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A BrainNet Classification Technique Based on Deep Convolutional Neural Network for Detection of Brain Tumor in FLAIR MRI Images

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Abstract*: *Classification process plays a key role in diagnosing brain tumors. Earlier research works are intended for identifying brain tumors using different classification techniques. The logical gap between the visual representation of data captured by MRI device and the information apparent to the person evaluating poses a key challenge in the medical field. Research in computerized segmentation of tumor is widely gaining popularity nowadays, which may lead to an accurate analysis of MRI images and planned treatment of patients. The recent field of deep learning and neural networks promises to classify images with higher accuracy. This work proposes a new BrainNet classification technique that combines fuzzy c means, morphological operators and CNN to identify image regions that are suspicious. The proposed method is assessed with the help of imaging data obtained from Multimodal Brain Tumor Image Segmentation Challenge (BRATS) 2015 and IXI dataset. The effectiveness of the proposed method is computed with traditional machine learning and Convolutional Neural Networks. Experimental results show that our proposed method outperforms state-of-the-art classification on the BRATS 2015 dataset.

Keywords* : *Convolutional Neural Network, Fuzzy C Means, Morphological Operator, Classification, Segmentation, MRI Image.

I. INTRODUCTION

Timely detection and treatment of brain tumors is vital in order to prevent fatal brain damage in patients. Feature selection and classification techniques are useful method for analysing the medical data and to decide whether the patient needs to be treated for any disease. An unrestricted and uncontrollable creation of cells is the root cause for brain tumors, which is a tissue mass, built with abnormal cells. It is observed that this deadly disease is affecting people of all age groups. Figure 1 exhibits the normal image obtained from IXI data set and the brain tumor images got from BRATS 2015.

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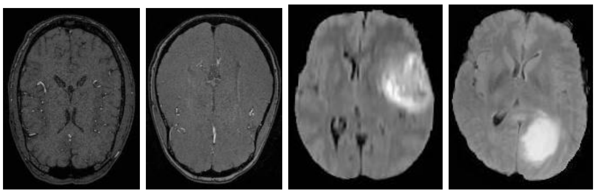

(a) (b) (c) (d)

Figure 1: (a) and (b) An normal image taken form IXI dataset, (c) and (d) The Brain Tumor Flair image taken from BRATS 2015 data set.

For preparing an effective treatment plan and to take care of the patients, brain tumors have to be diagnosed on time. The process of classifying MR images of an brain tumor manually after comparing with similar structures or appearances is a tedious and challenging task. The classification process also depends on the timely availability and proficiency of radiologists who will classify the brain tumors into two types: (i) Identification of normal or abnormal brain MR images and (ii) Classification of the image based on tumor types. Thus classifying the brain tumor by manual examination of MRI data is not practical and also labour-intensive. Hence, to address the above-mentioned challenge, research work proposed to detect brain tumor in MRI images.

For diagnosing cancer, segmentation of a brain tumor should be accurate. Laborious manual segmentation of brain tumors has led to the development of automatic detection of brain tumors. It is observed from the literature that several works has been proposed for diagnosing/detection brain abnormalities in MRI images. Support Vector Machine (SVM) was used by a researcher for classifying epileptic seizures in an effective way [2]. Yet, due to False Alarm Rate (FAR), it took a long time to diagnosis the disease. A hybrid machine-learning model using SVM and an artificial neural network proposed by a researcher displayed an improved accuracy rate in classifying brain tumors [3]. However, the model was unsuccessful in minimizing the computational complexity while classifying tumors. Tortaja et al have developed a method called incremental Ga ussian Discriminant Analysis for the screening of brain tumors. [4] in MRI images. It noted that the method did not reduce the rate of false recognition. In order to enhance the discovery process of brain seizures, a supervised machine learning technique was proposed [5] in the literature. It noticed that the diagnosis/detection of abnormalities in brain MRI images was not satisfactory in this method.

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Deep learning techniques are being used lately in the field of medical diagnosis, especially to detect brain tumors. Zikic et. al.,[6] have used the CNN (Convolutional Neural Networks) based on deep learning for the detection of brain tumor. Xiaomei Zhao et. al.[7] have used RCNN (Recurrent Neural Networks) and Fully connected Neural Network for the diagnosis of brain abnormalities in the images. The method was evaluated with the help of data obtained from BRATS 2013, 2015 and 2016.

Ambeshwar Kumar et. al.[8] have developed a method which consist of feature selection by using weighted correlation and multivariate deep neural networks for early detection of brain tumor.

