ISSN (Print) : 2320 – 3765
ISSN (Online): 2278 – 8875

International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 6, Issue 2, February 2017

A Survey on Brain Tumor Detection Using Neural Network

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ABSTRACT: Among cerebrum tumors, Glioma are the most widely recognized, forceful, prompting a short future in their most elevated evaluation. Thus, treatment arranging is a key stage to move forward the personal satisfaction of oncological patients. Thus, programmed and reliable techniques are required. Propose a automatic division strategy in light of Convolutional Neural Networks (CNN), investigating little 33 kernel. The use of this kernel permits outlining a more profound design, other than having a constructive outcome against over fitting, given the less number of weights in the system. We also examined the utilization of power standardization as a pre-preparing step, which however not basic in CNN-based division techniques, ended up being exceptionally powerful for mind tumor division in MRI pictures.

KEYWORDS*:* MRI, Feature Extraction, Segmentation, Gabor, BPN

I. INTRODUCTION

Glioma is a broad category of brain and spinal cord tumors that come from glial cells, brain cells that can develop into tumors. Low-grade versions of gliomas can occur in children. Brain tumors are slightly more likely to occur in males. Prior radiation to the brain is a risk factor for malignant gliomas. The precise Segmentation of gliomas and its intra-tumoral structures is imperative for treatment arranging, as well as for follow-up assessments [1]. Be that as it may, it is a testing assignment, since the shape, structure, and area of these anomalies are profoundly factor. In mind tumor division, we discover a few techniques that expressly build up a parametric or non-parametric probabilistic model for the basic information.

II. PROBLEM STATEMENT

Glioma leads to very short life expectancy. In previous techniques of segmentation the accuracy of the algorithms is less. Making use of an automatic segmentation method based on Convolutional Neural Networks (CNN) to overcome above drawbacks.

III. MOTIVATION

The symptoms, prognosis, and treatment of a malignant glioma depend on the person’s age, the exact type of tumor, and the location of the tumor within the brain. Previously many techniques are applied to detect the brain tumor segmentation and detection[6]. Magnetic resonance imaging (MRI) is a noninvasive method for producing three-dimensional (3D) tomographic images of the human body. MRI is most often used for the detection of tumors, lesions, and other abnormalities in soft tissues, such as the brain. Clinically, radiologists qualitatively analyze films produced by MRI scanners.

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IV. LITERATURE REVIEW

Sr No	Name of Author	Publication	Work Reference
1.	Sheela.V.K and Dr.S.SureshBabu [3]	"Processing Technique for Brain Tumor Detection and Segmentation," International Research Journal ,June-2015	1. In this paper, we studied the different Pre-Processing Techniques which enhances the quality of the image and finally removes the noise present in the Image.
2.	Jay patel and KaushalDoshi [4]	"A study of Segmentation Method for detection of Tumor in Brain", Advance in Electronic & Electric Engineering,2014.	In this paper various clustering methods that have been used for segmentation in MRI are reviewed.
3.	J.Selvakumar, A.Lakshami and T.Arivoli [5]	"Brain Tumor Segmentation and Its Area Calculation in Brain MR Images using K-mean Clustering & Fuzzy C-Mean Algorithm, March 30,2012.	The paper described clustering algorithms for image segmentation and effectiveness of Fuzzy C-Mean Algorithm
4.	RaunaqRewari [6]	"Automatic Tumor Segmentation Using Convolutional Neural Network", BRATS 2015	The motive of this paper is to come up with a fully automatic tumor segmentation approach using CNN.

V. PROPOSED SYSTEM

The figure below shows the existing system of the detection of brain tumor segmentation. In this method, the pre-processing is used to enhancement of the image without altering the information content.The main causes of image imperfections are as Low resolution, Simulation, Presence of image artifacts, Geometric Distortion, Low contrast, High level of noise. The feature Extraction is used to extract the feature from the image. This system gives the moderate result i.e. the detection of the tumor is accurate but the classification of the tumor is not done in the circuit.

