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Brain Tumour Classification Using Convolutional Neural Networks

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ABSTRACT

Recently deep learning has been playing a major role in the field of computer vision. One of its applications is the reduction of human judgment in the diagnosis of disease. Especially, brain tumour diagnosis requires high accuracy, where minute errors in judgment may lead to misfortune. This project focuses on a solution to identify brain tumour using convolutional neural network. The classification mainly depends on segmentation and region estimation. The segmentation process mainly includes feature extraction by the use of convolutional layer and pooling layer. The pooling layer performs max pooling and average pooling. Segmentation includes training and testing. In segmentation, the intensities get standardized and then the non tumor regions are masked. CNN classifier is used for the classification of type of tumor in the brain. Region growing is used to locate the exact region where the tumor is present. The proposed method is easy to perform when compared to the manual segmentation.

Keywords - Brain extraction, MRI brain, Brain structure segmentation, CNN.

I. INTRODUCTION

Recently, Medical Image Processing has transformed to facilitate its diagnostic medical images precisely in MRIs, CT scans, PET scans and other techniques. The vivid informative imaging favors the doctors to detect the affectation of a patient and diagnose meticulously in an advanced perspective. Nevertheless, the treatment becomes more successful and simple.

The Technique of Magnetic Resonance (MR) was discovered by researchers at Stanford and Harvard, while analyzing how the process of physical matters interacts with magnetic waves. Magnetic Resonance Imaging (MRI) became a powerful test tool used to take detailed picture of soft tissue which includes sensitive body parts like brain[3]. MRI imaging technique can be useful in diagnosing a wide variety of diseases and conditions within the body parts by the medical professional mainly in Chiropractors, Dentists, Orthopedics specialists and surgeons [3].

Human brain is the most important and most complex organ which controls the whole human body. Diagnosing of brain tumor is a challenging task, because of its complex nature [1]. Brain tumor is the abnormal growth of cells in the brain which is one of the life-threatening disease for all mankind [2]. Different types of image processing techniques are being used for diagnosis, treatment and surgical planning. Mr Brain image techniques contribute a significant role in diagnosing the different kind of brain disorders. However, number of pre-processing methods are used to get a relevant and accurate segmentation results. Skull stripping is an important step in the Mr.Brain images [4]. Skull stripping is the process of eliminating non-brain tissues from the MR brain images such as eye ball, skin, muscle and skull. In this paper we propose an automatic and very accurate Skull stripping method for MR Brain images.

In recent years, computer-aided diagnosis technology based on machine learning has become increasingly popular in medical image analysis. Since the machine learning algorithm can train model parameters using different features of medical images and then use the trained model to predict the extracted features, it can solve classification, regression, and aggregation problems in medical images. Simultaneously, deep learning technology in machine learning can directly obtain high-dimensional features from data and automatically modify model parameters through forward propagation and back-regulation algorithms, allowing the model's output in related tasks to be optimized. As a result, medical data analysis using deep learning technology has become a research hotspot [1].

The rest of the paper presents as follows: Section II describes the related works. Section III describe Materials and Proposed Methodology. Section IV describes results and discussion Finally, Section V conclude the proposed method..

II. RELATED WORKS

Brain imaging is a commonly used technique for identifying many brain disorders such as tumor, stroke, paralysis etc. Non-brain tissues present in the MR brain images is the main problem for the accurate segmentation of brain parts. Many researchers have worked on different kinds of image processing techniques for the classification of brain part from MR images.

Asit Subudhi, Jitendra Jena and Sukanta Sabu introduced an extraction of Brain from MRI Images by Skull Stripping using Histogram Partitioning with Maximum Entropy Divergence [5]. Their algorithm includes different stages. First stage includes the process of enhancement with particle swarm optimization (PSO) to improve the performance. The quality of the enhanced image is evaluated automatically by using transformation function. Histogram partitioning with maximum entropy divergence technique is used to find the background. Threshold selection, Rough binary classification and Binary morphology methods are used for extracting the brain from the skull.

