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Original scientific paper

Bidirectional ConvLSTMXNet for Brain Tumor Segmentation of MR Images

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Abstract: In recent years, deep learning based networks have achieved good performance in brain tumour segmentation of MR Image. Among the existing networks, U-Net has been successfully applied. In this paper, it is propose deep-learning based Bidirectional Convolutional LSTM XNet (BConvLSTMXNet) for segmentation of brain tumor and using GoogLeNet classify tumor & non-tumor. Evaluated on BRATS-2019 data-set and the results are obtained for classification of tumor and non-tumor with Accuracy: 0.91, Precision: 0.95, Recall: 1.00 & F1-Score: 0.92. Similarly for segmentation of brain tumor obtained Accuracy: 0.99, Specificity: 0.98, Sensitivity: 0.91, Precision: 0.91 & F1-Score: 0.88.

Keywords: ConvLSTM; GoogLeNet; Linear Transformation (LT); Notch Filter; X-Net

1 INTRODUCTION

The brain controls and co-ordinate many important body functions. Normal cells generate, grow and die, abnormal cells grow when the body doesn't require them is known as cancer. A brain tumor occurs when abnormal cells produce within any part of the brain. There are two main types of tumors namely, malignant and benign tumors. Benign brain tumors are non-cancerous, malignant tumors are cancerous. Metastatic brain tumors occur when cancer located in another organ of the body spreads to the brain, 40% of all cancers spread to the brain and central nervous system, up to half of metastatic brain tumors are from lung cancer. Among 10,000 populations 5 to 10 people affected Central Nervous System (CNS) tumors in India [1].

Basically, the brain regions diagnosed/scanned by CT, X-ray, Ultrasound, PET and MRI. MRI is preferred over other imaging modalities because not harm and malaco tissue contrast in the brain [2, 3]. MRI produces different types of sequenced contrast images, which allow MRI extraction of valuable information of tumor and sub-regions, the deferent pulse sequences like, T1, T2, T1C and FLAIR. These sequenced images are diagnosed slice by slice manually is a laborious and time consuming process for radiologists/doctors. This manual burden process can be replaced by automatic enhancement, segmentation and classification with the use of computer-vision technique. To boost the visual appearance of an image, segment the Region of Interest (ROI) and classify them into the given class. Image processing is widely used.

In the present study, we present a techniques for enhancement, classification and segmentation of tumor from MR images using Notch filter & Linear Transformation (LT), GoogLeNet and Bidirectional Convolutional Long Short Term Memory (LSTM) X-Net (BConvLSTMX-Net). Classified and segmentation results are compared with other methods (AlexNet, VGG-16 & GoogLeNet) and (Seg-Net, UNet & XNet) respectively.

The remaining contents of the paper are arranged as follows: Section 2 gives the brief review of literature. In Section 3 discuss the present study. Section 4 shows comparative analysis, finally, in Section 5 interpret the present and future scope of the work.

2 STATE OF THE ART WORK

A brief review of literature on the topic of enhancement, segmentation and classification of MR brain tumor image is discussed below.

To enhance the contrast of MRI brain images, deferent spatial domain techniques were proposed like Histogram Equalization (HE) [4, 5, 7, 9, 10], Adaptive Histogram Equalization (AHE) [4, 5], Contrast Limited Adaptive Histogram Equalization (CLAHE) [4, 7], LHE [4], BBHE [5, 10], MMBEBHE [5, 6], BPDHE [5, 6, 8], RMSHE [6], BPDHE [6], DSIHE [6], BPDFHE [7], Deferent Techniques like GHE [8], Modified BHE, Brightness preserving BHE (BBHE) [10], Fuzzy logic based Adaptive Histogram Equalization (AHE) [5], Multi Scale Retinex (MSR) [9] and Non-sub sampled Contour-let Transform (NSCT)-FU [9].Different frequency based domain methods were proposed to enhance MRI brain images. Methods are Gabor Filter [13], Gaussian Filter [13, 23, 30, 29], salt and pepper-noise [13, 23], Median Filter [16, 17, 18, 20, 22, 25, 26, 30], An-isotropic Diffusion Filter[15, 17], Linear Filter [29], Wiener Filter [33], Discrete Wavelet Transform (DWT) [14, 15, 18, 21, 23, 27, 30] and Dynamic Stochastic Resonance (DSR) [17, 27, 29].

