

Fully Connected Pyramid Pooling Network (FCPPN) – A Method For Brain Tumor Segmentation



S.Fathima Suhara, M.Safish Mary

ABSTRACT: The procedure of separating the tumor from ordinary cerebrum images is called as brain tumor Segmentation . In segmenting the tumor it allows us to visualize the size and position of tumor within the brain. In Manual segmentation there is less accuracy so there is a need for fully automatic segmentation. A fully automatic segmentation called Semantic segmentation is a technique that classifies all the pixels of an image into meaningful classes of objects. Semantic Segmentation is mainly used in the area of medical imaging. It is mainly used for the doctors to identify the tumor in a clear and exact way. In this paper, we propose a new way of semantic segmentation technique to separate the tumor from the brain . The methods like Segnet, FCN, PSPNET are used for fully automatic segmentation and are used to predicate all types of Tumor. These methods are used to predicate the tumor. Our paper proposes a new architecture called FCPPNET which is a hybrid combination of FCN and PSPNET. Our proposed strategy is assessed utilizing Performance measurements, for example, the Dice coefficient, Accuracy, Sensitivity, and the outcomes appear to be more productive than the current strategies.

Keywords: FCN-Fully connected network, PSPNET-Pyramid Scene Parsing Network, VGG-Visual Geometry Group, NCUT-Normalized Cut , PET-Positron Emission Tomography, MRS-Magnetic Resonance Spectroscopy.

I. INTRODUCTION

A cerebrum tumor is a development of irregular cells in our minds. Our skull, which encases our cerebrum, is extremely unbending. Any development inside the mind causes an issue. Brain tumors are differentiated into two parts. One is Benign or low grade and another one is malignant tumors or high grade. Benign is the simpler one and they can't spread anywhere whereas Malignant are complex, grows rapidly and spread everywhere. Gliomas are the one sort of cerebrum tumor that begins from glial cells. This is the main type of brain tumor segmentation where the researcher focus on [1]. Brain tumor division is one of the fundamental pieces of medical image processing. At the starting stage of diagnosing the brain tumor involves in improving the treatment for the patient. Manual segmentation of Brain tumor troublesome and long undertaking, so there is a requirement for automatic brain tumor segmentation [2].

The brain tumor segmentation method is classified into various types according to various principles.

Revised Manuscript Received on October 30, 2019.

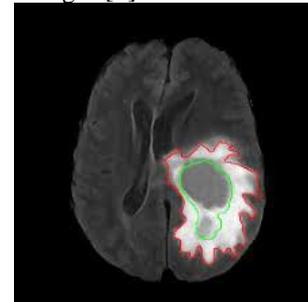
* Correspondence Author

S.Fathima Suhara* Research Scholar, Manonmaniam Sundaranar University, Tirunelveli. suharairfaan@gmail.com

Dr.M.Safish Mary Assistant Professor, Department of Computer Science, St.Xaviers College, Tirunelveli. marysafish@gmail.com

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The Division strategy for the segmentation is characterized into three kinds, they are Manual, Semi-automatic and Fully automated Segmentation [3]. Automatic detection of brain tumors is a difficult task that involves pathology, physical functions of MR images. [4]



Fig(a) Brain Tumor

Early determination of gliomas assumes an effective job in improving treatment potential outcomes.. Medical Imaging techniques such as CT, SPECT, PET, MRS, and MRI are utilized to give significant data, for example, size, shape, and area of the tumor in the brain. Brain MRI images are used to detect the tumor and tumor modeling process. This MRI Image gives more information on the medical field than ultrasound or CT scans .MRI method is one of the best methods for higher resolution and enhancing quality. Brain MRI is used to analyze and diagnosis the tumor. MRI is a non-intrusive in vivo imaging strategy that uses the radio recurrence signal that distinguishes the tumor. Segmentation of the brain into dark issue, white issue and cerebrospinal liquid utilizing Magnetic reverberation assume a significant job in medical research. Ordinarily, the tumor can show up anyplace in the mind and it very well may be of any sort, shape, and complexity.

