A Review on Brain Tumor Detection and Segmentation: Inferences, Key Achievements and Future Road Map

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Abstract - *Automatic systems for tumor detection from Magnetic Resonance Imaging is most widely researched areas of this era. Timely and accurate detection of tumor is a challenge to the medical field. Automated systems are fruitful in the sense that they reduce the human errors during detection of tumor. A number of methods have been proposed in the recent years to achieve this, but there are still many limitations to these methodologies and have a wide scope of improvement. This study presents a comprehensive review of such methodologies for tumor detection using several Image Processing and Deep Learning techniques. In addition, the study discusses and draws attention to some key findings and also gives a road map for the future.*

Key Words*: *Brain tumor segmentation, MRI, Machine learning, Deep learning, Convolutional Neural Networks, U-net, Stack Autoencoder, Watershed Segmentation, Morphological Operations.

1. INTRODUCTION

As the brain gathers an utmost importance in a human life, it is very important to take care of it and protect it against any harms or diseases.

Brain tumor, is one of those harms. Brain tumor is a medical condition, or more precisely a disease of the brain, caused by abnormal or irregular growth of brain cells [1].

Brain tumor, which is one of the most common brain diseases, has affected and devastated many lives in this world. According to study of International Agency for Research on Cancer (IARC), approximately more than 126,000 people are diagnosed for brain tumor per year around the world [28]. The number of deaths is around 97,000 per year [2]. The statistical reports show that the survival rate of brain tumor patients is low although brain tumor diseases has been the center of attention of thousands of researchers over several decades, around the world. In the recent years, researchers from different disciplines like medical, mathematical and computer science have combined their knowledge and efforts to understand brain tumor effectively and to find more effective treatments.

Brain tumor must be diagnosed accurately and on-time before it can impose a life-threatening situation [3]. Locating the tumorous part in the brain and identifying it as tumor is known as tumor detection [4].

In primary stage, the tumor can be removed but in secondary stage, the tumor disease spreads, due to this after removal of tumor the seldom remains and grow back again. This occurs due to inaccurate location of the area of tumor. There are multiple techniques to detect the tumor such as - MRI scan, CT scan, Ultra sound etc. Out of these techniques MRIs are most accurate and are thought to be superior in regards to the detail of the image. MR images are widely used because of their high resolution that helps interpreting fine details [5].

1.1 Brain Tumor

A brain tumor is an uncontrollable abnormal growth of cells, which apparently affects the control over normal cells. The growth of tumor occupies space within the skull and interferes with normal brain activity. If tumor shifts the brain or pushes against the skull, it can cause serious damage, as the pressure in the brain increases, and thus damages nerves and healthy brain tissues. Brain tumors are classified based on the type of tissues involved in the brain, the positioning of the tumor in the brain, whether it is benign or malignant tumor and other different considerations. Brain tumors are the solid portions that spread throughout the surrounding structures. Fig.1 shows different types of brain tumor.

