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AUTOMATED 3D VISUALIZATION OF BRAIN TUMOR USING FCPPN ARCHITECTURE IN MR IMAGES

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Abstract:
Medical Imaging is a technique that is used to process the various parts of the body and diagnoses the diseases and further treatment is made for the disease. Medical Imaging includes MRI Scans, CT Scans, Mammograms, and so on. The most commonly used Medical imaging is MRI. The location of the brain tumor in Magnetic Resonance Imaging (MRI) is a very critical yet perplexing undertaking, in which various segmentation techniques get evolved. This paper aims to get an accurate view of the tumor. In this paper, the image is segmented using the technique called FCPPN(Fully connected pyramid pooling module) and the segmented image is in the 2D image[1]. It is converted into a 3D image by a marching cube algorithm that is used for rendering medical data[2].The segmented tumor of the proposed algorithm are compared with 3D volume rendering of FCPPN using performance metrices.

Keywords: *FCPPN-Fully Connected Pyramid Pooling Network ,GP-Genetic Programming,3D-Three Dimension,*

1.INTRODUCTION

Medical Imaging plays a vital role in current medical research studies. Medical imaging needs an image processing technique for segmentation and 3D visualization. We focus on Brain MRI images in Medical Imaging. The human brain is the central organ of the human nervous system with the spinal cord that makes up the central nervous system. Most of the human brains are affected by tumors, Masses, and Increased pressure. In this paper, we aim to identify the tumor and 3D view of the tumor.
To detect the tumor the brain is segmented either manually or automatically. There is some drawback in manual segmentation and to overcome the drawback there is a need for automatic segmentation. There are various types of segmentation techniques and in our paper, the image is segmented using FCPPN.

The conversion of 2D to 3D gives a clear view of the brain. The 2D image shows only the height and width of the brain. The 3D reconstruction of the tumor helps the physicians in identification, surgical planning, and biological investigation. The 3D images show the depth assessment of an image. When depth is shown, the created left view and right view images yield the ultimate 3D reconstruction outcomes[3]. The 3D image provides more information and gives a better real-time world experience than a 2D image. The conversion of 2D image to 3D image consists of two methods namely semi-automatic and fully automatic conversion.

In our proposed work, the 3D visualization is obtained by the marching cube algorithm used for volume rendering of the brain that is segmented. Section II deals with the Literature survey of the tumor segmentation and 3D visualization of the segmented tumor. Section III deals with the methodology of the tumor segmentation and 3D visualization of the brain. Section IV proposes an experimental result. Section V deals with the conclusion.

2. LITERATURE SURVEY

A semantic segmentation like 2CNET,3CNET, and ENSEMBLE NET uses a deep convolutional neural network for segmenting the tumor[4]. Zhao, Hengshuang, et al proposes a deep convolutional neural network and they analyzed the segnet segmentation and compared with the various segmentation methods and proved that segnet is more efficient than others[5].

U SEGNET which is the combination of U NET and SEGNET is used for semantic segmentation and it finds relevance in other medical imaging using deep neural networks[6].[7] deals with the different 2D sectional appearances of 3D anatomical structures of 3D cases. Mehmood, Irfan, et al[8]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[9] proposes an approach of 3D Segmentation and volume rendering for brain tissues and tumors.

Rajeev Ratan .et al[10] deals with to calculate the area for a single slice of MRI and further than to calculate the volume of the tumor from multiple image MRI sets. S. Shen, et al, 2003, proposed [11], a new brain tumor diagnostic procedure using magnetic-resonance imaging (MRI) only. First, the MR images were preprocessed, using standardizing, non-brain removal and enhancement. Second, an improved fuzzy clustering algorithm was applied to segment the brain into different tissues. Finally, brain tumor diagnosis was performed using fuzzy logic based genetic programming (GP) to search for classification rules. Classification results on a variety of MR images for different pathologies indicated that the technique was promising. It proposes the counter information to group the images into coherent images and the depth regions are computed by gradient MTF squeeze function[12]. An adaptive version of the marching cube called adaptive marching cube is created to reduce the number of triangles representing the surface by adapting the size of triangles to the shape of the surface[13].

In 3D reconstruction, the skull stripped is reconstructed using depth map guided filters. By using the depth map left to view and right view images are produced. AviKanchan, Tanyamathir deals with the two depth maps namely the geometric depth map and the qualitative depth map. Final these two depth maps are combined to form the final depth map[14].