Before the revolution of deep learning, traditional semantic segmentation and handcrafted feature based classification methods were used. From the last decades deep-learning based approaches outstanding improvement in enhancement, segmentation and classification of images, they are CNN, RNN, FCN and GCN. Different CNN techniques were used for segmenting the brain of tumors like SegNet [34, 35], U-Net [35, 36, 37] and X-Net [38]. Similarly, AlexNet [39, 40], VGG-16 [39, 40] and GoogLeNet [39, 40] techniques are used to perform classification brain tumor.

From the related work, it is observed that most of the work done on enhancement, segmentation and classification of brain tumor from MR Images, still there is much scope for improvement. In this paper, Bidirectional Convolutional Long Short Term Memory (LSTM) X-Net (BConvLSTMX-

Net) is proposed as an extension of X-Net, The proposed method performs better than the existing methods.

3 PROPOSED METHOD

Here, the study focused on classification of tumor & non-tumor and also segmenting the brain tumor. The flow of the present methods is shown in Fig. 1 and deferent stages are described below.

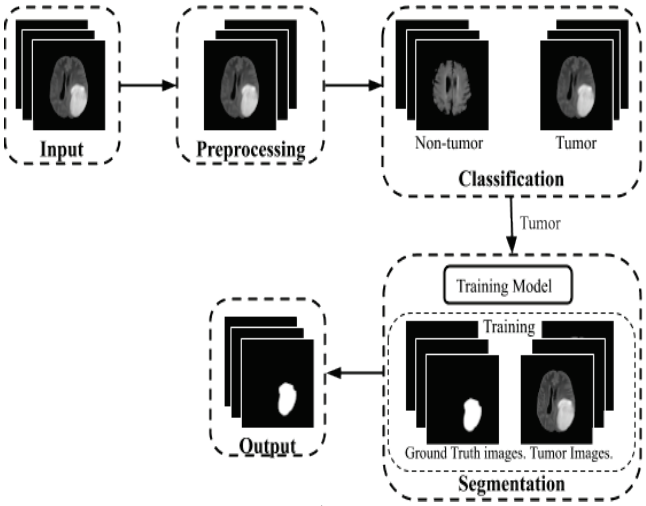

Figure 1 Flow of present method.

3.1 Prepossessing

Initially, we take BRATS-2019 brain images, to improve quality of the image, Notch & LT methods are applied. We tried a different inner & inter class combination of spatial, frequency and fuzzy logic methods, in that Notch & LT method gives good qualitative results.

3.2 Data Augmentation

Since the data-set considered for experimentation is very small i.e., only 284 images, therefore, we artificially augment the training images to create larger data-set to avoid over-fitting. Generally augmented images are obtained by using the geometrical operations like translations, rotation, shear and cropping.

3.3 Classification

For classification of tumor and non-tumor, we used predefined CNN based 22 layered GoogLeNet, The number of variables is small compared to Alex-Net & VGG-Net. The architecture of the Inception layer is given in Fig. 2.

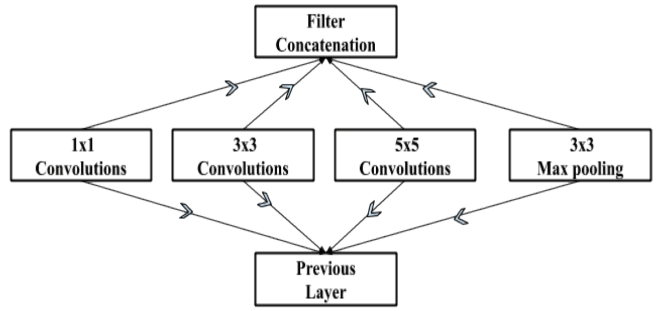

Figure 2 Architecture of the Inception Layer.