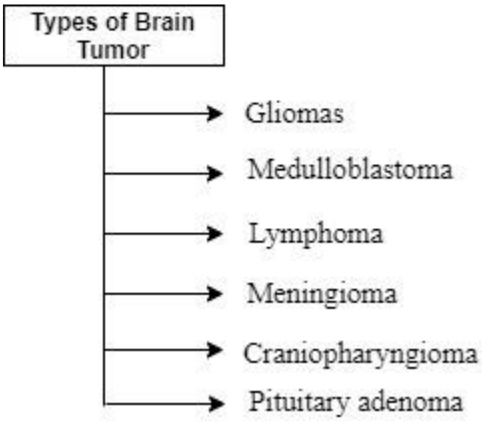

Fig. 1: Types of Brain Tumor

1.2 Magnetic Resonance Imaging

Some of the important brain imaging modalities are x-ray, computed tomography (CT), positron emission tomography (PET), single-photon emission computed tomography (SPECT), ultrasound magnetic resonance imaging (MRI) and Cerebral angiography. Magnetic Resonance Imaging (MRI) is a non-invasive method that can be used for brain imaging.MR images are used to produce detailed and accurate pictures of human organs from different angles for diagnosing abnormalities in the body. MRI is excellent for showing abnormalities of the brain such as tumor, multiple sclerosis or lesions, stroke, haemorrhage.Fig.2 shows a 2D image of brain tumor which is sliced from 3D MRI. Accurate anatomical three-dimensional (3D) models derived from 2D MRI medical image data helps in providing accurate and precise diagnostic information by identifying exact location of tumor and information about spatial relationships between critical anatomical structures such as vascular structures, eloquent cortical areas, etc. and other small internal injuries that cannot be seen by naked eye. MRI is commonly used for brain tumor imaging because of the following reasons: i) It does not use any ionizing radiations like CT, SPECT and PET. ii) Its contrast resolution is higher than techniques mentioned in (i). iii) Ability of MRI devices to generate 3D space images enables us to locate tumor accurately. iv) Its ability in acquisition of both anatomical and functional information about the tumor during the same scan.

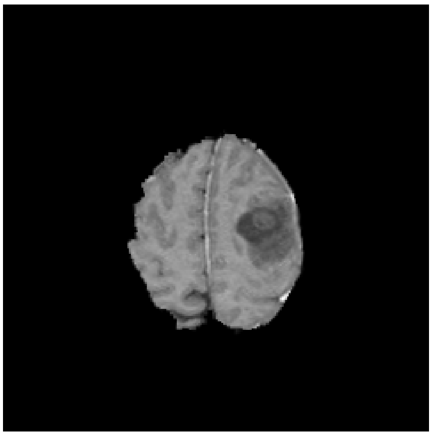

Fig. 2: An MR image of brain tumor

An MRI sequence can be grouped by general image weighting (e.g. T1 or T2) and additional features (e.g. fat suppressed or gadolinium enhanced).
Some MRI sequences are :
1)T1-W(T1 weighted image) is basic pulse sequences in MRI which demonstrates differences in the T1 relaxation time of tissues.Fig.3 shows T1-W MR image.

2)T2-W(T2 weighted image) is also a basic pulse sequence in MRI which demonstrates differences in the T2 relaxation time of tissues.
Fig.4 shows T2-W MR image.
3)FLAIR(Fluid-attenuated inversion recovery) is MRI sequence in which inversion recovery is set to null fluids.Fig.5 shows FLAIR MR image.

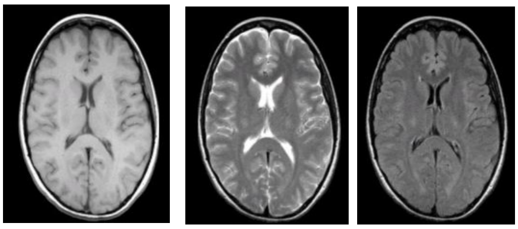

Fig. 3: T1-W Fig. 4: T2-W Fig. 5: FLAIR

2. LITERATURE REVIEW

Timely diagnosis and quick treatment are a basic requirement to encounter any health issue appropriately. Brain is the most vital organ; hence it requires early treatment which in turn require timely diagnosis. Thus, the need of automated and computer aided systems arises to assist doctors to ensure speedy diagnosis.

Therefore, a lot of work is being carried out in the domain of detecting the tumor at early stage with the help of automated frameworks that produce quick and efficient results.

In this regard, Junejo et al. in [6], presented a computer aided method for detection of Brain tumor. In this methodology, the input to the system was a 3D image with. MHA format and a resolution of 1 mm^3 voxels. This 3D image was converted into 155 slices using a slicer. After slicing during pre-processing stage for de-noising purpose, techniques such as image enhancement and gradient magnitude computations were used. After pre-processing, for segmentation Watershed algorithm was used. A problem with watershed is over-segmentation, hence, marker-controlled approach was used. Watershed segmentation considers the image as a geographical plain, in which the ridgelines give the tumor boundaries and catchment basins give the actual tumor portion. After segmentation for post-processing, morphological operations such as erosion and dilation were performed. And finally, the system outputs a segmented tumor region.