In deep learning Techniques, CNN plays an important role in the Biomedical and Biological image analysis application. By using CNN we can classify the Brain Tumor in MRI Images. CNN is the feed-forward neural network. It is also called a shift variant or space-variant based on its shared weight architecture and translation invariance characteristics.

Our paper deals with the new Image segmentation technique called FCPPN. In Section II, we deal with the related work of Image Segmentation. In Section III, the existing methods of semantic segmentation technique are presented. In Section IV, the proposed method is discussed. In Section V the experimental results of image segmentation are reported. Conclusions are given in Section VI.

II. RELATED WORK

Brain tumor segmentation methods on MRI images are classified into two categories, one based on generative models and another is discriminative models. The segmentation method such as Fuzzy C Means is applied to isolate the tumor and non-tumor district of the brain[5]. Deep Neural network(DNN) is used for brain tumor classification for high accuracy.

Five different types of semi-automated segmentation technique that are used for image segmentation and that are compared to extract the tumor from the brain Image[6].Mohsen,Heba,et al[7] present the combination of DWT with DNN to categorize the brain MRI into Normal and 3 different types of malignant brain tumors. This combination of DWT with DNN yields good results. The M³Net Model is used for Segmentation to segment GM, WM and CSF in brain tumor Images[8].

C.Anitha and S.Gowsalya proposed[9] a new model for brain tumor segmentation is initiated which is also called a multimodal brain tumor segmentation technique.Ahamed,Amir and Lipika Dey [10] deal with the modified K-Means algorithm for clustering data. A New distance measure is also introduced to find the attribute values.There are various segmentation methods are compared and are used to analyses the brain tumor.Among various segmentation methods, the seeded Region growing method seems to be better for analyzing the brain tumor.

Ahamed O,Algohary,et al[11] deals with the technique that is based on the consecutive application of Bayer's classifier, otsu's thresholding algorithm, Morphological opening, and FCM technique.Good outcomes are accomplished even if the Images are experiencing from high commotion levels. Xu,Yongchao,Thierry Geraud.,et al proposes the segmentation of the brain from neonates to aging adults. This mainly focuses on transfer learning and 3D like color images obtained by stacking successive MRI Images[12].

Chen,Guanzhou,et al[13]deals with the semantic segmentation namely SNFCN and SDFCN for VHR remote sensing images. An adopted overlay fusion and post-processing method, which increased the overall accuracy by 1% to 2% that helps to eliminate the "Salt and Pepper" Phenomena and block efforts. Kumar,pulkit,et al deals with the U-SEGNET architecture, which is a combination of U-NET and SEGNET architecture for semantic segmentation. It finds relevance in other medical imaging using Deep learning[14].

The hierarchical brain tumor segmentation in context to FCN.These Networks achieve better regularization. Segmentation using FCN it not only for distinguishing the tumor as a whole but also for better outline of core and upgrading the tumor[15].Zhou,Xiangrong,et al [16] deals with the concept of deep learning of different 2D sectional appearances of 3D anatomical structures of CT cases.

The review of the state of art methods based on deep learning and an overview of traditional techniques. Image modalities such as PET, MRS, and DTI are used to improve the current methods and leads to the development of automatic glioma segmentation methods for better diagnosis.

Mehmood, Irfan,et al[17]deal with computing medical images, perception-based models to detect brain tumors and NCUT segmentation are used to find the effective prioritization of brain MR images.

Chen,Yao-Tien[18] proposes an approach of 3D Segmentation and volume rendering for brain tissues and tumors.

Semantic segmentation methods such as 2CNET, 3CNET and ENSEMBLE NET are used for the segmenting the brain tumors by using the deep convolutional neural networks[19].CNN methods are used for brain tumor segmentation methods. The input to the network is of 2D patches sizes of (32*32)pixels. These networks are divided into two paths, one is CNN architecture and another is a fully connected Maxout Layer. Finally, these layers are connected at the end of Softmax Layers[20].

Zhao,Hengshuang,et al[21] deals with the deep convolutional network for semantic segmentation. They analyzed the segnet and compared it with the various architecture for segmentation.Segnet is more efficient because it only stores the max-pooling Indices on the feature map and uses them on the decoder section to achieve good performance.PSPNET architecture is proposed for complex scenes. The global pyramid pooling feature gives additional information[22].

