Segmentation of Brain Tumour using Deep Neural Network

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Abstract— BRAIN MR Image segmentation is a very important and challenging task that is needed for the purpose of diagnosing brain tumors and other neurological diseases. Brain tumors have different characteristics such as size, shape, location and image intensities. They may deform neighboring structures and if there is edema with the tumor, intensity properties of the nearby region change. Deep Neural Networks (DNNs) have recently attracted more attention due to their state-of-the-art performance on several datasets. DNNs have also been applied successfully to segmentation problems using DNNs in order to find the brain tumor. Deep Neural Networks (DNNs) are often successful in problems needing to extract information from complex, high-dimensional inputs, for which useful features are not obvious to design. To apply DNNs to brain tumor segmentation for the BRATS challenge.

Key words: DNNs, Brain Tumour, MRI

I. Introduction

Magnetic resonance imaging (MRI) is a medical imaging technique used in radiology to form pictures of the anatomy and the physiological processes of the body in both health and disease. MRI scanners use strong magnetic fields, radio waves, and field gradients to generate images of the inside of the body.

The brain is a soft, spongy mass of tissue. It is protected by:

- The bones of the skull
- Three thin layers of tissue
- Watery fluid (cerebrospinal fluid) that flows through spaces between the meninges and through spaces (ventricles) within the brain.

A. Brain Tumour

- Primary brain tumour can be either malignant (contain cancer cells) or benign (do not contain cancer cells). A primary brain tumour is a tumour which begins in the brain. If a cancerous tumour which starts elsewhere in the body sends cells which end up growing in the brain, such tumour are then called secondary or metastatic brain tumour.
- Brain tumour can occur at any age.
- The exact cause of brain tumour is not clear.
- The symptoms of brain tumour depend on their size, type, and location.
- The most common symptoms of brain tumour include headaches; numbness or tingling in the arms or legs; seizures, memory problems; mood and personality changes; balance and walking problems; nausea and vomiting; changes in speech, vision, or hearing.

II. Proposed System

Deep Neural Networks (DNNs) have recently attracted more attention due to their state-of-the-art performance on several datasets. DNNs have also been applied successfully to segmentation problems using DNNs in order to find the brain tumour. Deep Neural Networks (DNNs) are often successful in problems needing to extract information from complex, high-dimensional inputs, for which useful features are not obvious to design. To apply DNNs to brain tumour segmentation for the BRATS challenge.

A. Block Diagram

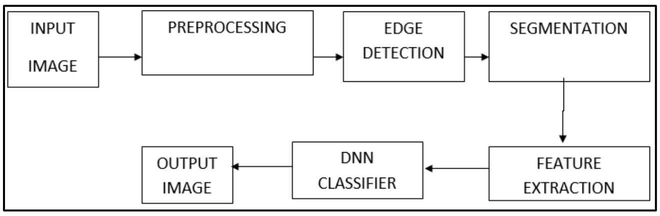

Fig. 1: Block Diagram of DNN

1) Pre-Processing

Pre-processing images commonly involves removing low-frequency background noise, normalizing the intensity of the individual particles images, removing reflections, and masking portions of images. Image pre-processing is the technique of enhancing data images prior to computational processing.

Pre-processing functions involve those operations that are normally required prior to the main data analysis and extraction of information, and re generally grouped as radiometric or geometric corrections. Some standard correction procedures may be carried out in the ground station before the data is delivered to the user.

2) Edge Detection

Edge detection is the name for a set of mathematical methods which aim at identifying points in a digital image at which the image brightness changes sharply or, more formally, has discontinuities. The points at which image brightness changes sharply are typically organized into a set of curved line segments termed edges. The same problem of finding discontinuities in 1D signals is known as step detection and the problem of finding signal discontinuities over time is known as change detection. Edge detection is a fundamental tool in image processing, machine vision and computer vision, particularly in the areas of feature detection and feature extraction.

