Detection and Classification of Brain Tumor Using Artificial Intelligence

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Abstract: Brain Tumor is an abnormal intracranial growth caused by cells reproducing themselves in an uncontrolled manner. Most researches in the developed countries shows that main cause of death of people having Brain Tumor is incorrect detection of Brain Tumor. It is one of the most dangerous diseases and therefore it should be detected quickly and accurately. Generally, MRI or CT scan that is directed into the intracranial cavity produces the complete image of the Brain Tumor. Magnetic Resonance Imaging (MRI), a highly developed technique of medical imaging is used to visualize internal structure of human body without any surgery. For the accurate detection of Brain Tumor segmentation of MRI image is important. Classification of Brain Tumor through segmented MR images, is a difficult task due to complexity and alteration in Tumor tissue characteristics like its location, size, gray level intensities and shape. Nowadays due to increasing Tumor cases it is difficult to examine all the reports manually also it sometimes becomes hazardous for a patient due to delay in the detection of the Tumor or the right time required for its surgery.

In order to eradicate this problem an intelligent system is required for the detection and classification of brain Tumor automatically. Intelligence can be generally described as the ability to perceive information and retain it as knowledge to be applied towards adaptive behaviors within an environment or context. We propose a method which can automatically consider the MR images as an input and further analyze and process the input image and classify according to its presence and absence along with the type of Tumor detected. This can be done using two machine learning based techniques like neural networks and deep learning which can be used to solve many real-world problems.

Index Terms **- Brain Tumor, MR Images, Neural Networks, Deep Learning, Intelligent System.**

I. INTRODUCTION

Human Body comprises of several types of cells with each cell having a precise function. These cells grow and divide in an orderly manner which forms new cells to keep the body in good physical condition. Sometimes few cells cease their capability to control their growth and they grow in an improper fashion which leads to growth of extra cells forming a mass of tissue which is called a Tumor. Tumor when formed within a brain is called “Brain Tumor.” Brain Tumor is one of the most difficult types of Tumor to fight because of its vast variety of types. In total, there are more than 120 different types of Brain Tumors. Brain Tumors are classified as either Primary or Secondary. A Primary Brain Tumor means the cancerous cells originate in the Brain. A Secondary Brain Tumor is a mass of cells that originates elsewhere in the body, then it spreads through the bloodstream to the brain in a process known as Metastasis. The most common secondary brain tumors arise from the lung, breast, kidney, colon and blood cells. Once a diagnosis is made, the medical team attempts to determine whether the Tumor is intra-axial (within the central nervous system) or extra-axial (located outside the central nervous system). Brain Tumors are classified as either Benign or Malignant, although this classification is not always precise. [14]

Everything in our surrounding is evolving rapidly whether it is case of humans or machines. In this rage of evolution another concept emerged, having both the efficiency of machine and thinking ability of humans, we recognize it as “Artificial Intelligence”. AI can be applied to any field which requires the ability of thinking and analysis. Medical domain is one of such fields. Mostly doctors spend much of their time in the analysis of the medical reports. There are various machines available which can be used to find flaws in human body but it requires human intervention to reach conclusion. In order to reduce time of detecting issues and utilize that valuable time in treatment of the patient an Intelligent system is needed. So, we decided to develop an Intelligent system which will assist Neurological Surgeons in Detecting and Classifying Brain Tumor using Artificial Intelligence.

II. LITERATURE SURVEY

Brain Tumor Segmentation based on a Hybrid Clustering Technique, Eman Abdel-Maksoud et.al (2015) presented their methodology at Egyptian Informatics Journal, describing image segmentation as a process of partitioning an image into mutually exclusive regions. It can be considered as the most crucial process for facilitating the delineation, characterization and visualization of regions of interest in any medical image. A methodology of integrating K-mean clustering technique with Fuzzy C-mean algorithm for image segmentation is proposed. This process partitioned the image into mutually exclusive regions. The proposed technique can get benefits of the K-means clustering for image segmentation in the aspects of minimal computational time. In addition, it also gets advantages of the Fuzzy C-means in the aspects of accuracy. [1]