III. EXISTING METHODS

A.SEGNET:

A method called Segnet is used for deep fully convolutional neural network semantic pixel-wise segmentation. This segmentation technique consists of Encoder and Decoder for Pixel-wise classification.



Figure(b) SEGNET Architecture

Encoder:

The encoder consists of 13 VGG 16 convolution layers and it is not fully connected.



Figure (c) Encoder Part in SEGNET

The above fig.represents the SubSampling stage. Both MaxPooling and SubSampling leads to each pixel governing a larger input image context. These method improves the better classification and reduces the feature Map size. The output image resolution should be the same as the input image resolution, to achieve this Segnet Upsampling is done in Decoder. Segnet Stores only the max-pooling Indices. Only two bits are needed for each window of 2*2, Slight loss of precision.

Decoders:

For every 13 Encoders, there is a parallel decoder which upsamples the component guide utilizing remembered Max Pooling Indices.

In Upsampling it takes out the requirement for figuring out how to Upsample. The Upsampled maps are meager and are then convolved with trainable channels to deliver thick feature Maps.

B.FCN (FULLYCONNECTEDNETWORK)

It is manufactured distinctly with privately associated layers, for example, Convolution, pooling, and Upsampling. In FCN design no thick layers are utilized. This lessens the quantity of parameters and calculation moreover. To get the division guide yield, division Networks more often than not have two sections:

- (i) DownSampling way: keep semantic/relative data
- (ii) UpSampling Path: improve spatial data

It is utilized to separate and translate the unique circumstance, the upsampling way is utilized to empower exact limitation. To improve the fine-grained spatial data lost in the pooling or downsampling layers, we use skip association. A Skip association is an association that sidesteps at any rate one layer. It is regularly used to move neighborhood data by adding highlights maps from the downsampling way with highlight maps from the upsampling way. Consolidating highlights from different goals levels joins setting data with spatial data.

There is 3 Architecture that offers the equivalent downsampling way yet contrasts in their separate upsampling way.

- (i) FCN 32: Directly delivers the division map from Conv7, by utilizing a transposed convolution layer with walk 32.
- (ii) FCN 16: Sums the 2* upsampled prediction from conv7 with pool4 and produces a division map, by utilizing a transposed convolution layer with walk 16 in addition.
- (iii) FCN 8: Sums the 2* upsampled prediction from conv7 with pool4, upsamples them with a walk 2 transposed convolution and aggregates them with pool3 and applies a transposed convolution layer with walk 8 on the subsequent component maps to acquire the divisionMap.

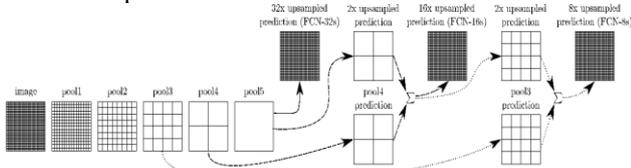


Figure (d) Fully connected Layer

C. PSPNET (PYRAMID SCENE PARSING NETWORK)

PSP Net uses semantic segmentation and the aim of PSP net is to assign each pixel in an image as a category label. The pyramid pooling module for the global scene is constructed on the top of the final layer featured map. The PSPNET deals with a clear way of using **Multiple Scales Of Pooling**. It has a standard feature extraction network (RESNET,DenseNet) and takes the features of the third downsampling for further processing. PSPNet architecture applies Four different Max pooling operation with four different size and Strides. It uses 1*1 convolution layers to reduce the number of channels. The output of this pooling operation has four different scales without the need for heavy individual processing of each one. A Convolution process is done on each scales one after the other and Upsampling is done on the feature map and then it is concatenated.

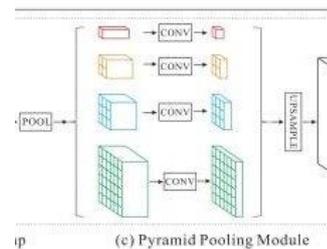


Figure (e) PSP Net

The semantic segmentation such as segnet,FCN, PSPNet gives the best result when they work in individuals, but when FCN is incorporated with PSP NET it gives a better result and it is called as FCPPN.