3) Image Segmentation

The term image segmentation refers to the partition of an image into a set of regions that cover it. In other analysis tasks, the regions might be sets of border pixels grouped into such structures as line segments and circular arc segments in images of 3D industrial objects. Regions may also be defined as groups of pixels having both a border and a particular shape such as a circle or ellipse or polygon. The following categories are used:

1) Threshold based segmentation. Histogram thresholding and slicing techniques are used to segment the image. They may be applied directly to an image, but can also be combined with pre and post-processing techniques.
2) Edge based segmentation. With this technique, detected edges in an image are assumed to represent object boundaries, and used to identify these objects.
3) Region based segmentation. Where an edge based technique may attempt to find the object boundaries and then locate the object itself by filling them in, a region based technique takes the opposite approach, by (e.g.) starting in the middle of an object and then "growing" outward until it meets the object boundaries.
4) Clustering techniques. Although clustering is sometimes used as a synonym for (agglomerative) segmentation techniques, it denote techniques that are primarily used in exploratory data analysis of high-dimensional measurement patterns.
5) Matching. When an object is identified in an image (approximately) looks like, it us used to locate the object in an image. This approach to segmentation is called matching.
6) Clustering Methods.Clustering is the process of partitioning a set of pattern vectors into subsets called clusters. Clustering consists of finding subsets of points that are close to each other in Euclidean two-space. The components of these vectors can include:

– Intensity values
– RGB values and colour properties derived from them
– Calculated properties
– Texture measurements

B. *Convolution of Neural Network*

In machine learning, a convolutional neural network (CNN) is a type of feed-forward artificial neural network where the individual neurons are tiled in such a way that they respond to overlapping regions in the visual field. Convolutional networks were inspired by biological processes and are variations of multilayer perceptrons which are designed to use minimal amounts of preprocessing. They are widely used models for image and video recognition

C. *Markov Random Field*

Markov Random field models have been recently suggested for MRI brain segmentation by a large number of researchers. By employing Markovinity, which represents local property, MRF models are able to solve a global optimization problem locally. Previously this model has been tuned by the principle of SA (system annealing) and GA(genetic algorithm).

MRF addresses both de noising and segmentation by means of labelling problem. Each MRI image together with its segmentation result, which is a label field, is considered as pair <xMRI,Y>defined on a 3D lattice S={si|1≤i≤N}, where *S* is a set of sites or voxels, *N* is the number of voxels, xMRI={xj ∈G|j ∈S}represents the MR image, G∈[0,255]is the grey-level range, y={yj ∈Γ| j∈S}is a label field called configuration, *Y* is the set of all possible configurations, Γ=(λ1,λ2,...,λM) is the label set of all tissues types, and *M* is the number of tissue types. MRF seeks for a label field according to MAP criterion

$$y \arg\max\{ p(xMRI \mid y,)p(y)\}, y\, Y * \theta = \in \quad (1)$$

Where, the priori density of the tissue, p(y), concedes spatial coherence constraints present in an image by means of specifying a neighbourhood structure and depends upon the type of scene.

$$p(y) = \left(\frac{1}{z}\right) e^{\frac{E(y)}{T}} \quad (2)$$

Where Zis a normalizing constant, T is the system temperature, and E(y) is an energy function, which is a sum of clique potentials over all possible cliques.

1) *Improved Genetic Algorithm (IGA)*

One of the most important definitions in GA is individual and coding. In order to consider the correlation between voxels, we have used a new 2-D label field as individual which is noise insensitive against the grey level coding.

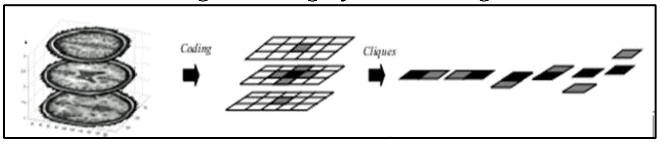

Fig. 2: Clique Configurations

2) *Individual fitness function*

Fitness value of each individual indicates its survival ability. Since the purpose of the problem is minimizing the energy function stronger individuals should have lower energy values and subsequently higher fitness values.