3.4 Segmentation

The BConvLSTMXNet method is proposed for segmentation of brain tumor, it is inspired by BConvLSTM [32] and X-Net [33] methods. The different stages of segmentation are discussed below and architecture is shown in Fig. 3.

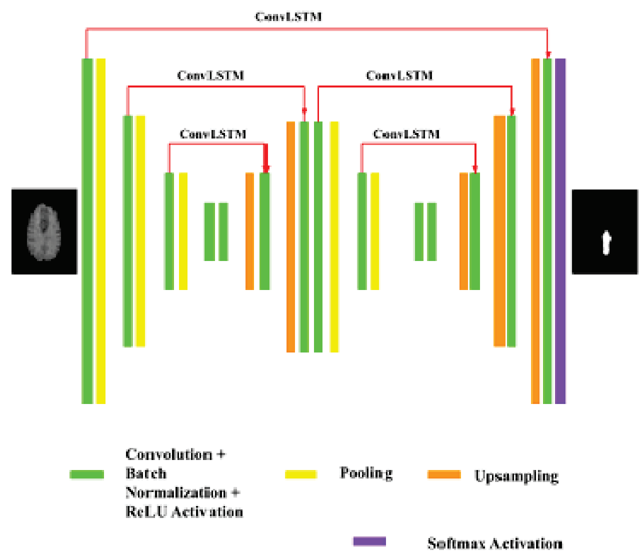

Figure 3 X-Net with BConvLSTM architecture

3.4.1 Encoding Path

The encoding path incorporates a sequence of steps. Each move consists, two convolutional 3×3 filters used for feature extraction along with 2×2 max-pooling function for down-sampling the input image and the activation function i.e, ReLU. Breaking up the down-sampling into multiple stages, features are doubled at each polling stage. The final encoded foot-path makes a big size with information.

3.4.2 Decoding Path

After feature extraction from the encoded path, decoded step to perform up-sample to make segmented mask-of equal size to the input image. Decoded step to perform an up-sample to make a segmented mask of equal size to the input image. In XNet, the encoded steps feature maps are duplicated to decoded steps. The extracted features are map-ed to concatenate with BConLSTM, and we used two encoder-decoder modules in succession. Compared to other networks we avoid larger serial down-sampling of the input, due to the small data-sets. Number of down-sampling in series can determine accurate boundary level on details and also avoid reducing image resolution.

3.4.3 Training and Optimization

An augmented data is trained, so increase the number of samples and lower the over-fitting. Soft dice metric is used as cost function and Adam optimization is used to minimize the cost function. Stochastic gradient based Adam optimization with learning rate 0.0001 [30, 31] is initialized.

The ground truth masks used for training and optimize by using cross-entropy loss.

$$L(N, m) = -\sum_{p=1}^{q} R(m, p) \log t(Q = p \,||\, N) \tag{1}$$

where, N is input pixel, m is the output, $t(Q = p \,||\, N)$ is probability, p given as input and $R(m, p)$ is in Eq. (2).

$$R(m, p) = \left\{ \frac{0 \text{ if } m \neq p}{1 \text{ if } m = p} \right\} \tag{2}$$

Without augmented data testing process is performed. The next section, experimentation and results are described.

4 RESULTS AND DISCUSSIONS

Here we give the detailed experimented discussion.

4.1 Result

For the purpose of experimentation, we have used 284 MRI brain images collected from BRATS-2019 repository to enhance, segment and classify brain images. Notch & LT methods are used to enhance brain image, GoogLeNet & BConvLSTM X-Net based deep convolutional networks are used for classification & segmentation of brain tumor. Result shows in Fig. 4 and Fig. 5.