Manit Chansuparp , Annupan Rodtook , Suwanna Rasmequan and Krisana Chinnasarn presented an Automated Skull Stripping of Brain Magnetic Resonance Images using the Integrated Method [6]. The main aim of the presented system is remove non-cerebral tissues from the 2D MRI axial brain images. This brain tumor classification method consists of four stages. First stage is Object Attribute Thresholding used to produce binary image. Next process is morphology erosion for separating the touching object was applied. Third stage is component labeling is adopted to find the brain. Final stage is morphology dilation and region filling in order to enhance image and obtain lost edge.

K.Somasundaram and IIR.Siva Shankar implemented an Automated brain tumor classification Method using Clustering and Histogram Analysis for MRI Human Head Scans [7]. Initially they used Otsu thresholding technique to find the threshold value in order to eliminate low intensity pixels then the brain images are classified into three parts such as non-brain tissues and background. Finally non brain parts are removed from the brain part.

Andre G.R. Balan, Agma J.M. Traina, Marcela X. Ribeiro, Paulo M.A. Marques And Caetano Traina proposed a Smart histogram analysis applied to the brain tumor classification problem in T1-weighted MRI. In this proposed method they have introduced the Human Encephalon Automatic Delimiter (HEAD) for T1-weighted MRI. They used histogram analysis and binary morphological operations to obtain an accurate mask of the brain. The method consists of two steps background removal and brain extraction. Background removal method Isolate the highest peak in the gray-level histogram, aiming at identifying and discarding the background region.

III. MATERIALS AND PROPOSED METHODOLOGY

Image pre-processing is an important stage in the medical image processing applications. In medical images, a good pre- processing method will leads to the better segmentation results. So in order to obtain relevant and accurate segmentation results, we have to apply several pre-processing steps.

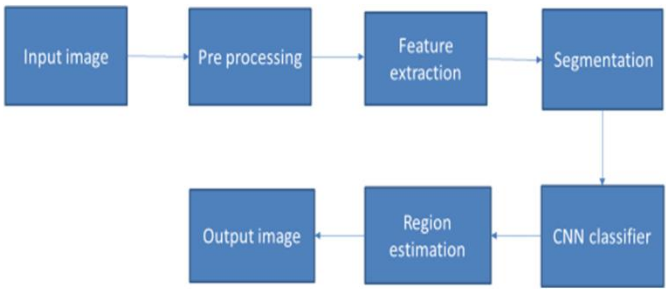

Figure1. Process flow of proposed brain tumor classification system.

A. Preprocessing

The aim of the pre-processing is an improvement of the image that suppresses unwanted distortions or enhances some image features important for further processing. It enhances the quality of the image and finally removes the noise present in the Image. Pre-Processing techniques aim the enhancement of the image without altering the information content. Image pre- processing is the operations on images at the lowest level of abstraction whose aim is an improvement of the image data that suppress undesired distortions or enhances some image features important for further processing. It does not increase image information content.

Steps involved in Pre Processing,

- Read image.
- Resize image.
- Remove noise(Denoise)

Image processing is important to get an enhanced image or to extract some useful information from the given image. To get an optimized workflow and to avoid losing time, it is important to process images after the capture of the image. In this method the pre-processing is done by removing the unwanted noise and distortions. Then they are converted to the Gray scale images and then to binary data. MRI images are given as the input and they are the Gray scale images. Then the Gray scale images are converted to the binary data. Then the morphological operation is done for the removal of skull. The morphological operation includes dilation and erosion. The dilation and the erosion operation is used for skull stripping in order to perform the process fast and accurately.

Gray Scale Images

The input image given to Pre-Processing is first converted to Gray scale images. As MRI images are Gray scale images it does not show any difference between input image and Gray scale image. Gray scale images are then converted to the binary image as they make the further process easier for segmentation and classification.

Binary Data

The Gray scale images are then converted to binary data. Gray level value below the threshold value is given as 0 and the Gray level value greater than the threshold value is given as 1. The binary data values are zeros and ones and they make the system to perform the operation effectively. Image normalization is done to change the range of pixel intensity value.

