Research Journal of Pharmaceutical, Biological and Chemical Sciences

Brain tumor segmentation in MRI Images using Convolutional Neural Networks.

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ABSTRACT

Among the occurrences of brain tumours, glioma is the foremost common and aggressive severely affected one, resulting in an awfully short life in its highest grade. Thus, treatment designing may be a key stage to enhance the quality of lifetime of oncologic patients. Magnetic Resonance Imaging (MRI) is a widely used imaging technique to assess these tumours, however a big quantity of knowledge created by magnetic resonance imaging prevents manual segmentation in a very affordable time, limiting the use of precise quantitative measurements within the clinical apply. In this paper, it is proposed to associate degree automatic segmentation methodology based on Convolutional Neural Networks (CNN), exploring small 3x3 kernels. The employment of small kernels permits a deeper architecture, besides having a positive impact against over fitting. It is been investigated that the employment of intensity normalization as a pre-processing step, which though not common in CNN-based segmentation methods well-tried in conjunction with an information augmentation to be terribly effective for neoplasm segmentation in magnetic resonance imaging pictures.
Keywords: image processing, brain tumour, CNN, HGG and MRI.

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INTRODUCTION

In this paper, the set-up and results of Multimodal Brain Tumor Image Segmentation Benchmark (BRATS) organized in conjunction with the MICCAI 2012 and 2013 conferences has been reported. Twenty state-of-the-art tumor segmentation algorithms were applied to a set of 65 multi-contrast MR scans of low and high grade gliomas patients manually annotated up to four raters and to 65 comparable scans generated using tumor image simulation software. Quantitative evaluations revealed considerable disagreement between the human raters in segmenting various tumor sub-regions (Dice scores in the range 74%–85%), illustrating the difficulty of this task.

This paper is structured in such a way that the section II overviews the fundamentals of digital image processing techniques and its applications. Section III explains about the methodology used and the individual module descriptions. Section IV describes the implementation of CNN by accessing and analyzing various images with the simulation software MATLAB with neural network toolbox. Section V concludes the paper with research outcomes which detects the brain tumor effectively from the given MRI images.

II.IMAGE PROCESSING- AN OVERVIEW

Digital image processing refers processing of particular image in the digital form. Modern cameras are capable of taking the image in digital form but generally images are originated in optical form. They are captured by video cameras as well and digitized. The digitalization process includes sampling and quantization apart from the five fundamental processes which include image enhancement, image restoration, image analysis, image compression and image synthesis, at least any one of them could be used, not necessarily all.

This section briefs about the various image processing techniques.
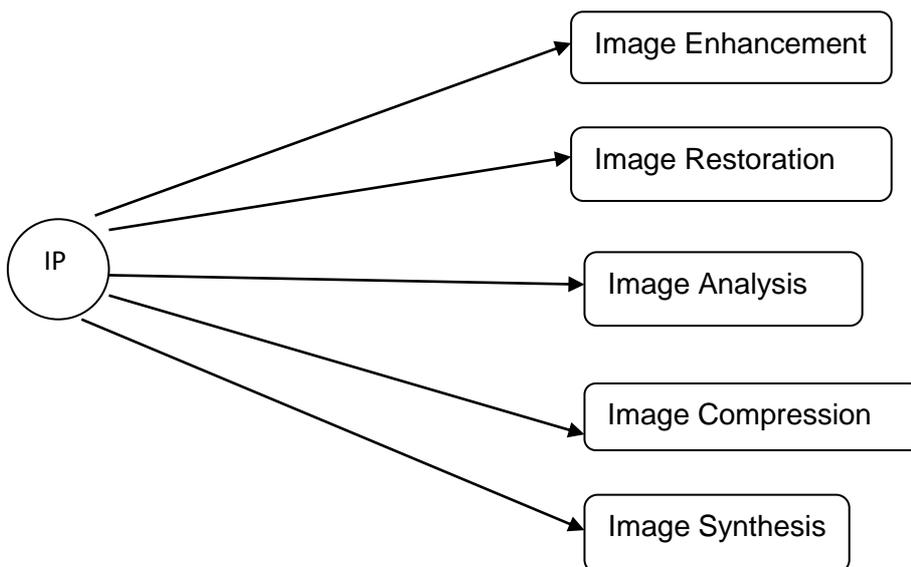
Fig.1. Image processing techniques

Image enhancement improves the qualities of an image in terms of contrast and brightness characteristics of an image, reducing its noise content, or sharpens it. It just enhances the image and sustains the same information in more understandable way without adding anything.

