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Brain tumor detection on MRI images using deep learning

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Abstract: Tumor detection is one medical issue that still remains challenging in the field of biomedical. Early imaging tech- niques such as cerebral angiography had thesurgeons in providing a drawback of being invasive and hence the CT and MRI imagingtechniques help surgeons in providing a bettervision. The computer assistance is also de- manded in medical institutions because it could improve the results of disease identifi- cation and negative cases should be very low. So, the Processing of Magnetic Reso- nance Imaging (MRI) images is one of the techniques to diagnose the brain tumor. The project describes the strategy to extract and detect brain tumor from patient's MRI scanned images. In this the Steps includes are pre-processing, feature extraction and estimation like accuracy, specificity, sensi- tivity, precision, and Mean IOU (Intersec- tion over Union)'

The deep learning model based on Convolu- tional Neural Network (CNN) algorithm fordetectingbrain tumors on MRI images. The proposed CNN model consists of multiple layers of convolutional, pooling, and fully connected layers that automatically learn and extract relevant features from the input MRI images. The dataset used in this study comprises of 1000 MRI images, which were preprocessed and augmented to en- hance the model's performance. This demonstrates the potential benefit of deep learning techniques for improving the accu- racy and efficiency of brain tumor detection on MRI images, which can aid in early di- agnosis and treatment planning.

Keywords: *Convolution Neural Network (CNN), Deep Learning, Brain Tumor.*

I. INTRODUCTION

The brain is one of the organs most im- portant organs in the human body and it is responsible for our ability to Think, Vol- untary Movement, Language, Judgment, and Perception. Responsible for the func- tions of Movement, Balance, and Posture. Without it, we would act like a 'walking puppets'. The word cerebellum comes from the Latin for "small brain". A brain tumor is characterized by the growth of a tumor in the brain, distinguishing it as be- nign (non-cancerous) or malignant (can- cerous). A brain tumor is a collection, or mass, of abnormal cells in your brain.Your skull, which encloses your brain, is very rigid. Any growth inside such a restricted space can cause problems. Brain tumors can be cancerous (malignant) or noncan- cerous (benign). Whenbenign or malig- nant tumors grow, they can cause the pressure inside your skull to increase. This can cause brain damage, and it can be life-threatening. Brain tumors are cat-egorized as primary or secondary. A primary brain tumor originates in your brain. Many primary brain tumors are benign. A secondary brain tumor, also known as a metastatic brain tumor, oc- curs when cancer cells spread to your brain from another organ, such as your lung or breast.

A brain tumor is a mass or growth of abnormal cells in your brain. Many dif- ferent types of braintumors exist. Some brain tumors are noncancerous (benign), and some brain tumors are cancerous (malignant). Brain tumors can begin in your brain (primary brain tumors), or cancer can begin in other parts of your body and spread to your brain as sec- ondary (metastatic) brain tumors. How quickly a brain tumor grows can vary greatly. The growth rate as well as the location of a brain tumor determines how it will affect the function of your nervous system. Brain tumor treatment options depend on the type of brain tu- mor you have, as well as its size and location.

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II. LITERATURE SURVEY

Raheleh Hashemzehi Sayyed Javad Sayyed Mahdavi Maryam Khairtabad Sayed Reza Kamel 2020[1]: A brain tumor is an abnormal growth of cells in-side the skull. Malignant brain tumors are among the most dreadful types of cancer with direct consequences such as cognitive decline and poor quality of life. Analyzing magnetic resonance im- aging (MRI) is a popular technique for brain tumor detection. In this paper, we use these images to train our new hybrid paradigm which consists of a neural au- toregressive distribution estimation(NADE) and a convolutional neural network (CNN). We subsequently test this model with 3064 T1-weighted con- trast-enhanced images with three types of brain tumors. The results demonstratethat the hybrid CNN-NADE has a high classification performance as regards the availability of medical images are limited.1

Javeria Amin Muhammad Sharif Mudassar Raza Mussarat Yasmin 2018[2]: Brain tumor is the growth of abnormal cells in brain some of which may leads to cancer. The usual method to detect brain tumor is Magnetic Reso-nance Imaging (MRI) scans. From the MRI images information about the ab- normal tissue growth in the brain is iden-tified. In various research papers,the de-tectionofbrain tumor is done byapplying Machine Learning and Deep Learning algorithms. When these algorithms are applied on the MRI images the predic- tion of brain tumor is done veryfast and a higher accuracy helps in providing thetreatment to the patients. This predic- tion also helps the radiologist in makingquick decisions. In the proposed work,a self-defined Artificial Neural Net- work (ANN) and Convolution Neural Network (CNN) is applied in detecting the presence of brain tumor and their performance is analyzed.

