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A Review: Brain Tumor Detection Techniques

Dr. Prathibha M K[1] and Mrs. Harshitha N[2]
[1-2]ATME college of Engineering / Department of Electronics and Communication Engineering, Mysore, India
Email: dr.prathibamk_ec@atme.edu.in, harshithan_ec@atme.edu.in

***Abstract*—One of the most life-threatening diseases is a brain tumor. It is critical to notice disease at an early stage in order to protect the lives of those who are affected. Because of the complicated structure of the brain, detection of a tumor is difficult. A medical imaging procedure is used to detect and analyze brain tumors. Brain tumors are detected via Magnetic Resonance Imaging (MRI). The brain anatomy is imaged in great detail using the MRI technique. Because it is difficult to determine the position and size of a tumor using this information, a brain tumor is detected using an image segmentation process. The appearance of a tumor, such as contour, size, location, and grey level intensities, differs from person to person, making tumor detection is more difficult. Taking into account all of these factors, this research study focuses on previous proposed classification systems.**

***Index Terms*— Tumor, Segmentation, deep learning, Classification, MRI.**

I. INTRODUCTION

The term "brain tumor" refers to a collection of abnormal cells in certain brain regions. There are two types of cancers: primary tumors and secondary tumors. Brain tumors begin in the brain, whereas secondary cancers begin elsewhere in the body. A brain tumor can be Malignant or non-malignant.

Both types of tumors can damage body components, putting a person's life in threat [1]. When a tumor grows, it induces Edam, which decreases blood flow, causes displacement, and promotes degeneration of healthy tissue by raising intracranial pressure in the skull. Because MRI pictures provide extensive information on the anatomy of brain cells, and they are utilized to identify brain cancers [2].

Brain tumors that are Malignant grow quickly. They pose a greater risk of death than non-Malignant tumors. Meningioma, glioma, and pituitary adenoma are the three forms of brain tumors based on the location of the tumor in the brain. Glioma is a critical and dangerous kind of brain tumor that predominantly affects adults. Gliomas can be extremely harmful in some cases. Most of the time, it has been proven to be life threatening. As a result, patients should receive the most appropriate treatment in order to safeguard and save their lives. Gliomas are fast-growing tumors that can be treated if caught early enough [3].The procedure of tumor detection using Computer Aided Diagnosis CAD is depicted in Figure 1.

The first step is image acquisition, which involves retrieving a dataset from a source and then collecting data depending on a set of parameters. Image segmentation is vital in clinical diagnosis in the medical industry since most medical images have poor contrasts, which might be influenced by noise or diffusive borders [4]. The preprocessing of these images includes noise removal [5].Noise is removed from the image after it has been preprocessed. Image segmentation is the next phase, which divides an image into several segments for object recognition. After that, certain approaches are used to extract and select features. The next phase is dimensionality reduction, followed by classification, which categorizes an image. The term "performance

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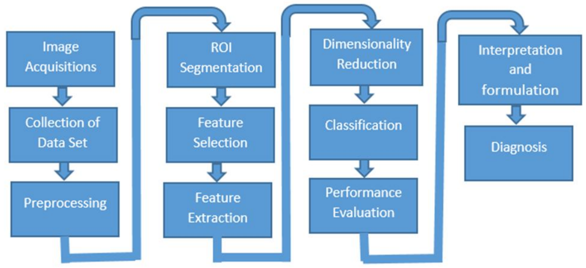

Figure 2. Note how the caption is right aligned

evaluation" refers to the process of calculating accuracy based on a set of parameters. We provide a meaning to the object that has been recognized in the interpretation step, and the diagnosis procedure is completed at the conclusion.

II. Literature Survey

Image Segmentation [6] is carried out, which entails manually or automatically separating the image into a set of reasonably homogeneous portions with equivalent qualities. Image segmentation allows radiologists to precisely locating malignancies. As a result, it's becoming an increasingly significant stage in medical image processing. For large numbers of MR images, the manual procedure of picture segmentation is time consuming and challenging [7]. For the reasons stated above, an automatic approach of segmentation of MR images is necessary. Segmentation is the process [8,9]of recognizing and segregating a segment of an image for subsequent diagnosis. To keep track of therapy progress, schemes, and predicted outcomes, segmentation is essential. There are several methods for doing this, including employing a heuristic algorithm and thresholding.

