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AUTOMATED BRAIN TUMOR DETECTION USING DEEP LEARNING IN MR IMAGES

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ABSTRACT: Brain tumor detection is an important diagnostic process in medical field. Magnetic resonance imaging (MRI) is the prime imaging technique while analyzing the brain/skull with respect to brain tumor localization and detection. Brain tumor is one of the major reasons for human death every year. Around 50% of brain tumor diagnosed patient die with primary brain tumors each year in the United States. Electronic modalities are used to diagnose brain tumors. Among all electronic modalities, Magnetic Resonance Imaging (MRI) is one of the most used and popular for brain tumor diagnosis. This paper presents, automated Brain Tumor Detection using Deep Learning in MR Images. The dataset was collected from the website figshare, which consists of 2,123 images of MRI scans of the brain. This study proposed an automated approach that includes enhancement at the initial stage to minimize gray-scale color variations. To increase the efficiency and accuracy of diagnoses by the radiologists and neurologists, we propose a model which uses Convolutional Neural Networks (CNN) based on deep learning techniques to classify the common types of benign tumor. Experimental results affirm that described model provides better results compared to existed models.

KEYWORDS: Image segmentation, Brain Tumor, MRI Images, Deep Learning, Convolutional Neural Networks (CNN).

I. INTRODUCTION

Brain tumor is caused by the uncontrolled magnification of tissue in the brain or central spine that can disrupt proper brain function. Primary brain tumors originate from cells within the brain and secondary (metastatic) brain tumors begin in another part of the body and then spread to the brain [1].

Primary brain tumor affects 250,000 people around the world even in children below 15 years. The brain is a complicated part of the body and until the person presents with life-threatening symptoms like seizures or memory loss, it is impossible to know if the person has a brain tumor. Any type of brain tumor has its own risks that can ultimately cause death and the cause of the brain tumor is unknown. The growth rate, as well as the location of the tumor, can affect the function of the nervous system which can cause headaches, seizures, problem in balancing, memory loss and various other symptoms.

Among all electronic modalities Magnetic Resonance Imaging (MRI) is one of the most used and popular for brain tumor diagnosis. It takes a high resolution and high contrast images of the brain in the axial, coronal and sagittal orientation providing a three-dimensional assessment of the lesion [2]. The conventional method for CT and MRI brain images classification and tumor detection is still mostly based on a direct human inspection of those images, although other methods are being proposed. The MRI images visual evaluation and examination by radiologists is subjective by its nature and is time consuming and prone to errors or omissions, however due to the complexity of information at this point, it cannot be

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substituted with a fully automated evaluation.

Sometimes, the existence of abnormal tissues can be clearly noticed. Image segmentation is a key problem of image analysis. There are number of image segmentation techniques applied on MR images such as clustering method, histogram based method, region based method, fuzzy based method and threshold based method [3]. But the difficult task is to select an appropriate technique for a particular kind of image. Automatic segmentation is better than manual segmentation as, manual segmentation is a hard and time consuming work. Brain tumor may be of any size, shape and may appear at any location with different image intensities. In biomedical imaging segmentation is separating the tumor tissues such as tumor, solid, necrosis and edema from the normal brain tissues such as gray matter (GM), cerebrospinal fluid (CSF) and white matter (WM).

Brain tumor is broadly divided into two types: Malignant tumors contain primary tumors and metastatic tumors. It varies in size and shape. Its behavior, growth and function are quite differently from the normal tissues. In adults, Glioma is the most common brain tumor. It is slow in growth and stable at one place. It doesn't spread into other parts of the body. Brain tumor categorized different classes; primary and secondary brain tumors. Primary brain tumor originates in the brain itself like Meningiomas (MEN), child tumor Medullostroma (MED), Astrocytoma (AS), Gliboblastroma -Multiforme (GBM) whereas other brain tumors are cancer cells and originate in another part of the body and expand to brain like Metastatis (MET) tumors.

