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A Literature Review on Brain Tumor Detection and Segmentation

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***Abstract*—A tumor is a swelling or abnormal growth resulting from the division of cells in an uncontrolled and disorderly manner. Brain tumors are an exceptionally threatening kind of tumor. There exist several types of brain tumors which are classified into four grades. The process for the medical treatment of brain tumors depends on the type, the grade as well as the location of the tumor. If not detected at the early stages, brain tumors can turn out to be fatal. Magnetic Resonance Imaging (MRI) images are used by specialists and neurosurgeons for the diagnosis of brain tumors. The accuracy depends on the experience and domain knowledge of these experts, and is also a time consuming and expensive process. To overcome these restrictions, several deep learning algorithms have been proposed for the detection of presence of brain tumors. In this review paper, an extensive and exhaustive guide to the sub-field of Brain Tumor Detection, focusing primarily on its segmentation and classification, has been presented by comparing and summarizing the latest research work done in this domain. This research work has made a comparison between 28 research papers and highlighted the different state-of-the-art approaches. With a lot of ongoing research work in this area, this paper would assist all future researchers.**

***Keywords*—Brain Tumor Detection, Deep Learning, Image Segmentation, MRI images, Medical Imaging, Tumor Segmentation.**

I. INTRODUCTION

The brain is one of the most vital and sensitive organs of the body and is the centre of all nervous activity. Issues pertaining to the brain are widely considered the most difficult to operate on. There are roughly 350,000 new brain tumor cases across the world each year and the 5-year survival rate for people diagnosed with a brain tumor is only 36% [11]. Brain tumors can be classified as benign (non-cancerous tumors) or malignant (cancerous tumors) [18]. The World Health Organisation (WHO) has classified brain tumors into four grades from Grade I to Grade IV depending on the severity of the case. Neurosurgeons often recommend surgery for the treatment of brain tumors. However, for the latest stages of the tumors, alternative approaches using radiation and chemotherapy are often suggested, since the only possible diagnosis is to try to kill or slow down the growth of the cancerous cells [15]. Since the fatality rate of people diagnosed with brain tumors is very high, the detection of brain tumors at the early stages is extremely important for correct treatment. For diagnostic purposes, images can be gathered from several medical imaging techniques. Some of the medical imaging techniques are PET(Positron Emission Tomography), MRI(Magnetic Resonance Imaging), CT(Computed Tomography) [13]. Among these, MRI is considered to be the most effective medical imaging technique, especially for taking a look at soft tissues and the nervous system. MRI makes use of a powerful magnet and radio waves to produce images of body structures by causing them to emit faint signals. Unlike CT scans, MRI does not use radiation of X-rays which can be damaging. MRI images have high resolution and are quite detailed, due to which they can even detect tiny things [6, 17]. The tumor may show up as a white area, or bright white-coloured pattern. However, there are other parts of the brain which have a similar behaviour as these cells and can lead to a wrong diagnosis.

With tens of thousands of patients suffering from brain tumors each year, the use of deep learning techniques for the purpose of automatic detection and classification of brain tumors has become an area of interest. These techniques have also been employed for the segmentation of brain tumors, and this area is getting widespread attention from the medical community [16]. The aim of segmentation is to change the representations of the different areas of an image, making areas of the image having different characteristics easier to interpret. By dividing the image of the brain into these different and unique areas, each area becomes spatially contiguous [1, 2]. Some of the common problems in manual detection of the brain tumors are the significant time requirements and the possibilities of misclassifications due to the complexity of the problem. Therefore, the automatic segmentation of MRI images of brain tumors can significantly improve the diagnosis and methods of treatment, especially in cases where access to trained experts and radiologists is difficult [3]. This paper will discuss about the latest research work done in this domain.