In [15] deals with a novel method that automatically converts 2D to 3D. It is reconstructed by using the MTF squeeze model and determination of gradient map related to each depth level. S.Bharathi and A.vasuki deal with the 2D to the 3D reconstruction of images using Edge information. It uses Edge information to group the images into coherent regions[16]. A method based on ROI boundary by MTF squeeze function estimation of depth levels is

proposed. This method is compared with depth with edge and depth with fusion and the proposed method seems to be better than the existing method[17].[18]describes the estimation of depth levels by using the MTF Squeeze model and determination of gradient map related to each depth level.[19]
Willam E Lorensen and Harvy E cline create a new algorithm called marching cube that uses the divide and conquer technique to create a slice and a case table is created for triangle topology. Results from various images such as CT, MRI shows the quality and functionality of marching cubes.[20] introduces the concept of dual surface which eliminates the poorly shaped triangles often present in MC surfaces. The comparison of 2D and 3D is performed on subjective and objective measures of laparoscopic surgery skill set.3D seems to be greatly better than 2d in subjective as well as objective measures.3D avoids headaches and no eye strain and no other problem and so the participants are going with 3D[21].

3. METHODOLOGY

The proposed work consists of two main parts.

(i) Tumor segmentation using FCPPN.

(ii) 2D to 3D Visualiztion .

3.1 Tumor segmentation using FCPPN:

The segmentation can be manual and automatic. In Manual segmentation, there is less accuracy and so there is a need for automatic segmentation. The Automatic segmentation is also called semantic segmentation and it is mainly used in the area of medical imaging. In our work, the brain is segmented using a new way of segmentation technique FCPPN that combines the work of FCN and PSPNET. It is a fully convolutional neural network and it consists of three parts. The First part is the Encoder Section of FCN and it has several layers such as RELU, Maxpooling, Batch Normalization, and so on. The second part is the PSPNet and it is used to reduce the number of channels. The third part is the Decoder of FCN. Finally, the output image is obtained from the decoder part of FCN.

3.2 2D to 3D Visualization:

There are various techniques for 3D Visualization such as Volume Rendering, Isosurface and Marching cubes, and so on.

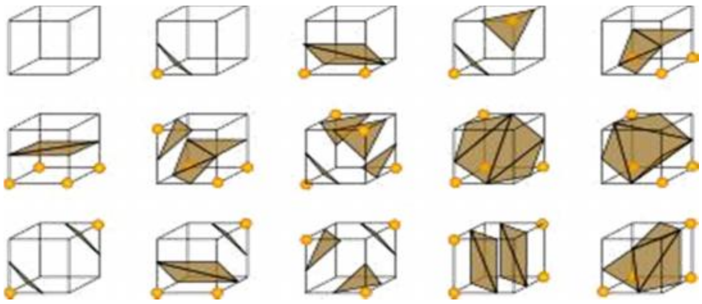
3.2 (a)Marching Cubes:

Marching dice is a simple iterative set of rules for a growing triangular surface for a 3-D characteristic. The vertices of the dice are voxels. The function of the algorithm determines whether or not the triangular floor passes through his dice or now not. The predominant purpose of the marching dice set of rules encompass five tasks to extract the surface from volume data

(i) calculation of the case index of every cell.
(ii) calculation of intersected edges.
(iii) computation of linear Interpolation.
(iv) Triangular of Intersection.

(v) computation of outward pointing surface ordinary for illumination.

Marching cubes is a simple algorithm for developing a triangle mesh from an implicit feature (one of the shape f(x, y, z) zero). It works by using iterating ("marching") over a uniform grid of cubes superimposed over an area of the feature. If all 8 vertices of the dice are high-quality, or all 8 vertices are negative, the dice is entirely above or totally under the surface and no triangles are emitted. Otherwise, the dice straddles the feature and a few triangles and vertices are generated. Since each vertex can both be positive or negative, there are technically 2^8 possible configurations, but lots of these are equal. There are the simplest 15 particular cases, proven here:



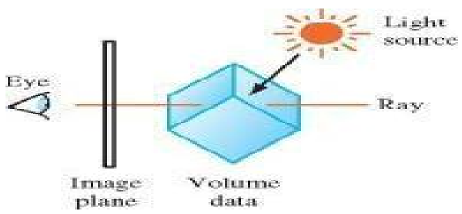
Fig(a) Marching cube Possible cases

We iterative over all cubes, including triangles to a listing, and the final mesh is the union of some of these triangles. The smaller we make our cubes, the smaller the mesh triangles maybe, making our approximation more carefully healthy the target characteristic function.

