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# Brain Tumor Segmentation Using Convolutional Neural Networks in MRI Images

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**ABSTRACT:** Segmentation of brain tumor from the surrounding healthy brain tissues by a radiologist is a tedious task. For a safe brain surgery, it is essential to define the contour of brain tumor, for complete resection of tumor Active exploration is being carried out in automatic tumor segmentation using deep literacy networks for precise segmentation of tumor factors. Deep literacy networks are more effective at learning patterns and the performance of deep network increases when trained with further data. The provocation behind this study is to descry brain tumor and give better treatment for the mourning's. The abnormal growths of cells in the brain are called tumor and cancer is a term used to represent nasty tumor. Generally CT or MRI reviews are used for the discovery of cancer regions in the brain. Positron Emission Tomography, Cerebral Arteriogram, Lumbar Perforation, Molecular testing are also used for brain tumor discovery. In this study, MRI checkup images are taken to analyses the complaint condition. Ideal this exploration workshop are i) identify the abnormal image ii) member tumor region. Viscosity of the tumor can be estimated from the segmented mask and it'll help in remedy. Deep learning fashion is employed to descry abnormality from MRI images. Multi-level thresholding is applied to member the tumor region. Number of nasty pixels gives the viscosity of the affected region.

**KEYWORDS:** deep learning, brain tumor, computer vision, CNN, segmentation, medical images, review

## I. INTRODUCTION

Brain tumor is a dreadful disease that causes death in most of the cases due to lack of proper diagnosis and effective treatment. According to global cancer observatory, 296,851 people were diagnosed with brain and Central Nervous System (CNS) tumor worldwide in the year 2018. Brain tumor is an abnormal mass of cells. Brain tumor can either originate in the brain (primary brain tumor) or originate in some other part of the body and move to the brain (Metastatic). Primary brain tumor can be either cancerous (malignant) or non-cancerous (benign).

Gliomas are the most common type of the brain tumor. It has several components such as tumor core, edema, enhancing tumor and necrosis as shown in fig 1. In other types of oncologic surgery, complete resection of a tumor with wide margins is critically important in controlling the disease; however, Gliomas invade the surrounding brain, so wide resections are typically not possible because adjacent or nearby areas sub serve important neurologic functions.

In order to know the treatment possibilities, it is very important to diagnose gliomas early. In neuro-oncology, brain tumors can be assessed using several imaging modalities to form a differential diagnosis. Of the various medical imaging modalities, MRI is most commonly used. A standard brain MRI has sequences such as T1-weighted, T2 -weighted, T1 with gadolinium contrast and FLuid Attenuated Inversion Recovery (FLAIR). T1 weighted images highlight healthy tissues, T2 weighted images highlight Cerebrospinal fluid (CSF), T1 with Gadolinium contrast images highlight the neoplasm and FLAIR images suppress Cerebrospinal Fluid, highlighting edema.

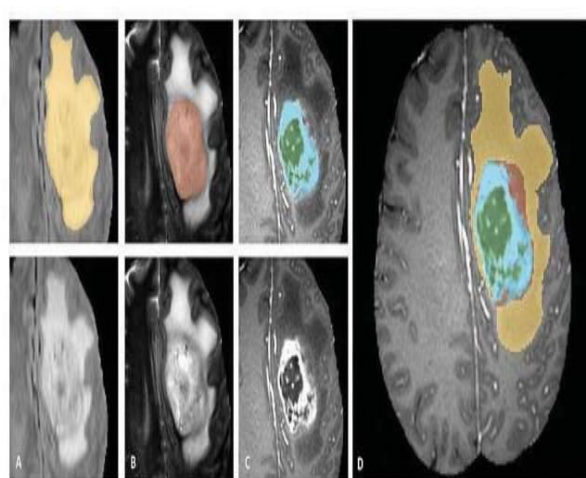


Fig 1: Glioma sub-regions. Image labeled A indicates the whole tumor, image B is the tumor core, Image C shows the enhancing tumor (light blue) and necrosis (green). Image D shows all the segmentations together (Figure taken from [4]).

Automatic tumor segmentation from brain MRI is essential for defining the contour of enhancing tumor, tumor core, edema and necrosis. Automatic segmentation can be well implemented using the deep learning architectures. There are several CNN architectures used for image processing such as Alex Net, ResNet, VGG and U-Net. This paper reviews the various automatic segmentation methods using U-Net. All the segmentation methods discussed in this paper have used BraTS '2018 challenge dataset.