Image restoration further improves the quality of an image based on known, measured or degradations of the original image. It restores images with problems such as geometric distortion, improper focus, repetitive noise and camera motion. It is also used to correct images for known degradations.

Image analysis gives the numerical or graphical information based on the characteristics of the original image. In this process images are broken into objects and then classified. They depend on image statistics. The common operations include extraction and description of scene and image features, automated measurements and object classification. Image analysis is mainly used in machine vision applications.

Image compression and decompression reduce the data content to describe the image effectively. Most of the images contain lot of redundant information while compression removes all the redundancies. Because of the compression the size is reduced, so the image is efficiently stored or transported. The compressed image is decompressed when displayed.

Lossless compression preserves the exact data in the original image, but compression with loss does not represent the original image as such. Image synthesis creates images from other images or from non-image data that are either physically impossible or impractical to acquire.

In medical applications, these image processing technique is used to process images like chest X-rays, cineangiograms, projection images of trans-axial tomography and other medical images that occur in radiology, nuclear magnetic resonance (NMR) and ultrasonic scanning. These images may be used for patient screening and monitoring or for detection of tumors or other disease in patients.

III. METHODOLOGIES USED AND MODULE DESCRIPTIONS

Gliomas are the brain tumors with the highest mortality rate and prevalence. These neo-plasms can be graded into Low Grade Gliomas (LGG) and High Grade Gliomas (HGG) with the former being less aggressive and infiltrative than the latter. Even under treatment, patients do not survive on an average of more than 14 months after the diagnosis. Current treatments include surgery, chemotherapy, radiotherapy, or a combination of them. MRI is especially useful to assess gliomas in clinical practice, since it is possible to acquire MRI sequences providing complementary information.

Magnetic Resonance Imaging (MRI) is a widely used imaging technique to assess these tumors, but the large amount of data produced by MRI prevents manual segmentation in a reasonable time, limiting the use of precise quantitative measurements in the clinical practice. So, automatic and reliable segmentation methods are required; however, the large spatial and structural variability among brain tumors make automatic segmentation which poses a challenging problem. An automatic segmentation method based on Convolutional Neural Networks (CNN) is proposed exploring small 3x3 kernels. The use of small kernels allows designing a deeper architecture, besides having a positive effect against over fitting, given a fewer number of weights in the network.

It is also investigated that the use of intensity normalization as a pre-processing step, which though not common in CNN-based segmentation methods, proved together with data augmentation to be very effective for brain tumor segmentation. MRI images are altered by bias field distortion and thus the intensity of the same tissues varies across the image. To correct it N4ITK method is applied. However, this is not enough to ensure that the intensity distribution of a tissue type is in a similar intensity scale across different subjects for the same MRI sequence, which is an explicit or implicit assumption in most segmentation methods. In fact, it can vary even if the image of the same patient is acquired in the same scanner in different time intervals or in the presence of

pathology. So, to make the contrast and intensity ranges more similar across patients or on an acquisition, the intensity normalization method are implemented. After normalizing the MRI images, the mean intensity value and the standard deviation across all training patches extracted for each sequence are computed. In order to have zero mean and unit variancethe patches on each sequence are normalized.

METHODOLOGY USED:

CNN is used to achieve some breakthrough results and the Convolutional layers are used to convolutea signal or an image with kernels to obtain feature maps. So, a unit in a feature map is connected to the previous layer through the weights of the kernels. Sometimes small clusters may be erroneously classified as a tumor. To deal with, volumetric constraints are utilized to remove clusters in the segmentation obtained by CNN that are smaller than a predefined threshold value.
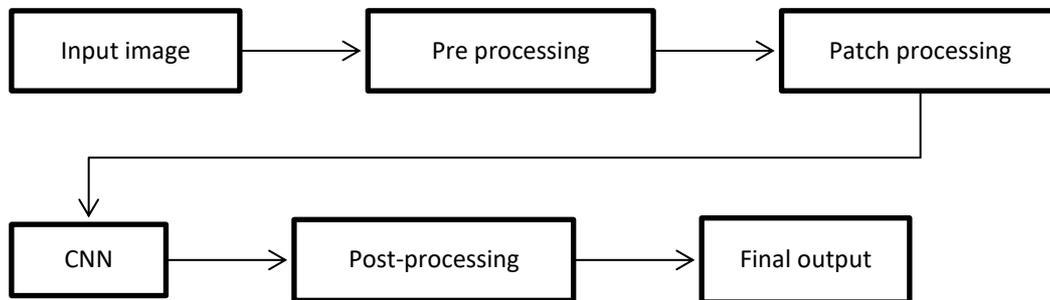
Fig.2. Block diagram showing various steps used in CNN

The block diagram in Fig 1.4 depicts the various steps involved in the image processing technique such as pre-processing, GLCM feature extraction, implementation of CNN and the post-processing and so on.

