© March 2022| IJIRT | Volume 8 Issue 10 | ISSN: 2349-6002

Detection and Classification of Brain Tumor in MRI Images Using Deep Convolutional Network

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***Abstract* - The detection, segmentation, and extraction from Magnetic Resonance Imaging (MRI) images of contaminated Tumor areas are important concerns; however, a repetitive and extensive task executed by radiologists or clinical experts depend on their expertise. Image processing concepts can visualize the various anatomical structure of the human organ. Recognition of human brain abnormal structures by basic imaging techniques is challenging. To overcome this issue, in this paper, CNN deep learning algorithm was proposed for detecting the Tumor and marking the area of their occurrence with Regional morphological convex hull algorithm. The selected MR image dataset consists of two primary brain Tumors namely malignant and Benign. The proposed algorithm uses CNN architecture for both the region identifier and the classifier network. Here various Feature extraction methods are also extracted. Detection and classification results of the algorithm demonstrate that it is able to achieve a standard deviation 89.77% for meningioma and benign Tumor. As a performance measure, the algorithm achieved a Homogeneity of 92% for all the classes.**

***Index Terms* - Brain Tumor detection, Malignant, Benign, CNN, Homogeneity, MRI.**

I.INTRODUCTION

Cerebrum growths are known as the majority shaped by the unusual multiplication of synapses by disposing of the mind's control components. Cancers that might shape in the skull can develop, put squeeze on the cerebrum and unfavorably influence body wellbeing. Early identification and grouping of cerebrum growths is a significant exploration space in the field of clinical imaging and as needs be helps in choosing the most advantageous treatment technique to save patients life. Cerebrum cancers can be grouped in more ways than one. For example, one of the famous grouping types is to arrange the cerebrum growths as harmless and threatening cancers. Cerebrum harmless growths are typically cancers that create inside the skull however outside the mind tissue. Meningiomas structure a significant piece of this gathering. Dissimilar to harmless cancers in different organs, mind harmless growths can now and again cause perilous circumstances. Some (for instance, meningiomas) may seldom transform into harmful growths. Since they typically don't spread to the encompassing cerebrum tissue, they have a high possibility being taken out by a medical procedure. Growths that beginning in pituitary organs which control chemicals and direct capacities in the body are called pituitary cancers. Pituitary cancers are known as harmless growths and don't spread to different pieces of the body. Albeit the vast majority of the pituitary cancers are harmless, they seldom return to dangerous growths. The complexities of pituitary growths can cause super durable chemical lack and loss of vision. Cells in harmful growths are strange cells that imitate in an uncontrolled and sporadic way. These cancers can pack, invade or obliterate ordinary tissues. Metastatic mind growths are known as cerebrum cancers that rise out of one more piece of the body and spread to the cerebrum. They generally start from the lung, bosom, digestive organ, stomach, skin or prostate. Gliomas are the most widely recognized cerebrum dangerous growths. They are the reason for the greater part of the cerebrum tumors and contain cells with uncontrolled expansion. Despite the fact that they can seldom spread to the spinal rope or even to different organs of the body, they develop quickly and may stretch out into the encompassing sound tissues.

The unusual development of cells in human cerebrum is called as mind growth. A growth which happens in the cerebrum or spinal line is called as glioma and the cancer that emerges from the meninges is called as meningioma. The strange cell development in the pituitary organ is seen as pituitary cancer. The T1-

weighted contrast improved Magnetic Resonance (MR) pictures can be utilized for the recognition and confinement of cerebrum cancer. In view of shading contrast contrasts, it is additionally ready to separate cerebrum tissues, edema and cerebrospinal liquid [1]. The early cerebrum growth recognition is especially required for powerful treatment. For clinical picture analysis, the pictures can be gotten from different imaging modalities specifically Positron Emission Tomography (PET), Magnetic Resonance Imaging (MRI) and Computed Tomography (CT). Among this large number of modalities, MRI is viewed as best for mind cancer finding. X-ray is innocuous in light of the fact that it depends on attractive field and radio waves and represent no radiation risk to human body [2]. Programmed cancer recognition and characterization strategies are expected to lessen analysis time and conquer human mistakes prior to settling on any choices. Generally major picture division methods were applied to confine mind growth locale. Profound learning calculations were broadly utilized for distinguishing the visual items in shading pictures. In this work, Faster R-CNN calculation was picked for distinguishing and ordering the cerebrum cancer types. The CNN model purposes base organization. The calculation features the cancer district and distributes the certainty scores alongside limit. The calculation was prepared to distinguish three essential mind growths in particular glioma, meningioma and pituitary.