The deep learning based technique was created by Ambeshwar Kumar et. al.[8], which considers a brain image dataset for tumor classification at a beginning period. The system does a Feature Selection based on Weighted Correlation by picking therapeutic element subsets that are applicable for grouping brain tumors.

Pablo Ribalta Lorenzo et al.[9] presented a technique based on deep learning for separation of brain abnormalities from brain images. The method utilizes fully convolutional neural networks complemented with augmentation techniques, for reducing the low false positive rate for small training sets.

Muhammad Sajjad et. al.[10] have used fine-tuned CNN model for classification of brain classes. The brain tumor datasets clustered using fuzzy based on unsupervised clustering [11]. It observed that the fuzzy C-means method could handle overlapping of tissues in a powerful for all tissue types [21]. Phillips et al. [13] presented a fuzzy C-means based brain abnormalities segmented section with incorporation of knowledge-based methods for better results [14].

From the literature, we observed that the classification error, high of incorrect positive rate and poor feature selection method influence the accuracy of the method. To address the issues mentioned in the literature survey, the BrainNet classification method is proposed.

The organization of research paper is as follows. detection and segmentation in MRI images are briefly explained In Section 2. In Section 3, the results of proposed method and the performance are discussed. Finally, summary and conclusion are showed in Section 4.

II. DETECTION AND SEGMENTATION OF BRAIN TUMOR USING BRAINNET METHODOLOGY

This work has employed a novel BrainNet classification technique based on deep CNN by integrating fuzzy c means and morphological operators. The proposed technique works in three stages as shown in Figure2. The brain images, which contain abnormalities, are enhanced and given as input for convolutional neural network. The suspicious regions are segmented in the post-processing module[20]. The steps of the framework are as follows.

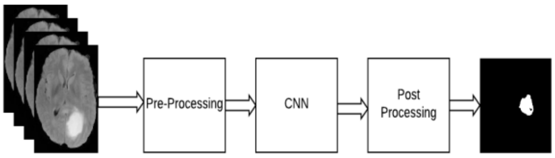
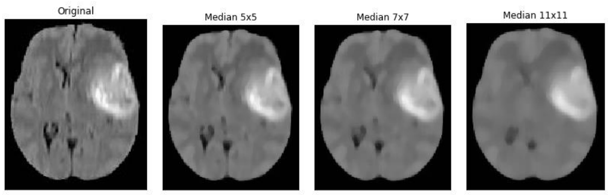


Figure 2. The steps of the developed method

A. Pre-Processing

Artefacts like motion and field in homogeneity, have an effect on the images obtained from different MRI modalities. These artefacts can originate incorrect grey levels, thus leading to the appearance of incorrect class prediction as an output. In order to remove noise from two-dimensional signals without edge blurring, a powerful median filtering technique is used which is found to be suitable for enhancing MRI images. A median filter with a correctly selected support value smoothens noise in the original image [15]. Also, the median filter may nearly remove the lesions from the original image. Various support regions applied in the Flair MRI image is illustrated in Figure 2. Figure 3 (a–d) shows the feature images produced on the original image in the presence of a median filter with various filter size. Obviously, by increasing the support region size, suppression of both noise signals and signals from tumors takes place. In case of 7 x 7 and 11 x 11 sizes, more of distinct tumorsis found to be eliminated than in case of 5 x 5 size. Thus, it can be concluded that 5 x 5 window size is suitable for noise removal from medical images.



(a) (b) (c) (d)

Figure 3. Resulting images by using enhancement technique (a) Original Image b) Median filter with window size of 5x5, (c) and (d) Median filter with 7x7 and 11x11 window size.

B. Image enhancement

In order to enhance the quality of the image, unshap masking technique has applied.

After applying the unsharp masking filter on input image f(x,y), it produces an output image g(x,y) via

$$g(x,y) = f(x,y) - f_{smooth}(x,y)$$

where is an enhanced image.

This edge can be utilized for honing in the event that one includes it over into the first signal. The resulting image f sharp(x,y) is get it from the original image f (x,y) as

$$f_{sharp}(x,y) = f(x,y) + \lambda g(x,y)$$

where λ in the range 0.0–1.0 and g(x, y). The discrete Laplacian gradient function is as shown below.

$$g(x,y) \triangleq f(x,y) - \frac{1}{4}[f(x-1,y) + f(x,y-1) + f(x+1,y) + f(x,y-1)]$$

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C. BrainNet Classification Technique

After pre-processing of the image, the tumor can be identified from the brightest portion in the enhanced image. Therefore, it is hard to find the suspicious region of interest in a meaningful way. Hence, it is advisable to consider each pixel for tumor detection.