They are given by,

$g(x,y)= 1$, if $f(x,y) \geq T$ 0, otherwise

$g(x,y)$ represents thresholding value

$f(x,y)$ represents gray scale image pixel

Skull Stripping

Skull striping refers to the removal of non-brain structure and unwanted portions of image from scanned image to have the required image for tumour detection. Scanned image consists of brain area, scalp, skull and dura. The unwanted portions can be separated. Skull removing can be done with the help of intensity thresholding followed by morphological operation to obtain required brain area for tumor detection.

Dilation operation is one of the bases of morphology processing. Dilation is the operation of “lengthening” or "thickening" in a binary image. This special way and the extent of thickening are controlled by structural elements. The dilation operation add pixels to boundaries of the object. The output pixel is the maximum value of all pixels in the neighbourhood and then they are more visible and fills in small holes in objects.

Erosion operation is also one of the bases of morphological processing. Erosion “shrinks” or “thins” the objects in the binary image. As in the dilation, the way to shrink and the extent is controlled by a structure element. Erosion is used mainly to remove the pixels from the object boundaries. The output pixel is the minimum value of all pixels in the neighbourhood and then only substantive object remains others get eliminated.

B. Feature Extraction

Feature extraction is a process of dimensionality reduction by which an initial set of raw data is reduced to more manageable groups for processing. They may be specific structures in the image such as points, edges or objects. The features are extracted by convolutional layer and pooling layer. This process is used to reduce the dimensions for the further processing. The convolutional layer and the pooling layer is used to reduce the dimension using the feature map.

Convolutional Layer

It is the first layer to extract features from an input image. The mathematical operation that takes two inputs such as image matrix and a filter matrix. An image matrix multiplied with filter matrix gives the convolved feature. The convolutional layer operation is shown in figure 3.2. Here from the image matrix a 3x3 matrix is considered and they are multiplied with kernel matrix to obtain convolved feature.

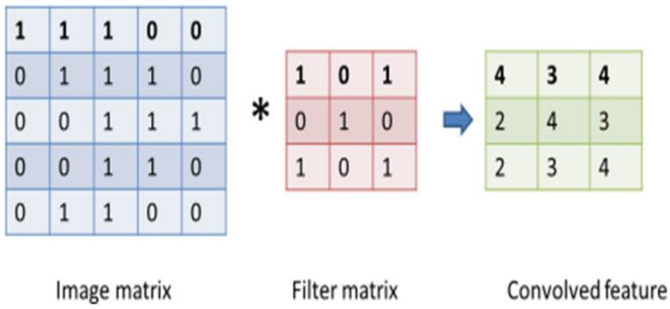

Figure 3.2 Operation in convolution layer

Pooling Layer

Pooling layers are used to reduce the dimensions of the feature maps. Thus, it reduces the number of parameters to learn and the amount of computation performed in the network. A pooling layer is another building block of a CNN. Its function is to progressively reduce the spatial size of the representation to reduce the amount of parameters and computation in the network. Pooling layer operates on each feature map independently. The most common approach used in pooling is max pooling. A pooling layer is a new layer added after the convolutional layer. The pooling layer summarises the features present in a region of the feature map generated by a convolution layer. So, further operations are performed on summarised features instead of precisely positioned features generated by the convolution layer. This makes the model more robust to variations in the position of the features in the input image.

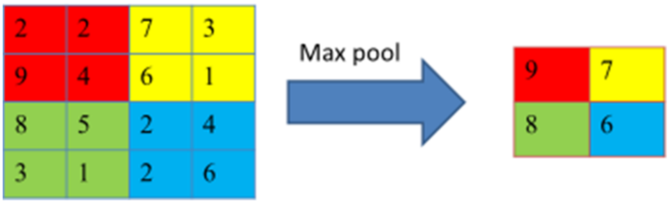

Figure 3.3 Operation in max pooling

Figure 3.3 shows the operation in max pooling. In max pooling the operation done by considering 2x2 matrix from each matrix and the maximum value of each 2x2 matrix gives the value. Thus from all the 2x2 matrix the maximum values are considered and that provides the maximum pooling. The features are extracted by reducing the dimension of the images to get the features very accurate and also for the effective features then these features can be very much useful in the classification using CNN and also for the feature map. The convolved feature gives the features for the classification.