This section discusses the many approaches used for segmentation and classification brain tumors. In a well-organized manner, typical machine learning, deep learning, and heuristic techniques that have been used in the previous work are discussed.

A median filter is used by E. Abdel-Maksoud et al. [10] to remove noise. The main technique here is to use K-means clustering in conjunction with FCM clustering. The level set and thresholding approaches can be used to improve the segmentation procedure.

The Gaussian mixture modelling (GMM) approach is used by N.J. Tustison et al. [11] to solve the tumor problem. For segmentation, the probability obtained from the random forest is used.PCA is used to derive primary characteristics. N. Nabizadeh et al. [12] implement several classifiers along with Gabor wavelet and statistical characteristics.

A. Sehgal et al. [13] propose using FCM in conjunction with an anisotropic diffusion technique to segment tumorous cells.K. Kamnitsas et al. [14] created a dual pathway architectural strategy for giving local as well as global knowledge. The 3D fully connected CRF was used to extract false positives.

AUC (Area under Curve) and ACC (Accuracy) were the primary approaches utilized by J. Amin et al. [15]. It was also advised to use the SVM classification algorithm in conjunction with the ROI (region of interest).

To gain more correctness, S. Deepak et al. [16] used Transfer learning, which resulted in a significant increase. Because an image has so many components and properties, classifying it is a difficult undertaking. In this paper, R. Ito et al. [17] use an algorithm termed EN in conjunction with a deep neural network approach.

In M. Mittal et al. [18], the authors proposed a hybridization of the Stationary Wavelet Transform (SWT) and Growing Convolution Neural Network (GCNN) in the tumor segmentation process to improve the accuracy of the CNN method. The SWT and Random Forest methods are used to retrieve the features and to classify them.

M. Talo et al. [19] demonstrated an automated deep transfer learning system for classifying typical and unfamiliar MRI scans. For dataset growth, the ResNet34 Convolutional Neural Network was introduced, along with a data augmentation approach.

Authors in A. Pratondo et al. [20] proposed an integrated SVM with KNN for detecting inhomogeneous boundaries. The active contour model technique was used to implement brain tumour segmentation.

The authors of R. Saouli et al. [21] introduced three forms of Deep CNN: Ensemble Net, 2CNet, and 3CNet. The BRATS 2017 dataset was utilized to apply the ensemble learning technique in this paper.

The Naive Bayes classifier is utilised for classification in N. Gupta et al. [22], and the validity of the segmentation technique is increased using the threshold function.

For the diagnosis of glioma and different grades of brain tumour, A.K. Anaraki et al. [23] presented a hybrid technique based on CNN and GA (genetic algorithm).

In P. Shrivastava et al. [24], the author described a method for classifying brain tumours that combined PNN and PCA.

Y. Pan et al. [25] offer a deep learning-based brain tumour classification system. Here's a comparison between CNN and back propagation neural networks. The CNN that was employed here has two levels.

In K. Bhattacharjee et al. [26], a multilayer perceptron is used to classify molecular brain neoplasia.A. Kumar et al. [27] introduced an SVM-based strategy for brain MRI classification, as well as a hybrid model using PSO to extract the features.S. Alagarsamy et al. [28] and T. Kaur et al. [29] show how the BAT algorithm can be used to classify brain tumors. The BAT algorithm has selected the best cluster placement.

TRS (Tolerance Rough Set) and FA (Firefly algorithm) are used to select tumor traits; this approach was proposed by G. Jothi et al. [30].A. Dixit et al. [31] present the application of PSO and SVM to classify tumorous and non-tumorous brain tumors. PSO is used for segmentation, DWT is used to extract features, and an SVM classifier is used to train all of the extracted features.

K. V. Ahammed Muneer et al. [32] suggested two AI techniques for glioma tumor grade classification: Compound Hierarchy of Algorithms Representing Morphology tool and VGG-19 deep learning networks were used to calculate Weighted Neighbour Distance. In this article, a high level of classification accuracy is attained.