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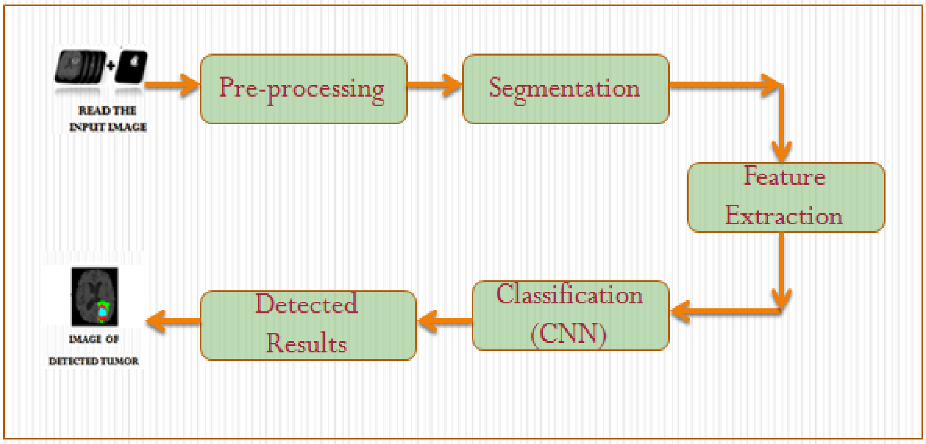

Fig. 1: Block diagram of the proposed method

There are different stages: pre-processing, segmentation, feature extraction & classification using Convolutional neural network.The brief description of each step of the block diagram is given below.

A. Pre-Processing:

Pre-Processing strategies point the upgrade of the picture without changing the data content. The primary driver of picture flaws are as Low determination, Simulation, Presence of picture antiquities, Geometric Distortion, Low complexity, High level of clamor. The most applicable and essential pre-preparing systems for MRI pictures before managing cerebrum tumors is division.

The principal preparing venture in the division of mind tissues is skull stripping. The skull evacuated MRI pictures are utilized for further arrangement of the mind tissues into WM, GM and CSF. The accompanying are the means required in the proposed approach for cerebrum MRI division: • Skull Stripping. • CSF Segmentation. • GM and WM Segmentation. The got tested outcomes by the proposed strategy are given as follows in Figure 2. Here, we have given every one of the results of the info picture with tumor and without tumor locale[3].

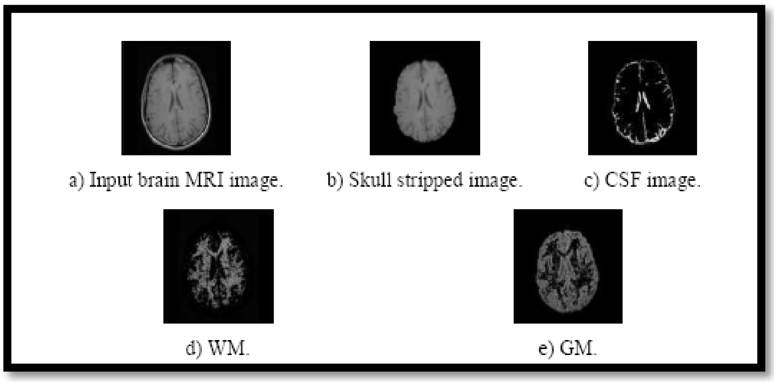

Fig.2: Segmented results of brain MRI without tumor.

Locale developing is a basic district based picture division strategy. It is additionally delegated a pixel-based picture division strategy since it includes the determination of introductory seed focuses. This way to deal with division inspects neighboring pixels of introductory seed focuses and figures out if the pixel neighbors ought to be added to the district. The procedure is iterated on, in an indistinguishable way from general information grouping calculations. A general discourse of the locale developing calculation is depicted underneath.

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1. Parcel the picture into starting seed districts $\mathbf{R_i^{(0)}}$.

2. Fit the planar model to each seed district. In the event that $\mathbf{E(R_i^{(0)},a,m)}$ is sufficiently little, acknowledge $\mathbf{R_i^{(0)}}$and its model; otherwise dismiss it.

3. For every district, find all focuses that are perfect with the area by considering the neighbors of the locale.

$\mathbf{Ci(k) =[(x,y):(g(x,y)-f(x,y,a,m))^2< \varepsilon}$ and (x,y) is a 4-neighbor of $R_i^{(k)}$. **(1)**

4. In the event that there were no perfect focuses, then **m= m+1**. In the event that **m > M**, don't develop $R_i^{(k)}$ further; generally, go to step 3.

