

Efficient Deep Learning Neural Network Based Brain Tumour Detection System

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Abstract: *The work of this project is applying the convolution neural network concept to perform brain tumors segmentation using MRI images of brain and to measure its accuracy. The used method aims to find cancerous cells in brain using Deep learning based fully convolution network using U-net model. It has been compared with various other techniques and conclusions are made.*

Keywords: U-net, glioma, pooling, segmentation, edema, necrosis

1. Introduction

Brain is one among the important organs within our body that consists of billions of cells. The abnormal cluster of cell that is created from the uncontrolled division of cells, that is additionally known as as tumour. The tumour area is unit divided into 2 sorts such low grade (grade1 and grade2) and high grade (grade3 and grade4) tumor. Low grade neoplasm is named as benign. Similarly, the high grade tumour is additionally known as as malignant. The benign tumour isn't cancerous tumor thus it doesn't affect different elements of the brains. But the malignant tumour is a cancerous tumor thus it spreads speedily with indefinite boundaries to different region of the body. It could end up in immediate death.

Brain magnetic resonance imaging image is especially accustomed to discover the growth and growth progress modeming method. This data is especially used for growth detection and treatment processes. Magnetic resonance imaging image provides a lot of data regarding given-medical image than the CT or ultrasound image. Magnetic resonance imaging image provides elaborate data regarding brain structure and anomaly detection in brain tissue. In contrast to machine driven ways for brain tumors, finding and kind cataloging victimization brain magnetic resonance imaging pictures from the time once it became attainable to scan medical images. Conversely, Neural Networks (NN) and Support Vector Machine (SVM) are the usually used ways for his or her sensible enactment over the foremost recent few years but freshly, Deep Learning has become a new important branch of machine learning because the used architecture can effectively be used to solve complicated problems while not having an over sized range of nodes like-in the superficial architectures.

In this work we try to perform segmentation of tumour pictures by CNN algorithmic rules in deep learning technique. We cut back the result variance of antecedently used ways and compare it with our technique recommended. Together with this ,we tend to implement the algorithmic

rule to medical pictures of brain and compare the quantity of epochs needed for coaching a precise reasonably image class.

2. Data Used

^[13]The dataset employed in this study were taken from BRATS 2015 competition. The BRATS 2015 provided clinical imaging dataset of around sixty five brain tumour patients. It has fourteen patients with the Low Grade gliomas (LGG) and also fifty one patients with high gliomas (HGG). These datasets have been acquired by different type of techniques from four places viz. Bern University, Heidelberg University, Debrecen University and Massachusetts General Hospital. All the data from the dataset had 4 parts by how the MRI was scanned; T2 weighted fluid attenuated inversion recovery (Flair), T1 weighted (T1), T1-weighted contrast-enhanced (T1c), and T2 weighted (T2). Out of the whole data some part was used for training the algorithm and some was used for testing it. The part used for training had 30 HGG and also 10 LGG cases. The training part had 10 HGG cases. To handle the low amount of data we have resorted to data augmentation. In this approach we rotate the data and apply other random orientations to get a large amount of dataset. The image data from BRATS2015 dataset is in .mha format, to show the representation we convert it into image format.

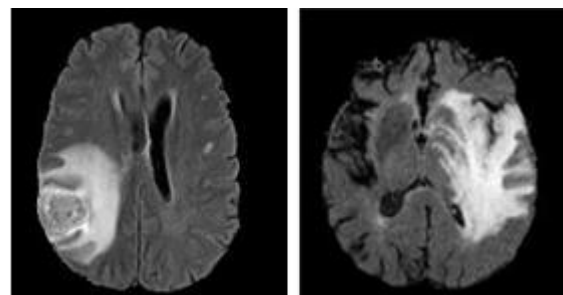


Image 1, 2: Representation of dataset images

3. Literature Survey

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[1] Segmentation of Brain MR Images through a Hidden Markov Random Field Model and the Expectation-Maximisation Algorithm. The variance produced the result output are significant. [2] Simple Convolutional Neural Network on Image Classification. This paper talks about the simple CNN method which is used. It lacks comparison with other deep learning image classification techniques. [4] Action Recognition with Dynamic Image Networks. The complexity of the temporal data i.e. the images from the video format depends highly on the type of video. It becomes difficult to operate on fast or complex videos using this method. [5] Marker-based image recognition of dynamic content for the visually impaired. The marker used is four point marker. The accuracy of this can be increased by using an infinite point marker. [6] Machine Learning framework for image classification, Uses only stop sign for its classification. [7] Ask the locals: multi-way local pooling for image recognition, The paper talks about simple pooling each component of an image separately whereas we face a difficulty now while pooling across features when there is a topography on the feature extractors.

4. Architecture

The design used is absolutely convolutional network (FCN) engineered upon U-net model and it makes uses residual units and not plain units to hurrying coaching and convergence. The tumour segmentation downside exhibits severe category imbalance. the problem is self-addressed by adopting a patch primarily based coaching approach and employing a custom loss perform that accounts for the imbalance. throughout coaching, 2nd patches of size 128x128 from the axial plane area unit every which way sampled. And by doing therefore it permits to dismiss patches from pixels with zero intensity and thus it helps a small amount to alleviate the matter.