3) *Selection*

In order to achieve the idea of 'Survival of the fittest', selection is performed. In this paper the roulette wheel method has been used for selection. Roulette wheel is based on spinning a biased roulette wheel sized in proportion of the fitness of each individual.

4) *Crossover*

In the proposed algorithm used two point crossover on 2-D individuals. For this goal two individuals are selected as Parent1 and Parent2by considering the fitness values.

5) *Mutation*

Mutation is an operation by which the degree of population diversity could be enhanced. The definition of mutation is a tradeoff between computing time and accuracy.

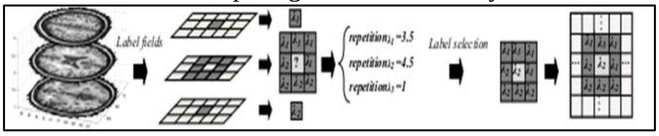

Fig. 3: Mutation

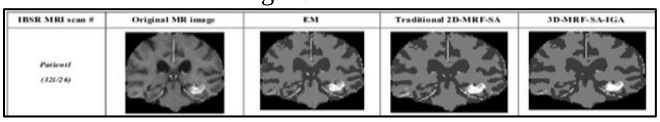

Fig. 4: Markov Random Process

D. *Deep Neural Network*

Deep Neural Network (DNN) used as a pixel classifier. The network computes the probability of a pixel being a membrane, using as input the image intensities in a square window cantered on the pixel itself. An image is then segmented by classifying all of its pixels. Many other types of learning classifiers have been applied to segmentation of TEM images, where different structures are not easily characterized by intensity differences, and structure boundaries are not correlated with high image gradients, due to noise and many confounding micro-structures. In most binary segmentation problems, classifiers are used to compute one or both of the following probabilities:

- Probability of a pixel belonging to each class
- Probability of a boundary dividing two adjacent pixels.

Segmentation through graph cuts uses

- As the unary term
- As the binary term.

E. DNN Architecture

A DNN consists of a succession of convolutional, max-pooling and fully connected layers. It is a general, hierarchical feature extractor that maps raw pixel intensities of the input image into a feature vector to be classified by several fully connected layers. The biggest architectural difference between the DNN and earlier CNN are max-pooling layers instead of sub-sampling layers. Their outputs are given by the maximum activation over non-overlapping square regions. Max-pooling are fixed, non-trainable layers which select the most promising features.

- Maxout convolutional layer: This is a variant of a convolutional layer. In this case, each feature map is instead associated with 2 kernels.
- Max pooling layer: In order to introduce invariance to local deformations such as translation, it has been found beneficial to subsample feature maps by taking the maximum feature (neuron) value over sub-windows, within each feature map.
- Fully connected layer: Neurons in a convolutional layer have limited receptive field, meaning that each neuron only depends on a small local patch within the image.
- Fully connected Maxout layer: This is simply the fully connected version of the Convolutional Maxout layer. In practice use 5 set of weights for this layer instead of 2 as opposed to the convolutional Maxout layer.
- Softmax layer: This is a special case of fully connected layer, where the activation function is the softmax function: softmax(a) = exp(a)=Z where Z is a normalization constant.
- Dropout: It is a regularization method that stochastically adds noise in the computation of the hidden layers of a DNN. This is done by multiplying each hidden or input unit by 0 (i.e. masking) with a certain probability (e.g.0.5), independently for each unit.

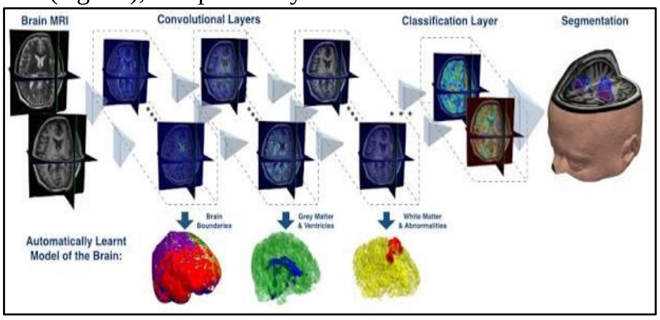

Fig. 5: Working Process of DNN

Figure 5 represents the working procedure of deep neural network along with convolution layer, classification layer and segmentation process.