Rajeshwar Nalbalwar Umakant Majhi Raj Patil Prof. Sudhanshu Gonge 2014[3]: Brain tumor is a life-threatening disease. The brain contains more than 10 billion working brain cells. The damaged brain cells are diag-nosed themselves by splitting to make more cells.This regeneration takes place in an orderly and controlled manner. If the regeneration of the cells gets out of control, the cells will continue to di- vide developing a lump which is called tumor. In this paper a Brain Cancer De- tection and Classification System has been designed and developed. The sys- tem uses computer-based procedures to detect tumor blocks and classify the typeof tumor using Artificial Neural Net-work in MRI images of different pa- tients with astrocytoma type of brain tumors. The image processing tech- niques such as histogram equalization, image segmentation, image enhance- ment, and feature extraction have been developed for detection of the brain tu- mor in the MRI images of the cancer Detected patients **[3]**

III. METHODOLOGY

We proposing a novel technique for brain tumor classification using image processing techniques and CNN. For getting accurate output for classifying brain tumor, we have collected images of brain tumor images of different pa- tients. By building and training network using CNN layers for classifying brain tumor. Firstly, we take the image da- taset of different patients and train CNN using images of the different pa- tients. After training the network with dataset then we will take one input one patient image are thentested with CNN network which will classify the input image as Normal and Tumor. Here we investigate a better and accurate method for brain tumor classification using deep learning techniques.

The MRI dataset consists of around 1000 MRI images, including normal, benign, and malignant. These MRI im- ages are taken as input to the primary step. The pre-processing is an essential and initial step in improving the quality of the brain MRI Image. The critical steps in pre-processing are the reductionof impulsive noises and image resizing. In the initial phase, we convert the brain MRI image into its corresponding gray- scale image. The removal of unwanted noise is done using the adaptive bilateral filtering technique to remove the dis- torted noises that are present in the brain picture.

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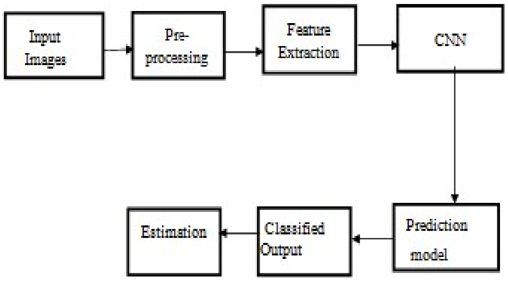

Fig 1; Block diagram of brain tumor detec-tion

MRI images can have different intensi- ty ranges, making it difficult to com- pare them. Intensity normalization techniques are used to rescale the inten- sity values of the images to a common range, making it easier to compare them. Data augmentation techniques such as rotation, scaling,and flipping are used to increase the size of the dataset and improve the robustness of the seg- mentation model. These preprocessing techniques can improve the accuracy and efficiency of brain tumor segmenta- tion and are essential for accurate diag- nosis and treatment planning.

Convolutional Neural Networks (CNNs) are a type of deep learning algorithm that has proven tobe highly effective in image classification tasks, including medical image classification such as brain tumor classification. Here are the basic steps involved in using a CNN for brain tumor classification. In CNN classification is to prepare the data. This involves acquiring a dataset of la- beled medical images, splitting it into training, validation, and test sets, and preprocessing the images by resizing, normalizing, and augmenting them. The next step is to build the CNN model. This involves defining the architecture of the network, including the number and type of layers, activation functions, pooling methods, and other hyperpa- rameters.

Once the CNN model is defined, the next step is to train the model using the train- ing dataset. This involves feeding the im- ages into the network, computing the loss, and adjusting the weights of the network through backpropagation to minimize the loss. After training the model, the next step is to evaluate its performance on the validation dataset. This involves calculat- ing metrics such as accuracy, precision, recall, F1 score, and confusion matrix to assess the model's ability to classify the images correctly. Once the CNN model has been trained and evaluated, the final step is to test the model on the test da- taset. This involves using the trained model to predict the labels of the images in the test dataset and calculating the final metrics such as accuracy.