Another notable work done was by Jemimma et al. in [7], where image processing and deep learning techniques were combined for tumor segmentation. In this methodology, Watershed was used for accurately segmenting the tumorous region. The dynamic angle projection pattern (DAPP) extracted the textured features of the brain. And finally, these features are provided as inputs to the convolutional neural network which classifies the tumor and non-tumor regions of the MRI brain image. The system was trained using BRATS database and gives an accuracy of about 94.2%.

One more remarkable work is done by Swe Zin Oo, Aung Soe Khaing in [8], where segmentation of tumor was done using Watershed segmentation. A notable aspect of this paper is the skull stripping done before the actual segmentation. Skull stripping involves removal of extra tissues like skull, fats, etc. After pre-processing, watershed algorithm is used for segmentation and then morphological operations are performed to highlight the tumor. The advantage of this paper is that it not only segments out the tumor but also calculates the size of the tumor in square inches.

Andriy Myronenko in [9], proposed Variational autoencoder (VAE) based approach to segment out brain tumor. VAE helps to cluster the features at encoder endpoint. Dataset from BraTS 2018 challenge was used which consists of data of 285 patients (210 HGG (High Grade Glioma) and 75 LGG (Low Grade Glioma)). All the sliced images are normalized to zero mean and unit std. To make the intensity uniform throughout the slice random intensity shift and random mirror axis flip was applied. For regularizing the data L2 norm regularization with different weights was used. The encoder part in this architecture consist of ResNet blocks which carries two convolutions per block with normalization and ReLU activation function. For downsizing strided convolutions of 3*3*3 with 32 filters and group normalization was applied. In Decoder, only one block for each spatial level was used. The VAE part consist of two functions-mean and std deviation that uses Gaussian distribution. To find individual learning rate for different parameters Adam optimizer was used. Loss Function consist of 3 terms-soft dice loss, VAE output loss and penalty term. Results of [9] are in the form of segmented image in which tumor is divided into 3 parts-whole tumor (WT), Tumor core (TC) and enhanced tumor core (ETC) with average dice value of 0.8233,0.9100,0.8668 respectively.

Mallick et al. in [10], described Deep Wavelet Autoencoder (DWA) method for image compression. This autoencoder blends the basic feature reduction property of autoencoder along with image decomposition property of wavelet transform. The objective was to establish a high-level feature learning and automatic fault diagnosis technique using DWA and to build a system that would help in cancer determination and detection of the Brain MR image through the process of the proposed image classifier. For this research work, RIDER (Reference Image Database to Evaluate Therapy Response) was used [29]. The performance has been measured with four parameters - Accuracy, Specificity, Sensitivity and F-Score. DWA-DNN comes out with average accuracy of about 93%.

3D reconstructed shapes are of low quality because CT and MR images have low resolution in z direction compared to x and y directions. In [11], convolutional auto-encoders (CAEs) approach is given to address this drawback. To get a better reconstruction quality, interpolation approach for 2D images is given. For this dataset described in [12] was used, which consists of 3064 segmented brain tumor images. The PSNR value obtained from this model are - 26.23, and 24.55 for bilinear interpolation. This proposed approach has the capability of producing shapes with higher qualities. Stacked denoising autoencoder can also be used to detect brain tumor. This autoencoder is used in [13] for brain lesion detection, segmentation and false positive reduction. For this BraTS-2015 data set was used to train the networks. The average dice score achieved by this system for single time point patients, longitudinal patients and the entire BraTS 2015 training data set are 0.83, 0.71, 0.78 respectively.