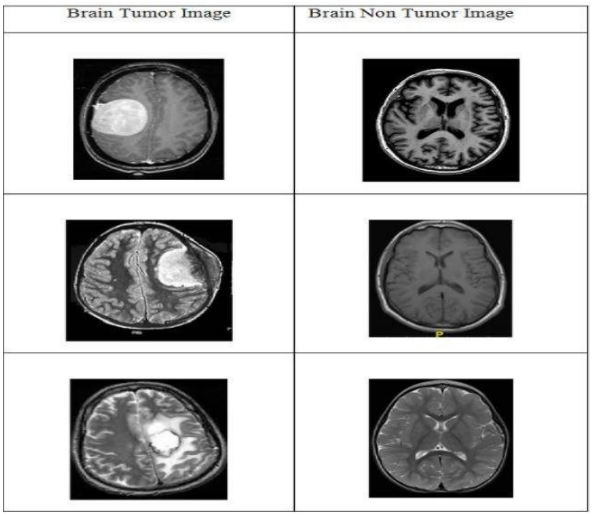

Fig. 1. Positive vs Negative Image.

II. Literature Survey

Research work by 9 different authors has been discussed on the basis of varied deep learning techniques and architectures adopted by them.

Sakshi Ahuja et al.,[1] used transfer learning and superpixel technique for detection of brain tumor and brain segmentation respectively. The dataset used was from BRATS 2019 brain tumor segmentation challenge and this model was trained on the VGG 19 transfer learning model. Using the superpixel technique the tumor was divided between LGG and HGG images. This resulted in an average of dice index of 0.934 in opposition to ground truth data.

Hajar Cherguif et al.,[2] used U-Net for the semantic segmentation of medical images. To develop a good convoluted 2D segmentation network, U-Net architecture was used. BRATS 2017 dataset was used for testing and evaluating the model proposed. The U-Net architecture proposed had 27 convolutional layers, 4 deconvolutional layers, Dice_coef of 0.81.

Chirodip Lodh Choudhury et al.,[3] made the use of deep learning techniques involving deep neural networks and also incorporated it with a Convolutional Neural Network model to get the accurate results of MRI scans. A 3-layer CNN architecture was proposed which was further connected to a fully Connected Neural Network. F-score equal to 97.33 and an accuracy equal to 96.05% was achieved.

Ahmad Habbie et al.,[4] MRI T1 weighted images were taken and using semi automatic segmentation analyzed the possibility of a brain tumour using an active contour model. The performance of morphological active contour without edge, snake active contour and morphological geodesic active contour was analyzed. MGAC performed the best among all three as suggested by the data.

Neelum et al.,[5] used a concatenation approach for the deep learning model in this paper and the possibility of having a brain tumor was analyzed. Pre trained deep learning models which are Inception - v3 and DenseNet201 were used to detect and classify brain tumors. Inception - v3 model was pre trained to extract the features and these features were concatenated for tumor classification. Then, the classification part was done by a softmax classifier.

Ms. Swati Jayade et al.,[6] used Hybrid Classifiers. The classification of tumors was done into types, malignant and benign. Feature dataset here was prepared by Gray level Co-occurrence Matrix (GLCM) feature extraction method. A hybrid method of classifiers involving KNN and SVM classifiers was proposed to increase efficiency.

Zheshu Jia et al.,[7] the author made a fully automatic heterogeneous segmentation in which SVM (Support Vector Machine) was used. For training and checking the accuracy of tumor detection in MRI images, a classification known as probabilistic neural network classification sytem had been used. Multi spectral brain dataset is used and this model focused on the automated segmentation of meningioma.

DR. Akey Sungheetha, DR. Rajesh Sharma R.[8] used Gabor transform along with the soft and hard clustering for detecting the edges in the CT and MRI images. A total of 4500 and 3000 instances of MRI images and CT were used respectively. K-means clustering was used for the separation of similar features into sub-groups To represent the images in the form of histogram properties, the author used Fuzzy c means.

Parnian Afshar et al.,[9] used a bayesian approach for the classification of brain tumor using capsule networks. To improve the results of tumor detection, capsule network instead of CNN was used as CNN can loose the important spatial information. The team proposed BayesCap framework. To test the proposed model they used a benchmarkbrain tumor dataset.

Further, 19 other research papers regarding the latest research work done in this domain have been reviewed and tabulated in Table 1. Key details such as the dataset and techniques used, year of publication, major observations and accuracy achieved have been presented to aid further research work in this domain.

Table 1: The following table contains different techniques opted by researchers on Brain Tumor Detection and Segmentation.

