2D-CNN Based Segmentation of Ischemic Stroke Lesions in MRI Scans

Pir Masoom Shah[1], Hikmat Khan[1], Uferah Shafi[2], Saif ul Islam[3], Mohsin Raza[4], Tran The Son[5](✉), and Hoa Le-Minh[6]

[1] COMSATS University Islamabad, Islamabad, Pakistan
[2] National University of Science and Technology (NUST), Islamabad, Pakistan
[3] Institute of Space Technology (IST), Islamabad, Pakistan
[4] Edge Hill University, Ormskirk, UK
[5] Vietnam – Korea University of Information and Communication Technology, Da Nang City, Vietnam
ttson@vku.udn.vn
[6] Northumbria University, Newcastle Upon Tyne, UK

Abstract. Stroke is the second overall driving reason for human death and disability. Strokes are categorized into Ischemic and Hemorrhagic strokes. Ischemic stroke is 85% of strokes while hemorrhagic is 15%. An exact automatic lesion segmentation of ischemic stroke remains a test to date. A few machine learning techniques are applied previously to beat manual human observers yet slacks to survive. In this paper, we propose a completely automatic lesion segmentation of ischemic stroke in view of the Convolutional Neural Network (CNN). The dataset used as a part of this study is obtained from ISLES 2015 challenge, included four MRI modalities DWI, T1, T1c, and FLAIR of 28 patients. The CNN model is trained on 25 patient's data while tested on the remaining 3 patients. As CNN is only used for classification, we convert segmentation to the pixel-by-pixel classification tasks. Dice Coefficient (DC) is used as a performance evaluation metric for assessing the performance of the model. The experimental results show that the proposed model achieves a comparatively higher DC rate from 4–5% than the considered state-of-the-art machine learning techniques.

Keywords: Stroke · MRI · Deep learning · Convolutional Neural Network

1 Introduction

Stroke is a medical condition of the brain, happens due to the short supply of oxygenated blood to the brain cells. Thus, cells begin dying. Sometimes in the brain, clots are produced in blood vessels and cause a limited supply of oxygenated blood to the brain that in turn causes a stroke. Stoke is the second leading death in humans [1] while the survivors are left with disability [2]. Generally, stroke-disability includes memory loss, paralysis, movement control, emotional disturbances [3], and so on. The primary drivers of strokes are

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hypertension and high blood pressure [4]. Despite the fact that a stroke may happen at any age, most of the stroke patients are more than 65 years old [5]. Stroke is mainly categorized as Ischemic and Hemorrhagic Stroke. 85% of stroke patients are diagnosed with Ischemic type while the remaining 15% has Hemorrhagic-Stroke [6]. The Ischemic-Strokes is additionally divided into four stages, Hyper-Acute, Acute, Sub-Acute, and Chronic. All these four stages are categorized on the time-period basis. Hyper-acute refers to the first 4 h onset while acute is more than 6 and less than 24 h. In contrast, Sub-acute are one to seven days longer while chronic is longer than a whole week. This study focuses on the Sub-Acute Stage of Stroke. Techniques like computed tomography (CT), MRI (magnetic resonance imaging), and X-Ray are used to observe the detailed structure and condition of an organ, tissue, or cell in the human body. Each of these techniques has particular advantages and disadvantages associated with them and can be used for the specific application. Among all imaging techniques, MRI is found non-invasive which also offers intensive information in regards to ischemic stroke even in early stages [6]. Commonly after ischemic stroke, numerous changes happen in brain water content, while the MRI is extremely sensitive to detect alteration in tissue-free water content even after 1-h onset of ischemic stroke.