The main purpose of the RGB color model is for sensing, representation and display of images in electronic systems such as televisions and computers and also in conventional photography. In photography and computing, a grayscale or grayscale digital image is used in which the value of each pixel is a single sample, that is, it carries only intensity information. Images of this sort also known as black-and-white, are composed exclusively of shades of gray, varying from black at the weakest intensity to white at the strongest. Grayscale images are often the result of measuring the intensity of light at each pixel in a single band of the electromagnetic spectrum (e.g. infrared, visible light, ultraviolet, etc.) and in such cases they are monochromatic proper when a given frequency is captured. But also they can be synthesized from a full color image.

MODULE DESCRIPTIONS:

MODULE 1/PRE-PROCESSING:

MR images are altered primarily by bias field distortion. This makes the intensity of the same tissues varies across the image. The intensity normalization method proposed by Nyul et al. on each sequence is proposed. In this intensity normalization method, a set of intensity landmarks IL = {pc1; ip10; ip20; ⋯; ip90; pc2}are learned for each sequence from the training set. Pc1 and pc2 are chosen for each MRI sequence as

described and ip represents the intensity at the il percentile. After training, the intensity normalization is accomplished by linearly transforming the original intensities between two landmarks into the corresponding learned landmarks. In this way, the histogram of each sequence is obtained which is more similar across subjects. After normalizing the MRI images, the mean intensity value and standard deviation across all training patches extracted for each sequence has been computed.

MODULE 2/CONVOLUTIONAL NEURAL NETWORK:

CNN is used to achieve some breakthrough results and win well-known contests; the application of convolutional layers consists in convolving a signal or an image with kernels to obtain feature maps. So, a unit in a feature map is connected to the previous layer through the weights of the kernels. The weights of the kernels are adjusted during the training phase by back propagation method, in order to enhance certain characteristics of the input. Since the kernels are shared among all units of the same feature maps, convolutional layers have fewer weights to train than dense FC layers, making CNN easier to train and less prone to over fitting. Moreover, since the same kernel is convoluted over all the images, the same feature is detected independently by the location-translation invariance. By using kernels, information of the neighborhood is taken into account, which is a useful source of context information. Usually, a non-linear activation function is applied on the output of each neural unit. If several convolutional layers are being stacked, the extracted features become more abstract with the increasing depth. The first layers enhance features such as edges, which are aggregated in the following layers as motifs, parts, or objects. In the following subsections, important concepts in context with CNN are discussed.

a) Initialization: it is important to achieve convergence. Xavier initialization method is adopted over here.. With this, the activations and the gradients are maintained in controlled levels; otherwise back-propagated gradients could vanish or explode.

b) Activation Function: it is responsible for non-linearly transforming the data. Rectifier linear units (ReLU) defined as

$$f(x)=\max(0,x) \tag{3.1}$$

that are found to achieve better results than the more classical sigmoid or hyperbolic tangent functions, and speed up training. However, imposing a constant 0 can impair the gradient flowing and consequent adjustment of the weights. These limitations using a variant called leaky rectifier linear unit (LReLU) introduces a small slope on the negative part of the function. This function is defined as

$$f(x)=\max(0,x)+\alpha\min(0,x) \tag{3.2}$$

Where α is the leakiness parameter. In the last FC layer, tmax is used.

c) Pooling: It combines spatially nearby features in the feature maps. This combination of possibly redundant features makes the representation more compact and invariant to small image changes, such as insignificant details; it also decreases the computational load of next stages. To join features it is more common to use max-pooling or average-pooling.

d) Regularization: It is used to reduce over fitting. It removes nodes from the network with a probability of p by dropping-out one by one in FC layers. In this way, it forces all nodes of FC layers to learn better representations of the data, preventing nodes from co-adapting with each other. At the test time, all nodes are used. Drop-outs can be seen as an ensemble of different networks and forms a bagging, since each network is trained with a portion of training data.