Year, Publication	**Dataset used**	**Technique**	**Observations**	**Accuracy**
2020,[10] (Elsevier)	BRATS 2013 BRATS 2015	FCNN	• F2 FCN was used in order to operate the pixel wisebrain tumor segmentation. • A feature reuse model was introduced in order to make thereuse rate of valuable features better.	Dice: 0.86 ± 0.14 PPV: 0.89 ± 0.15 Sensitivity: 0.87 ± 0.16
2020,[11] (Wiley)	BraTS2015 BraTS2017 BraTS2018	3D CNN,SVM Feature Selection Architecture, FNN,KNN, Decision Trees VGG19	• The tumor was correctly identified in poorly contrasted MRI scans using this architecture. When a model which is pertained by using the extraction of the tumor images the classification accuracy of tumor type's became better from earlier.	BraTS 2015-98.32% BraTS 2017-96.97% BraTS 2018-92.67%
2020,[12] (IEEE)	ImageNet Dataset (http://www.image-net.org/download)	HCNN, CRF-RRNN	• A deep learning technique consisting of the combination HCNN and CFR in a single system was proposed for the segmentation. • The experimental results show that integration with CRF-RRNN andHCNN can increase segmentation robustness.	Precision Ratio – 96.5% Recall Ratio – 97.8%
2020,[13] (IEEE)	Kaggle Dataset Warehouse (https://www.kaggle.com/navoneel/brain-mri-images-for-brain-tumor-detection)	CNN	• Used augmentation in the dataset and expanded its size to 14 times. • ACNN was designed for the classification of MRI images. Images are labeled , label 1(having tumor) and label 0(not havingtumor).	ACNN – 96.7%
2020,[14] (Wiley)	BraTS 2015 (https://www.smir.ch/BRATS/Start2015)	CNN,MKKMC	• The performance of the proposed method is evaluated using PPV, NPV, FPR, FNR, sensitivity, specificity and accuracy. • To analyse the performance of the model the proposed method iscompared with the existing method.	Accuracy - 99% Sensitivity -93.5% Specificity –99.22%
2019,[15] (IEEE)	BraTS 2013	Two path architecture, CNN, Cascade architecture	• The model was primarily focused on the disease Glioblastomas. • A new model was built which consisted of two path and cascade architecture.	Dice Index- 0.95 Sensitivity -0.925 Precision -0.961
2019,[16] (IEEE)	3D MRI dataset from the BRATS challenge in MICCAI 2016.	Random Forest Classifier	• For the classification of existence of a unique class a total of five random forest classifiers were used and all the classifiers were trained in two-class fashion. • Experimental results showed a very good improvement in segmentation for all the three tumor sections.	Whole Tumor -89.53% Tumor Core - 79.86% Active Tumor - 76.92%
2019,[17] (IEEE)	MICCAI BraTS2015	Image Processing Technique, SVM, Random Forest	• Using image processing techniques Brain tumors are segmented and shape-based features are used for feature extraction . • Extracted shape-based features are given to ML algo as SVM & random forest algorithm to find malignant and benign brain tumors.	Accuracy – 86.66%
2020,[18] (Wiley)	https://figshare.com/articles/dataset/brain_tumor_dataset/1512427	CLFAHE, DBN	• The proposed model had a total of five phases in the evaluation process. • The main aim of the paper was to first select the hidden neurons in DBN and then select the bounding limits using the new hybridisation optimization algorithm	Accuracy–92.15% Sensitivity -77.5% Specificity –9926%
2020,[19] (IEEE)	https://figshare.com/articles/dataset/brain_tumor_dataset/1512427	R-CNN. RPN	• VGG-16, a CNN architecture was used as a base layer for the proposed networks(classifier network and region proposal network) • This paper work can be extended further for calculating the percentage area of the tumor with respect to brain region of human.	Glioma Tumor -75.18% Meningioma – 89.45% Pituitary – 68.18%
2020,[20] (Elsevier)	BraTS 2017 (https://www.med.upenn.edu/sbia/brats2017/registration.html)	sparse constrained level set algorithm	• The method mentioned in thi paper found out common characteristics of brain tumor shape and was able to make asparse representation model for it. • A method energy function ground on level set was constructed.	Accuracy – 96.2%
2020,[21] (Wiley)	Flair dataset, T1 dataset, T2 dataset	ISOA algorithm, DBN,SVM	• An automated system was proposed for the diagnosis of brain tumors.	Seagulls Population - 150

