Segmentation of Brain Tumor from MR Images using the Hybrid Architecture: "BConvLSTMSegX-Net"

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Abstract

In medical image segmentation, deep learning-based network methods perform well, during the last few years, most of them are using U-Net, X-Net and SegNet. In this paper, we propose hybrid BConvLSTMSegX-Net with the concatenation of SegNet and X-Net. Instead of simply adding skip connections in SegX-Net, we take full advantage of BConvLSTM and also batch normalization is used to accelerate the network. Experimentation is carried out and the results are obtained for segmentation of brain tumor obtained Accuracy:0.98, Specificity:0.96, Precision:1.00 & F1- Score:0.95.

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

1 Introduction

The brain controls and co-ordinate many important body functions. Normal cells generate, grow and die, whereas abnormal cells grow, die and replace with a new cell is known as cancer cells. These cancer cells produce within the brain is called brain tumor. Brain tumor broadly classified into beginent and malignant tumor, beginent tumor not harm to the brain, malignant tumor is dangerous to the brain and it can be derived from different organs of the human body. 40% of brain tumors are spread from different organs, 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. Basically, the brain regions are diagnosed/scanned by different techniques like CT, X-ray, Ultrasound, PET and MRI. MRI is preferred over other imaging modalities because not harm and tissue contrast to the brain (Bedi & Khandelwal, 2013;). MRI produces different types of sequenced contrast images, which allow MRI extraction of valuable information of tumor and subregions, the different pulse sequences like, T1, T2, T1C and FLAIR. Manually diagnosing these sequenced MRI images is laborious and time consuming for radiologists/doctors. This manual process can be replaced by automatic enhancement, segmentation and classification with the use of computervision techniques. 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.

Our work mainly focuses on segmentation of brain tumor from MRI images. A hybrid deep learning based BConvLSTMSegX-Net segmentation is proposed, it is based on X-Net, SegNet and BConvLSTM. The network architecture is improved from earlier methods and effective results are obtained.

The remaining paper is arranged as: Section 2 gives the brief review of literature. In Section 3 discuss the proposed method. Section 4 shows comparative analysis, finally interpreting the present work and future scope of the work.

2 Review of Literature

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

To segment brain MRImages many algorithms have been developed in the last few years. The authors have tried to improve the traditional algorithms, like, a novel VoxResNet is build with 25 layer deep network with hand craft features, segmentation of brain tumor from Spectral clustering algorithm. The features are reduced by using K-Means algorithm (Bedi & Khandelwal, 2013;), K-means and fuzzy c-means clustering algorithm is used to locate and extract brain tumor, Adaptive threshold and k-means clustering algorithm Morphological operations, pixel subtraction, threshold based segmentation and image filtering techniques (Senthilkumaran & Thimmiaraja, 2014), Watershed algorithm and neural network Bayesian fuzzy clustering approach A kernel clustering algorithm based on dictionary learning (Senthilkumaran & Thimmiaraja, 2014;), An improved anisotropic multivariate student t-distribution based hierarchical fuzzy c-mean method (IAMTHFCM) EMLike algorithm and level set methods (ELSM) (Oak & Kamathe, 2013;), Fuzzy C-Means Integrated thresholding and morphological process with histogram (Milletari, Ahmadi, et al., 2016;), Watershed method Hybrid fuzzy probabilistic-mean (FPCM) and morphological operations Pixel based Threshold value using standard deviation kmeans clustering and Morphological operations hybrid spatial fuzzy c-mean clustering (SFCM) and Novel NonNegative Matrix Factorization (NMF) and Self Organization Map (SOM)

After the emergence of deep learning, researchers began to study and presented different neural network architectures. It basically includes convolution, pooling layer and activation function. Deep learning broadly classified into CNN, FCN and RNN. Different CNN techniques were used for segmenting the brain of tumors like SegNet, U-Netand X-Net Similarly, AlexNet VGG16 and GoogLeNet techniques are used to perform classification brain tumor.

From the related work, we realized the majority of work done on segmentation and classification of brain tumor from MR Images, still there is much scope for improvement. In this paper, with the inspiration of Bidirectional Convolutional Long Short Term Memory (BConvLSTM), SegNet and XNet, we propose the hybrid BConvLSTMSegX-Net method. A hybrid method is proposed to segmentation of brain tumors and performs better than the existing methods.