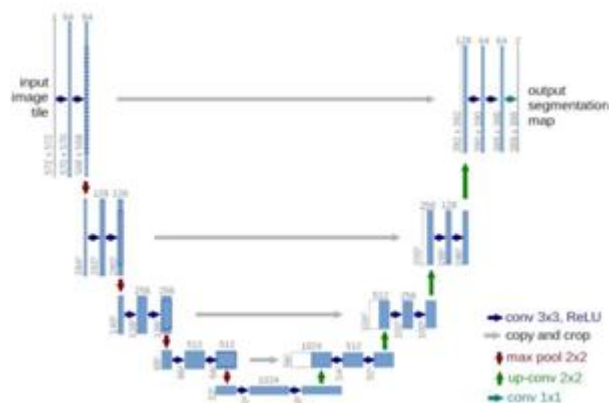


Figure 1: U-Net Architecture

The architecture used (U-Net) is divided into the following parts; Contracting/ downsampling path, Bottleneck, Expanding/ upsampling path

- 1) Contracting/down sampling path
This path has 4 blocks. All of which are made up of Convolution Layer and activation function , Convolution Layer and activation function and Max Pooling. At each pooling the amount of feature maps is doubled, with 64

feature maps in the first block and with 128 in the second block, and so on.

- 2) Bottleneck
This part is in between the up sampling and down sampling. The bottleneck is constructed from a set of two convolutional layers, with the dropout.
- 3) Expanding/ up sampling path
This path has 4 blocks. All of which are made up of a Deconvolution layer. A feature map, Convolution layer and activation function, Convolution layer and activation function.

5. Method

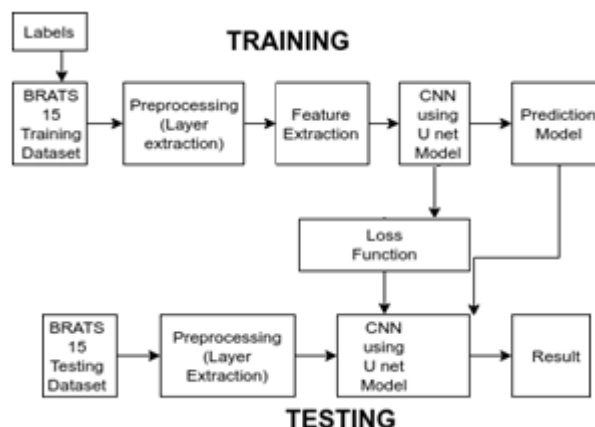


Figure 2: Block Diagram

- 1) Normalize t1 and t1c data because they have drastic intensities. We use N4BiasFieldCorrection from nipy.interfaces. ants. The N4bias field correction algorithmic rule is a widespread technique for correcting low frequency intensity non-uniformity in tomography image information called a bias or gain field. The tactic has conjointly been with success applied as flat-field correction in research information. This technique assumes an easy constant model and doesn't need tissue classification.
- 2) Extracting .mha files and storing in .png format using SimpleITK package in conda or which environment you are using.
- 3) Generate a sequence of labels - In the ground truth data mark each pixel as a label. Brain tumours are classified according to wherever the tumor is found, the sort of tissue concerned, whether or not the tumour is benign or malignant, and different factors. If a tumour is decided malignant, the tumour cells square measure physically examined to work out however malignant they are. Supported this analysis, tumors square measure rated, or graded, by their level of malignancy from high to low malignant. Factors that verify the tumour grade embody how briskly the cells square measure growing, what proportion blood is activity the cells, the presence of dead cells within the middle of the tumour , if the cells square measure confined to a selected space, and the way similar the cancerous cells square measure to traditional cells. viz. 0-nothing, 1-edema (this is caused by trauma in brain or meningitis) ,2-necrosis (this is caused when cells die due to injury in the cells) , 3-advancing tumor, 4-non advancing tumor.
- 4) Extract patches for training, here size is 30*30 pixels

- 5) U-Net on patches and label patches accordingly. The U-Net architecture used here consists of 2 paths; a down sampling path and an up sampling. This can be seen in figure 1. The down sampling path has blocks with convolutional layers which have a filter of size 3x3. Such 5 blocks are present and each block has 2 such convolution layers. All this increases the feature map size from 1 to 1024. Harm pooling is done at each block level which decreases the feature maps size again from 240x240 to 30x30 in our case. In the up sampling the filter size used is again 3x3. The feature map increases from 30x30 to 240x240 again with a stride of 2x2. Here the feature map size is doubled at each level. The conventional U-Net architecture decreases the feature map size from 240x240 to 15x15 but we have reduced it from 240x240 to 30x30 to give a different result.
- 6) Calculate the accuracy by comparing each pixel label to the ground truth pixel label.

6. Results

Accuracy = (Correctly classified pixels / Total pixels) × 100%

Our method gives a accuracy of 92%.

	KNN	Support vector classification ^[12]	Linear support vector classification	Stochastic gradient descent	U-Net
Accuracy	87.43%	90.22%	84.05%	92.77%	92%

7. Conclusion

An efficient approach to solving the problem of brain tumor segmentation is used which is the U-Net model. We have used BRATS2015 dataset that contain each High Grade Glioma and Low Grade Glioma patients, we are positive that our technique will offer better economical output as compared to alternative deep learning models for tumour segmentation. Additionally, compared to alternative progressive strategies, U-Net based deep convolution networks distinguishes between the core tumour cells and also the close cells. The projected algorithmic rule helps to come up with an automatic tumour segmentation model, and this doubtlessly permits assistance for clinical tasks like identification, treatment designing and patient watching.

We have compared various other machine learning methods with our method and is portrayed in table 1. We have achieved accuracy of segmentation as 92%. We have achieved correct results of segmentation that effectively extract the growth region of cancerous cells from brain photos.

8. Scope for Future Works

Some future works can be done to this work. Firstly, our methodology has a cross-validation theme, which could provide unbiased solution, but if we use a different dataset it may give lots of errors. Secondly, we have used many assumptions which are related to our architecture. The

parameters were determined by empirical study. Also we have used less dataset to train the algorithm because of the hardware limitations. There are be other problems which can occur when using high amount of data. Another limitation was the dataset provided, it has less HGG and LGG data to work upon if we want to create state of art algorithm for tumour segmentation.

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