While providing treatment to patients of Ischemic-Stroke, a specialist is interested in discovering total volume, mass, and location of the lesion from MRI scans [7]. A conventional way of estimating the nature of the lesion is manual segmentation, in which physicians or radiologists manually assess the location and size of the lesion in all slices of MRI scans. Although this technique is effective but has several weaknesses. For instance, it is tedious and different observers may reach different conclusions. Due to the aforementioned problems, an extreme need for an automatic solution for localization and segmentation of lesions of ischemic-stroke exists. Although many CAD (Computer-Aided Diagnosis) based frameworks are proposed earlier for ischemic stroke lesions segmentation, they still lag to beat human observers.

Automatic lesions segmentation in MRI isn't a simple task, as the location and shapes rely upon several factors, such as occlusion site, time after symptom onset, and contrast in vessel anatomy of different patients. The presence of white matter hyper-intensities is another challenging issue as it intrudes on the accurate segmentation [8]. While dealing with these challenges, we implemented CNN for ischemic-stroke lesions segmentation and enhanced accuracy. The main contributions of this study are given below:

- A deep 2D-CNN technique is proposed for ischemic-stroke lesion segmentation.
- We achieved stat of the are results.
- Our proposed model is robust to overfitting issues on limited data.
- Additionally, batch normalization is applied before each LeakyReLU layer.

The organization of the paper is described as follows: detailed literature of ischemic-stroke lesion segmentation and classification is presented in Sect. 2.

Section 3 presents the methodology of the proposed approach. Section 4 contains the performance evaluation of the proposed scheme and includes experimental setup, performance measures, and evaluation of the proposed technique. Section 5 concludes the paper.

2 Literature Review

A considerable measure of work has already been done in the domain of medical image segmentation to achieve high accuracy and efficiency. It is one of the difficult but interesting research topics. Liang et al. [8] proposed a new technique for the segmentation of sub-acute stroke lesions. In this framework, the random forest was used as a classifier and intensities of the patches as features. The task was performed by the SISS data set, achieving a dice score of 0.55.

Maier et al. in [9] proposed an automatic sub-acute lesion segmentation, based on extra tree forest. They used a local dataset comprised of MRI scans of 37 patients with modalities of T1 weighted, T2 weighted, FLAIR, and DWI. Intensities based features were extracted and extra tree forest was used for segmentation. Their results show a DC value of 0.65.

Maier et al. [10] presented a Random Forest-based segmentation for stroke lesion. A total of 50 trees of the random forest were trained by 1,000,000 random samples. The technique was applied to ISLES 2015 challenge dataset. This framework achieved the mean DC, ASSD, and HD of 0.58, 7.91, and 34 respectively.

In this article [11] the authors extended their previous work from brain tumor segmentation to ischemic-stroke lesion segmentation. Initially, they extracted Local Texture Feature (LTF) from the MRI scans and subsequently performed Intensity Inhomogeneity correction. In order to get the local gradient, eigenvalues decomposition of the 2D structure tensor matrix was applied. Feature ranking techniques were further applied in order to select the top-ranking features. Only 19 of 35 features were selected for training the random forest. The experiments were performed on ISLES 2015 challenge dataset, their results show a mean dice score of 59%.

Mahmood et al. [12] presented a random forest-based technique to perform the automatic segmentation of ischemic-stroke lesions. The dataset was obtained from ISLES 2015 challenge. Bias field correction and normalization were applied in initial steps. Specific features were extracted by various techniques such as intensity, intensity difference, and gradient in the x-direction. They normalize all the selected features by zero mean and the resultant features were used by the random forest. The proposed model achieved the mean ASSD, Dice, Hausdor Distance, Precision and Recall of 10.30, 0.54, 82.78, 0.67, and 0.50 respectively.

2.1 CNN Based Approaches for Stroke Lesion Segmentation

In [13] the author proposed a CNN based approach for ischemic lesion segmentation in DWI MRI scans. The proposed framework consists of two convolutional neural networks, MUSCLE and EDD Nets. In the first phase, EDDNet was applied for the detection of lesions in scans while MUSCLE Net was used to evaluate the detection of EDD Net. The dataset used was obtained from a local hospital containing DWI scans of 746 patients. The model achieved a dice coefficient of 0.67.