## I. DATA

Automatic brain tumor segmentation methods can be very well compared using the widely used benchmark datasets BraTS. U-Net based tumor segmentation methods have used BraTS'18 challenge datasets. They are the MRI scans collected from multiple medical institutions. BraTS dataset contains several sequences of MRI such as T1-weighted (T1), T1-weighted with Gadolinium contrast (T1Gd), T2-weighted (T2) and FLAIR. It also has ground truth of the tumor components. It has both training and validation dataset for low grade glioma (LGG) and high grade glioma (HGG).

## II. Deep Learning

Deep learning networks uses multiple hidden layers to make predictions. They outperform human. The deep neural network consists of more than one hidden layer between the input layer and output layer. The performance of deep learning is higher when more data are used for training. Using deep networks, both features and classification are learned directly from images.

### CNN Algorithm:

CNNs, in discrepancy, scale veritably well with the number of object classes to descry because nearly all calculation is participated between all object orders. The only class-specific calculations are a nicely small matrix-vector product and greedy non-maximum repression. Although these calculations scale linearly with the number of orders, the scale factor is small. Measured empirically, it takes only 30ms longer to descry 200 classes than 20 classes on a CPU, without any approximations. This makes it doable to fleetly descry knockouts of thousands of object orders without any variations to the core algorithm. Despite this graceful scaling geste, an R-CNN can take 10 to 45 seconds per image on a GPU, depending on the network used, since each region is passed through the network independently. Recent work from Heetal. ("SPPnet") improves R-CNN effectiveness by participating calculation through a point aggregate, allowing for discovery at a many frames per second. Structure on SPPnet, Girshick shows that it's possible to further reduce training and testing times, while perfecting discovery delicacy and simplifying the training process, using an approach called "Fast R-CNN." Fast CNN reduces testing times to 50 to 300ms per image, depending on network armature.



## II. LITERATURE SURVEY

**2.1 Varshali Jaiswal, Varsha Sharma, Sunita Varma** The color image segmentation is one of utmost pivotal operation in image processing. It can apply to medical image segmentation for a brain excrescence and skin cancer discovery or color object discovery on CCTV business videotape image segmentation and also for face recognition, point recognition etc. The color image segmentation had faced the problem of multidimensionality. The color image is considered in five-dimensional problems, three confines in color (RGB) and two confines in figure (refulgence subcaste and value subcaste). In this paper the,  $L * a * b$  color space conversion had been used to reduce the one dimensional and geometrically it converts in the array hence the farther one dimension has been reduced. The  $a * b$  space is clustered using inheritable algorithm process, which minimizes the overall distance of the cluster, which is aimlessly placed at the launch of the segmentation process. The segmentation results of this system give clear parts grounded on the different color and it can be applied to any operation.

**2.2 NurIriawan; Anindya Apriliyanti Pravitasari** Image segmentation has been popularly performed for experimenters in the field of Biomedical, Informatics Engineering, and Statistical Calculation. This study tries to compare several styles for brain excrescence image segmentation, especially in handling noise. The styles are K-means Cluster, Fuzzy C- Means (FCM) Cluster, Gaussian Mixture Model (GMM), and Fernandez-Steel Skew Normal (FSSN) Admixture model. K- means and FCM are the popular Partitioning styles for clustering, while GMM is model- grounded clustering system. The FSSN admixture model is the new model- grounded clustering introduced in this study. Both GMM and FSSN are formed through a finite admixture model with Bayesian Markov Chain Monte Carlo (MCMC) optimization. The dataset is the MRI brain excrescence image from General Regional Hospital (RSUD)Dr. Soetomo Surabaya. Gaussian noise and Swab pepper noise are generated to see the robustness of each system.

**2.3 Pravitasari, Iriawan, Safa, M. A. I , Irhamah<sup>1</sup>** Finite Mixture Models have been developed for brain excrescence image segmentation using the Glamorous Resonance Imaging (MRI) as a media. The thing is to gain the stylish model with the applicable segmentation results to describe the Region of interest (ROI). Image segmentation ways with admixture model are used for clustering pixels grounded on the same color intensity (grayscale). Numerous studies of admixture models using asymmetric distributions, similar as skew normal and dispose-t distribution, have been expanded, owing to the fact that the data pattern in the MRI isn't always symmetrical.

**2.4 Anindya Apriliyanti Pravitasari, Nur Indah Nirmalasari** Brain scanning using Glamorous Resonance Imaging (MRI) can be used to descry the brain excrescence. MRI could descry the soft towel abnormalities better than the other radiological bias. Still, the noise in the image of the MRI occasionally appears aimlessly, so that it's delicate to descry the excrescence more precisely. The image segmentation, thus, is demanded to be suitable to diagnose the position of the brain excrescence by separating the excrescence as the Region of Interest (ROI) from other regions. Gaussian Mixture Model (GMM) is generally used for image segmentation. This system, still, constantly provides a poor affect since it's lower suitable to explain the skew pattern of MRI data. Also, the GMM isn't considering the spatial dependences between pixels, thus it's lower able of handling noise. This study tries to employ the Fernandez Steel Skew Normal (FSSN) distribution as the relief of the Gaussian in the GMM.