An Improved Brain MR Image Binarization Method as a pre-processing for abnormality detection and feature extraction, Sudipta Roy et.al (2017) proposed methodology in a Research Article, introducing a computerized method of MRI of Brain binarization for the uses of pre-processing of feature extraction and brain abnormality identification. One of the main problems faced in binarization is that many pixels of brain part cannot be correctly binarized due to extensive black background or large variation in contrast between background and foreground of MRI. In order to overcome such problems Binarization that uses mean, variance, standard deviation and entropy to determine a threshold value followed by a non-gamut enhancement is used. The proposed binarization technique after testing with a variety of MRI generated good binarization with improved accuracy and reduced error. Here experimentation was performed on two steps and proved that the proposed method is capable of working in MR images and their application domains. This method overcomes the problem of large intensity difference of foreground and background of MR images and it does not have any over binarization or under binarization problem for different kinds of images. [12]

Classification using Deep Learning Neural Networks for Brain Tumors, Heba Mohsen et.al (2017) proposed an automated technique at Future Computing and Informatics Journal, introducing Deep Learning which is a new Machine Learning field that gained a lot of interest over the past few years. It is widely used and applied in several applications and has been proven to be a powerful machine learning tool for solving complex problems. The technique proposed used Deep Neural Network classifier which is one of the Deep Learning architectures for classifying a dataset of Brain MRIs into various classes like normal, glioblastoma, sarcoma and metastatic bronchogenic carcinoma Tumors etc. It was observed that the classifier was combined with the discrete wavelet Transform a powerful feature extraction tool and principal components analysis which proved to be performing better over all the performance measures. The advantage of using this technique is that it requires less hardware specifications and takes a convenient time of processing for large size images. In addition, using Deep Neural Network classifier accuracy rate was higher as compared to other traditional classifiers. In future it is possible that more better results can be achieved if Discrete Wavelet Transform is used with Convolutional Neural Network. [7]

III. PROPOSED METHOD

The purpose of this paper is to detect and classify the Tumorous region of the Brain which will be further used for detailed diagnosis of Tumor essential for the treatment of the patient. The details about the proposed method is given below.

Neural Networks and Deep Learning provide the best solutions to many problems in fields of image recognition, speech recognition, natural language processing etc. Earlier technical methods used for the detection of Brain Tumor were efficient but in some cases the methods failed to notice the Tumorous part correctly from MR images because the image consists of non-Tumor tissue. (various types of tissues which makes it difficult to identify or differentiate between tumor affected and unaffected region) For this reason we propose method which uses Convolutional Neural Networks which is best for image segmentation and classification of objects. Segmented image helps to detect the tumorous region (Region of Interest) and based on the detected ROI we classify the Tumor whether it is Cancerous or Non-Cancerous.

3.1 Dataset

The Dataset which we used for experimentation is obtained from BraTS 2018 Challenge. This data is basically provided for segmentation challenge. It has four modalities T1, T1c, T2 and Flair. It consists of training datasets, validation datasets and test data. The dataset received is pre-processed and is used for training the model along with comparing the result with ground truth which is already provided in the dataset.

We used **Fluid Attenuated Inversion Recovery (Flair)** MRI sequence to train our model for Detection and Classification of Brain Tumor because the Flair sequence is similar to a T2-weighted image except that the TE (Time to Echo) and TR (Repetition Time) are very long. By doing so, abnormalities remain bright but normal CSF fluid is attenuated and made dark. This sequence is very sensitive to pathology and makes the differentiation between CSF and an abnormality much easier.

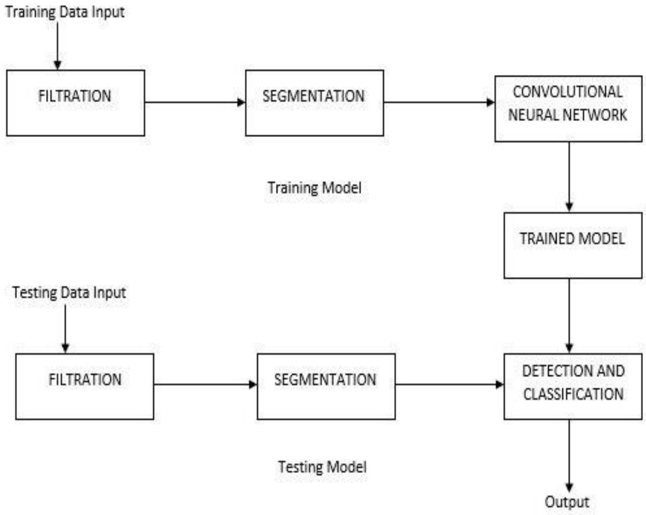
Dataset used is of two types Low-Grade Gliomas also known as Benign and High-Grade Gliomas also known as Malignant. Dataset consists of 210 cases of HGG and 75 cases of LGG which we used for training the model. We also used 67 cases of unknown data for testing the trained model.