III. RESULTS AND DISCUSSION

The process that is performed in the system is shown through the below snapshots. The process is based on OpenCV (Open Source Computer Vision). The trained images are included to provide a proper result. The various module output and detection is carried out using OpenCV source and the output is indicated in the monitor. The input is given as image feed to the system. It involves pre-processing, extraction, description and detection techniques. The reason for using MRF algorithm is that it results in improved accuracy than other algorithm techniques.

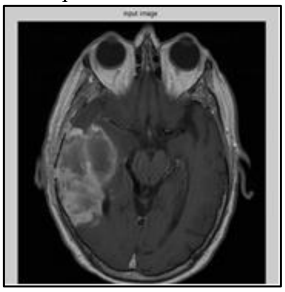

Fig. 6: Input Image

Figure 6 represent the input image that is used for detecting the tumour cell with the helpof deep neural network classifier. The input image can be obtained from all the three stages of brain tumour such as Normal, Malignant and benign stages.

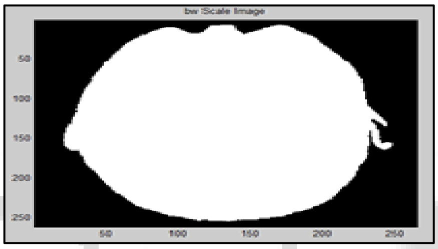

Fig. 7: BW Scale Image

Figure 7 represent the black and white scale that indicate the scanned area to be represented as white and the remaining area will be represented in black colour.

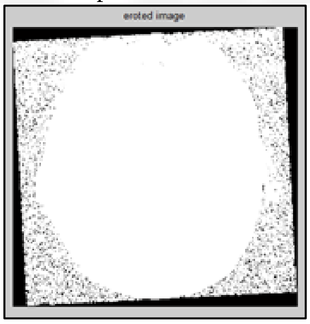

Fig. 8: Eroded Image

Figure 8 represents the eroded form of image that is to provide the black and white scaled image in different form. The eroded form of image get appear as dot spots that indicates compressing and enhancing the image to remove unwanted area in that image.

Fig. 9: Segmented Output

Figure 9 represent the process of segmentation for the respective original image. The segmented image covers the boundary area along with the tumour to be represent in the form of white and the remaining area to be in black.

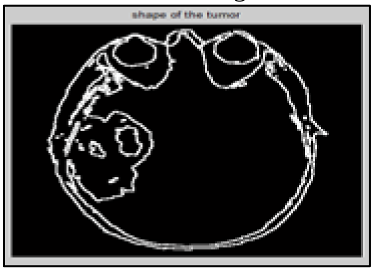

Fig. 10: Shape of the Tumour

Figure 10 represents the shape of tumour that covers the entire size of the brain along with tumour cell, it represents the boundary object to be white and remaining to be in the form of black. The below image shows the hole area to be filled with colour.

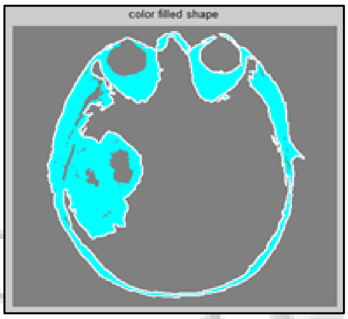

Fig. 11: Colour Filled Shape

Figure-11 represent the colour filled shape and Figure 12 represent the boundary representation is obtained after converting the black and white image into colour form of image the red colour denotes exterior boundary object and green colour represent the boundary along with the inner part.