A Convolutional Neural Network has several layers namely pooling, convolution, dense, dropout etc. which serves as the building blocks of it. Hierarchical piling of layers leads to the formation of feature maps. A feature map generated in the preceding layer is supplied as an input to each convolution layer. By forming a hierarchy of feature maps, the CNNs learns complex features from the input images. The convolution layer portions are joined with the input sample for producing different feature maps. These features are used for classification.

In order to enhance the accuracy of the brain tumor detection system, BrainNet classification method is proposed which consist of CNN, fuzzy c means and morphological operators in the FLAIR MRI image. The figure 4 shows the proposed method of BrainNet system.

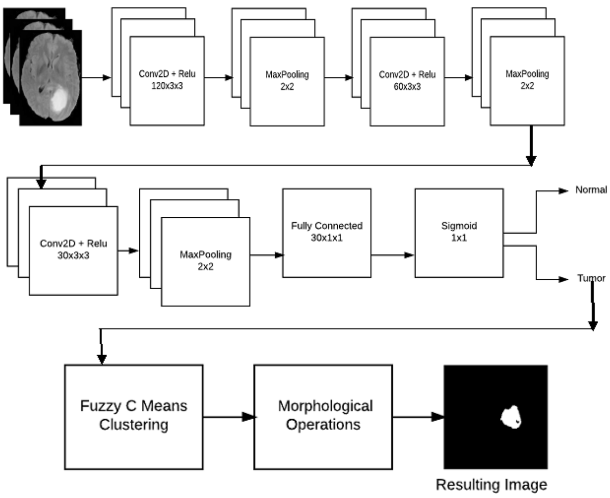

Figure 4. The proposed classification technique of the BrainNet system

BrainNet Algorithm

CNN is used to implement the whole segmentation procedure by processing a 2D MxM image to predict the label of the image. Therefore, the training dataset with four modalities is forwardly propagated through the stacked convolutional layers, fully connected (FC) layers and other

The detailed steps of CNN involved in this method are as follows:

Step 1 : INPUT [240x3x3] will contain raw pixel values of the image.

Step 2: Convolution preserves the relationship between pixels by learning image features using small squares of input data. It is a mathematical operation that takes two inputs such as image matrix and a filter [120x3x3].

Step 3 :RELU layer will use an activation function on each element, such as the max(0,x), max(0,x) threshold reaches zero. Here, the volume size remains unchanged ([120x3x3]).

Step 4 : Down sampling operation is performed by POOL layer along the spatial dimensions (2x2).

Step 5: Steps 2, 3 and 4 are repeated for [60x3x3] and [30x3x3].

Step 6: Fully-connected (FC) layer will calculate class scores thus resulting in volume of size [30x1x1], where each of the normal and tumor pixels have a close similarity to the class score.

D. Post Processing Fuzzy C Means for segmentation of suspicious region

While detecting a tumor in an image, regions with high average grey levels is also observed from the MRI image, which creates difficulty in segmenting the necessary region in a reliable way. Therefore, fuzzy c-means clustering algorithms are applied to segment the suspicious region from the MRI image. FCM is a clustering technique developed by James [17]. Fuzzy c-means (FCM) is a data clustering technique in which a data set is grouped into *N* clusters with every data point in the dataset belonging to every cluster to a certain degree. It starts with a random initial guess for the cluster centers; that is the mean location of each cluster. Next, fcm assigns every data point a random membership grade for each cluster. By iteratively updating the cluster centers and the membership grades for each data point, fcm moves the cluster centers to the correct location within a data set and, for each data point, finds the degree of membership in each cluster. This iteration minimizes an objective function that represents the distance from any given data point to a cluster center weighted by the membership of that data point in the cluster.

The systematic algorithm is given below:

Let the set of pixels is represented as $X = \{x_1, x_2, x_3, \dots, x_n\}$ and the set of centres is represented as $V = \{v_1, v_2, v_3, \dots, v_n\}$.

1. Select the cluster point c randomly.
2. Compute the fuzzy point associated with membership 'μ_{ij}' using

$$\mu_{ij} = 1/\sum_{k=1}^{c}\left(\frac{d_{ij}}{d_{ik}}\right)^{\left(\frac{2}{m}-1\right)}$$

3. Calculate the Vi called as fuzzy centre by using the flowing formula:

$$v_j = \frac{\left(\sum_{i=1}^{n}(u_{ij})^m x_i\right)}{\left(\sum_{i=1}^{n}(u_{ij})^m\right)}, v_j = 1,2,\dots,c$$

4. Repeat the steps 2 and 3 until the minimum value of 'j' is achieved or $\left\|U^{(k+1)} - U^{k}\right\| < \beta$

Where, k is the iteration step

β is the value between [0,1]. It is treated as termination criteria.