Deep learning is a training-based artificial intelligence (AI) method, which allows creating multiple layers of computation to teach multi-level machine representations of data [4]. This approach enhanced up-to-date technologies, such as speech recognition, identification of objects and many other domains. Training can be supervised or unsupervised. In a Tumor recognition applications, the raw input will represent pixel matrix, the first layer in the representation could abstract the pixels and put them into a code that detects edges of tumor, in next layer it put the code of the arrangement of tumor edges, the third representation layer put into the code of the representation of circles, and the next layer might be able to identify that the image comprises tumor. Essentially, a process in deep-learning is capable to pick up features and fit them in the proper place by itself. This paper used Convolutional neural networks, (CNNs or sometimes called ConvNets) which is considered one of the key classes for recognition and classifications of brain images.

II. LITERATURE SURVEY

A. Hazra, A. Dey, S. Gupta and M. Ansari, et. al. [5] proposed a method to detect and localize brain tumor from patients MRI images. The proposed method includes three stages: pre-processing, edge detection (Sobel, Prewitt and Canny edge) and segmentation (thresholding). Finally, k-means clustering was performed to identify the tumor region. But in their proposed method more regions exist besides tumor region in the output image which may cause confusion.

Eman Abdel-Maksoud, Mohammed Elmogy, Rashid Al-Awadi et. al. [6] presented an image partition in which k-means clustering method escorted by fuzzy

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c-means technique. K -means clustering technique detected the brain tumor faster than fuzzy c-means and it minimized the computational time. It used three benchmark datasets: digital imaging and communication in medicine (DICOM) dataset, brain web dataset and BRATS database. The algorithm was developed using MATLAB. The performance of KIFCM was better than FCM. KIFCM gave 90.5% accuracy of dataset1 and 100% accuracy of dataset2, 3. Rohini Paul Joseph, C. Senthil Singh, M.Manikandan, et. al. [7] explained that the very first step taken by doctors to treat brain tumors is to detect the tumor in the MRI. The paper mentions that 10 and 30% of tumors are missed when the traditional method is used. The proposed methodology uses clustering techniques along with morphological filtering for segmenting brain MRI images to detect tumor.

Ed-Edily Mohd. Azhari, Muhd. Mudzakkir Mohd. Hatta, Zaw Zaw Htike and Shoon Lei Win et. al. [8] presents a mothod for Detection and localization of the brain tumor is done using 5 different steps. The MRI images should be in .jpg format. Pre-processing includes image enhancement and edge filters are used to detect edges. Modified histogram clustering is applied to the enhanced image which represents the various grey areas present in the image. Morphological methods include dilation and erosion. The tumor in the brain can be detected and localized and shows up as white color in the dark image with a very low error rate. J.Vijay, J.Subhashini, et. al. [9] implemented a method called Brain tumor detection is done by implementing segmentation along with the help of K-means Clustering algorithm using the Matlab Simulator. The brain MRI which is given as input can be divided into four areas i.e. grey matter, cerebrospinal fluid, white matter and background. The morphological operation is applied to obtain the desired region. The unsupervised segmentation methods are better due to lesser preprocessing, less number of training and testing data when compared to supervised segmentation methods.

John et. al [10] introduced a new method that divides the images into cancerous and non-cancerous classes. The proposed algorithm consists of three steps: in the first step, the images are converted to different levels of coefficients using DWT, then the color intensity matrix is obtained, and using this matrix, features such as energy and solidarity and some other features that relate to the texture of images are extracted. In the final step, the type of class that each image belongs to is determined.

III. AUTOMATED BRAIN TUMOR DETECTION

The block diagram of automated Brain Tumor Detection using Deep Learning in MR Images is represented in below Fig. 1.