5. From the new district $\mathbf{R_i^{(k+1)} = R_i^{(k)} U C_i^{(k)}}$, refit the model to$\mathbf{R_i^{(k+1)}}$and register $\mathbf{E(R_i^{(0)},a,m)}$.

6. Register the distinction blunder:

$\boldsymbol{\rho^{(k)} = E(R_i^{(k+1)},a,m) - E(R_i^{(k)},a,m)}$ **(2)**

7. In the event that $\boldsymbol{\rho^{(k)} < T1}$, go to step 3.

8. **m = m + 1**. On the off chance that m > M, don't develop district facilitate.

9. Refit the locale at the new model f(x,y,a,m). In the event that the blunder of fit declines, acknowledge the new model and go to step3; something else, don't develop the district facilitate.

B. Feature Extraction:

The next step for diagnosis is to extract features. Highlight extraction is the way toward characterizing an arrangement of components, or picture attributes, which will most effectively or seriously speak to the data that is critical for investigation and characterization. Normal element extraction strategies incorporate Histogram of Oriented Gradients (HOG), Speeded Up Robust Features (SURF), Local Binary Patterns (LBP), Haar wavelets, and shading histograms.

LBP (Local Binary Patterns):

The local binary pattern[7] is a simple, quick, and very efficient method for extracting feature from image texture. In this method, first a neighborhood of an image is selected. Then, the intensity of the points existing in this neighborhood is compared with the intensity of the pixel located in the center of the neighborhood and a binary code is considered for each pixel according to equation (3).

In order to make the algorithm rotation-invariant usually circular neighborhood is considered. The pixels whose coordinates are not exactly located on the neighborhood of pixel center are obtained by interpolation. In equation 3, P represents the number of neighborhood pixels of a considered center pixel, R is the neighborhood radius, $g_i$is the intensity of the neighborhood pixels, and g_c is the intensity of the central pixel.

$$LBP_{P,R} = \sum_{i=0}^{P-1} s(gi - gc)2i \quad (3)$$

$$s(x) = \begin{cases} \mathbf{1}, & x \geq \mathbf{0} \\ \mathbf{0}, & x < 0 \end{cases}$$

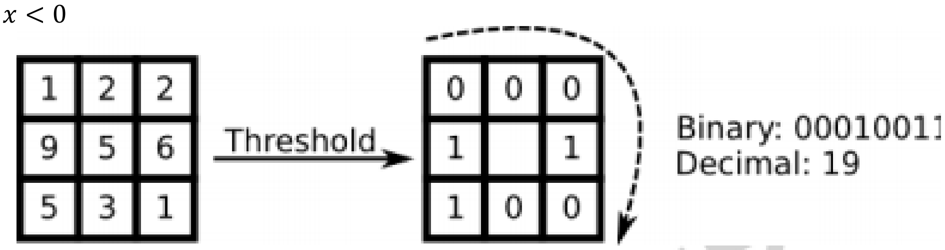

Fig 3: Binary code of each pixel in LBP

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ISSN (Online): 2278 – 8875

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A measure called consistency was proposed in the changed adaptation of LBP. A bit example is called uniform in the event that it has no less than two round piece moves from zero to one or bad habit versa. For example, the bit design (00000000) has a zero move and it is uniform; while, the bit design (01010011) has six moves and it is not uniform. In the uniform double example mapping, there is a different yield name for each uniform example and all non-uniform examples are doled out to a mark. There are two motivations to expel non-uniform twofold examples and relegate them to a name. To start with, it has been demonstrated that most nearby twofold examples are uniform in normal pictures. The second reason is that considering uniform examples rather than every single conceivable example gives better recognition comes about. There are signs that show uniform parallel examples have more strength and less affectability to clamor. In this technique, every pixel is named by a code of the principle surface, which is the best match with nearby neighbors.

C. Neuro-Fuzzy Classifier:

Neuro-Fuzzy Classifier Any two features with correlation coefficient that exceeds 0.9 in both spaces can be combined together and thought as one feature reducing the dimensionality of the feature space by one. Therefore the maximum probability and contrast can be removed and the numbers of features are reduced to seven features. A Neuro-fuzzy classifier is used to detect candidate circumscribed tumor. Generally, the input layer consists of seven neurons corresponding to the seven features. The output layer consists of one neuron indicating whether the MRI is a candidate circumscribed tumor or not, and the hidden layer changes according to the number of rules that give best recognition rate for each group of features.