$U = (\mu_{ij})_{n*c}$ is the fuzzy membership matrix

J is the objective function

The final cluster is known as the suspicious region.

Method for reshaping the suspicious regions

For performing image shape analysis, mathematical morphology is found to be a great tool. Binary morphological operators are used to recreate the lesions shape. The reshaping of suspicious regions method is given below.

Step 1: Input the resulting image denoted as R(x,y) received from fuzzy c means algorithm.

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Step 2: Morphological dilation operator is applied to make the suspicious region more enhanced and fills in small holes in the region.

$$R_1(x,y) = \{x | (\hat{B})x \cap R(x,y) \neq \emptyset\}$$

Step 3: To remove the isolated pixels and small regions in the image, Morphological erosion is applied.

Step 4 To smooth the contour and removing bridges between regions, morphological opening operator is applied

$$R_3(x,y) = (R_2(x,y) \odot B) \oplus B$$

Step 5: In order to fill the gaps between the regions and holes, closing operator is applied.

$$R_4(x,y) = (R_3(x,y) \oplus B) \odot B$$

Step 6: Reconstruction of suspicious region is done using combined operator called close opening

$$R_5(x,y) = (R_4(x,y) \cdot B) \circ B$$

In the above equations, B which is a small image area, is called as structure element. In this experiment, a 2 X 2 square structure element is used.

III. EXPERIMENTAL RESULTS AND DISCUSSIONS

Experiments are carried out on BRATS Challenge 2015 datasets [13] and IXI dataset. It contains different kinds of MRI modalities along with segmentation labels for the training data. The BRATS 2015 dataset comprises of 274 training MR images, out of which, 220 are HGG and 54 are LGG images. The experiments were conducted on FLAIR MRI images of BRASTS 2015 and IXI dataset. The whole dataset is categorised into training and testing sets. The training set consist of 100 normal image from IXI dataset and 100-tumor image from BRATS 2015 dataset. Similarly, testing set consists of 100 normal and 100 tumor images. The BrainNet classification method is trained and tested by using Anaconda and Keras Framework.

The method is executed with cross-entropy loss function for the training and testing sets. The model is trained for 3 epochs to 100 epochs in order to increase the accuracy level. Table 1 shows the summary of evaluation parameters. It is observed from the table that 100% accuracy has reached by using validation data.

Table 1. The summary of training loss, training accuracy, validation loss and validation accuracy

Epoch s	Training loss	Training Accuracy	Validation Loss	Validation Accuracy
1	0.0341	0.9850	0.1308	0.9600
2	0.0308	0.9950	0.0316	0.9845
3	0.0277	0.9850	0.0020	1.0000
4	0.0244	0.9950	0.0064	1.0000
5	0.0212	0.9950	0.0039	1.0000
25	0.0136	0.9950	0.0170	0.9948
26	0.0020	1.0000	0.0139	0.9897
27	0.0236	0.9900	0.0024	1.0000
28	0.0132	0.9950	0.0022	1.0000
29	0.0066	0.9950	0.0133	0.9948
30	0.0081	0.9950	0.0133	0.9897
50	0.0036	0.9950	0.00047	1.0000
51	0.00012	1.0000	0.00004	1.0000
52	0.0121	0.9950	0.0046	1.0000
53	0.0094	0.9900	0.000641	1.0000
54	0.0010	1.0000	0.000141	1.0000
55	0.0727	0.9800	0.0260	1.0000
75	0.0037	0.9950	0.000126	1.0000
76	0.0037	0.9950	0.000117	1.0000
77	.000348	1.0000	0.000097	1.0000
78	0.0036	0.9950	0.000079	1.0000
79	0.0038	0.9950	0.000083	1.0000
80	0.0071	0.9900	0.000063	1.0000
96	0.0071	1.0000	0.000087	1.0000
97	0.0037	1.0000	0.000064	1.0000
98	0.0035	1.0000	0.000052	1.0000
99	0.000060	1.0000	0.000029	1.0000
100	0.0035	1.0000	0.000042	1.0000

In order to avoid the under fitting problem, the number of epochs were increased during the training period. It is observed from the Table 1 and Figure 4, the validation data are classified correctly and 100% average 5-fold validation accuracy is reached. Figure 5 is used to demonstrate the robustness of the proposed approach.