e) Data augmentation: It is used to increase the size of training sets and reduce over fitting. Since the class of patch is obtained around central voxel, the data augmentation is restricted by means of rotation operations. Sometimes image translations could also be considered, but for segmentation this may result in attributing a wrong class to the patch. So, the data set can be increased during training by generating new patches over the rotation along with the original patch. In this implementation, multiple angle of 90◦ is used, though another alternative could be tried.

f) Loss Function: It is the function to be minimized during training. Here, inCategorical Cross-entropy,

$$H = -\sum_{j \in voxels\ k \in classes} c_{j,k} \log(c_{j,k}) \tag{3.3}$$

where $\hat{c}$ represents the probabilistic predictions (after the soft-max) and c is the target.

g) Architecture: Brain tumors present large variability in the intra-tumoral structures, which makes the segmentation a challenging problem. To reduce such complexity, a multilayer CNN is used to tune intensity normalization transformation for each tumor grade viz. LGG and HGG respectively.

The architecture of HGG is deeper than the one used in LGG, because going deeper did not improve results in the latter. To go deeper, one must include more layers with weights, which may increase over fitting, with the smaller training set of LGG. This is supported by setting Dropout with p = 0:5 in LGG, while it is p = 0:1 in HGG, since the database used for evaluation contains more HGG then LGG cases. Additionally, the appearances and patterns are different in HGG and LGG. Also, a precise sense of location is needed to do segmentation; Pooling should be positive to achieve invariance and to eliminate irrelevant details, however, it can have a negative effect by eliminating important details. Overlapping pooling with 3 × 3 receptive fields and 2×2 stride to keep more information of location is used here. In the convolutional layers the feature maps are padded before convolution, so that the resulting feature map could maintain same dimensions. In the case of HGG there are 2,118,213 weights to train, while in LGG it lowers down to 1,933,701 weights because it has less convolutional layers. All sequences were used as inputs and LReLU is the activation function used in all layers with weights, except the last layer which uses softmax.

i) Training: To train CNN, the loss function must be minimized, but it is highly non-linear in its operation. Stochastic Gradient Descent is used as an optimization algorithm, which takes steps proportionally to negative gradient in the direction of local minima. Nevertheless, in regions of low curvature it can be slow. Nesterov's Accelerated Momentum is also usedto accelerate the algorithm in those regions. The momentum i is kept constant, while the learning rate e was linearly decreased after each epoch. An epoch is a complete pass over for training all the samples.

MODULE 3/GLCM FEATURE EXTRACTION:

The co-occurrence matrix and texture features were initially used for the automated classification of rocks. The fourteen Heraldic measures were used to extract useful texture information from the co-occurrence matrix. From then on, the GLCM has been one of the commonly used tools for texture analysis because it can estimate image properties related to second-order statistics. An image with the size of pixels and gray levels could illustrate the frequency of pixel (i.e) at the position occurrence with gray level and in accordance with a distance d from a certain pixel at the position ( ) with gray level. Frequency is denoted by ( ) and its mathematical expression is

$$P_d(i,j) = |\{((r,s),(r+dx,s+dy)); I(r,s) = i, I(r+dx,s+dy) = j\}| \tag{3.4}$$

Heraldic Features describe the correlation in intensity of pixels that are next to each other in space. Heraldic proposed fourteen measures of textural features which are derived from the co-occurrence matrix a well-known statistical technique for texture feature extraction. It contains information about how image intensities in pixels with a certain position in relation to each other occur together. Texture is one of the most important defining characteristics of an image. The grey level co-occurrence matrix is the two dimensional matrix of joint probabilities between pairs of pixels separated by a distance in a given direction. The second order image histogram referred as the Grey Level Co-occurrence Matrix (GLCM) of an image offers greater information about the inter-pixel relationship, periodicity and spatial grey level dependencies. This matrix is a source of fourteen texture descriptors.

MODULE 4/POST-PROCESSING:

Some small clusters may be erroneously classified as a tumor. To deal with that, volumetric constrains were imposed by removing clusters in the segmentation obtained by CNN that are smaller than a predefined threshold tVOL.

IV.ACCESSING AND ANALYZING IMAGES

Using MATLAB language, programming and developing algorithms are faster than with traditional languages because there is no need to perform low-level administrative tasks such as declaring variables, specifying data types and allocating memory. In many cases, MATLAB eliminates the need of for loops. As a result, one line of MATLAB code can often replace several lines of C or C++ code. By using the interactive tool GUIDE (Graphical User Interface Development Environment) the layout, design and edit user interfaces are drawn and includes list boxes, pull-down menus, push buttons, radio buttons, and sliders as well as MATLAB plots. Alternatively, GUIs programmatically use MATLAB functions to support entire data analysis process right from acquiring data from the external devices and databases through preprocessing, visualization and numerical analysis to produce presentation-quality output.