Maier et al. performed a comparative study in [14] where several machine learning techniques such as Generalized Linear Models, Random Decision Forests, and CNN were applied to an MRI sequence of 37 sub-acute patients of ischemic-stroke. The performance of these techniques along with the two human observers was compared and evaluated, but none of the machine learning techniques achieved an accuracy equivalent to the human observers. However, Random Decision Forest was found useful among all methods which outperformed all other techniques on the same dataset.

In [15] Dutil et al., used different Deep Neural Networks (DNN) architectures on ISLES and SPES challenge datasets. A two-pathway architecture was found useful, as it performed better than the rest of the network architectures. This model is a refined version of the network used in the MICCAI brain tumor segmentation (BRATS) challenge by the same author. In the CNN model, input images are passed to both path layers where each path layer is responsible to learn local or global details from the images. After passing images from these layers, the output features maps of these layers are rejoined at last convolutional layer, before the final probabilistic layer. The model has achieved the mean ASSD, Dice, Hausdor Distance, Precision, and Recall of 8.92, 0.6, 31.75, 0.72, and 0.67 respectively on SISS dataset. While on the SPES dataset the model achieved ASSD, Dice, Hausdor Distance, Precision and Recall of 1.76, 0.85, 23.28, 0.83, and 0.88 respectively.

Kamnitsas et al. in [16] presented CNN 11-layer deep 3D CNN for the segmentation of brain lesions. This model is the winner of the ISLES 2015 challenge and achieved promising results of 64% in terms of dice score. They also made it possible to train a CNN model on the smaller datasets, to avoid over-fitting problems. Table 1 summarizes the related work.

3 Methodology

The proposed methodology is described as follows:

3.1 Data Acquisition

To evaluate the proposed technique, we use ISLES challenge dataset [17]. This challenge aimed to detect tissue loss during ischemic-stroke in MRI. Worldwide experts were invited to take part in this challenge. A total of 28 patient's data was obtained and each patient contains four MRI modalities DWI, FLAIR T1, and T1c along with pixel-wise ground truth as shown in Fig. 1.

Table 1. Summary of literature review

Authors/Techniques	Dataset/type	DC	Flaws
Reza/local gradient and texture feature [11]	ISLES 2015 challenge/MRI scans	0.59	Trained on selected features
Liang/random forest [8]	SISS/MRI scans	0.55	Trained on selected features
Maier/extra tree forest [9]	Local Dataset/MRI scans	0.65	Not tested on benchmark dataset
Mahmood/Random Forest [12]	ISLES 2015 challenge/MRI scans	0.54	Trained on selected features
Liang chen et al./CNN (EDD and MUSCLE Nets.) [13]	Local Dataset/MRI (DWI scans)	0.67	Data class Imbalanced
Maier et al./Generalized Linear Models, Random Decision Forests, and Convolutional Neural Networks [14]	Local Dataset/MRI scans	0.67	Not tested on benchmark
Dutil et al./CNN (two-pathway architecture) [15]	SISS dataset/MRI scans	0.6	Data class Imbalanced
Kamnitsas et al./CNN [16]	ISLES 2015 challenge/MRI scans	0.64	Data class Imbalanced

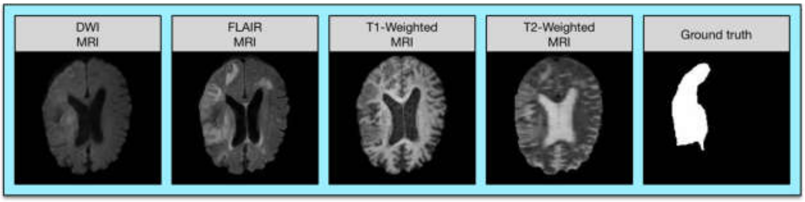

Fig. 1. Four different MRI modalities along with ground-truth against each patient.