2019,[22] (IEEE)	1667manually annotated images	Feature extracrion algorithm, CNN-Softmax	• The classification and segmentation were done through the combination of feature extraction algorithm and CNN. • RBF classifier and DT classifier were used to find the accuracy of CNN.	Accuracy – 99.12%
2019,[23] (Elsevier)	BraTS, SimBraTS	Dolphin-SCA algorithm	• Dolphin-SCA based depp CNN (a deep learning method) was proposed. • A total of four steps were followed including pre-processing, segmentation, feature extraction and its classification.	Accuracy – 96.2% Sensitivity –99.2% Specificity –91%
2019,[24] (ACM)	BraTS 2015 (https://www.smir.ch/BRATS/Start2015https://www.smir.ch/BRATS/Start2015)	Deep Learning, CNN	• The proposed architecture was tested on MRI images to identify the patients suffering from various type of tumors.	Dice Similarity Index – 86.7% Accuracy – 98.33%
2019,[25] (ACM)	BraTS dataset	Deep Learning, Fuzzy K-Means Clustering,	• The KMFCM was used as it can deal with higher number of segmentation problems and minimal execution time. • The model was evaluated on the basis of white pixels , black pixels, processing time, and the tumor detected area.	Accuracy – 97.3%
2020,[26] (Springer)	BraTS dataset	Deep Learning, Fuzzy K-Means Clustering, ANN	• For the segmentation of the brain tumor a model with the combination of both ANN and Fuzzy K-means algorithm was introduced. • When compared to K-Nearest Neighbour methodology the overall accuracy of the technique was increased by 8%.	Accuracy - 94% Sensitivity - 98% Specificity –99%
2019,[27] (Springer)	BraTSdataset	FractionalPartial Differential Equation(FPDE)	• Fractional calculus approach was used to achieve the accuracy which provided an abritary order of derivative. • Mesh free technique was been used to solve the proposed equaiton to achieve higher and faster response.	Accuracy – 85%
2020,[28] (Springer)	MMRI dataset	MKSVM algorithm , K-means clustering algorithm	• In segmentation process, MRI images were preprocessed first and then the feature extraction procees was proceeded using the preprocessed images. • For the extraction of the features a raised Gabor wavelet transformation was implemented. An algorithm called as rough K means clustering was introduced for segmentaion in this paper.	Accuracy rate – 0.997

III. Brain Tumor Detection

The brain is the most sophisticated organ in the human body. It is a mass of nerve tissue composed of roughly 100 billion neurons. The brain is responsible for integrating sensory information, motor responses and is the center of learning. The Central Nervous System is made up of the brain and the spinal column. The CNS is responsible for the control of the vital functions of the body such as thought, speech and body movements. A brain tumor is an abnormal growth caused by the uncontrolled multiplication of cells. This abnormal growth in the brain or central spine can disrupt the normal functioning of the body and can affect the way a person talks, moves and processes thoughts. There are two types of brain tumors, primary tumors and secondary tumors. Primary brain tumors originate from the brain, and can further be classified as low grade or high grade. Low grade tumors grow at a slower pace as compared to high grade tumors. Secondary brain tumors are cancerous, and can start from some different part of the body and then spread to the brain [2]. The brain has a highly complex structure, making the diagnosis of brain tumors difficult

Brain tumors take the lives of nearly 250,000 people each year. Accurate diagnosis of brain tumors can save the lives of people to some extent. MRI images are extensively used to detect brain tumors. The following steps are involved in detection and treatment of brain tumors:

1. Pre-processing: This is done to improve the quality of the raw MRI images and transform them into a form, suitable for processing by humans or machines. This step also helps in removing undesired noise and enhancing overall appearance of the MRI images. Image pre-processing involves steps such as creating functions to load image datasets into arrays, resizing raw images to an established base size before feeding it to the neural network, applying normalization to rescale the pixel values so they lie within a fixed range, data augmentation to increase the size of the dataset if insufficient number of images are available, among other steps [19, 28]. These preprocessing tasks help improve classification accuracy and also speed up the training process.