Kermi et al. in [14], used U-net [15] architecture for segmentation of brain tumour. They used the dataset from BraTS 2018 challenge Minimal Pre-processing of MRI data was done as in [16] by removing 1% highest and lowest intensities. Data augmentation [17] technique was also employed. The architecture in [14] is similar to U-net, and has contracting path and expanding path. Contracting path has 3 pre-activated residual blocks [18, 19]. Each block consists of two convolutional units, consisting of Batch Normalisation layer, and activation function Parametric Rectified Linear Unit (PReLU) [20] and a convolution layer of 3*3 size filter, padding =2, stride = 1 as in [21], instead of max-pooling. For down-sampling a convolution layer of 2*2 filter and stride of 2 is used. A residual block acts as a bridge between contracting and expanding path. The expanding path consists of 3 residual blocks. Before each block there is an up-sampling operation. At last, a convolution layer of 1*1 with softmax activation function is used. Loss function. Loss function that adds the Weighted Cross Entropy (WCE) and Generalized Dice (GDL) [22] is used. Output is in a form of segmented image which consists of tumor divided into three parts -whole tumor (WT), Tumor core (TC) and enhancing tumor (ET). The mean dice score achieved by the system for enhancing tumor (ET), whole tumor (WT) and Tumor core (TC) are 0.783, 0.868 and 0.805 respectively.

Ezhilarasi et al. in [23] proposed an AlexNet model [24] for classification of tumors as a base model along with Region Proposal Network (RPN) by Faster R-CNN algorithm. The concept of transfer learning was used. The dataset was pre-processed using Continuous Adaptive Mean Shift (CAMSHIFT) algorithm with the help of Visual Object Tagging Tool (VOTT). CAMSHIFT is used to increase the window size with orientation to calculate best fix box until it obtains the accurate result and hence produce box parameters. VOTT helps to divide dataset into positive, negative and training images with bounding boxes and class label. A class map is created. Faster R-CNN used AlexNet as the CNN model and Region Proposal Network. Alexnet consists of 5 convolutional layers and three fully convolutional layers. Dropout was used to prevent overfitting. RPN generates candidate Region of Interests for given brain input images. It was a fully convolutional network which includes 3 convolutional layer and 1 proposal layer. The occurrence of tumor is checked using regression and classified using bounding boxes provided by RPN. Non-Maximum Suppression (NMS) are used to find the exact location of tumor by merging it with ROI. NMS helps to identify tumor by selecting high confidence region of interest and discard the other ROIs that overlaps the same class this ROI belongs.

Thaha et al. in [25] proposed an ECNN (Enhanced Convolutional Neural Network) based model. BAT algorithm was used for automatic segmentation. Skull Striping and image enhancement algorithms are methods used for pre-processing. An ECNN model was used for training. Novel BAT optimization algorithm (NBOA) was used for loss function.

Shreyas et al. in [26] proposed a Fully convolutional network model which helps in faster performance. In pre-processing N4ITK method was used for bias correction and also an intensity standardization method was used to solve cross patient non-standard intensity ranges. Model has a U-Net based architecture. Categorical Cross Entropy is used as a loss function since it is a multi -class problem. Optimization was done using Adam optimizer. BRaTS 2015 dataset was used for training. Dice scores of 0.83 in the whole tumor region, 0.75 in the core tumor region and 0.72 in the enhancing tumor region was achieved.

Pereira et al. in [27] used a CNN based architecture. They used small 3 * 3 kernels, as they help to prevent overfitting. They used BRATS 2013 database for training and validation. N4ITK algorithm and intensity normalization. Also, data augmentation was used. ReLU was used as activation function. Dropout layer was added to prevent over fitting. For Loss function Stochastic Gradient Descent was used. Dice Similarity Coefficient 0.88, 0.83, 0.77 for the complete, core, and enhancing regions, respectively was achieved.