3.2 Pre-processing

We use 25 patients' data for training and validation while the remaining three patient's data for testing the proposed model. The training and testing of patient sets are exclusive. The images are already skull-stripped and registered. As the convolutional neural network is only limited to image classification, we convert segmentation to the pixel classification task. Moreover, we extracted 50,000 patches of dimension 33×33 randomly while the number of strokes and health pixels are extracted in an equal ratio to avoid the imbalanced class distribution problem.

3.3 Proposed Model

Convolutional Neural Network (CNN) is a biologically inspired DNN. The self-feature learning capability of CNN enables it to produce better performance than other existing techniques for computer vision tasks. Due to the record-shattering performance of CNN, it is applied extensively to biological classification and segmentation problems during the last decade. Generally, a CNN model is composed of several layers including convolutional layers, pooling layer (max-min), and fully connected layers. Grouping these layers for a problem in an effective way is a key factor that subsequently produces the finest results. The upcoming sections will discuss the order and nature of layers used in the proposed model. Figure 2 shows the system model of the proposed scheme.

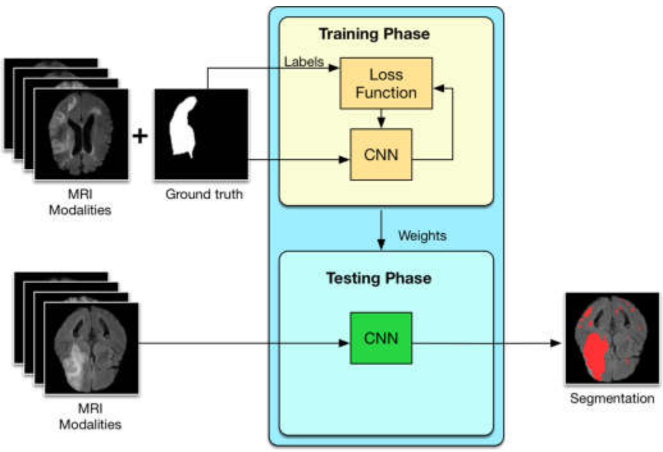

Fig. 2. Proposed framework for segmentation of Ischemic Stroke lesions.

3.4 Proposed Network Architecture

In this study, we propose 2D-CNN for Ischemic stork brain lesions segmentation. This model has the advantage of a small convolutional kernel of the size 3×3 for the entire network. Since we deal with limited data, therefore, the smaller conventional kernel with less parameter was a better option. However, on the other hand, a larger convolutional kernels demand a high amount of training data as the larger convolutional kernels have large parameters. In the proposed model we used advanced LeakyReLU action function and every convolutional kernel is followed by LeakyReLU. The LeakyReLU has the ability to sort out ReLU issues like dying ReLU, where LeakyReLU addresses this issue by adjusting negative gradients on backpropagation. We used batch normalization to enhance performance and training. This model takes the patches of the size 33×33 as input. Moreover, we used max-pooling layers to reduce learn-able parameters. Three max-pooling layers with the kernel size of 3×3 and stride 2×2 are placed between the 1st three convolutional layers, more precisely the first three convolutional layers are followed by max-pooling layers. The generated feature maps of the 1st three convolutional layers are input to the further three convolutional layers and thus the output of these layers is then forwarded to another max-pooling layer with the kernel size of 3×3 and stride 2×2. The final output (feature maps) of the pooling layer has the dimensions of $128 * 7 * 7$. Further, these feather maps are then connected to the fully connected layers. In the proposed model we used only two fully connected layers the first fully-connected layer is consists of 512 while the second is consists of 256 neurons. In both fully connected layers, we used advanced regularization technique, dropout with 0.1 value, in order to reduce overfitting. The Soft-max layer is used to get the segmentation probabilities. The graphical illustration of the network is shown in Fig. 3.