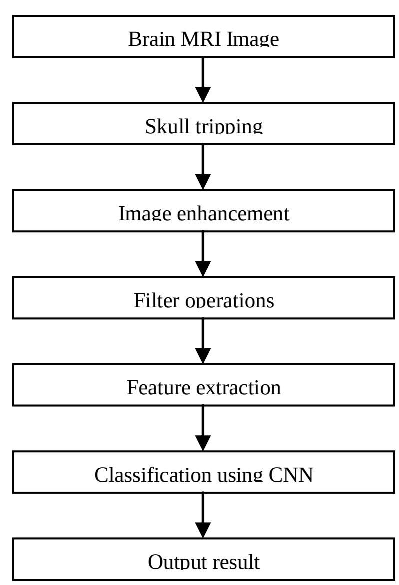

Fig. 1: BLOCK DIAGRAM OF BRAIN TUMOR DETECTION

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The dataset was collected from the website figshare, which consists of 2,123 images of MRI scans of the brain. The images are divided into 3 types of commonly found primary brain tumor, meningioma (710), glioma (704) and pituitary adenoma (709).

Skull stripping is a very important step in medical image processing as the background of the MRI image not containing any useful information, and it only increases the processing time. For skull removal, at first we used Otsu's Thresholding method which automatically calculates the threshold value and segments the image into background and foreground. After binarization of the MRI, erosion operation had been performed before applying connected component analysis.

Image enhancement is used as the first step of image preprocessing for this study. This study used contrast stretching as it comparatively performs better on the gray scale image as contrast increased without distorting relative gray level intensities. As a result, it does not yield any artificial looking image like histogram equalization.

Filter operation is performed on the image to increase the smoothness, sharpness as well as edge enhancement. Median filter has been applied in our proposed method instead of any other filters like mean filter and Gaussian filter.

Segmentation divides the image into regions based on the similar attributes. Basically, segmentation was performed to extract important features from the image for further analysis. Thresholding based Otsu's method is used of its wide uses to segment an image for further processing like feature analysis as well as to do the binary transformation of an image. It also takes less time to compute the threshold value than other techniques as the mathematical expression is simple.

Various shape features are required to identify the brain tumor. Our paper used four properties which include area, circularity (roundness and diameter), and solidity. We extract features of images to use in classification part. We also applied PCA feature selection algorithm to verify that the selected features are appropriate to detect the ROI (region of interest).

After feature extraction, we need to classify of the extracted features. In the Convolutional Neural Network, the neuron in a particular layer is connected to a limited number of neurons in the previous layer whereas in a fully connected network, each neuron in a layer is connected to all the neurons in the previous layer. CNN compares images part by part and these parts that it looks for are called features or filters. By matching these features in similar locations of the image, CNN sees similarity in a better way. Convolutional Neural Networks have the following layers- Convolution Layer, ReLU Layer, Pooling Layer, Fully Connected Layer.

IV. RESULT ANALYSIS

This section presents experimental performance analysis of described model. The dataset was collected from the website figshare, which consists of 2,123 images of MRI scans of the brain. The input MRI images are shown in below Fig. 2.

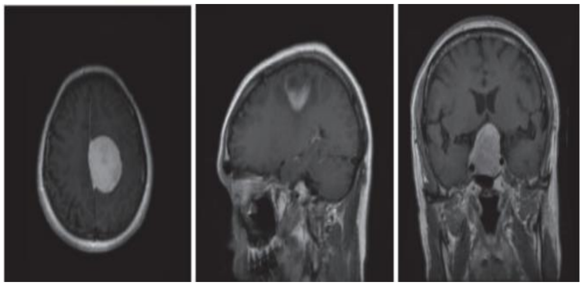

Fig. 2: TYPES OF TUMOR NAMELY MENINGIOMA, GLIOMA AND PITUITARY ADENOMA

The dataset is split the following way, 30% of the image dataset is assigned for testing the accuracy and loss from the dataset and the rest 70% of the image dataset is assigned for training the dataset. Based on the training data provided, the model is trained. When an image is fed into a CNN model some of the top features are extracted in each layer and the model produces the result based on that. Accuracy, Precision and Recall are used parameters in this study. The equations of these parameters are shown below:

$$Accuracy = \frac{TP + TN}{TP + TN + FN + FP} \ldots (1)$$

$$Recall = \frac{TP}{TP + FN} \ldots (2)$$

$$Precision = \frac{TP}{TP + FP} \ldots (3)$$

Below Table 1 show the classified brain tumor performance parameters values using described model. Fig. 2 shows the performance of described model for three classes.