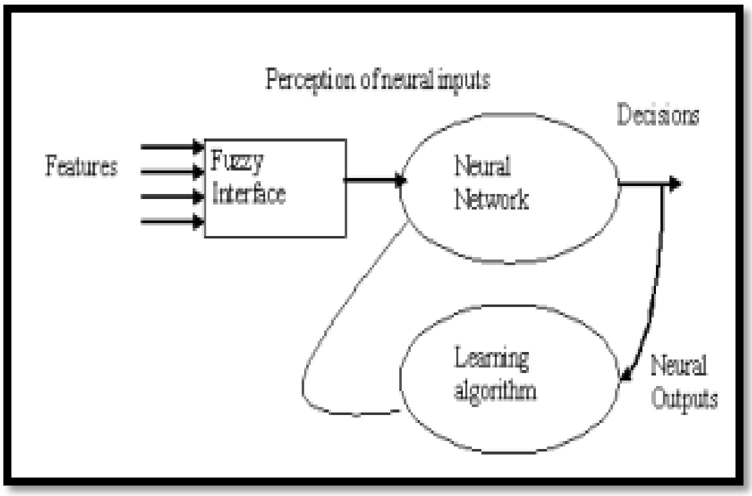

Fig. 4: Neuro fuzzy logic classification

Convolutional Neural Network (CNN) issued 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 adapted during the training phase by back propagation, in order to enhance certain characteristics of the input. CNN are easier to train and less prone to overfitting. Methodology like mentioned earlier in the report, we use a patch based segmentation approach. The Convolutional network architecture and implementation are carried out using CAFFE. CNNs are the continuation of the multi-layer Perceptron. In the MLP, a unit performs a simple computation by taking the weighted sum of all other units that serve as input to it. The network is organized into layers of units in the previous layer. The essence of CNNs is the convolutions. The main trick with Convolutional networks that avoids the problem of too many parameters is sparse connections. Every unit is not connected to every other unit in the previous layer, like in traditional neural networks.The following concepts are important in the context of CNN [1]:

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a) Initialization: It is important to achieve convergence. We use the Xavier initialization. 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

$$f(x) = \max(0,x), \qquad (4)$$

were 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. We cope with these limitations using a variant called leaky rectifier linear unit (LReLU) that introduces a small slope on the negative part of the function. This function is defined as

$$f(x) = \max(0,x)+\alpha \min(0,x) \qquad (5)$$

where α is the leakyness parameter. In the last FC layer, we use softmax.

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 the next stages. To join features it is more common to use max-pooling or average-pooling.

d) Regularization: It is used to reduce overfitting. We use Dropoutin the FC layers. In each training step, it removes nodes from the network with probability p. In this way, it forces all nodes of the FC layers to learn better representations of the data, preventing nodes from co-adapting to each other. At test time, all nodes are used. Dropout can be seen as an ensemble of different networks and a form of bagging, since each network is trained with a portion of the training data.

e) Data Augmentation: It can be used to increase the size of training sets and reduce overfitting. Since the class of the patch is obtained by the central voxel, we restricted the data augmentation to rotating operations. Some authors also consider image translations, but for segmentation this could result in attributing a wrong class to the patch. So, we increased our data set during training by generating new patches through the rotation of the original patch. In our proposal, we used angles multiple of 90◦, although another alternative will be evaluated.

f) Loss Function: It is the function to be minimized during training. We used the Categorical Cross-entropy,

$$\boldsymbol{H = -\sum_{j\in voxels} \sum_{k\in classes} Cj,k \log(\tilde{C}j,k)} \qquad (6)$$

Where$\check{C}$ represents the probabilistic predictions (after the softmax) and C is the target.

VI. CONTRIBUTION

The main contribution to the existing system is the Neuro fuzzy classifier which is used to classify the brain tumor which is detected in the system. A Neuro-fuzzy classifier is used to detect candidate circumscribed tumor.

VII.CONCLUSION

In this paper we propose a novel CNN-based technique for division of brain tumors in MRI images. We begin by a pre-preparing stage, then feature extraction, image segmentation and post-processing. Also, various existing segmentation methods for brain MR image have been discussed. We are able to successfully implement a Convolutional Neural Network based approach to segment tumors from MRI scans using a moderately deep network with not too many parameters. We are able to get high classification accuracy.

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