Systems that are proposed in above papers has some limitations. VAE which is used in [9] is less efficient in segmentation of brain tumor than any other system. In [10], determining fuzzy membership was hard and intense. In [11], there may be cases where bi-linear interpolation can occur as there is no geometrical match between consecutive slices. In the papers, which used watershed segmentation had limitations in the pre- processing stage. Many factors such as fats, skull will create hinderance in proper segmentation.To overcome this limitations,we propose an effective model to segment out tumorous part from healthy brain tissues.

3. PROPOSED METHODOLOGY

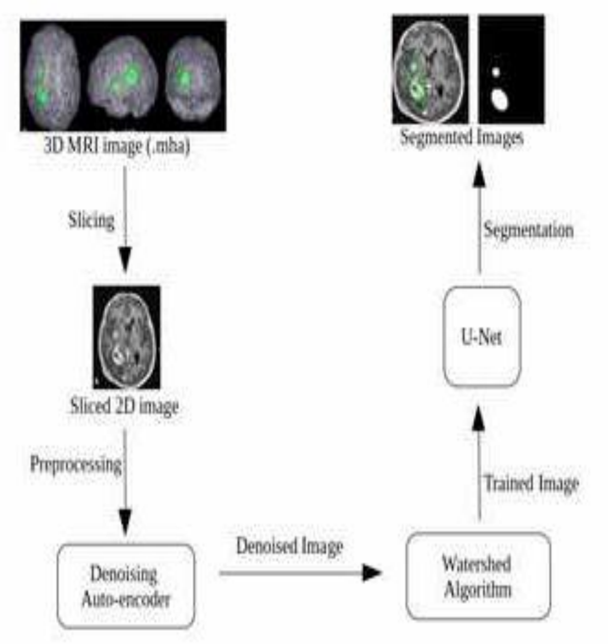

Fig 6. Proposed system architecture

The model that we propose is a combination of Deep learning and Image Processing techniques for detection and segmentation of tumor. Steps towards our methodology are as follows:

1. Slicing: 2D images are obtained from 3D MR images from the BraTs dataset using a slicer.

2. Pre-Processing: Before actual segmentation of the image, the image should be properly denoised and pre-processed. This denoising and pre-processing is done using Stacked denoising autoencoder.

3. Segmentation**:** After the image is denoised, this image will be given as the input to Marker-Controlled watershed segmentation. The reason for using marker-controlled watershed is the over segmentation problem of the watershed segmentation.

After watershed segmentation morphological operations will be performed and then area of the tumor will be calculated using the following formula:

Tumor Area = Horizontal dimension of image*Vertical dimension of image*total number of pixels in tumor area in "square inches".

4.Advance Classifications using Fully Convolutional neural networks: Watershed outputs of large number of images. This image will be given to Neural networks for feature extraction. Output of these neural networks will classify the tumor as benign or malignant.

4. CONCLUSION AND FUTURE WORK

We have discussed several deep learning and image processing methodologies for tumor detection. However, both the techniques when they standalone come up with few limitations. Deep learning seems to perform well with pre-processing and feature extraction whereas with proper pre-processing Image processing gives very accurate results. So, these two techniques when combined together, will work miracles. The future roadmap can go in the following ways:

1. Pre-Processing using Deep Learning (Stack Auto encoder).
2. Segmentation and tumor-area calculation using Image Processing (Watershed Segmentation).
3. Advanced feature extraction using Deep Learning (Fully Convolutional Neural Networks) for classifying tumor as malignant and benign, gliomas and glioblastomas, etc.

Combination of all these methods in collaboration with Transfer learning will help in building a highly automated, accurate, robust system for tumor detection. This system will be capable of performing everything right from tumor detection, segmentation, area calculation, and also classification of the tumor thereby reducing the human error to a large extent and will help in on-time detection of the tumor. Though the computation time increases, our proposed model will give accurate results. In the future scope, survival prediction of the patient can also be made possible.

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