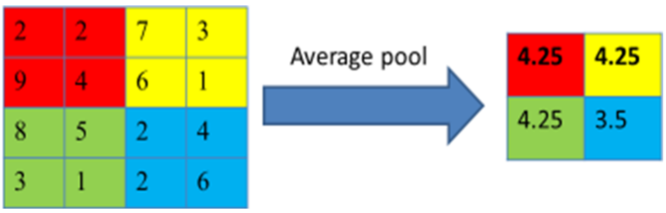

Figure 3.4 Operation in average pooling

Figure 3.4 shows the operation in average pooling. In average pooling the operation done by considering 2x2 matrix from each matrix and the average value of each 2x2 matrix gives the value. Thus from all the 2x2 matrix the average values are considered and that provides the average pooling.

C. Segmentation

Segmentation method mainly two class labels are there viz tumor and non tumor . To measure its accuracy four main parameters have been used. They are True positive, False positive, True Negative and False-negative.

True Positive: If the proposed framework correctly finds tumor then it is true positive. It is referred to as TP.

True Negative: If the proposed framework correctly finds out there is no tumor that means it is true negative. It is referred to as TN.

False Positive: If the proposed framework incorrectly shows the present of tumor then it is false negative. It is referred to as FP.

False Negative: if the proposed framework incorrectly shows that there is no tumor then it is false positive. It is referred to as FN.

These four parameters are used to calculate the following four metrics: **Accuracy, Precision, Recall and F1-Score.**

Accuracy is an important metric use to evaluate the proposed CNN-based classification model.

$$Accuracy = \frac{Number\ of\ Correct\ Predictions}{Total\ Number\ of\ Predictions}$$

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN}$$

Precision is the term used to define how positive identification is correct in classifications.

$$PRE = \frac{TP}{TP+FP}$$

Recall refers to the classifier in which propositions are correctly identified as actual positives.

$$REC = \frac{TP}{TP+FN}$$

The F1 score is used to measure the classifier's test accuracy. Is a function of Precision and Recall.

$$F1 = \frac{2 \text{ X } Precision \text{ X } Recall}{Precision+Recall}$$

The performance of these proposed algorithms has been evaluated with state-of-art CNN methods.

D. CNN Classifier

The CNN based brain tumor classification is divided into two phases such as training and testing phases. The number of images is divided into different category by using labels name such as tumor and non-tumor brain image…etc. In the training phase, pre-processing, feature exaction and classification with Loss function is performed to make a prediction model. Initially, label the training image set. In the pre-processing image resizing is applied to change size of the image.

Finally, the convolution neural network is used for automatic brain tumor classification. The brain image dataset is taken from image net. Image net is a one of the pre-trained model. If you want to train from the starting layer, we have to train the entire layer (i.e) up to ending layer. So time consumption is very high. It will affect the performance. The convolutional neural network is implemented in matlab programming. By using this, the accuracy of segmentation is improved and it has the features to process the larger dataset. To avoid this kind of problem, pre-trained model based brain dataset is used for classification steps.

IV. RESULTS AND DISCUSSION

A. Data Collections and System Configuration

In this project, we use 1264 images randomly selected from 187 patients with gastrointestinal tract tumor as our experiment. This includes 785 tumor affected images and 479 non tumor images. All these images were collected from the scan center in the Kims Hospital Trivandrum. Furthermore, 52% of these images were taken from male patients and the majority were between the ages of 50 and 60 years. The images are all pixel size of 620 * 480. As shown in Table I, divided this image data set into 4: 1 ratio for training and testing. Accordingly, 628 tumor images and 384 non- tumor images were taken for training and 157 tumor affected and 95 non-tumor images were taken for testing. To perform this experiment Matlab 2016 and Windows10 have been used and this software have been executed with a computer with Intel i5 1-8 GHz processor and a NVIDIA GeForce GPU.

