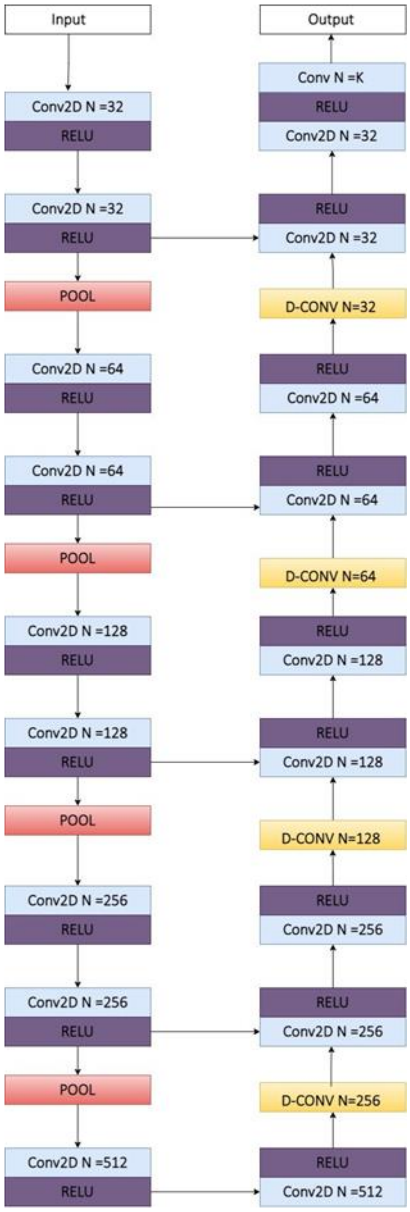

Fig. 1. Unet Architecture

III. Experiment

A. Implementation details

We used Keras to implement the three networks and ran the experiments on Google Colaboratory. We concatenated raw CT scans with CT perfusion images and fed them to the model. 80% of the data was used for training while the remaining 20% was for validation; we used this portion to evaluate the model since the test set provided was unlabeled. All images have the same size 256*256. We used Adam for optimization.

B. Results

a) *Experiment A:* Firstly, we trained the three architectures ResUnet++, ResUnet, and Unet with the training samples and evaluated them using the validation samples. After concatenation, we had 428 samples for training and

74 for validation. The model loss was assessed using dice loss, and dice coefficient (DC), MeanIOU, precision, and Recall were used as evaluation matrix. Hyper-parameter tuningwas the most important step in our experiment. We tried different settings of parameters through many experiments andevaluating their results until we reached the best results. Table I shows the results of ResUnet++, ResUnet and Unet after data augmentation. Fig. 4 shows the visualization of some validation samples, the non-contrast ct scan, the four perfusion images, the OT and lesion core prediction using ResUnet++ model.