3.2(b)Volume Rendering:

It is a technique that is used in Matlab for the efficient Visualization of 3D scalar records of 3-d scalar facts. It is used to render the quantity immediately. It is for visualizing sampled capabilities of 3 spatial dimensions by using computing 3D Projections. Volume Rendering produces a tender floor with the aid of mixing the contributions from a couple of floors [22].

Volume Rendering is of Four sorts (i) Ray casting (ii)Resampling (iii)Texture Slicing (iv) Splatting. The Most commonly used Volume Rendering is Ray casting and this type of volume rendering is used in our paper. It uses a simplified light transport version wherein a photon is believed to scatter exactly one, while it moves a voxel and is subsequently reflected. Using this it is computed using integrating the mild transmission alongside the ray. The ray casting is repeated until it reaches a unique ray for every pixel at the display screen [23].



Fig(b) Ray Casting

3.2(c) Isosurface:

It is a 3-d surface illustration of factors with equal values in a three-D information distribution.Iso surface are commonly displayed using laptop pictures and are used as records visualization strategies in numerous fields. In Medical Imaging, Isosurfaces can be used to represent areas of a specific density in 3d CT experiments, permitting the visualization of inner organs, bones, or different systems [24].

4 . Experimental Results:

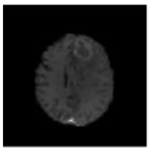
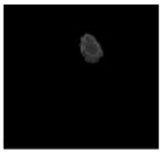
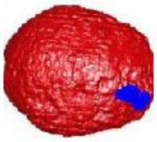
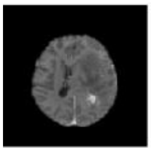
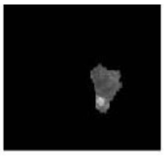
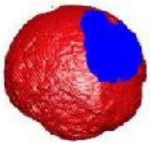
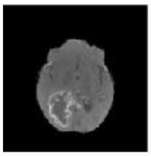
4.1 Brats Dataset:

Brain tumor segmentation is automated and it is compared with different methods, a dataset called **BRA**IN **T**UMOR **S**EGMENTATION (BRATS 2015)are used[25]. It is a dataset in which a huge quantity of MRI scans of tumor and edema regions were in brief defined. These datasets additionally incorporate floor fact segmentation. All pictures in the dataset have Low or high-grade glioma kinds. Each dataset has T1 MRI, T1 Contrast-improved MRI, T2 MRI, T2 FLAIR MRI volumes. From the dataset, we used 20 High-grade glioma patients in which seventy-five % of patients' facts are used for Training and 25% of sufferer's information are used for checking out. Our paper has used the handiest T1 pictures for segmenting the tumor.

4.2 Tabular Form of 3D Visualization:

The Tumor is segmented using the FCCPN technique and this type of segmentation is implemented using Phyton. The stimulation for Visualization is carried out using Matlab 2019. Datasets are obtained from BRATS 2015. The segmented tumor is automated using various 3D reconstruction techniques and the results are shown in the following table:

TABLE 4.1 Original Tumor and Segmented Tumor and 3D Visualization using Isosurface and Volume Rendering.

Original Image	Segmented Tumor	3D Visualization Using Isosurface	3D Visualization Using Volume Rendering
			
			
			

4.3 Quantitative analysis :

The Quantitative analysis in terms of accuracy of the proposed algorithm that is FCPPN segmentation is compared to the volume rendering of the proposed algorthim and this volume rendering gives the best result. The performance metrices used for the segmented tumor and they are compared with accuracy, sensitivity and Dice coefficient.

Accuracy:

It is the closeness of estimation result 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”.

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

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Sensitivity:

It is a procedure that is utilized to decide what autonomous factors esteems will mean for a specific ward variable under a given series of expectations is characterized as a Sensitivity examination. The sensitivity coefficient is a a partial derivative used to describe how the output estimate Y varies with respect to the value of the input estimateX1,X2,… … Xn. It is likewise called a true positive rate and it quantifies the extent of positives that are accurately distinguished.