3.2 Filtration

Filtration is a process of removing unwanted signals or noisy data that gets introduced in MR images during MRI scan due to electro-magnetic interferences. The MR images that we use for detecting Tumor thus consists of noisy data which is essential to be removed. Noise filtering techniques are basically of two types namely linear and non-linear. Linear filtering techniques apply the algorithm linearly to all the pixels of the image which defines the image as corrupted or uncorrupted pixel. Since, algorithm applies to all the pixels of image it causes the uncorrupted pixels to be filtered and hence becomes ineffective. The non-linear filtering technique is considered to be a two-phase process. In the first phase the pixels are identified as corrupted or uncorrupted and then further in the second phase corrupted pixel is filtered using specified algorithm while uncorrupted pixel value is retained. Most widely used non-linear filtration technique is median filter which uses median value to replace the corrupted pixel with the capability to remove impulsive noise while preserving the edges. Further on the basis of technique followed, median filters too are classified into many types out of which the Adaptive Median filter is found to be best. Adaptive Median Filter changes the size of the filtration window based on the conditions hence helps in retaining all the uncorrupted pixel values efficiently. It basically choses the median value of the pixel for filtration.

3.3 Segmentation

Segmentation is the process of partitioning an image into multiple segments (set of pixels also known as super-pixels.) Segmentation is done to simplify and change the representation of image into something which is easier and more meaningful to analyze. Human Brain is made of various soft tissues (White matter, Gray Matter and Cerebos Spinal Fluid) tumor is also a kind of tissue which is not the part of brain. Image segmentation is one of the most important steps in preprocessing as it provides the area of interest on basis of which it performs feature extraction. Segmentation is the most important process since the further training and testing of the model for its efficiency depends on it. Overview of the methodology is depicted below.



3.4 Convolutional Neural Network

In mathematical terms convolutional is a function derived from two given functions by integration which expresses how the shape of one is modified by the other.

$$(f * g)(t) \stackrel{\text{def}}{=} \int_{-\infty}^{\infty} f(\tau)\, g(t-\tau)\, d\tau$$

Convolutional Neural Networks like Neural Networks are made up of neurons with learnable weights as well as biases. Each neuron receives multiple inputs and takes weighted sum over them passing it through an activation function and responds with an output. Convolutional Neural Networks consists of many convolutional layers and each layer have its activation function (Rectified Linear Unit). After Convolutional layers there are fully connected layers with activation function at the output. These fully connected layers have various parameters due to which it is prone to overfitting.

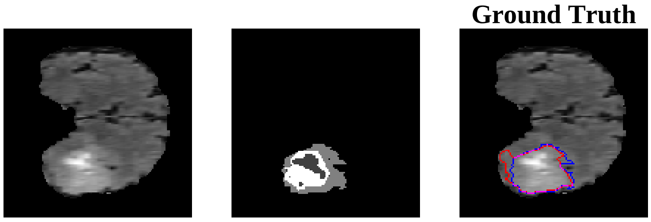
CNNs are basically used for the automation of models since it is capable of extracting features from datasets as well as training the model accordingly. On the basis of the pixel values the activation function provide output as an input to the next convolutional layer and in this manner all the values of the tumorous region get detected and it provides output as the detected Brain Tumor part. In case the Brain MR image is normal it will provide output as Tumor absent. Similarly, if the Tumor is detected it will use convolutional neural network to classify whether the Tumor is cancerous or non-cancerous. This model works in two parts. First part is the training part in which large amount of Tumorous Brain image dataset is provided so that the model can understand and learn the pattern of the Tumor pixels present in the MR image. Similarly, for the classification we provide dataset with two types of Tumor that is Benign and Malignant with corresponding labels. So that the model understands and learns the patterns of both Benign and Malignant Tumor. After successful training we perform validation in which the obtained outcome is compared with the ground truth received with the dataset to understand the accuracy rate of the model. The second part of the model consists of testing in which the model is checked against large number of datasets for its efficiency. Testing part is done to ensure the reliability rate, accuracy and the efficiency of the model.