Table2 Database Image Details

Data Split	Num. of Tumor Images	Num. of Non- Tumor Images
Training	628	384
Testing	157	95

B. Measurement Parameters

In a scenario where a segmented image needs to be compared with the ground truth image, the ground truth image is considered to be the base of the comparison considering foreground as "white" pixels and background as "black" pixels in ground-truth. Therefore the terms used as validation metrics to verify the quality of the segmented image are defined as:

1) **True positive (TP) :** pixels correctly segmented as foreground
2) **False positive (FP) :** pixels falsely segmented as foreground
3) **True negative (TN) :** pixels correctly detected as background
4) **False negative (FN) :** pixels falsely detected as background

These metrics are then used to calculate sensitivity and specificity.

Sensitivity: The sensitivity tells how likely the test is come back positive in someone who has the characteristic. This is calculated as in.

Sensitivity = TP/ (TP+FN)

Specificity: The specificity tells how likely the test is to come back negative in someone who does not have the characteristic. This is calculated as in (9). Few other metrics considered in this work for validation purpose are:

Specificity = TN/ (TN+FP)

According to our output, Iterative proposed CNN produce accurate result compared to traditional CNN method. This indicated that Iterative traditional CNN extract more unwanted tissue from head MRI. Figure 2 shows the graphical representation of the performance evaluation.

Table 3: Performance Evaluation of T1- Weighted, T2- Weighted AND FLAIR images

Data Set	Sensitivity		Specificity	
	Proposed CNN	Traditional CNN	Proposed CNN	Traditional CNN
T1-Weighted	95.0879	93.0329	94.9121	92.9697
T2-Weighted	97.0893	94.0361	92.9107	91.9639
FLAIR	96.4646	93.3646	93.5354	90.6354

Table 4: Time taken to extract the brain

Data Set	Time in second	
	Proposed CNN	Traditional CNN
T1-Weighted	0.03	0.21
T2-Weighted	0.04	0.27
FLAIR	0.12	0.31

Table 4 tabulated the time taken to extract the brain part from MRI using our proposed method. Traditional CNN method consume more time compare to proposed method. Figure 3 shows the graphical representation of time consumption.

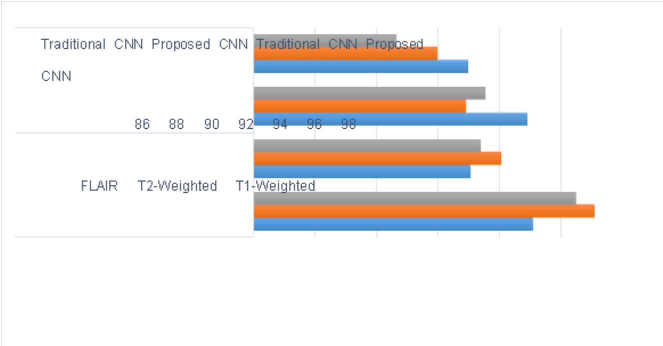

Figure: 2 Graphical representation of different time consumption.

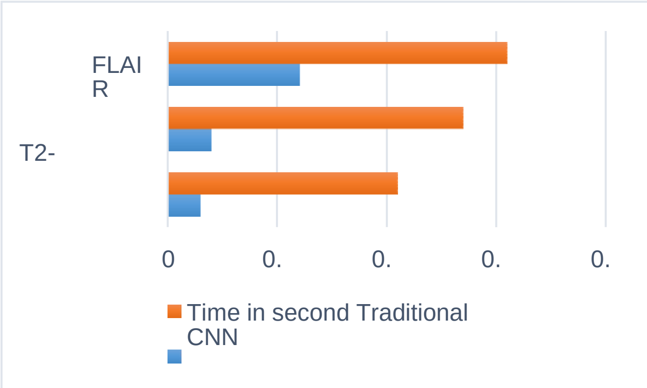

Figure:3 Graphical representation of different time consumption.

V. CONCLUSION

The method has been tested on three different types of datasets respectively T1-Weighted, T2-Weighted and FLAIR MR Images. The proposed method has been analyzed and tested with traditional CNN method. Also the method successfully produces better classification results for all three kinds of MRI images. The proposed method does not require any user intervention or setting any external initial parameters to extract the brain matter and thus qualify to be an automatic method. Experimental results ensure that our proposed method is suitable for any kind of human head MR images.

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