IV. PROPOSED METHODOLOGY(FCPPN)

In this architecture, a new way of Segmentation technique FULLY CONNECTED PYRAMID POOLING NETWORK(FCPPN) that concatenate the work of FCN and PSPNET is proposed. It is a fully convolutional neural network used in segmentation. The proposed approach consists of three parts. The first part is the encoder part of FCN and the input image is encoded.

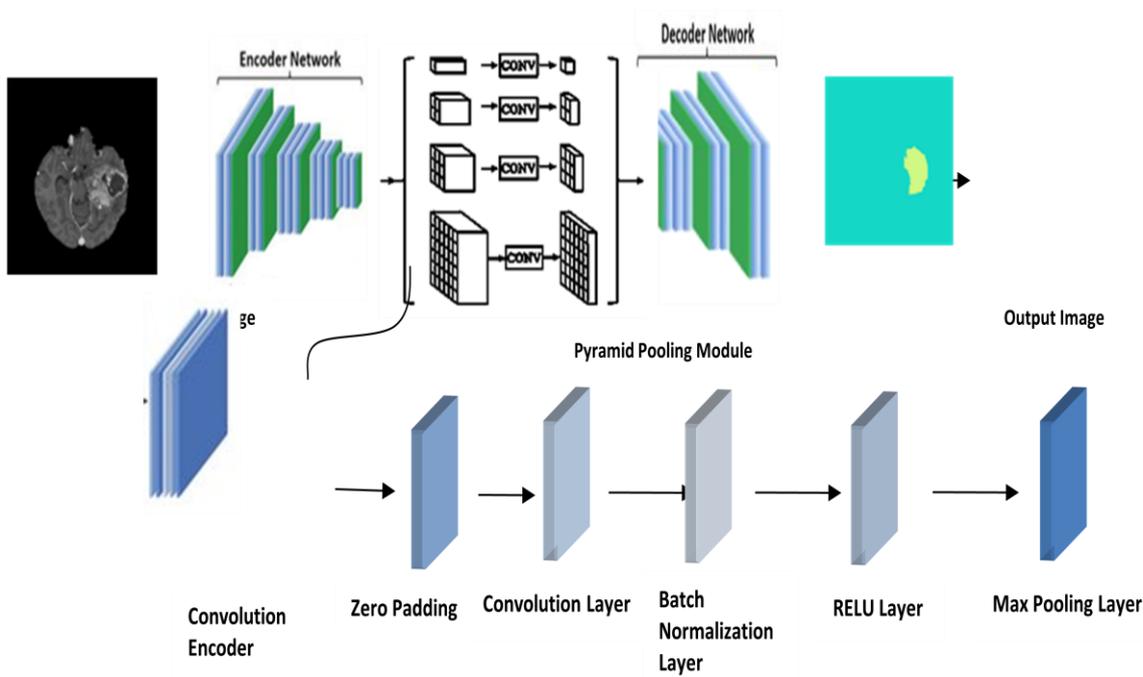


Figure (f) FCPPN

The Encoding part consists of many layers, such as the convolution layers is used to extract features from the input image. Padding means adding additional Layers to the border for an Image. Zero padding is the process of adding zeros to the input matrix. Zero padding is used to control the shrinkage of an image and also to avoid losing information around the boundaries.

Batch Normalization Layer: It is used to reduce the covariant shift. It allows each layer of a network to learn itself more independently of other layers.

Relu Layer: It is the rectified linear unit. It is the activation function defined as the positive part of its argument. A unit employing the rectifier is also called as RELU. It is also a piecewise linear function that will output the input directly if it is positive, otherwise output it to zero.

Max Pooling Layer: It is a sample-based discretization process. Max pooling is finished by applying a Max channel to the non-covering subregions of the underlying representations. It is a downsampling strategy in the convolutional neural network.

The second parts consist of Pyramid pooling Module of PSP NET. The pyramid pooling module aims to concatenate the features of four different scales. These pyramid modules separate the feature map into different subregions and form a pooled representation. The output is of various sizes. To maintain the weight of feature maps we use 1*1 convolution layers. These are used to reduce the number of channels. Then upsample them to the same size and concatenate all. The third part consists of the decoder of FCN. Finally, an output image is obtained from the Decoder section.