IV. IMPLEMENTATION

This provides the architecture of the sys-tem that would be developed by our hands. It consists ofseveral steps where the execution starts from taking an input image from the data set followed by the image pre-processing, feature extraction, and estimation using brain tumor classi- fication using Convolutional Neural Network. Finally, the output is observed after all the above-mentioned steps are completed. Each module is unique in its own way. Every step has its importance. This architecture also includes a testing and training data set that are used to test and train the system.

The input image is pre-processed by using the noise filter like Median Filter and Bi- lateral Filter and the image is enhanced. Then the obtained image using segment- ed. Finally, the image classification is done using Convolutional Neural Net- work to predict whether the tumor is pre- sent or not. In image processing, filters are mainly used to suppress the high fre- quencies in the image. The filtering tech- nique used to remove noise from the im- ages. It is performed by sorting all the pixel values from the window into numer-ical order and then replacing the pixel be-ing considered with the median pixel val- ue. This filter removes the specklenoise and salt and pepper noise through ‘ON’ and ‘OFF’ of pixels by white and dark spots. The Bilateral filter is also a non- linear, noise-reducing smoothing filter for images. It replaces the intensity of each pixel with a weighted average of intensity values from nearby pixels. This weight is based on the Gaussian distribution. Bilat- eral filtering smooth images while con- serving edges utilizing a nonlinear group- ing of neighboring image pixels.

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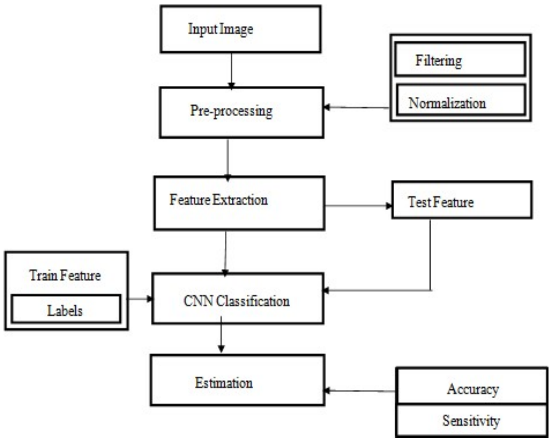

Fig 2: Flow chart of brain tumor detection

A. Pre-processing

The MRI images are taken as input to the primary step. The pre-processing is an essential and initial step in improving the quality of the brain MRI Image. The critical steps in pre-processingare the re- duction of impulsive noises and image resizing. In the initial phase, we convert the brain MRI image into its correspond- ing gray-scale image. The removal of unwanted noise is done usingthe adaptive
bilateral filtering technique to remove the distorted noises that are present in the brain picture. This improves the di- agnosis and also increase the classifica- tion accuracy rate. In image processing, image acquisition is done by retrieving an image from dataset for processing. It is the first step in the workflow sequence because, without an image no processing is possible. The image that is acquired is completely unprocessed.

B. Feature Extraction

feature extraction techniques used in brain tumor detection. Shape-based fea-tures are extracted from the contour of the tumor region, such as the area, pe- rimeter, circularity, and solidity. These features can help distinguish between different types of tumors and healthy tis- sue. Texture-based features are extract- ed from the texture patterns of the tu- mor and healthy tissue. These features can help differentiate between different tumor types and grades. Intensity-based features are extracted from the intensity values of the tumor and healthy tissue, such as mean, median, standard devia- tion, and entropy. These features can help distinguish between tumor and healthytissue and between different tu- mor types. Wavelet-based features are extracted by applying the wavelet trans- form to the medical images, which can help identify subtle changes in the tex- ture and intensity of the tumor and
healthy tissue.

C. CNN Classification

Classification is the best approaches for identification of images like any kind of medical imaging. All classification algo- rithms are based on the prediction ofimage, where one or more features and that each of these features belongs to one of several classes. An automatic and reliable classification method Convolu- tional Neural Network (CNN) will be used since it is robust in structure which helps in identifying every minute details. A Convolutional Neural Network (Conv Net/CNN) is a Deep Learning algorithm which can take in an input image, assign importance to various aspects/objects in the image and be able to differentiate one from the other. The pre- processing required in a Conv Net is much lower as compared to other classification algo- rithms.While in primitive methods filters are hand-engineered, with enough train- ing, Conv Net have the ability to learn these filters/characteristics