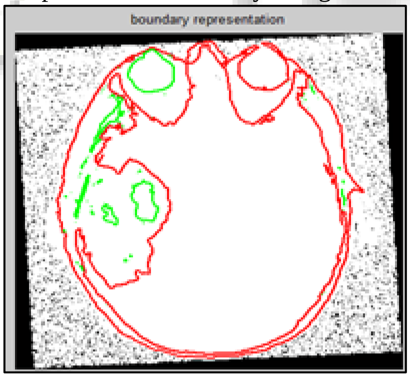

Fig. 12: Boundary Representation

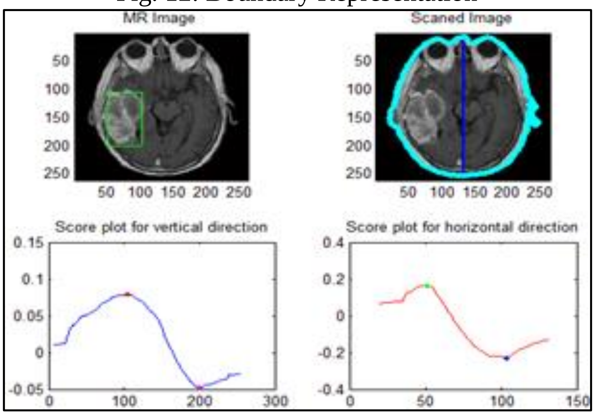

Fig. 13: Score Plot

Figure-13 represent the MR image and Scanned image the bounding box concept is used to cover the respective area that results in high intensity region. The respective horizontal plot determine the intensity by scanning the area neither from left to right or right to left and similarly the vertical plot determine the intensity by scanning the area neither from top to bottom or bottom to top.

The intensity refers to amount of light or the numerical value of a pixel. It is depicted by grey scale value of each pixel.

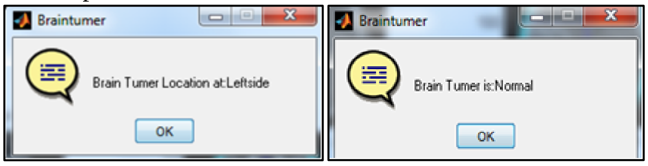

Fig. 14: Stages and Location

Figure 14represents the location of the brain tumour that is either in left side or right side and other part determine the stage of the brain of brain tumour (i.e.) Normal, Malignant or Benign

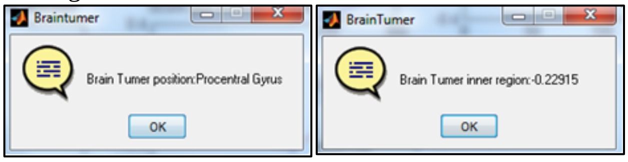

Fig. 15: Positions and Region

Figure15 represent the position of brain tumour apart from three main position of brain tumour and other part calculate the inner region of the brain tumour

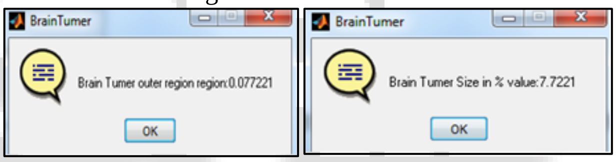

Fig. 16: Region and Size

Figure 16 represents the calculation of outer region and other part determines the entire size of brain tumour.

IV. Conclusion

Thus the proposed system is able to detect tumour cells from hidden layers with high accuracy and efficiency based on visual information. Quantitative analysis performed on a large image data set captured with different pattern and trained along with various locations in entire brain area.

The Deep Neural Network classifier reduces the effort the need for feature engineering, one of the most time consuming parts of the machine learning practice. It has best-in-class performance on problems other solutions in multiple domains. The main contribution lies therefore in the classifier itself. Others have used off-the-shelf random forest classifiers to compute unary terms of neuron membranes or SVMs to compute both unary and binary terms for segmenting mitochondria. The former approach uses haar-like features and texture histograms computed on a small region around the pixel of interest, whereas the latter uses sophisticated rotational and ray features computed on super pixels.

The Deep Neural Network classifier requires a large amount of data (if you only have thousands of example), deep learning is unlikely to outperform other approaches. It is extremely computationally expensive to train. The most complex models take weeks to train using hundreds of machines equipped with expensive GPUs. It does not have much in the way of strong theoretical foundation.

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