V. EXPERIMENTAL ANALYSIS

A. PERFORMANCE METRICS

DICE COEFFICIENT:

The dice coefficient is utilized to appraise the similarity between two samples. It is also called a proportion of specific agreement and a spatial overlap index and it is reproducibility metric. The estimation of the dice coefficient ranges from 0 to 1.

0 → No spatial overlap between the two sets.

1 → Indicates the complete overlap

The formula of the dice coefficient is given by

$$\text{Dice coefficient} = \frac{2 * |x \cap y|}{|x| + |y|}$$

SENSITIVITY:

It is a technique that is used to determine how independent variables values will impact a particular dependent variable under a given set of assumptions is defined as a Sensitivity analysis. The sensitivity coefficient is a partial derivative used to explain how the output estimate Y varies to the value of the input estimate X₁, X₂, X_n. It is also called a true positive rate and it measures the proportion of positives that are correctly identified.

$$\text{Sensitivity} = \frac{\text{No. of true positives}}{\text{No. of true positives} + \text{No. of false negatives}}$$

No. of true positives + No. of false negatives

ACCURACY:

It is the measurement results to true value (i.e) true positive or true negative value among the total number of cases examined. It calculates the analytical trail of the real circumstances. It is also called as “rand accuracy” or “Rand index”.

$$\text{Accuracy} = \frac{\text{No.of true positives} + \text{No.of true Negatives}}{(\text{No.of true positives} + \text{No.of true negatives}) + (\text{No.of false positives} + \text{No.of false negatives})}$$

B . BRATS DATASET

To mechanize the cerebrum tumor division and contrast it and various techniques,a dataset called **BRAIN TUMOR SEGMENTATION (BRATS 2015)**are used[25]. It is a dataset in which a large number of MRI scans of tumor and edema regions have been briefly explained.These datasets also contain ground truth segmentation. Images in the dataset are of type Low or high-grade glioma types. Each dataset has T1 MRI,T1 Contrast-enhanced MRI,T2 MRI,T2 FLAIR MRI volumes. From the dataset, we used 20 High-grade glioma patient’s in which 75% of patient’s data are used for Training and 25% of patient’s data are used for testing. Our paper has used only T1 images for segmenting the tumor [24].

C. Experimental Results and Discussion

The performance metric of the Dice coefficient with existing and proposed segmentation methods are tabulated as shown below.

TABLE I DICE ASSESMENT ON BRATS DATA SET

METHODS	DICE COEFFICIENT
SEGNET	0.829076
FCN	0.834709
PSP NET	0.814509
FCPPNNET	0.87

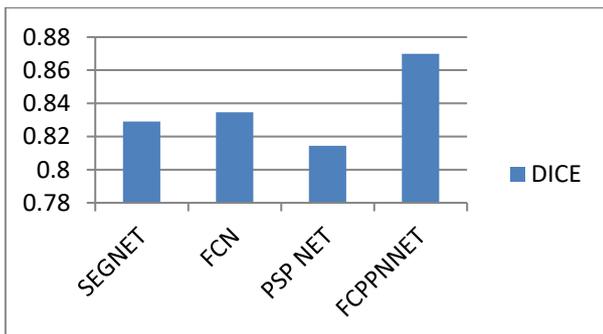


Figure (h) Comparison graph of the various algorithm with the performance metric Dice Coefficient

From the above graph and tabular values, it is stated that the various semantic segmentation is calculated for the Dice coefficient. From the Existing methods such as SEGNET,FCN,PSPNET our proposed method FCPPNET which is the hybrid of FCN and PSPNET seems to be better than the existing method.