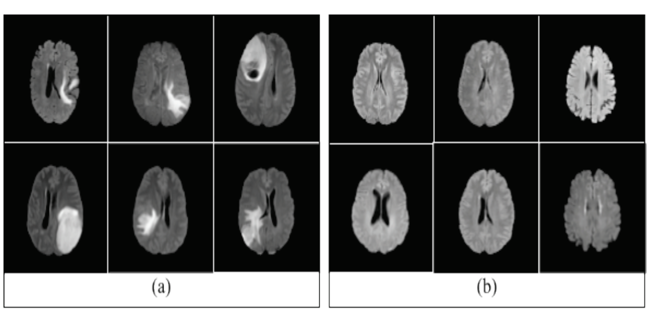

Figure 4 Classification of tumor and non-tumor results (a) Represents tumor and (b) Represents non-tumor.

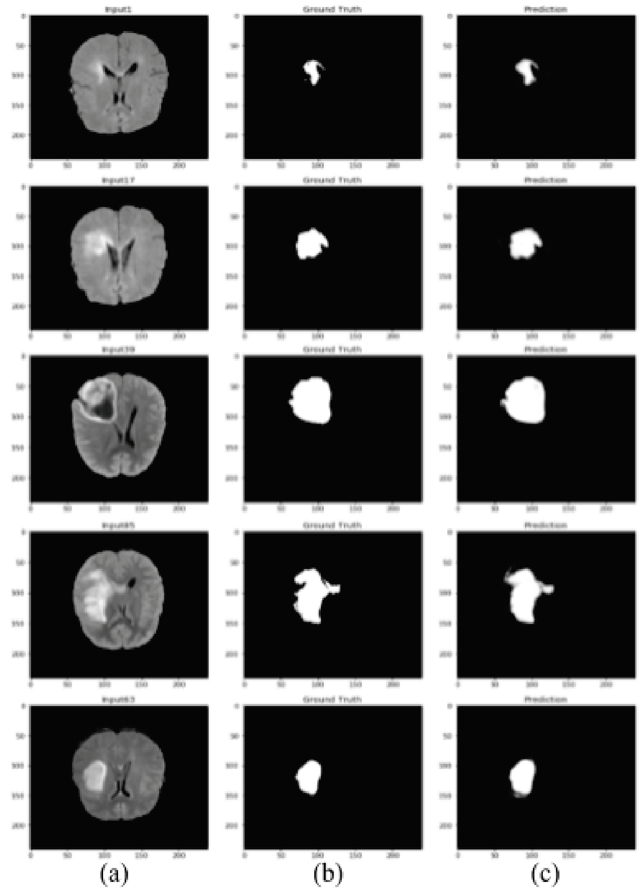

Figure 5 Segmentation of tumor results. Column, (a) Original image, (b) Ground truth and (c) Segmented tumor.

4.2 Discussion

To select the best segmentation and classification method quantitative analysis parameters are used, they are Accuracy, Specificity, Sensitivity, Precision, F1-Score and area under the curve (AUC). Tab. 1 and Tab. 2 gives the different quantitative measure results.

From Tab. 1 and Tab. 2, observed that the presented work obtained good quantitative measure result. In Fig. 4, shows the segmented result. In Fig. 5, the first column is tumor image, the second one is non-tumor images. Classification of tumor & non-tumor training loss and accuracy is shown in Fig. 6, the ROC is shown in Fig. 7 and segmentation Accuracy & Loss is shown in Fig. 8.