The majority of brain tumor categorization methods rely on segmentation. As a result, the researchers are focusing their efforts on applying deep learning algorithms to classify images. Deep learning has lately been employed in a number of studies have been proven to be useful instruments in the diagnosis of many vital diseases, such as heart disease, blood cancer , and lung cancer. [33, 34, & 35]

Rehman et al. [36] developed an outline for tumor categorization that used a configuration known as tri-architectural CNN (convolution neural network). Meningioma tumors, glioma tumors, and Pituitary gland tumors were all included in this categorization. The brain MRI was sliced to discover regions of interest using the method outlined above. The data sets were also fine-tuned and frozen in preparation for further classification. To ensure the correctness of the results, the authors examined data augmentation strategies. Using the VGG16 architecture to improve classification and detection, this study achieved a 98.69 % accuracy.

Deepak et al., [37], employed the identical data as and applied the same deep transfer concept to image categorization. Characteristics were extracted from images and used in the aggregation of testing and classifying models. At the patient level, the authors achieved a 98 % accuracy using a 5-fold classification model. Completely automated classification, according to the data, can aid in region categorization and surpasses manual classification.

Afshar et al. [38] used CapsNets as a Capsule network model to classify brain tumours in another investigation. By incorporating variance in CapsNet maps at a convolution layer, the analyses' accuracy was improved. The study claimed an accuracy of 86.50 % while using CapsNet in the convolution layer. A 64 feature map was employed in the setup to boost the accuracy measurements.

For feature extraction, Pashaei et al. [39] developed a CNN-based design. They also designed an adapted 33-layered configuration and a 5-layered architecture with all layers learnable. The accuracy of the study was stated to be 81 %, which was further improved by a CNN-based classification model based on ELM (Extreme Learning Machine).By examining categorization discrepancies in pituitary and meningioma images, the researchers discovered a shortcoming in the classifiers' discrimination capability.

NN.Sajjad et al. [40] suggested the neural network categorization system for assisting in the presentation of clear image fragments. Furthermore, the study applied transformation and invariance concepts to several noise reduction techniques. The CNN configuration could be used to fine-tune the accuracy of tumor grade prediction. The data was fed into a fine-tuned CNN for prediction accuracy. On two separate sets - Radiopaedia and brain tumor – several experiments were conducted. To measure system accuracy, the researchers used both original and supplemented datasets, totaling 90.67 %.

Pereira et al. [41] developed a 3D CNN that uses a region of interest to automatically evaluate glioma using traditional multi-sequence MRI. The anticipated grading method does two things: it extracts regions of interest and predicts glioma grade. The proposed method was evaluated on the BRATS 2017 Training set, a publicly available dataset that uses picture databases to identify patients. The system's accuracy was 89.5 %, with 92.98 % accuracy in predicting tumors established on sections of interest.

Anaraki et al. [42] recommended that MRI data be used to categorize different types of Glioma images using a CNN and GA technique (genetic algorithm).The proposed approach employed GA to choose a CNN structure automatically. They predicted Glioma pictures of three varieties with a 90.9 % accuracy. Furthermore, the study's Glioma, Meningioma, and Pituitary classifications were 94.2 % accurate.

Banerjee et al. [43] used a sequence of several MRI images to improve the classification of MRI images using a convolutional neural network. They proposed ConvNet models based on MRI image slicing and patching that were modified to be constructed from the ground up. Existing models for analyzing diverse MRI images, such as ConvNets and VGGNet, were merged in this study. The study evaluated the performance of presented models, claiming that when tested on various MRI datasets, they reached a 97 % accuracy rate.B.

III. Conclusions

There are several image segmentation methods available; nonetheless, a good segmentation methodology is essential to differentiate the brain tumor from MRI images in order to properly detect a brain tumor. This publications examines some of the most modern segmentation methods for detecting brain tumors. For appropriate diagnosis, planning, and therapy, precise data from many images from diverse slices must be analyzed. The goal of this study is to provide an overview of the strategies that are often used to classify and segment brain tumors. Other brain illnesses, such as Parkinson's disease, Alzheimer's disease, and stroke, can be treated with these techniques. The goal of all methods is to produce an accurate and efficient system that makes it simple to discover tumors in the shortest amount of time with the highest level of accuracy.

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