## III. EXISTING SYSTEM

In existing method, there are various kind of machine learning and deep learning algorithm has been implemented. Some of the conventional methods developed based on to improve the accuracy of the model. CNN, RNN, Fuzzy C-Means, SVM, Random Forest and logistic regression based algorithm are used in the existing methods.

## IV. PROPOSED SYSTEM

In the proposed method, the CNN method has been implemented in order to improve the flexibility and accuracy. CNN methods is a deep learning technique that combines several base models in order to produce one optimal predictive model.

### V. SYSTEM ARCHITECTURE

A system architecture is the abstract model that defines the structure, gesture, and further views of a system. An architecture description is a formal description and representation of a system, organized in a way that supports logic about the structures and actions of the system.

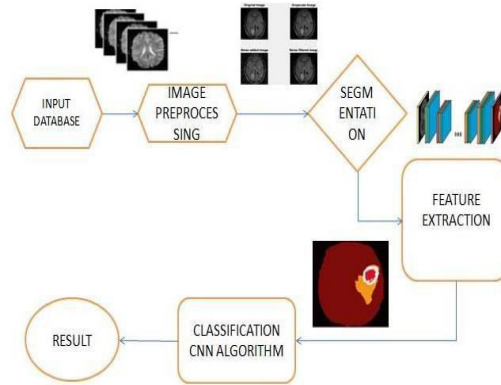


Fig: 3.5 System Architecture

### VI. MODULE IMPLEMENTATION

#### 6.1 MODULE LIST

- Dataset acquisition
- Preprocessing
- CNN Feature extraction
- Training of features
- Testing and performance evaluation

#### 6.2 MODULE DESCRIPTION

##### 6.2.1 DATASET ACQUISITION

- The data set is collected from the Kaggle website, Data set divided into three category A training set, A validation set, testing set
- This will split our dataset into training, validation, and testing sets in the ratio mentioned above- 80% for training (of that, 10% for validation) and 20% for testing. The original dataset consisted of 162 slide image scanned at 40x. an imbalance in the class data with *over 2x* the number of negative data points than positive data point

##### 6.2.2 PREPROCESSING

- Preprocessing is the process of image reduce the dimension of image
- To specify the input image volume shape to our network where depth is the number of color channels each image contains.
- The image resize according the deep learning layer size of rows and column of image

##### 6.2.3 CNN FEATURE EXTRACTION

- The network we'll build will be a CNN (Convolutional Neural Network) and call it Cancer Net. This network performs the following operations
- Use 3x3 CONV filters Stack these filters on top of each other Perform max-pooling Use depth wise separable convolution (more efficient, takes up less memory)
- Its consists of input layers, convolution layers, ReLulayer, maxpooling layers for extract the features of images of build model.
- Feature extraction train the model the build the model.

#### 6.2.4 TRAINING OF FEATURES

- The training process is implemented for the Adam Adaptive momentum as optimizer for gradient with epochs is implemented training process it' brain tumor , sorted by size, and the items at the beginning are more likely to be benign, and the ones at the end are more likely to be malignant, then you'll be training on benign data, and test on malignant, which isn't representative
- Based on feature vectors we build the model using Kera's system

#### 6.2.5 TESTING AND PERFORMANCE EVALUATION

- The testing process is enforced this function we can resolve the model with a test set of 30 of the original data set.
- The input just specify the size of the input and is called D (see the law above X, train shape).
- The thick subcaste is rather where the real work happens it takes the input and does a direct metamorphosis to get an affair of size 1. The direct metamorphosis we want to apply is the sigmoid activation function so that in affair we're in a range of 0 and 1.
- Loss per replication, training loss, validating loss is enforced in module. Delicacy and perceptivity of the anatomized.

### VII. CONCLUSION

This paper provides a new method for detecting brain tumor by deep learning method. The early detection of cancer helps timely and effective treatment. Kaggle dataset contains good quality of MRI images for research purposes. Different segmentation algorithms were experimented. From this, multilevel thresholding and OTSU thresholding are the best methods for the dataset. Convolutional Neural Network with modified approach helped to get a result with accuracy 98%. Density estimation method is also proposed using Gaussian kernel distribution.

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