Code implementation and snapshots:

```
clc;
clearall;
closeall
current=cd;
addpath(strcat(current,'\dataset'));
[im1,im2]=nyul_hist_normalization ('helium3.nii','t81slice.nii','he3mask.nii','t81mask.nii');
Imshow(im1(:,:,90));title('mri image 1 before preprocessing');
figure;imshow (im2(:,:,90));title('mri image 1 after preprocessing');
figure; imshow (im1(:,:,100));title('mri image 2 before preprocessing');
figure;imshow (im2(:,:,100));title('mri image 2 after preprocessing');
figure; imshow (im1(:,:,110));title('mri image  3 before preprocessing');
figure;imshow (im2(:,:,110));title('mri image 3 after preprocessing');
```

The following steps are involved in the implementation procedure as

i. Initializing GUI
ii. Getting the input image
iii. Preprocessing
iv. CNN Segmentation

The respective snapshots are shown in Figures3-8
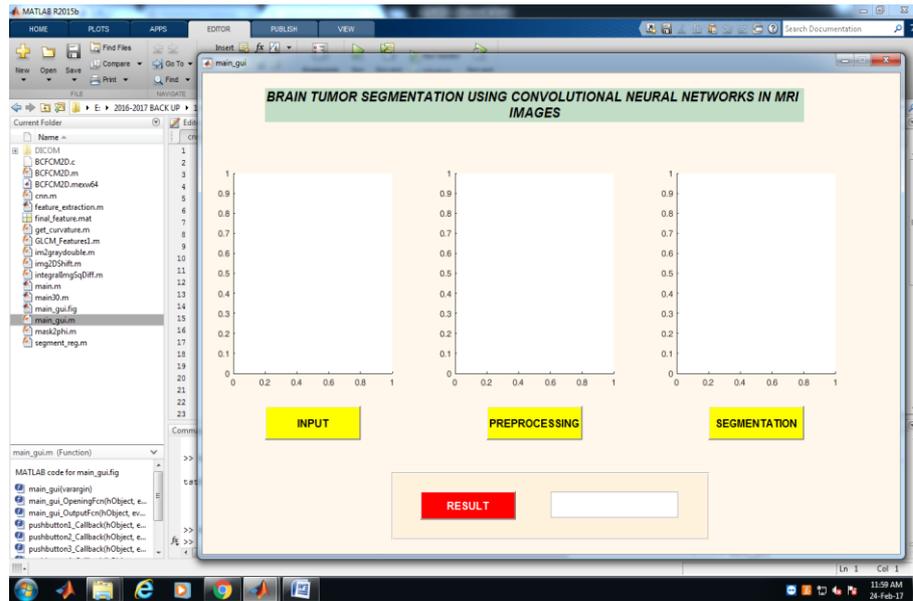