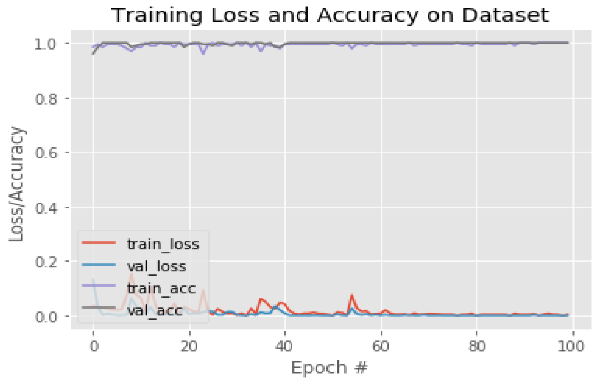
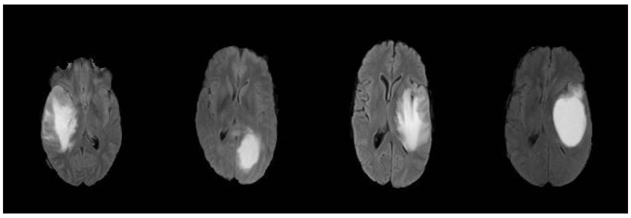
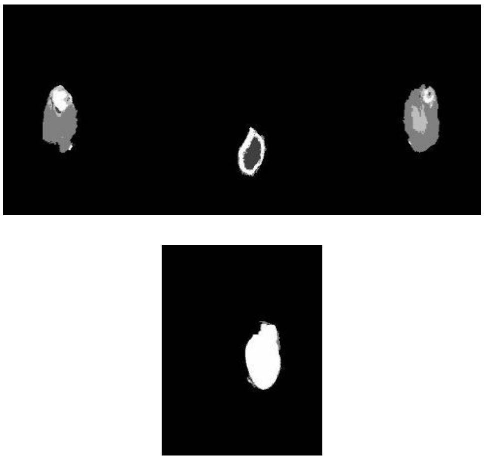


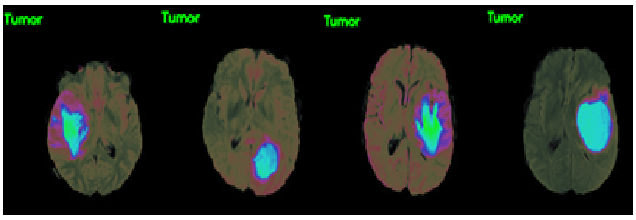
Figure 4. The training and validation loss and accuracy graphs for each epochs



(a)



(b)



(c)

(d)

Figure 5. Results of Sample segmentation on BRATS 2015 Challenge dataset.(a) The first row of the image shows the 77th slice of the axial view of subject pat121, pat162, pat165 and pat184. (b) The second row shows the ground truth result of the corresponding subjects. (c) The third row shows the prediction after applying the proposed method. (d) The fourth row shows the segmentation results of Fuzzy C means + morphological operator.

An comparison of the proposed method with that of Chaplot et al [18] and Gudigar et. al [19] are made. Table 2 shows the detection rates of the previous work of Chaplot et al., Gudigar et al., and the proposed work. A Chaplot et al proposed a detection method, by using 52 images and achieved an accuracy of 97%. In the Gudigar et al method, with 612 images, has achieved 98%. Our proposed method have been verified with 200 images has achieved 100%.

Table 2: Comparison of existing methods with state-of-art method

Author(s)	Number of images	Method used	Accuracy (%)
Chaplot et al. [18]	52	DWT + SVM	98
Gudigar et al. [19]	612	Wavelet + Curvelet + Sharlet+PSO+SVM	97.38
Proposed Method (BrainNet)	Training - 200 images Testing - 200 images	CNN+Fuzzy C Means + Morphological Operators	100

IV. CONCLUSION

A newly developed deep learning based BrainNet algorithm for detection of brain tumor in MRI images. It consist of fully Convolutional Neural Network, Fuzzy C Means and Morphological operators. The proposed method used a median filter and un-sharp masking filter as a pre-processing step.

The integrated deep learning BrainNet model was trained using 77th image slice of BRATS 2015 dataset. In post processing, Fuzzy C Means and Morphological operators were applied to segment the tumors in the image. It has proved a promising performance on the BRATS 2015 testing dataset and the results has been verified with 400normal and tumor brain image database. The experimental results show that the detection method provides an accuracy of 100% thus capable of detecting brain tumors of different types at low false positive rates.

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