Table 1 Performance comparison methods for classification

Methods	Accuracy	Precision	Recall	F1-Score
AlexNet	0.81	0.85	1.00	0.92
VGG-16	0.46	0.86	1.00	0.93
GoogLeNet	0.91	0.95	1.00	0.92

Table 2 Performance comparison methods for Segmentation

Methods	Accuracy	Specificity	Sensitivity	Precision	F1-Score
SegNet	0.92	0.70	0.91	0.86	0.89
U-Net	0.95	0.83	0.95	0.93	0.79
X-Net	0.97	0.94	0.87	0.83	0.88
Proposed	**0.99**	**0.98**	**0.91**	**0.91**	**0.88**

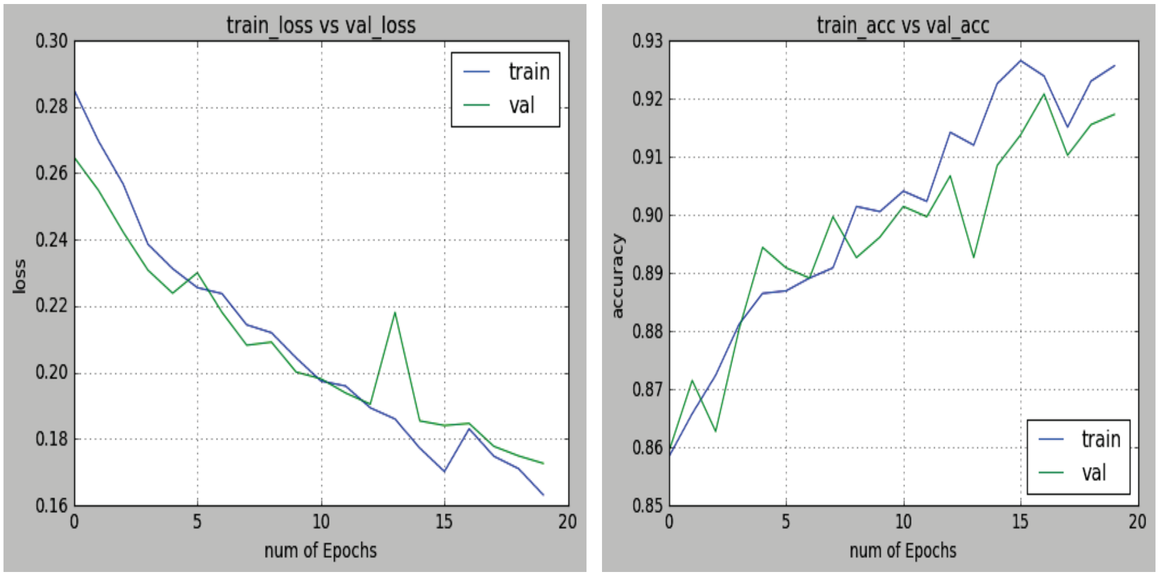

Figure 6 Accuracy and Loss for classification using GoogLeNet

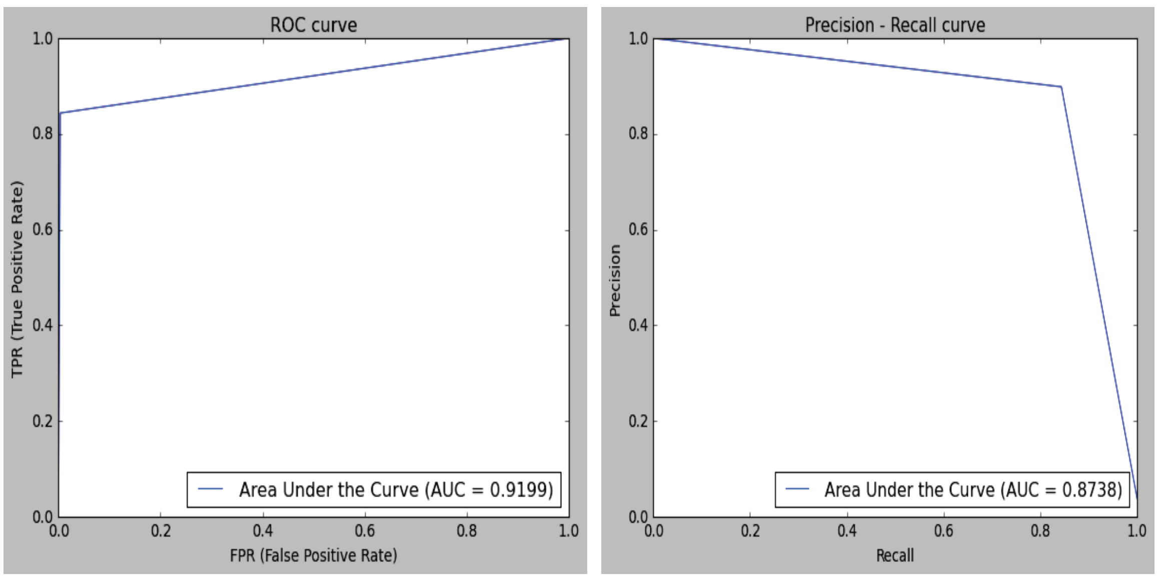

Figure 7 ROC diagrams of the present work for segmentation

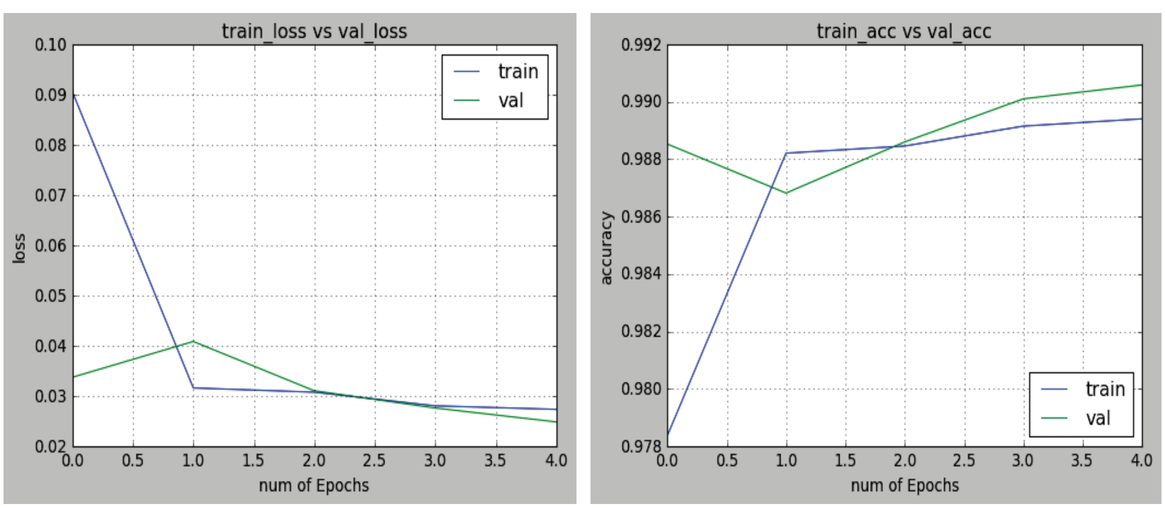

Figure 8 Accuracy and Loss diagrams for the proposed method

5 CONCLUSION

In this paper, proposed a deep-learning based Bidirectional Convolutional LSTM XNet (BConvLSTMXNet) for segmentation of brain tumor and using GoogLeNet classify tumor non-tumor. Evaluated On BRATS-2019 data-set and the results are obtained for classifica-tion of tumor and non tumor with Accuracy: 0.91, Precision: 0.95, Recall: 1.00 & F1-Score: 0.92. Similarly for segmentation of brain tumor obtained Accuracy: 0.99, Specificity: 0.98, Sensitivity: 0.91, Precision: 0.91 & F1Score: 0.88. Further we plan to extend our work towards the segmentation of core (major affected area), enhanced region.

Notice

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