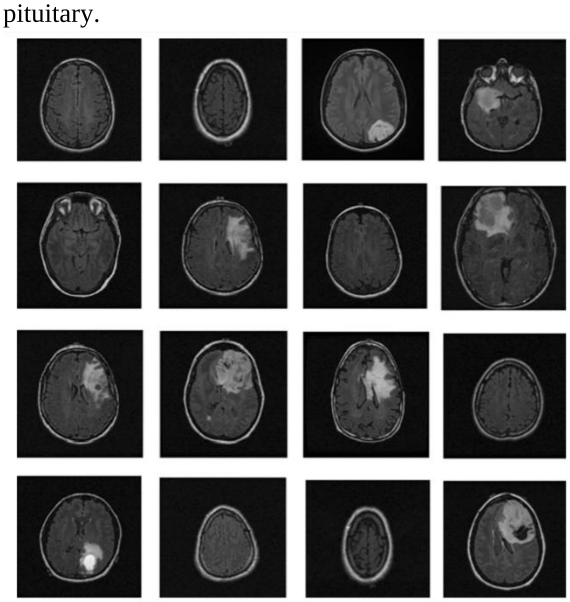

Fig 1: Examples of brain Tumor MRI images with different grades from data store (source from Google)

II.LITERATURE SURVEY

from the whole brain and from an automatically defined Tumor region. They achieved accuracy of 89.5% using the grade prediction from whole brain and accuracy of 92.98% using the grade prediction from the Tumor ROI. Abiwinanda et al. (2019) implemented the simplest possible architecture of CNN to recognize three most common types of brain Tumors, i.e., the glioma, meningioma and pituitary achieving a validation accuracy of 84.19% at best. In 2019, Hossam et al. (2019) proposed a CNN architecture to classify brain Tumors into meningioma, glioma and pituitary and differentiated between the three glioma grades (Grade II, Grade III and Grade IV). The following researchers have adopted pre-trained CNN models using transfer learning approach for brain Tumor classification. For instance, C¸ inar and Yildirim (2020) used a modified form of pre-trained ResNet-50 CNN model by replacing its last 5 layers with 8 new layers for brain Tumor detection. They achieved 97.2% accuracy using MRI images with this modified CNN model.

In a similar manner, Khawaldeh et al. (2017) proposed a modified version of Alex Net CNN model to classify brain MRI images into healthy, low-grade glioma and high-grade glioma. An overall accuracy of 91.16% was obtained using 4069 brain MRI images. Talo et al. (2019) suggested the pre-trained ResNet-34 CNN model to detect brain Tumor from MRI images. Although they achieved a detection accuracy of 100%, the number of images they used for the deep learning model was 613, which were not considered as a high number for machine learning studies. Rehman et al. (2020) proposed using three pre-trained CNN models known as Alex Net, Google Net and VGG16 to classify the brain Tumors into glioma, meningioma and pituitary. The best classification accuracy of 98.69% was achieved by the VGG-16 during this transfer learning approach. They used 3064 brain MRI images collected from 233 patients. Mehrotra et al. (2020) made use of deep learning-based transfer learning technique to classify the brain Tumor images as malignant and benign using 696 T1-weighted MRI images. The most popular CNN models such as ResNet-101, ResNet-50, Google Net, Alex Net and Squeeze Net have been used for the classification study and compared with each other. They achieved the highest accuracy of 99.04% with the help of transfer learning through pre-trained AlexNet CNN model. Deepak and Ameer (2019) used pre-trained Google Net CNN model to differentiate among glioma, meningioma and pituitary brain Tumor types. A mean classification accuracy of 98% was obtained in this 3-class classification problem using MRI images.

In 2018, Yang et al. (2018) investigated the effect of CNN trained with transfer learning and fine-tuning to noninvasively classify low-grade glioma (LGG) and high-grade glioma (HGG) by analysing on conventional MRI images. They achieved the accuracy of 86.6% using pre-trained Google Net and 87.4% using pre-trained Alex Net. There are also researchers who perform brain Tumor classification by combining the deep learning concept with other methods. For instance, Mohsen et al. (2018) used deep neural network (DNN) classifier combined with discrete wavelet transform (DWT) and principal component analysis (PCA) to classify brain MRI images into four classes as normal brain, glioblastoma, sarcoma and metastatic bronchogenic carcinoma Tumors. The accuracy rate was found to be 96.97%. Khan et al. (2020) proposed a deep learning method for classification of brain Tumors into cancerous and non-cancerous using 253 real brain MRI with data augmentation. They used edge detection to find the region of interest in MRI image prior to extracting the features by a simple CNN model. They obtained 89% classification accuracy.