3 Proposed Method

We develop a technique to classify and segment brain tumors. The flow diagram of the current method appears in Figure 1, which contains four different stages; they are talked about in the next part.

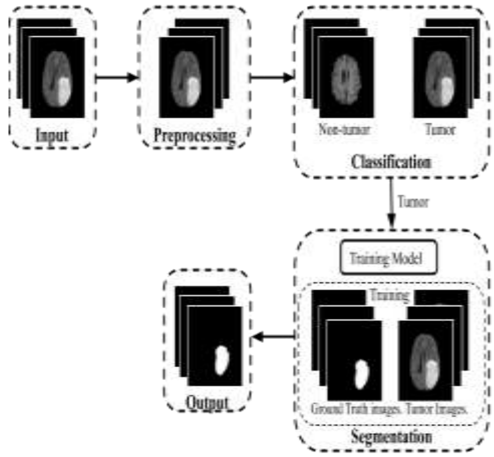

Figure1:Flowchart of the proposed method.

3.1 Prepossessing:

Initially, we take brain images from BRATS-2019 dataset, to enhance the quality of an image, because the intensity value varies on the imaging protocol and scanner used. Hence, intensity needs to be normalized to reduce the bias in image. Normalized images are given to Notch and LT methods.

3.2 Data Augmentation:

Since the data-set considered for experimentation is very small i.e, only 284 images. It is necessary to increase the training data to do this, we data augment techniques. 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. Here the numbers of variables are small compared to Alex-Net & VGG-Net. The

Inception layer framework is given in Figure 2

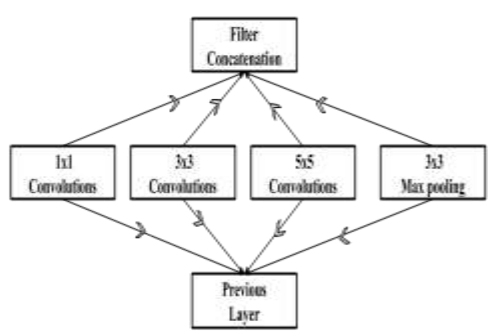

Figure2:The Inception Layer Framework.

3.4 Segmentation:

To segment brain tumor, Hybrid BConvLSTMSegXNet technique is designed, it is influenced by SegNet BConvLSTM and X-Net methods. The different stages of segmentation are Encoding path, Decoding path, Batch normalization, Bi-Directional ConvLSTM and Training & Optimization, which are discussed below and the architecture is displayed in Figure 3.

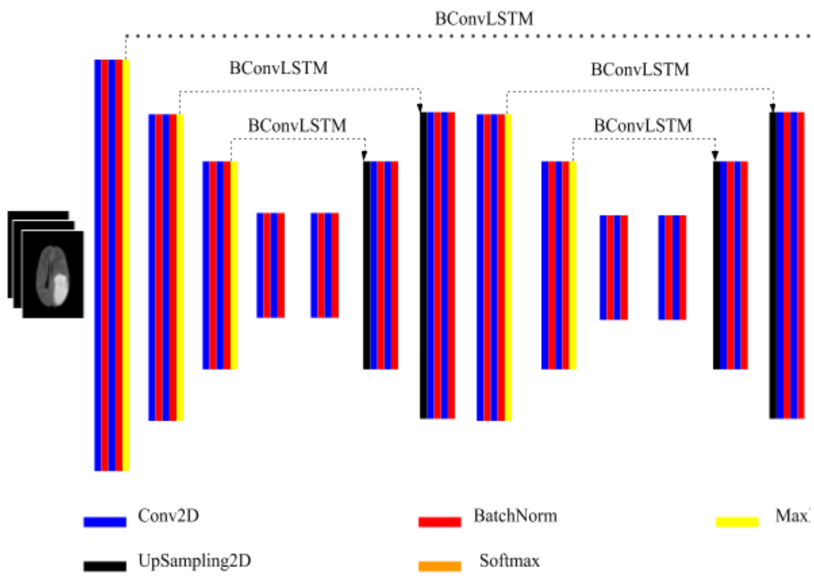

Figure3:SegXNet with BConvLSTM Framework.

3.4.1 Encoding Path

The hybrid SegNet includes eight blocks, in each block incorporate two convolution 3x3 filters, go along with 2x2 max-pooling and ReLU function. In each layer feature maps are doubled, in the last layer generate a more dimensional image representation with semantic information. The input $i^{th} (i \in \{1,2,3,\ldots N\})$ concatenation of feature maps i.e, $(x_e^1, x_e^2, x_e^3 \ldots x_e^{i-1}) \in R^{(i-1)F1*W1*H1}$.