Fig.3.Initializing GUI in MATLAB
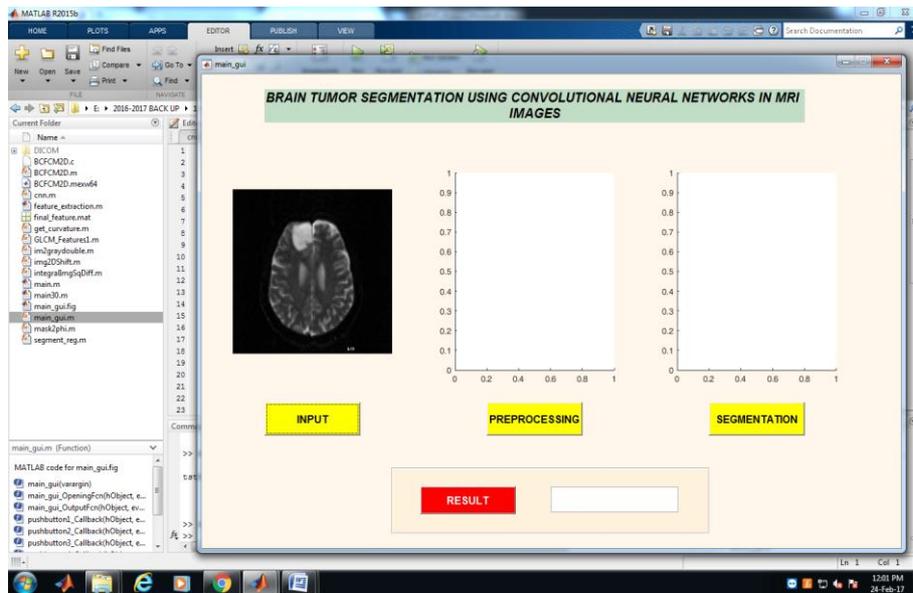
Fig.4.Getting an input image
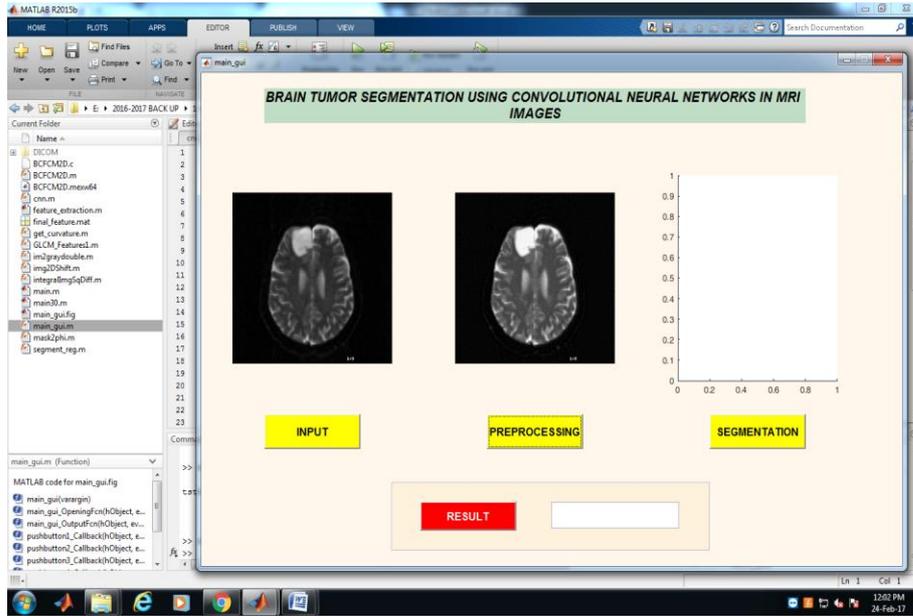
Fig.5.Image after preprocessing
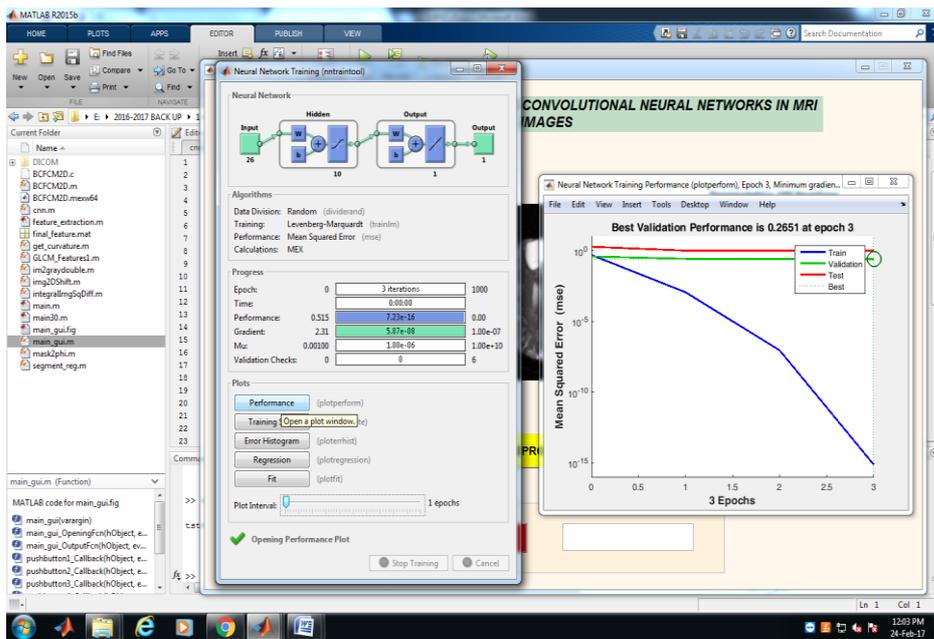
Fig.6.Validation Performance after CNN Segmentation
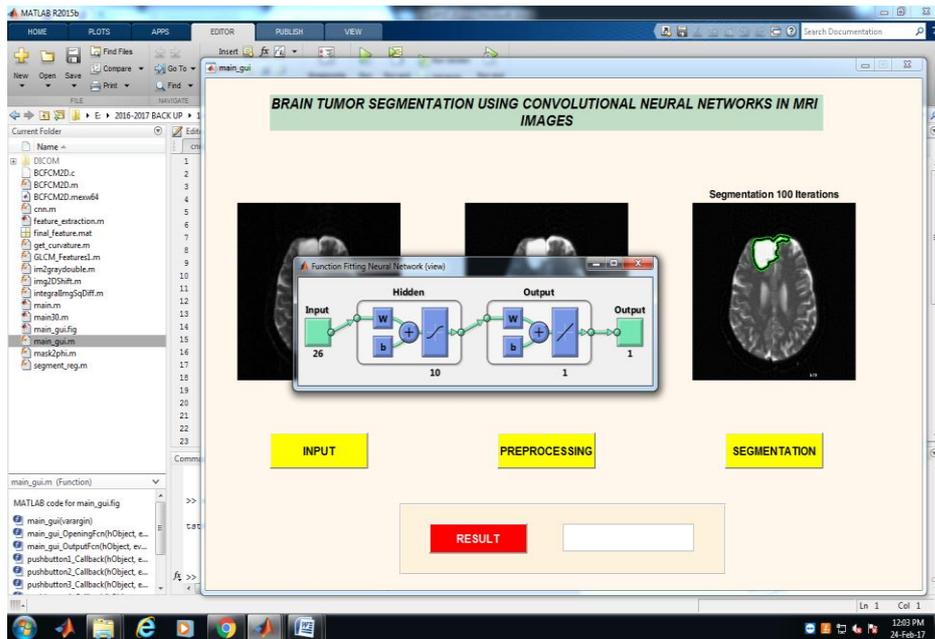
Fig.7.Function fitting neural network
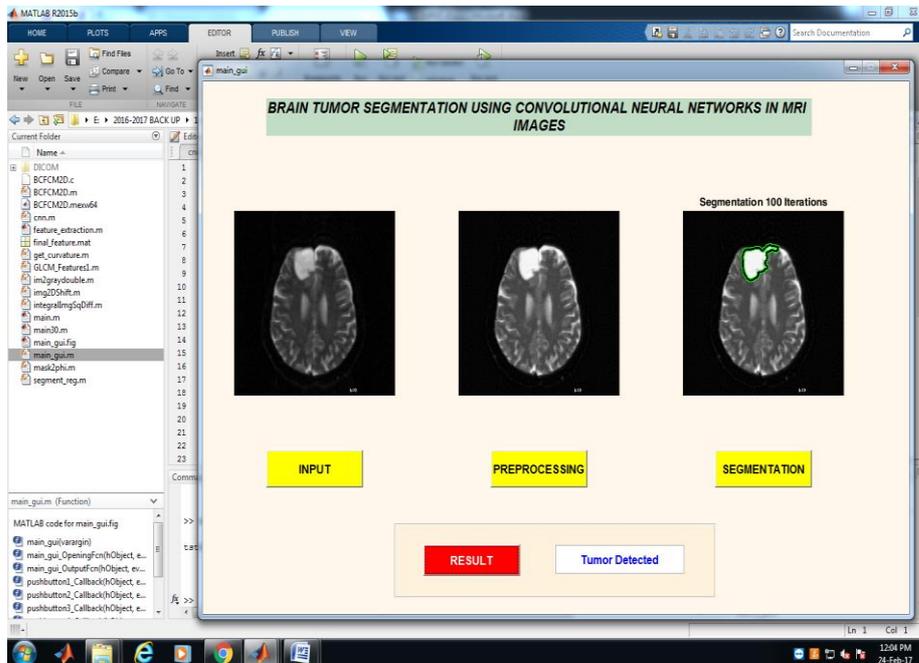
Fig.8.Result after 100 iterations