TABLE 2 ACCURACY, SENSITIVITY ON BRATS DATASET

METHODS	ACCURACY	SENSITIVITY
SEGNET	0.928892	0.754625
FCN	0.937056	0.764946
PSP NET	0.928559	0.75402
FCPPNNET	0.956682	0.797333

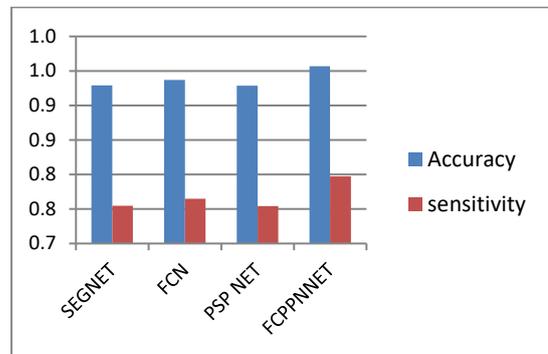


Figure (i) Comparison graph of the various algorithm with the performance metric Accuracy and Sensitivity

It is seen that from the above table and from the above chart that the complete brain tumor segmentation results better in all performance metrics when utilising the hybrid combination of FCN and PSP NET called FCPPNNET. FCPPNET has experimented on BRATS DATASET 2015 and the input image and the segmented image are shown below.

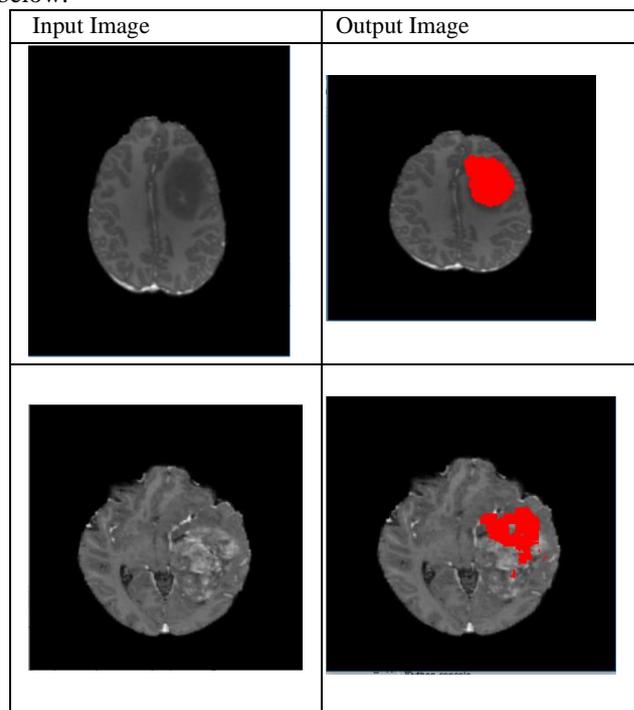


Figure (j) Brain tumor Segmentation. The left side represents Brain images and the Right side represents the segmented image.

VI. CONCLUSION

Automated brain tumor segmentation assumes a significant job in medical imaging. However, this method would be helpful for doctors and in Clinical laboratories to find the tumor for the patients. In this work, a novel architecture called FCPPNet is Proposed which is the combination of FCN and PSP NET. The FCPPN NET outperforms the state of art FCN and PSPNET models on the task. The semantic segmentation technique such as Segnet,FCN,PSPNET gives good results when they perform in an individual. But the fusion of PSPNET and FCN gives better results for brain tumor segmentation.



This approach is tested with the BRATS dataset 2015. Our proposed work also helps with other medical imaging applications using deep learning.

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AUTHORS PROFILE



S.Fathima Suhara is working as Assistant Professor, Department of Computer Science, Sadakathullah Appa College, Tirunelveli. She has completed M.Sc., in Sadakathullah Appa College and also M.Phil in Manonmaniam Sundarnar University. She is involved in various academic activities. She has presented international and national conference papers. She is a member of google scholar. She is a member of various committees in autonomous college and She is a Research Scholar of Computer Science in Manonmaniam Sundarnar University under the guidance of the Second author.



Dr.M.Safish Mary is working as Assistant Professor, Department of Computer Science, St.Xaviers College, Tirunelveli. She has completed M.C.A., M.Phil., and Ph.D. in Manonmaniam Sundarnar University. She is involved in various academic activities. She has presented numerous papers at various international conferences and attended the refresher course. She is a member of google scholar and has a 5 citation, 1 h-index. She is a member of various committees in autonomous colleges and has a specialization of research in Artificial Intelligence, Neural Network, Data Mining, and Image Processing.