D. Trained and Test the Datasets

Training and testing datasets are essen- tial for developing and evaluating Deep learning models, including those usedfor brain tumor detection. Here are the general steps for training and testingda- taset. Collect a diverse set of images forboth tumor and non-tumor cases. En- sure that the images have the same for- mat and resolution. Preprocess the im-ages to remove noise, normalizeintensi- ty, and segment the tumor region. This step can be performed manually or us- ingautomated techniques. Divide the da- taset into three subsets: training, valida- tion, and testing. The most common split is 70/15/15, where 70% of the data is used for training, 15% for validation, and 15% for testing. Apply data aug- mentation techniques such as

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rotation, flipping, and scalingto increase the da- taset's size and diversity.

V. RESULT

The model was trained with the specifi- cations. In the training process, 35 epochs were run to train this model. The challenge of identifying a tumor is quite difficult. The position, form, and structure of tumorsdiffer greatly from one patient to the next, making segmen- tation a difficult process. In figure, var- ious location of the scans of the same brain sliced segment from different pa- tients, clearly indicate the tumor diver- sity. The position of the tumor is obvi- ously different in each of the images- presented.

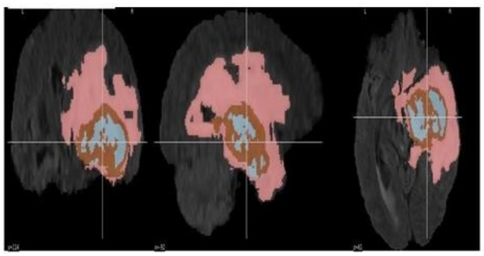

Fig 3: Regions in which brain tumor is shown in different locations

Training

Initially the model was trained with 15 epochs, but the nature of the graphs showed gradual improvement, then in order to get better results the number of epochs was increased to 25 where the results were better but in order to rein- force our results further it was in- creased to 35 epochs where the results were getting stabilized. Finally, the model was trained with 35 epochs and it was trained by the training process to be complete so that it be used further the model.

While training the model, we stored all the metrics for each epoch. Then the saved model was loaded and used to plotmetrics for training and validation. In Figure, the graphs show the trainingmet- rics where the blue line symbolizes the training metric and the red line de- scribes the validation metric, where the y-axis indicates the number of epochs and the x-axis indicates the score. Fig- ure (a) shows the accuracy of training and validation with varying epochs. It states that training accuracy is slightly higher than validation accuracy and they reach the plateau at about 20 epochs. Figure (b) shows training and validation loss, and the difference is about 0.01 so it can be concluded that it is a good fit. Figure (c) shows a signifi- cant increase in dice with a subsequent increase in the number of epochs in both training and validation. Finally, figure (d) shows the Mean IOU of the training and validation set. The mean IOU score of training and validation reached a value greater than 0.5 after about 15 epochs, and greater than 0.8 af- ter about 25 epochs which is a good score to have.

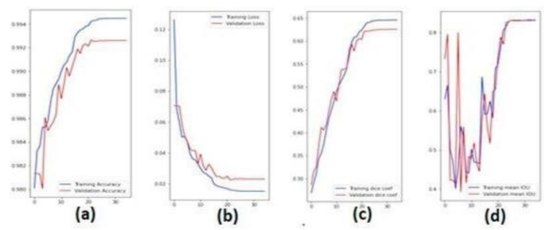

Fig 4: (a) Graph describing the accuracy, (b) loss for each epoch, (c) Graph describing the Dice Coefficient, (d) and Mean IOU for each epoch

VI. CONCLUSION

In this, we have developed a new brain tumor detection architecture that benefits from the characterization of the five MRI modalities. It means that each mo- dality has unique characteristics to help the network efficiently distinguish be- tween classes. We have demonstratedthat working only on a part of the brain im- age near the tumor tissue allows a CNN model (that is the most popular deep learning architecture) to reach perfor- mance close to human observers. More- over, a simple but efficient cascade CNN model has been proposed to extract both local andglobal features in two different ways with different sizes of extraction patches. In our method, after extracting the tumor's expected area using a power-ful preprocessing approach, those patchesare selected to feed the network that theircenter is located inside this area. This leads to reducing the computational time and capability to make predictions fast for classifying the clinical image as it re- moves a large number of insignificant pixels off the image in the preprocessingstep.

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