Various sample images have been taken for analysis and from the results obtained, it is able to identify whether tumour has been detected or not in the particular image.Table.1 depicts several images under test and the green

color patch prominently shown in the third column after segmentation gives the result whether the affected portion has tumour or not.

Table 1.Results of sample images with tumour detection

Sample no	Input image	Pre processing	Segmentation	Results
1.				Tumour Detected
2.				Tumour detected
3.				Tumour detected
4.				Tumour detected
5.				Tumour not detected
6.				Tumour not detected
7.				Tumour not detected
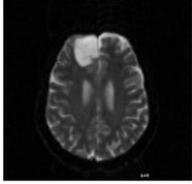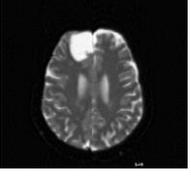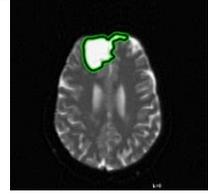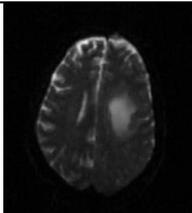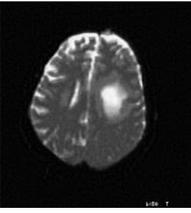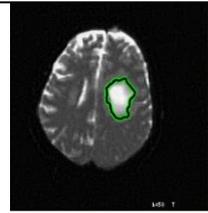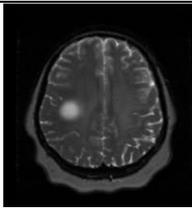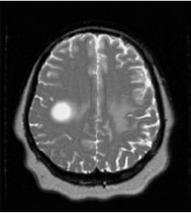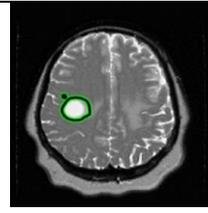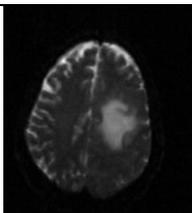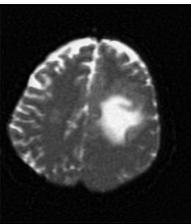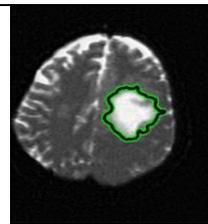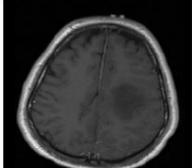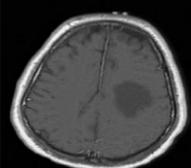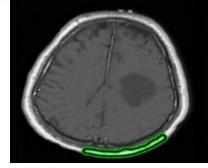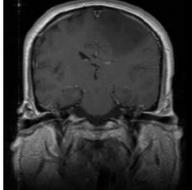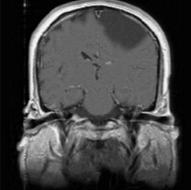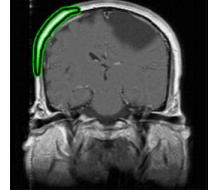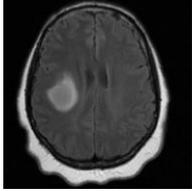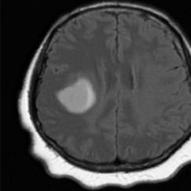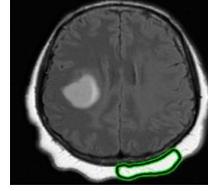
IV.

V.CONCLUSION

Here in this paper, a novel CNN-based segmentation method for detecting brain tumors in MRI images is proposed. Firstly a pre-processing stage consisting of bias field correction, intensity and patch normalization is carried out. After that, during training a number of training patches is artificially augmented by rotating the training patches, and using samples of High Grade Gliomas (HGG) to augment the number of rare Low Grade Glioma (LGG) classes. The CNN is built over convolutional layers with small 3x3 kernels to allow deeper architectures.

In the design procedure, it is addressed that the heterogeneity caused by multi-site multi-scanner acquisitions of MRI images using intensity normalization as proposed by Nyul et al. It is shown that good segmentation has been achieved by which the detection of images become easier. As brain tumors are highly variable in their spatial localization and structural composition, it is investigated that the use of data augmentation is necessary to cope with such variability. It is also studied that augmenting the required training data set by rotating the patches as well as by sampling from classes of HGG that were under represented in LGG. It is also found that the data augmentation was quite effective, although not thoroughly explored in deep learning methods for brain tumor segmentation. Also, it is investigated that the potential of deep architectures has been improved through small kernels by comparing the proposed deep CNN with shallow architectures with larger filters. It is understood that the shallow architectures presented a lower performance, even while using a larger number of feature maps. Finally, it is been verified that the piecewise linear activation function LReLU was more important than the ReLU for effectively training the proposed CNN architecture.

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