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

Dice Coefficient:

The dice coefficient is a statistic used to gauge 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 value of 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

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

Here x → segmented tumor using FCCPN Technique

Y → Ground truth of the tumor.

The performance metrics of the segmented tumor using FCPPN technique and ground truth are tabulated as

Table 4.2 Performance metrics and comparsion graph of Proposed algorithm FCPPN with FCPPN_Volume Rendering.

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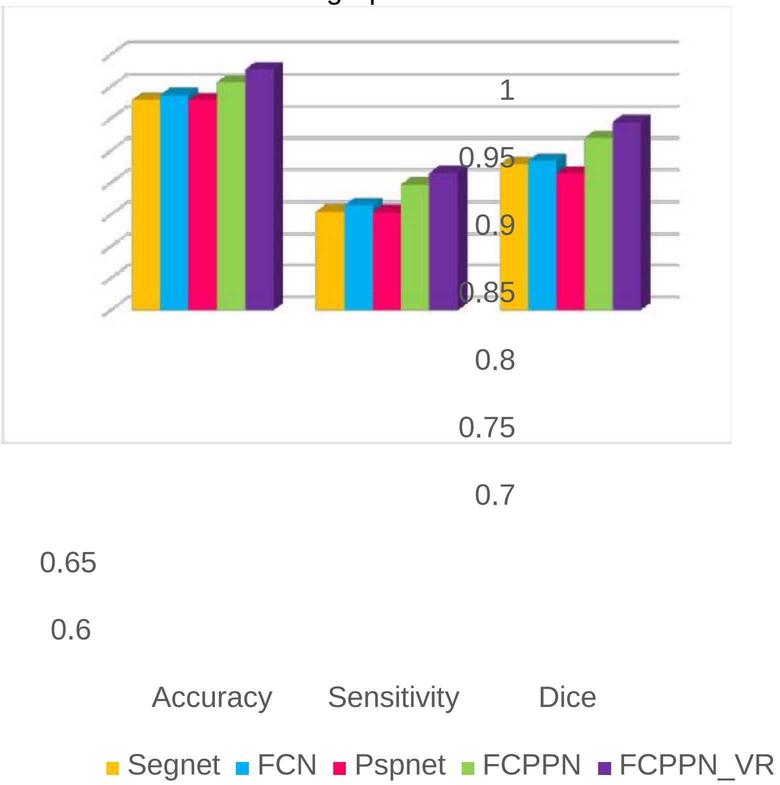
Performance metrics	SEGNET	FCN	PSPNET	FCPPN	FCPPN_VR
Accuracy	0.928892	0.937056	0.928559	0.956682	0.976971
Sensitivity	0.754625	0.764946	0.75402	0.797333	0.815632
Dice	0.829076	0.834709	0.814509	0.87	0.89453

Based on these values a graph is shown below



When using performance metrics for the proposed algorithm with 3D volume Rendering it gives best result. This worth obviously demonstrates the effectiveness of the outcomes created by the proposed approach and consequently making it appropriate for utilizing in applications where high accuracy is required. This guideline of estimating the after effect of a 3D information utilizing the strategies accessible for 2D information is in itself an advancement in the investigation stage in the area of PC illustrations. The below figure represents the quantitative analysis of proposed segmentation FCPPN with volume rendering.[26]

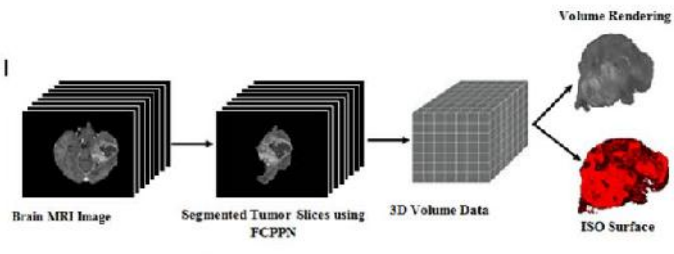


Fig (c) Quantitative Evaluation on 3D Brain MRI Image

5. CONCLUSION

2D visualization of the brain doesn't give a clear view of the brain and so the 3D Visualization is needed. In this paper, already the brain is segmented using FCPPN Technique, and to get an accurate view of the tumor, the tumor is visualized using the Marching Cube Technique by Isosurface and by using Volume rendering.Hence the tumor is visualized and shown as 3D Visualization of tumor.

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