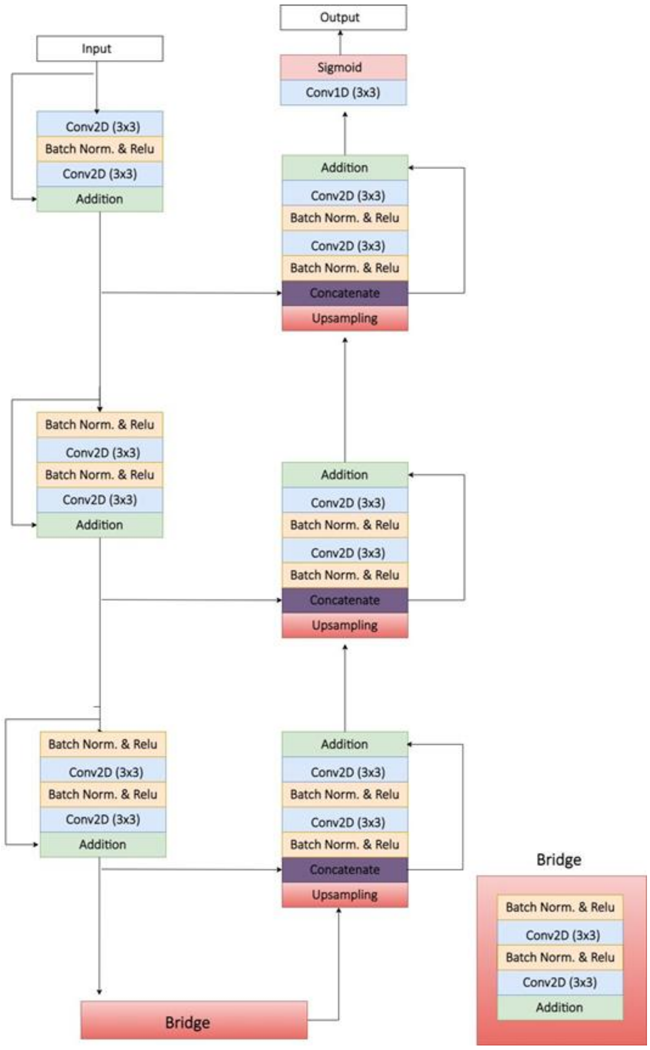

Fig. 2. ResUnet Architecture

b) *Experiment B:* As we have a small number of training data, we performed some data augmentation techniques to in- crease the number of training samples also compare the effect of using data augmentation between the three architectures. Data augmentation applied were horizontal and vertical flip, rotation, and scaling with 0.5 factor. We performed them on the training samples. They increased more than before by nearly 7%; we had 2996 training images. We used the same parameters settings in experiment A. Table II shows the results of ResUnet++, ResUnet and Unet after data augmentation. Fig. 5 shows the visualization of some validation samples, the non-contrast ct scan, the four perfusion images, the ground truth and the predicted lesion core using Unet with data augmentation model.

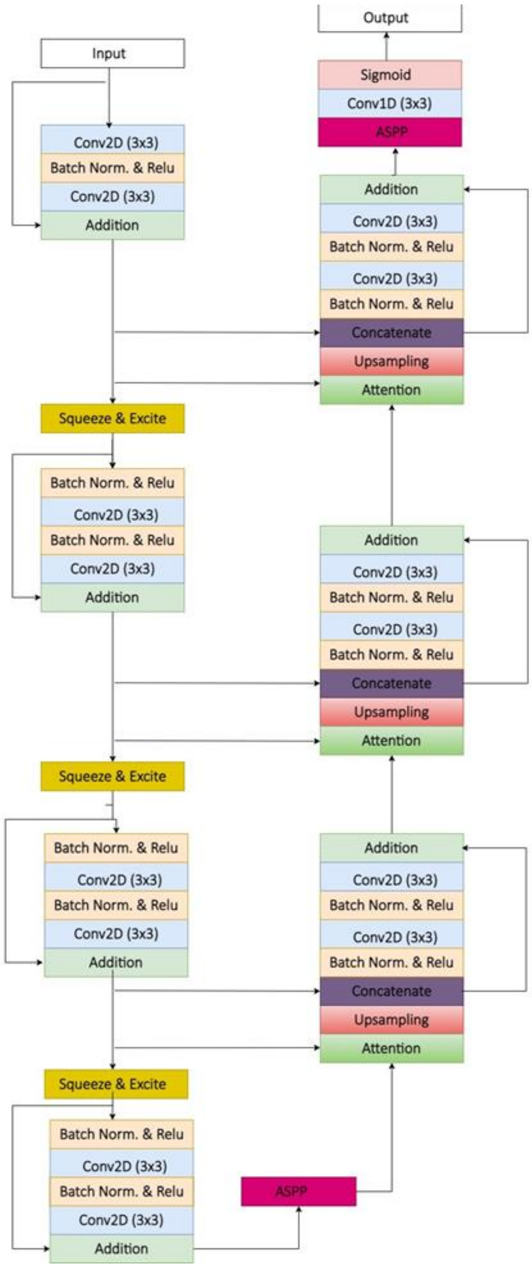

Fig. 3. ResUnet++ Network

TABLE I. EVALUATION METRICS ON ISLES 2018 WITHOUT DATA AUGMENTATION

Method	DC	*MeanIOU*	*Precision*	*Recall*
ResUnet++	**0.55**	0.6	0.71	0.45
ResUnet	0.45	0.69	0.78	0.46
Unet	0.43	0.72	0.80	0.45

TABLE II. EVALUATION METRICS ON ISLES 2018 WITH DATA AUGMENTATION

Method	DC	*MeanIOU*	*Precision*	*Recall*
ResUnet++	0.63	0.71	0.75	0.60
ResUnet	0.62	0.73	0.76	0.62
Unet	**0.65**	0.75	0.73	0.70

Compared to ISLES 2018 leaderboard [21], our methods achieved a high score of dice coefficient using U-net with data augmentation as Table III shows.