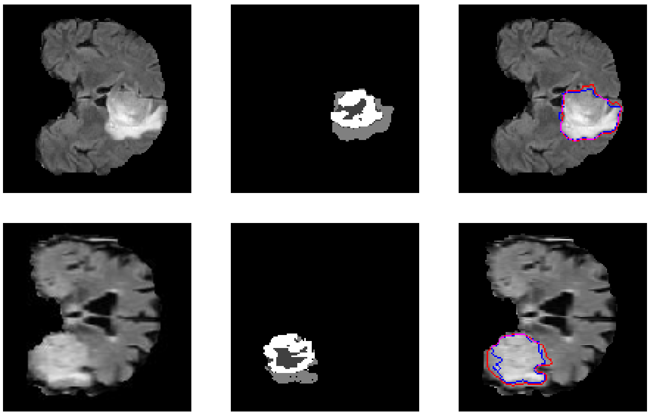
IV. RESULTS

4.1 Validation Testing Images

After the completion of Training Part of the model we performed testing of seen data which provided Disc Similarity Coefficient with maximum value of 0.96 and minimum value of 0.56. The visualization of the detected tumorous region by trained model is represented by red colored boundary and the ground truth which was provided as mask is represented by the blue color boundary.

Image **Segment** **Detection with Ground Truth**

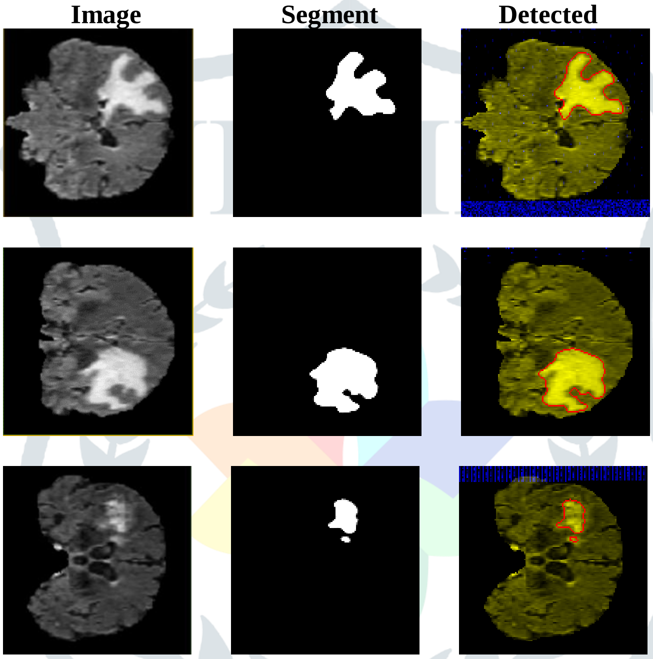




4.2 Performance on Unknown Images

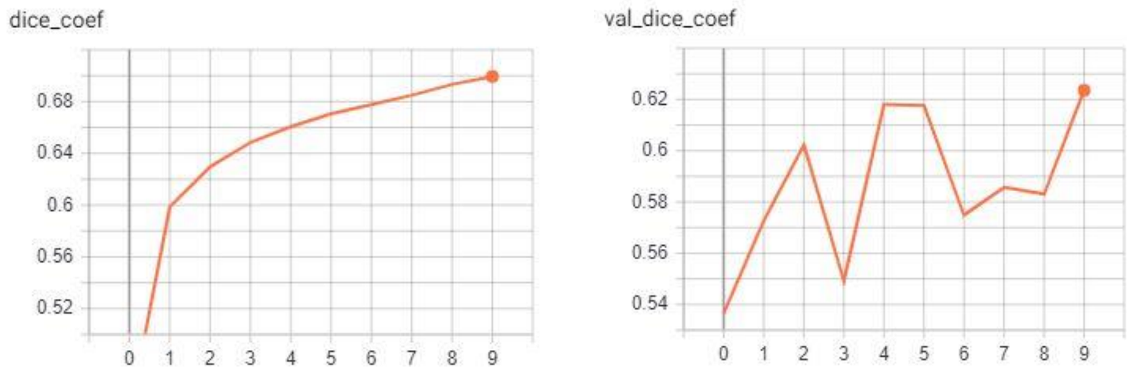
In order to check the performance of the trained model we performed testing on unknown dataset which was not used while training the model.