In 2019, Kabir Anaraki et al. (2019) proposed CNN and genetic algorithm (GA)-based method to noninvasively classify different grades of glioma using MRI images. They achieved an accuracy of 90.9% for classifying three glioma grade and accuracy of 94.2% for glioma, meningioma and pituitary Tumor types. Ertosun and Rubin (2015) developed a deep learning pipeline with ensemble of CNN for the problem of classification and grading of glioma from pathology images. Their method was considered quite successful in cases of lack of data, which is a common problem in the domain of deep learning approaches. They achieved 96% accuracy for HGG vs. LGG classification task and 71% accuracy for LGG Grade I versus LGG Grade II classification task. Researchers and readers who are interested in further papers on brain Tumor classification using CNN can examine the following review articles (Litjens et al. 2017; Lotan et al. 2019; Muhammad et al. 2021; Shaver et al. 2019; Shirazi et al. 2020; Tandel et al. 2019; Tiwari et al. 2020), which are very rich resources on this topic.

III.PROPOSED METHODOLOGY

For classifying each proposal, our aim is to crop the feature map regions and feed them to R-CNN which requires fixed-size input. The RoI Pooling layer crops the convolution feature maps and makes it to fixed using bilinear interpolation method. After cropping each proposal, max pooling is used to get a final feature map. Finally, R-CNN classifies the proposals into one of the three classes and adjusts the bounding box of each proposal with respect to Tumor region.

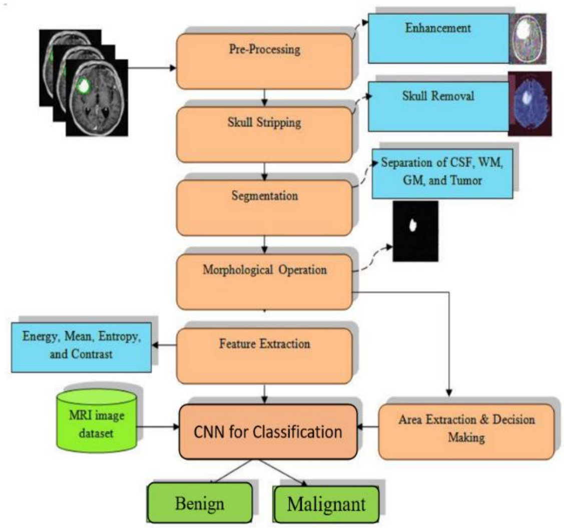

Fig 2: Proposed Architecture for Tumor Extraction

A)Steps involved in Proposed Architecture

i) Pre-Processing:

The essential activity of pre-handling is to improve the nature of the Magnetic Resonance pictures and to make them reasonable for additional handling by means of a human visual for individuals or PCs. Pre-handling prompts further developing explicit Magnetic Resonance picture boundaries like the upgraded SNR proportion, the improvement of the visual look of the Magnetic resonance Image, the end of pointless commotion, and the underseen parts from the image, smoothing the district's inward part and holding its edges. To apply versatile differentiation improvement in light of a changed sigmoid element to upgrade the SNR proportion

ii) Skull Stripping:

Skull stripping is a major biomedical image analysis procedure. It is essential for a practical test of brain Tumors from MR images, in which all non-brain tissue in brain imaging is removed. Skull stripping enables additional brain tissues like skull, skin, and fat to be extracted in brain images. There are a variety of skull stripping techniques available, some of which are common include the use of an automated skull stripping by image contour, segmentation-and morphological stripping of the skull, and hector graphic analysis or threshold-based skull stripping.

iii) Morphological Operation and Segmentation:

In the primary stage, the pre-handled mind Magnetic Resonance picture will be changed into a double picture with a limit of 128 for the end. Pixel values higher than the predetermined limits are planned as white, with different locales set apart as dark; these two permit different areas to be produced around the sickness. In the subsequent stage, a disintegration cycle of morphology is utilized to extricate white pixels. Ultimately, the disintegrated region and the first picture are isolated into two equivalent regions, and the locale with dark pixels from the dissolving is considered a cover of mind Magnetic Resonance picture. In this paper, wavelet change is utilized for the effective division of the cerebrum Magnetic Resonance picture.

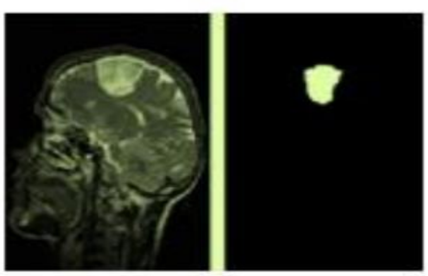

Fig 3: Fully Automatic Heterogeneous segmentation

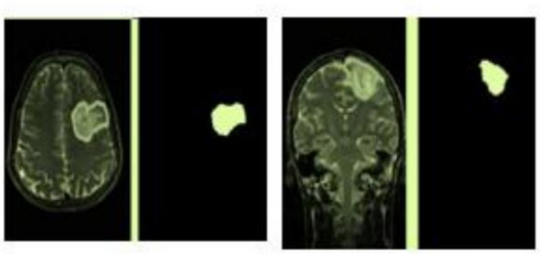

Fig 4: shows the axial image and Coronal image its segmentation.