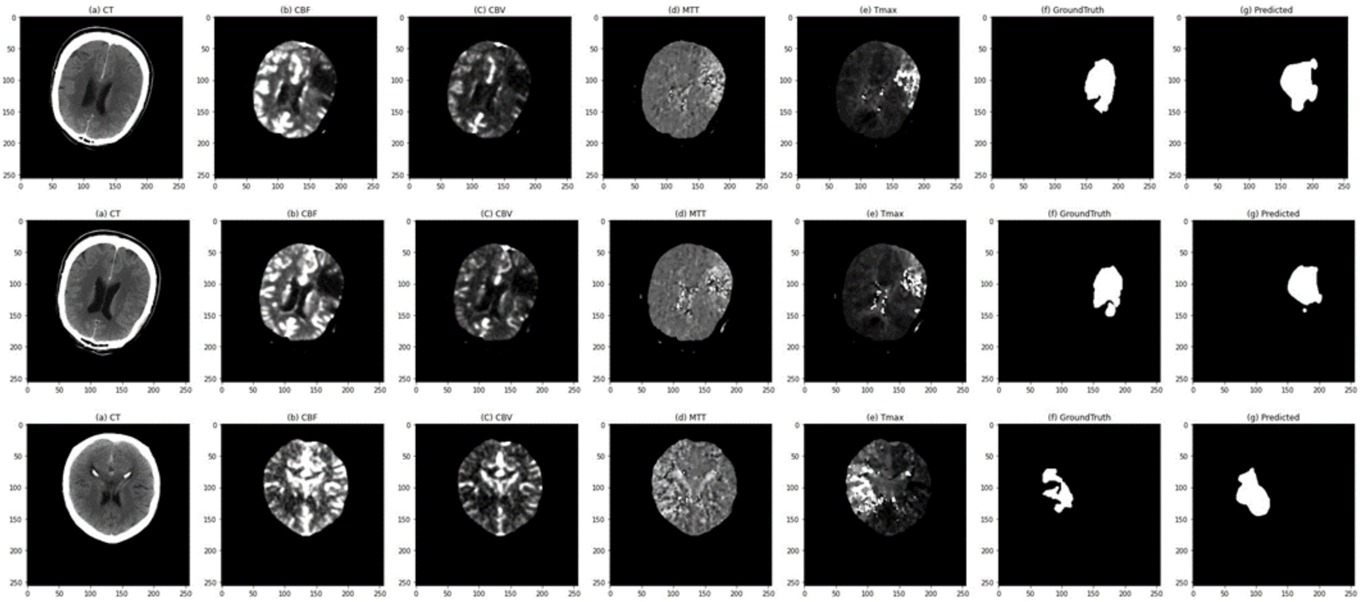

Fig. 4. (a) CT. (b) CBF. (C) CBV. (d) MTT. (e) Tmax. (f) GroundTruth. (g) Predicted lesion core using ResUnet++ model without DA.