2. Skull Stripping: This is the process of removing parts of the images which have non-brain tissues. Through this, cerebral tissue which is not required for the analysis of the brain tumor, such as fat or skin, is removed [18]. Some popular techniques for skull stripping are based on segmentation and contouring of images.

3. Segmentation: This step aims to differentiate abnormal brain tissue from the normal brain tissue. There are manual, semi-automatic and fully automatic segmentation techniques [20]. In manual segmentation, the outline of the affected tissue area is manually traced. This method has the highest accuracy, however, it is time-consuming and cumbersome. Semi-automatic segmentation involves the users inputting some initial data to obtain the final results. In fully automatic methods, the values of the parameters do not have to be set manually and these methods can automatically detect and segment the brain tumor.

4. Feature Extraction: This step will improve accuracy of the system by selecting the more prominent features for us. It is used as a method for dimensionality reduction, and the initial data is reduced into a format which is more suitable for processing.

5. Post-processing: Post-processing provides an insight into the brain image of the tumor area. This step can include methods such as limits on the shape of the samples, contextual limitations for more accurate results and spatial control.

Brain scans can be done through different methods, the most common of which is MRI scans. The proposed algorithms discussed in this paper make the use of MRI scans, and involve the discussion of three broad tumor types:

1. Benign Tumor: Benign tumors are not cancerous and do not spread to other parts of the body or invade adjoining tissues. They grow at a slower pace, however, benign tumors can pose a serious problem if they press on nerves, restrict the blood flow or crowd the normal parts of the brain [17]. They generally respond well to treatment and can be removed through surgery in most cases. These tumors have low chances of recurrence.

2. Pre-malignant Tumor: It is not necessary that benign tumors turn cancerous, they might not. However, they can turn cancerous if the uncontrolled multiplication of tumor cells continue. Such types of tumors need to be carefully monitored for changes in the cell such as the cell appearance and growth rate.

3. Malignant Tumor: Malignant tumors are cancerous and can invade nearby tissues. The cancerous cells may break away from the tumor, and can then spread to other parts of the body through the lymphatic system or the bloodstream [22]. This is known as metastasis. Malignant tumors grow rapidly and can also recur, not necessarily at the same area where they initially appeared. Treatment of this type of tumors requires aggressive treatment methodologies which may include chemotherapy, radiation techniques and surgery. They are life threatening and necessitate some sort of treatment.

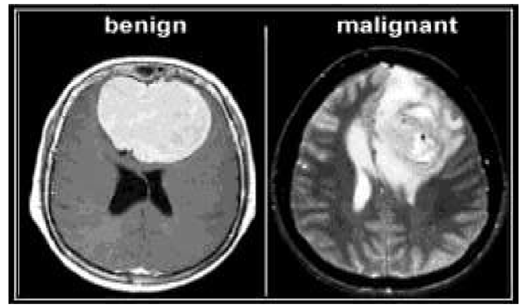

Fig. 2. Benign Tumor vs Malignant Tumor

IV. Image Segmentation

Image Segmentation involves partitioning images into its constituent segments or regions, which aids in detecting the objects and edges of the images. This partitioning is done on the basis of characteristics of the pixels in the image [16, 18]. The partitioning could separate the foreground from the background or group together pixels if they have similar shapes and colours. Image Segmentation forms an integral part of the field of medical imaging and is used extensively. Some of the common segmentation techniques are:

1. Threshold based segmentation: This is one of the simpler segmentation techniques. It replaces the pixels of the images with either black or white. In this technique, the comparison of the pixel value with a threshold value is done. If the value of the pixel is lower than the threshold value, the pixel is replaced with black colour, otherwise it is replaced with white. The value of the threshold can be changed as per the requirements. It is commonly used to separate the foreground and background, but the division is always into only 2 classes which is a drawback. This method can prove to be useful if the objects in question have more intensity than the background or the unwanted portions of the image.