Table 1: PERFORMANCE OF BRAIN TUMOR DETECTION USING CNN

Class	Accuracy	Precision	Recall
Meningioma	97	97	96
Glioma	96	96.5	95
Pituitary	96	96.2	95.6

The comparative accuracy analysis for automated Brain Tumor Detection using Deep Learning and other classifications as Support Vector Machine (SVM) and K-Nearest Neighbor (KNN) is elaborated in below Table 2. Fig. 3 shows the Pie chart representation of comparative accuracy analysis.

Table 2: ACCURACY ANALYSIS

Models	Accuracy
CNN	96.5
SVM	90
KNN	86

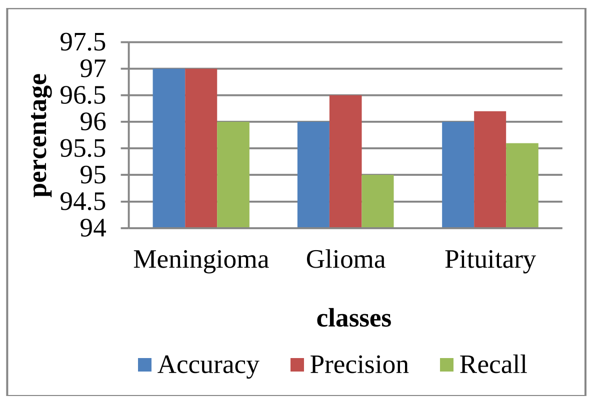

Fig. 3: PERFORMANCE OF DESCRIBED MODEL FOR THREE CLASSES

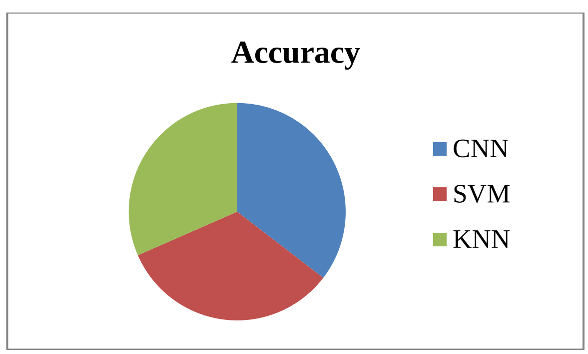

Fig. 4: ACCURACY ANALYSIS

Therefore, from results it is announced that, described automated Brain Tumor Detection using Deep Learning (CNN) is efficient than other classifications in terms of performance parameters as Accuracy (96.5%), Precision (96.4%) and Recall (95%).

V. CONCLUSION

In this paper, automated Brain Tumor Detection using Deep Learning in MR Images is described. Manual detection of brain tumor is not only a tedious process but also time consuming whereas an automated approach takes less time. The dataset was collected from the website figshare, which consists of 2,123 images of MRI scans of the brain. To increase the efficiency and accuracy of diagnoses by the radiologists and neurologists, we propose a model which uses Convolutional Neural Networks (CNN) based on deep learning techniques. Thresholding based Otsu's method is used of its wide uses to segment an image. Accuracy, Precision and Recall are used parameters in this study. Therefore, from results it is announced that, described automated Brain Tumor Detection using Deep Learning (CNN) is efficient than other classifications in terms of performance parameters as Accuracy (96.5%), Precision (96.4%) and Recall (95%).

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