The remaining part of the paper instead of x_e^N simply x_e is considered

3.4.2 Decoding Path

After words of feature extraction, the decoder conducts up-sampling to generate a segmented mask of the same dimension to the input image. The corresponding features are concatenated with output of upsampling functions. Let $x_e \in R^{F1*W1*H1}$ feature encoding path and $x_d \in$ feature maps from previous convolutional layers. xd is passed 2x2 convolutional, it duplicate the size of feature map i.e produce $x_d^{up} \in R^{F_{i+1}*W_{i+1}*H_{i+1}}$.

3.4.3 Batch Normalization (BN)

After the process of decoding the path undergoes Batch Normalization. the distribution of the actions varies in the intermediate layer is the problem. It makes the training process slow, because it has to learn and adapt them to a new distribution. Batch Normalization strength to the Neural network, this Normalized input gives to the neural network.

3.4.4 Bi-Directional ConvLSTM

After completing the BN the next step is to add BConvLSTM layer. No spatial information is encoded in LSTM, it is a major drawback while connecting input-to-state and state-to-state transitions. Figure 4: Bi-directional ConvLSTM. The ConvLSTM regulates the next state of determined cells in the framework, this makes operation in state-to-state and input-to-input easy. Represents it : input gate, ot :output gate, ft :forget gate and Ct : memory cell. These gates act as controlling gate to access, update and clear memory cell.

$$
\begin{aligned}
i_t &= \sigma(W_{xi} \star x_t + W_{hi} \star H_{t-1} + W_{ci} \star C_{t-1} + b_i) \\
f_t &= \sigma\left(W_{xf} \star x_t + W_{hf} \star H_{t-1} + W_{cf} \star C_{t-1} + b_f\right) \\
C_t &= f_t \circ C_{t-1} + i_t tanh(W_{xc} \star x_t + W_{hc} \star H_{t-1} + b_c) \\
o_t &= \sigma(W_{xo} \star x_t + W_{ho} \star H_{t-1} + W_{co} \circ C_t + b_c) \\
H_t &= o_t \circ tanh(C_t)
\end{aligned}
$$

Two ConvLSTM are used to construct BConvLSTM, it has a forward and backward path. The output of the BConvLSTM is determined as in equation 1.

$$Y_t = tanh\left(W_y^{\overrightarrow{H}} \star \overrightarrow{H}_t + W_y^{\overleftarrow{H}} \overleftarrow{H}_t + b\right) \qquad (1)$$

Where $\overrightarrow{H}$ and $\overleftarrow{H}$ forward and backward respectively.

In each convolution layer, ReLU activation is associated. The decode the image using nearest neighbors up-sampling, storage and use of the encoder feature maps is performed through filter copying between layers of equivalent dimensions. We employed L2 Norm regularization at each convolution layer with penalty parameter $\lambda = 5 \star 10^{-4}$,

3.4.5 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 (Milletari, Navab, et al., 2016;, Kingma and Ba, 2014;) is initialized.

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

$$L(N,m) = \sum_{p=1}^{q} R(m,p) \, logt(Q = p \mid N) \qquad (2)$$

Where, N is input pixel, m is the output, $t(Q = p \mid N)$ is probability, p given as input and R(m, p) is in equation 3.

$$Y_t = tanh\left(W_y^{\overrightarrow{H}} \star \overrightarrow{H_t} + W_y^{\overleftarrow{H}} \overleftarrow{H_t} + b\right) \qquad (3)$$

Without augmented data testing process is performed.

The next section, experimentation and results are described.