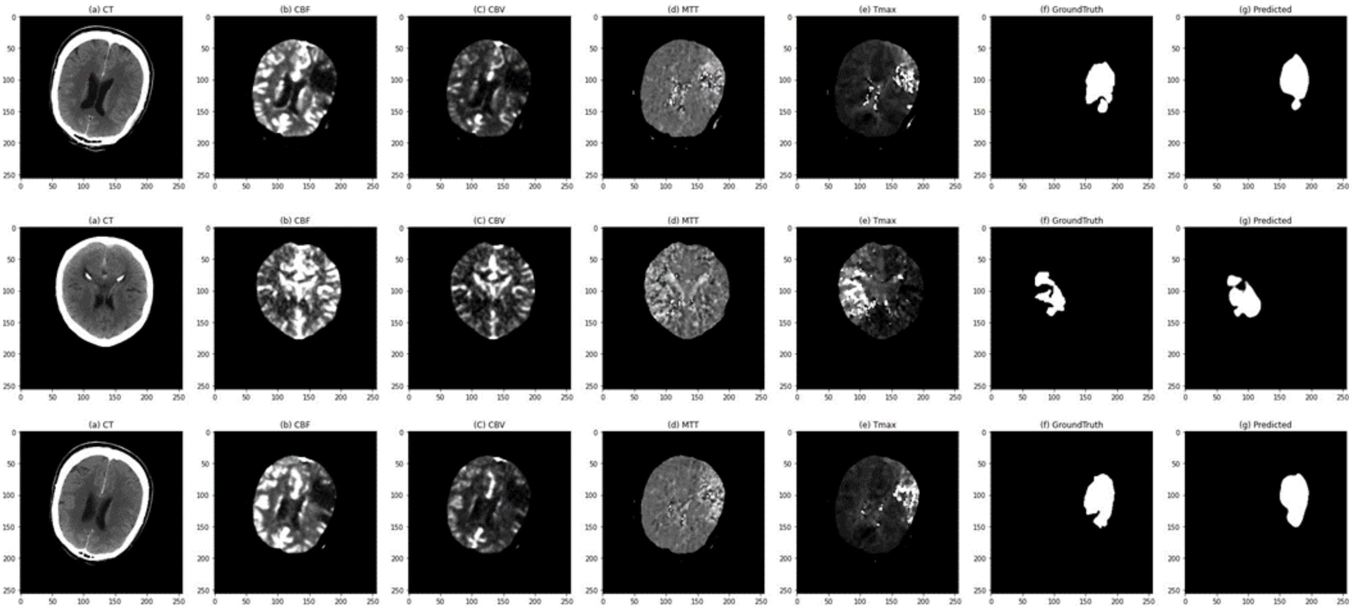

Fig. 5. (a) CT. (b) CBF. (C) CBV. (d) MTT. (e) Tmax. (f) GroundTruth. (g) Predicted lesion core using Unet model with DA.

TABLE III. COMPARISON WITH THE TOP FOUR METHODS FOR ISLES 2018 LEADERBOARD

Method	*DC*
Our work	**0.65**
Song et al. [11]	0.62
Liu et al. [12]	0.60
Clerigues et al. [14]	0.49
Chen et al. [15]	0.48

IV. Discussion

Concatenation between the non-contrast CT scans along with CTP maps is the key to our experiments. It increases the informative data about the stroke and improves the results comparing to direct segmentation using only CTP maps. We compare the performance of three networks using the concatenated data with the same settings. In the first experiment, with low input data ResUnet++ shows the best average dice coefficient over the testing samples equal to 55%. The small number of training samples inspires us to perform the second experiment using data augmentation techniques. Data augmentation helps in increasing the training samples and teaching architectures the invariance and robustness properties.

The results are increased in the three networks compared to the first experiment and Unet shows the best average dice coefficient over the testing samples equal to 65%. We have a direct segmentation technique using a single network with simple training procedures and achieve high results on ISLES 2018 dataset. We succeed to achieve a dice coefficient higher than the top four methods of ISLES 2018 leaderboard. The approach used by Song et al., the first ranked on the challenge, achieved a dice coefficient equal to 62.4% by GANs to generate DWI images from CTP maps for segmentation which increases the memory, processing time and need com- plex training procedures. Moreover, GANs suffer from non-convergence of parameters and diminished gradient problems.

However, achieving a high DC score, we will need to study the computational effect of reducing the perfusion maps and use the method of ensembling different models.

V. Conclusion

We suggested a direct framework for ischemic stroke segmentation with non-contrast CT images and CTP perfusion maps and make a comparative study between Unet, ResUnet, and ResUnet++ on ISLES 2018 dataset. We enhance the performance of the three networks using data augmentation. This framework can be a quick diagnostic tool for ischemic stroke using CTP images with the limited availability of MRI images.

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