2. Edge based segmentation: This technique detects edges in an image, which in turn can be used to identify certain objects [8]. Two of the common edge segmentation techniques are sobel and canny edge algorithms.

3. Clustering based segmentation: This technique creates segmented images from a rough initial pixel clustering. With the help of gradient ascent methods, these clusters are refined until the image is segmented. These methods try to minimize the distance between the pixels and the clusters formed [14, 28]. K- means clustering, SLIC, watershed etc. are commonly used clustering algorithms.

4. Graph based segmentation: In graph based segmentation, the individual pixels are considered as nodes of a graph. The degree of similarity between the adjacent pixels is then proportional to the weights of the edges between these nodes of the graph. Using the set of nodes and edges, pixels are grouped into superpixels or distinct segments. Graph cut and Normal cut are two commonly used graph based segmentation techniques.

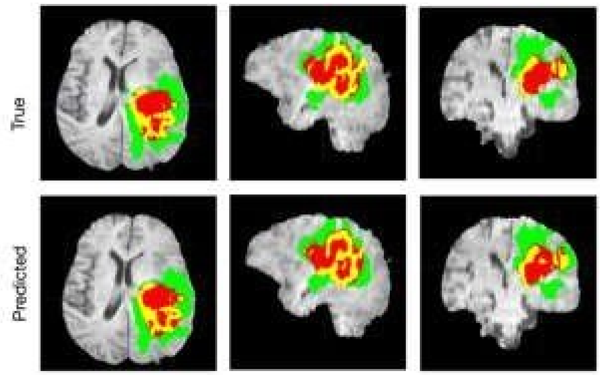

Fig. 3. Fully Automatic Brain Tumor Segmentation

V. Magnetic Resonance Imaging

Magnetic Resonance Imaging is a medical imaging technique in which radio waves generated by a computer and strong magnetic fields are used to provide detailed data and images of different parts and structures of the body. Unlike CT scans, MRI does not make use of damaging radiation of X-rays and is of no harm to the human brain [19]. It helpsin providing a cross-sectional image of the brain, which can be evaluated to ascertain the location and size of the tumor,if present. It is a non-invasive procedure. MRI machines are typically tube-shaped and surrounded by circular magnets. Thepatient is asked to lie on a table, which slides into the tube-shaped machine and examination is done. Normally, the water molecules in the body are arranged in a random manner. The working principle of MRI is that the magnetic field aligns the protons in the hydrogen atoms. These atoms are then exposed to a beam of radio waves, causing the protons to spin in a particular direction and emit faint signals which are received by the MRI machine. These signals are processed to form MRI images for further analysis [12]. Through this process, cross- sectional images of the brain can be created. These images can be used to locate the tumor and analyse its shape and size, and assess the best course of action to treat the brain tumor.

VI. Conclusion and Future Scope

This paper introduces the concept of brain tumor detection and segmentation and highlights and compares some of the key points of state-of-the-art approaches used in this domain. Some of the commonly used techniques are ML techniques like Fuzzy K-means clustering and Random Forests, as well as the use of CNN architectures is prevalent. In particular, S.Krishnakumar et al. [28] achieved the highest accuracy of 99.7% with the use of MKSVM algorithm on the MMRI dataset. High accuracy of classification of 99.12% was also achieved through the use of a combination of feature extraction algorithm and CNN [22].There are a few challenges encountered in further research work in this domain. Deep learning methods require large datasets for training purposes, and the lack of such large publicly available datasets is an obstacle. There is a scope for increase in the number of available datasets and improved access to them to aid future research work in this domain. Researchers have requested experts in this domain, such as neurologists and radiologists, to prepare structured labelling reports to aid further research. Another common issue is the presence of class imbalances in the types of tumor. This issue is commonly tackled through the use of data augmentation techniques by rotating or scaling down existing images [13]. At present, the majority of deep learning methods involve classification of tumor area, but the anatomical location of tumor region is not known to the network. Further research work in this domain can be directed towards incorporating this information in the neural network, possibly by feeding the entire image to the network. However, the size of brain tumor images are generally of high resolution and in the range of gigapixels, making the training of the network on such images unfeasible due to memory and computational power constraints.

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