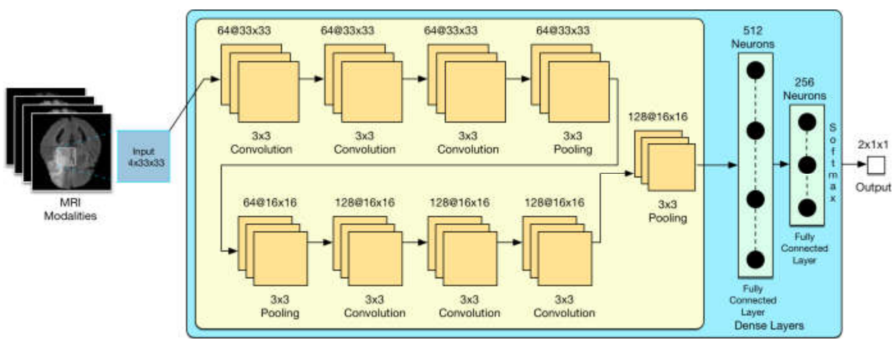

Fig. 3. Block diagram of CNN.

4 Performance Evaluation

As discussed earlier, in the pre-processing section, we divided the data into three sets, training, validation, and testing set. The training and testing of patient sets were exclusive. The training and validation progression of the model on the training data is shown in Fig. 4 while the respective minimization of the loss function can be seen in Fig. 5. We extracted 50,000 patches of dimension 33×33 randomly and in a balanced manner. (i.e. the count of stroke centered patch and a healthy brain are equal). This helped us to avoid the imbalanced class distribution problem. Our task is a binary classification. The CNN model has to classify the pixels as either stroke (i.e. lesion) or healthy. The coloring scheme is as follows, we used red color to refer to the stroked region. The pixel-wise classification of the proposed model results in the final lesion segmentation. The segmentation results are displayed without any post-processing. We used the Dice coefficient for the evaluation of the proposed model. It measures the overlap between the predicted outcome and provided ground truth. DC can be calculated as:

$$DC = \frac{2TP}{FP + 2TP + FN} \tag{1}$$

We used an exclusive set for testing the model after training on the training set. We reported DC for the middle 21 slices and for entire slices against each patient. Table 2 shows the DC obtained by the proposed model.

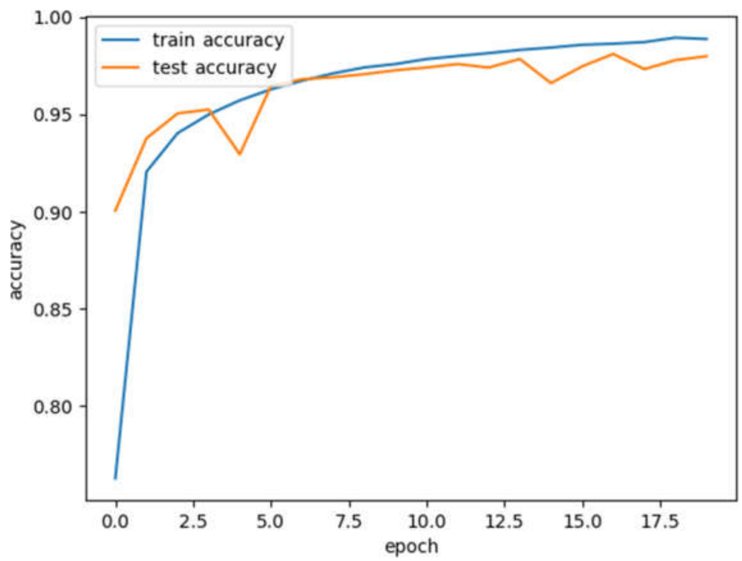

Fig. 4. This diagram shows the training and validation accuracy procession of the proposed CNN model.