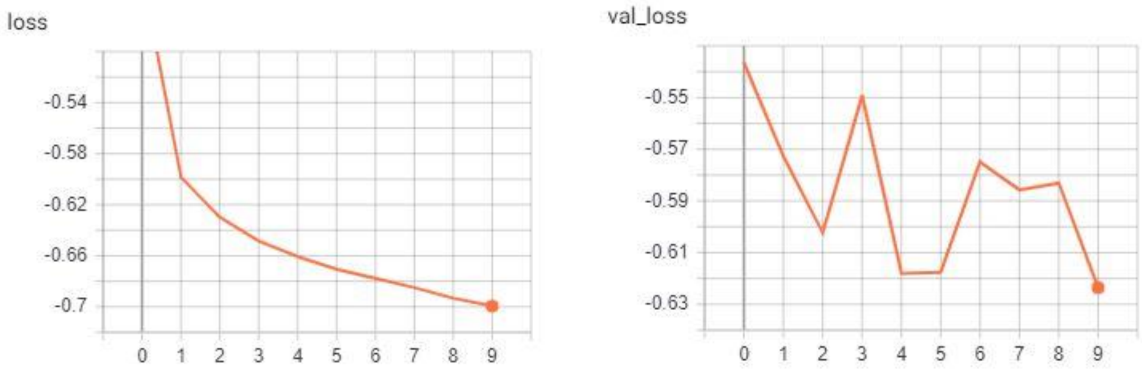
Image **Segment** **Detected**



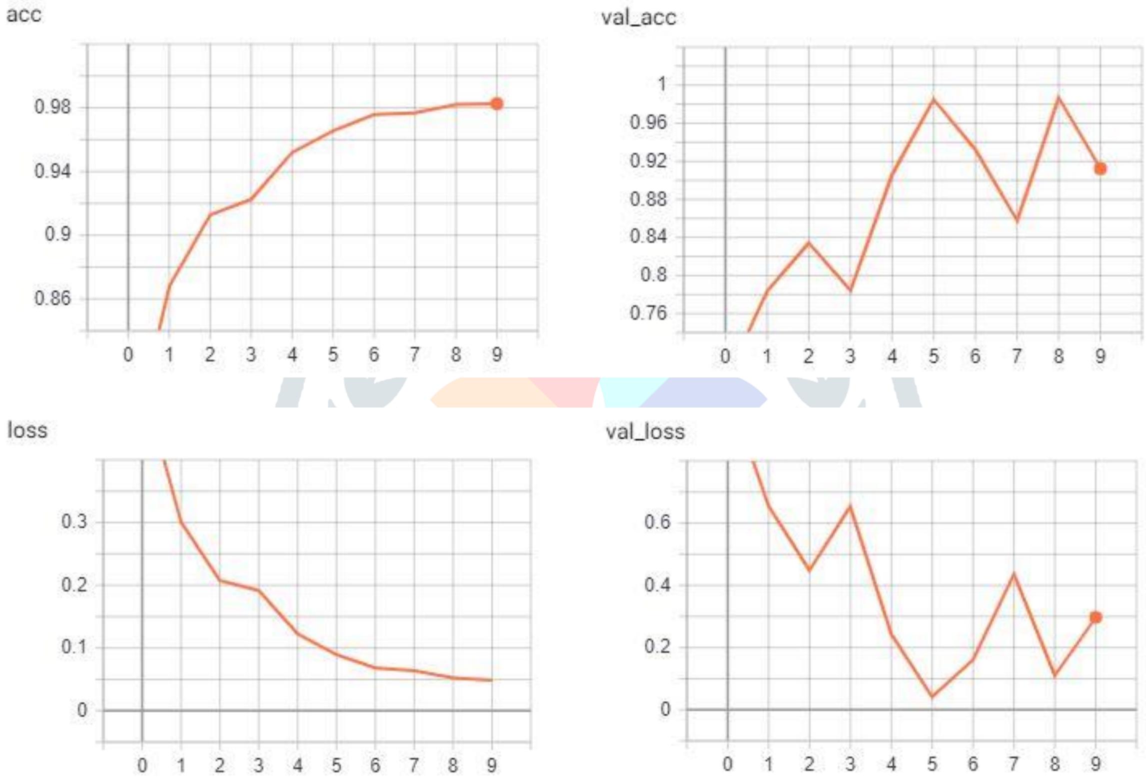
4.3 Graphs

I. Graph Generated While Training Detection Model

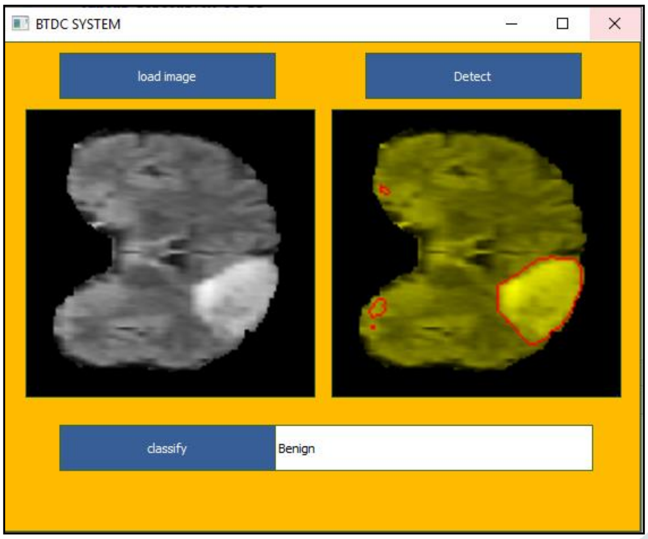




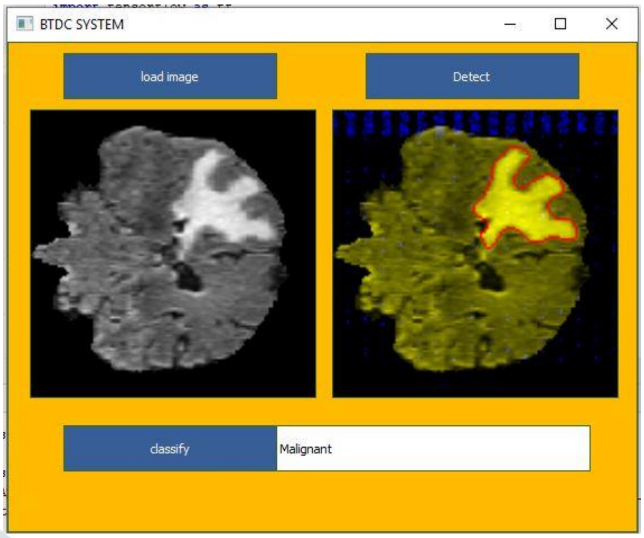
II. Graph Generated While Training Classification Model



4.4 GUI Displaying Detection and Classification Output



a. Model Classifying Detected Tumor as Benign



b. Model Classifying Detected Tumor as Malignant

V. CONCLUSION

The model is made in two parts Training and Testing. After successful implementation of the proposed method model worked well on seen i.e. validation image as well as on unseen Brain Tumor MR image. Trained Detection model gained Disc Similarity Coefficient value of 0.6994 and loss value of -0.6994. Meanwhile classification model also gained accuracy of 0.9231 and loss of 0.2051. Both models are trained for only 10 epochs and the result provided by the model is quite good. More epochs of training will help to gain accuracy of about 86%. The detected Tumorous region is represented by Red colored boundary and the classification represents type of Tumor i.e. Benign or Malignant.

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