iv) CNN Classification:

The block diagram of brain tumor classification based on convolution neural network is shown in fig. 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, preprocessing, feature exaction and classification with Loss function is performed to make a prediction model. Initially, label the training image set. In the preprocessing 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. To avoid this kind of problem, pre-trained model based brain dataset is used for classification steps. In the proposed CNN, we will train only last layer in Matlab implementation. We don't want to train all the layers. So computation time is low meanwhile the performance is high in the proposed automatic brain tumor classification scheme.

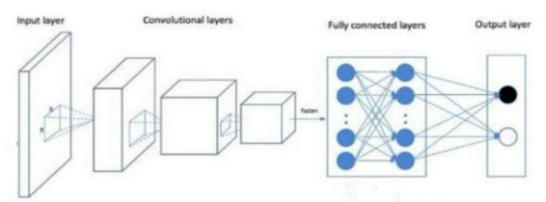

Fig.5: CNN Architecture

IV.EXPERIMENTAL RESULTS

It is vital to assess the characterization execution in picture order studies to deductively uphold the aftereffects of the review. In any case, the grouping study would stay fragmented and scholastically powerless. There are different execution assessment measurements that have been utilized for quite a while in picture grouping studies and have become standard execution assessment measurements in comparable examinations.

These are exactness, particularity, responsiveness. These measurements that are acknowledged as standard execution assessment measurements in picture grouping review are additionally used to quantify the precision and dependability of the characterization cycle in this paper.

Fig 6.1: Brain Tumor Result

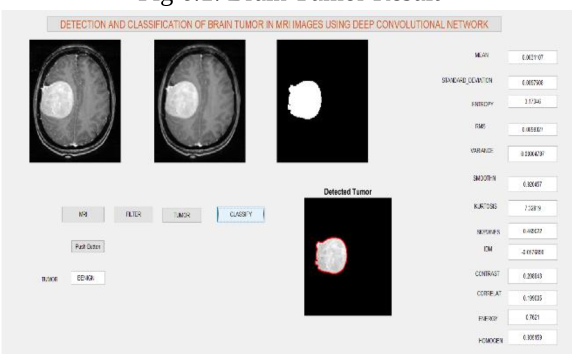

Fig 6.2: Benign Brain Tumor

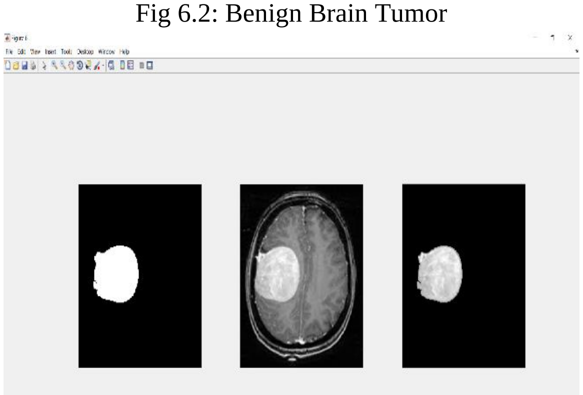

Fig 6.3: Identifying Benign Tumor location

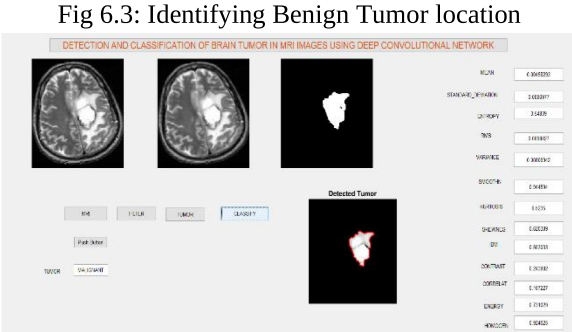

Fig 6.4: CNN Classified Output: Benign Tumor

Fig 6.5: Malignant Brain Tumor

V.CONCLUSION

The state-of-the-art advances in deep learning lead the studies and researches in machine learning to evolve from feature engineering into architectural engineering. This paper presents the multi-classification of brain Tumors for the early diagnosis purposes using CNN models whose almost all hyper-parameters are automatically tuned using grid search. Three robust CNN models for three different brain Tumor classification tasks by means of publicly medical image datasets are designated. Detection of brain Tumor is achieved with a high accuracy such as 90.33%. Moreover, classification of brain MR into Benign and Malignant Tumor.

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