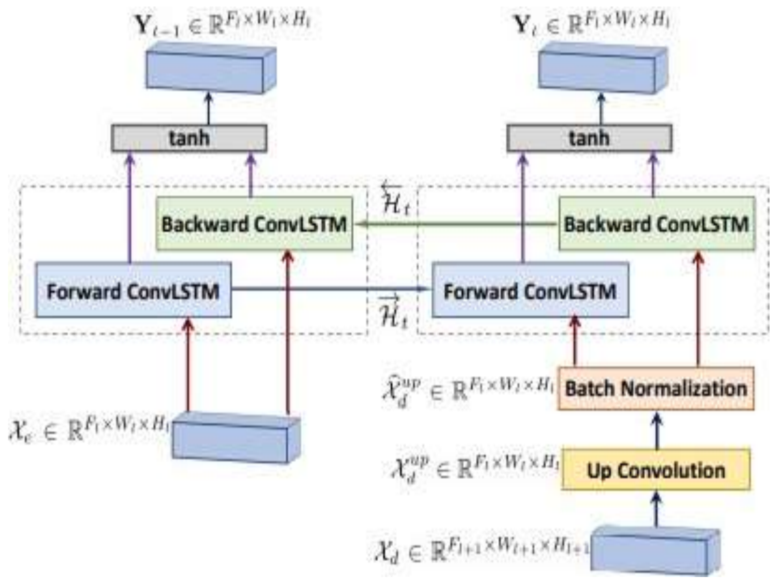

Figure 4: Bi-directional Conv LSTM.

4 Results and Discussion

The purpose of experimentation, we used 284 MR brain images collected from BRATS-2019 repository to evaluate hybrid BConvLSTMSegX-Net, for segmentation of brain tumor. To measure the performance Accuracy (AC), sensitivity (SE), specificity (SP), F1-Score, Jaccard Similarity (JS) and Area under the Curve (AUC) parameters are used.

Dataset consists of 138 training and 34 testing samples, a large training dataset is required to train a deep neural network. Since the dataset is small, we increased the training data by augmentation, it generates around 2,280 patches. The proposed network result for classification and segmentation appears in Figure 5, 12 and 13 . respectively. In Figure 5. the first column represents tumor images and the second column represents non tumors respectively. Similarly, Figure 12 and 13 first, second and third column represents input, ground truth and predicted images jointly. Table 1 and Table 2 list the qualitative outcome obtained by different methods for classification and segmentation. To ensure the proper convergence of the proposed network the training and validation accuracy is shown in Figure 6, 7 and 8. It shows that the network converges very fast, i.e, 10th epoch, the network is almost converged. We also saw that the first 5 epochs the validation accuracy is larger than the training, this is mostly because of the small size of dataset, ROC curves is shown in Figure 9, 10 and 11.

We have used a set of BConvLSTM to combine encoded and decoded features. The affection of two features maps rich in data local and semantic information, it helps the network to learn complex data.

Table1:Performancecomparisonmethodsforclassification.

Methods	**Accuracy**	**Precision**	**Recall**	**F1-Score**
AlexNet	0.84	0.85	1.00	0.92
VGG-16	0.86	0.86	1.00	0.93
GoogleLeNet	0.91	0.95	1.00	0.92

Table2:PerformancecomparisonmethodsforSegmentation.

Methods	**Accuracy**	**Precision**	**Recall**	**F1-Score**
SegNet	0.84	0.85	1.00	0.92
U-Net	0.86	0.86	1.00	0.93
X-Net	0.91	0.95	1.00	0.92
SegX-Net	0.95	0.94	1.00	0.93
Proposed	**0.98**	**0.96**	**1.00**	**0.95**

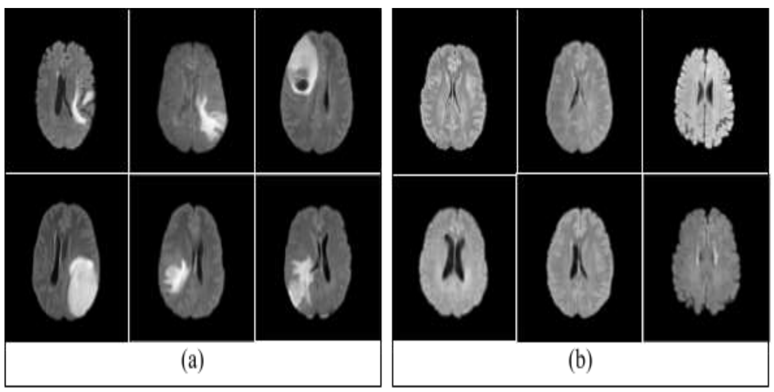

Figure 5: Bi-directional ConvLSTM

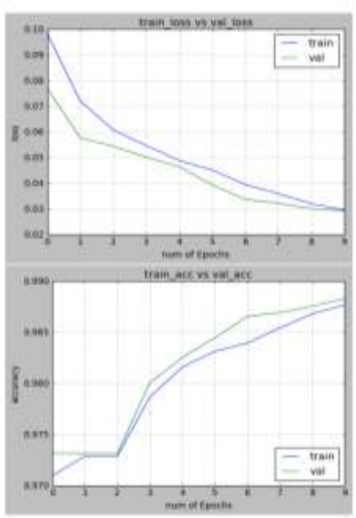

Figure 6: Accuracy and Loss diagrams for the proposed Enhance tumor method.