Figure 6 shows the slice wise segmentation performed by the proposed model, where row 1 shows the slice of segmented MRI while row 2 shows the respective ground-truth of the slice. The proposed model achieved better accuracy than the random forest, extra tree forest, and other deep neural networks. The reason is the better handling of class imbalance problems and the learning of automated (respective to the problem) features. The detailed comparison of the proposed model along with the other existing techniques are presented in Table 3.

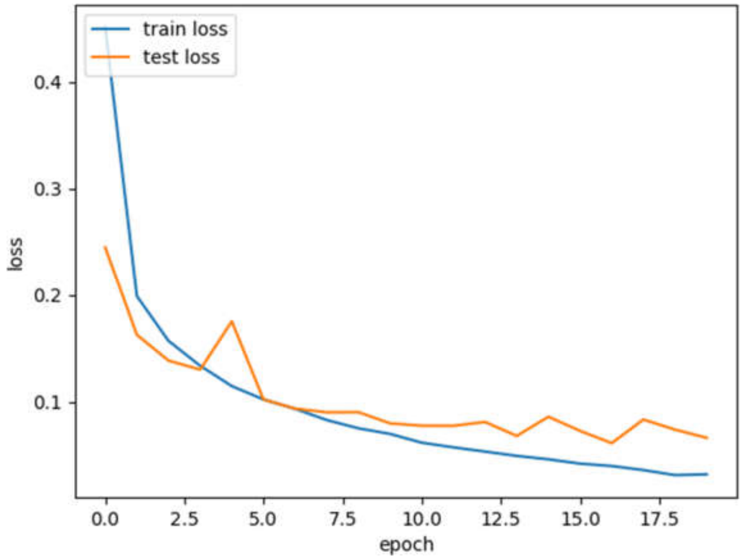

Fig. 5. This diagram shows the decrease in the loss (i.e. cost) function for the proposed CNN model.

Table 2. Model Performance on the test set

Test Patient	Mean dice coefficient over all slices	Mean dice coefficient over middle 21-Slices
Patient # 1	0.661320496	0.744979144
Patient # 2	0.822749173	0.869131752
Patient # 3	0.662616723	0.808938034
Mean Dice Coefficient	**0.715562131**	**0.807682977**

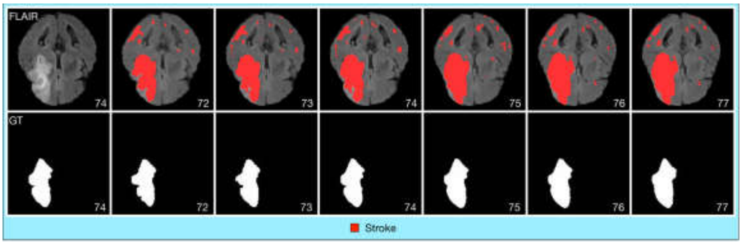

Fig. 6. Slice wise segmentation performed by the proposed model.

Table 3. Comparison of the proposed model with state-of-the-art machine learning techniques

Technique	Dataset/type	Mean dice coefficient
Random Forest [12]	ISLES 2015 challenge/MRI scans	0.54
Random Forest [8]	SISS/MRI scans	0.55
Extra tree Forest [9]	Local Dataset/MRI scans	0.65
CNN [16]	ISLES 2015 challenge/MRI scans	0.64
Proposed CNN	**ISLES 2015 challenge/MRI scans**	**0.71**

5 Conclusion

In this study, we proposed an entirely automatic brain lesion segmentation system based on CNN architecture. The proposed model with six convolutional layers is capable to learn the complex patterns of the lesions. The experiments are carried out on the benchmark ISLES 2015 challenge dataset. We extracted 50,000 patches of dimension 33×33 randomly and in a balanced manner. These patches were then incorporated into CNN. Since it is a binary classification task, CNN has to classify it as a lesion or a healthy pixel. During training, we noticed that limited samples of data are an issue for CNN that results in the model overfitting. However, the proper placement of dropout and the other network layers suppress the overfitting problem and efficiently improved the accuracy up to 10% when compared to other techniques.

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