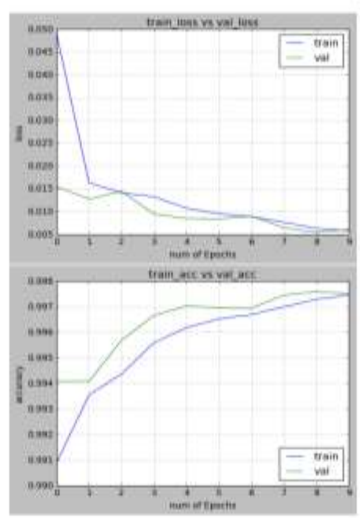

Figure 7: Accuracy and Loss diagrams for the proposed Core tumor method.

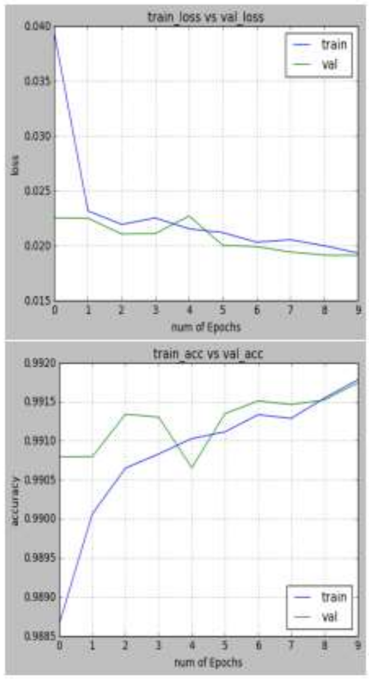

Figure 8: Accuracy and Loss diagrams for the proposed Whole tumor method.

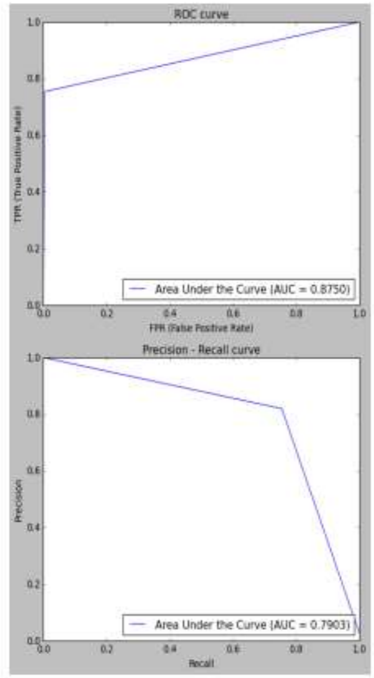

Figure 9: ROC diagrams of the present work for segmentation of whole tumor.

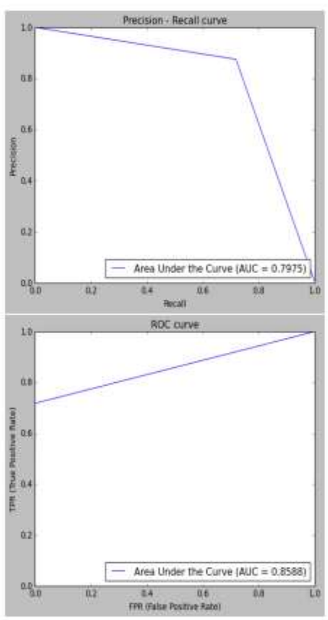

Figure 10: ROC diagrams of the present work for segmentation of Enhance tumor.

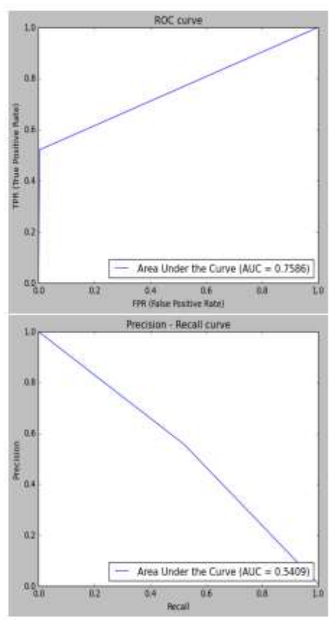

Figure 11: ROC diagrams of the present work for segmentation of Core tumor.

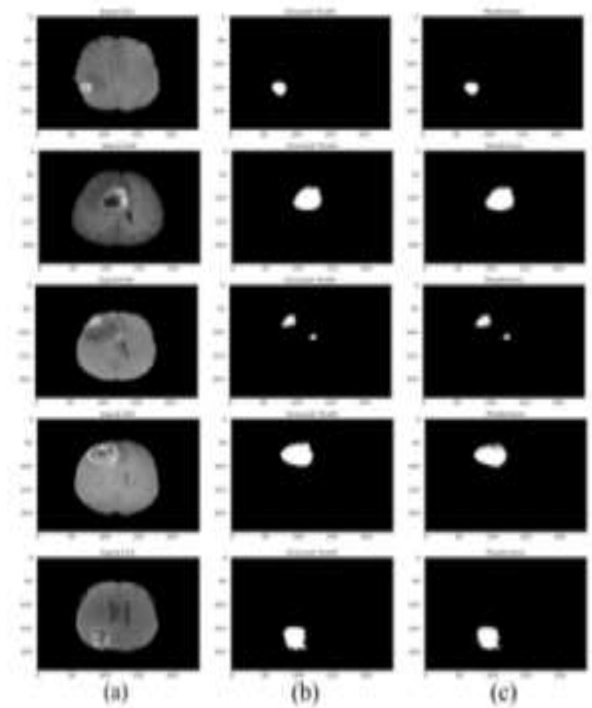

Figure 12: Segmentation of whole tumor results.

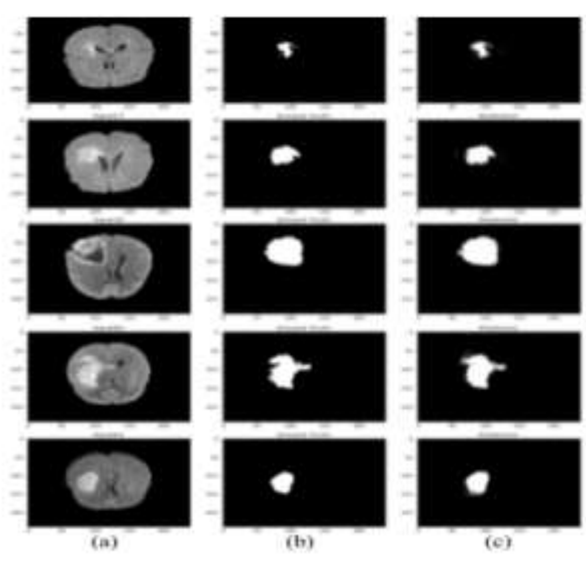

Figure 14: Segmentation of whole tumor results.

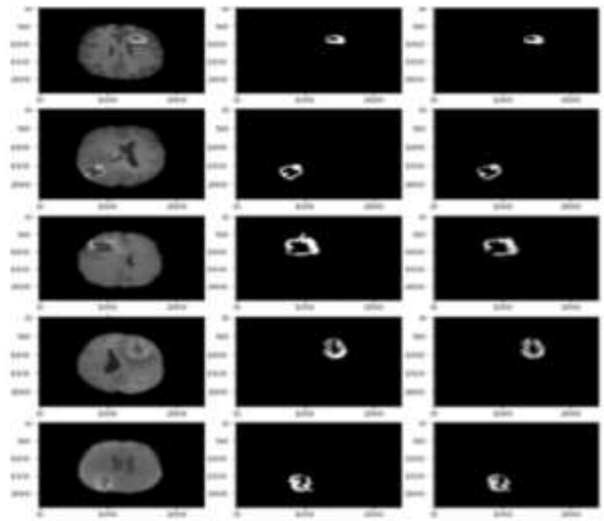

Figure 13: Segmentation of Core tumor results.

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We have used a set of BConvLSTM to combine encoded and decoded features. it helps the network to learn complex data. We include BN after each up-sampling layer to speed up the network learning process.

5 Conclusion

In the present work, to segment the core, enhance and hole tumor from MR brain images proposed hybrid BConvLSTMSegX-Net architecture. The present work achieved good result compared to other existing CNN models. Further, we plan to extend our work towards the segmentation of 3D MR Images.

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