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Analysis of Brain Tumor Detection Techniques

Aparna Das[1], Mrs. Keshika Jangde[2], Mrs. Debshree Bhattacharya[3]
[1] *Student, Computer Science Department, Rungta College of Engineering and Technology, Raipur*
[2]*Assistant Professor, Computer Science Department, Rungta College of Engineering and Technology, Raipur*
[3]*HOD, Computer Science Department, Rungta College of Engineering and Technology, Raipur*

Abstract: ***The bio-medical image processing is the application of image processing to process medical data. The techniques of feature extraction and machine learning are efficient techniques brain tumor detection. Various network architectures are utilized, ordinarily with hundreds or thousands of adjustable parameters. The resulting condition forms are sufficiently general to unravel a large class of nonlinear classification and estimation problems and sufficiently complex to hide a multitude of sins. In this paper, various brain tumor detection techniques are reviewed analyzed in terms of certain parameters. It is analyzed that textual feature extraction and classification techniques give maximum accuracy for the brain tumor detection.***
Keywords: Brain tumor, MRI, Image segmentation, Textual Feature analysis, Classification.

I. INTRODUCTION

The brain is a vital organ that regulates bodily functions as well as other organs, and tumors occur due to uncontrolled cell division. Tumors are classified as low or high grade, with low-grade tumors being non-cancerous and benign, while high-grade tumors are malignant and can spread to other parts of the body, potentially leading to death. Brain tumors are prevalent among young adults, ranking as the third most common cancer in those between 15 and 39 years of age [1]. Appropriate treatment for tumors depends on the type, and misdiagnosis can be fatal. Diagnosis of tumors is based on size, location, and intensity, which is useful if surgery is necessary. However, the type of tumor is a critical factor in determining the appropriate remediation. Pre-surgical prediction and classification of tumors are essential for making informed clinical decisions and planning.To diagnose tumors, effective prediction and classification methods based on medical imaging techniques such as Medical Resonance Imaging (MRI), Computed Tomography (CT), and ultrasound are needed. MRI is a non-invasive diagnostic mechanism that can aid medical professionals in diagnosing brain tumors. MRI has demonstrated more encouraging results compared to CT and ultrasound [2].

A. Brain Tumor Detection Process

Medical image analysis has undergone a significant transformation due to the rapid advancement of hardware and the use of sophisticated mathematical tools. These developments have made it possible to obtain clear medical images, which can aid doctors in making accurate diagnosis and administering appropriate treatments. Consequently, medical image analysis has become a crucial tool in modern medicine, enabling doctors to provide better care for their patients.

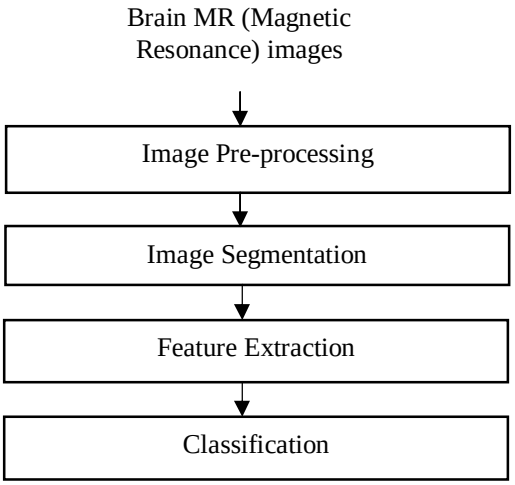

Figure 1: Brain Tumor Detection Process

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The MRI-based brain tumor detection process is presented in Figure 1. The brightest area in the MRI image typically corresponds to the brain tumor. This imaging technique creates an image based on the number of hydrogen atoms present in the body. Areas with a high concentration of hydrogen atoms appear bright in the image [3]. In cases where the tumor is not easily visible using a regular MRI scan, a contrast agent called gadolinium can aid in highlighting the tumor. Gadolinium is rich in glucose, which in turn contains a high concentration of hydrogen atoms. Tumors tend to absorb glucose, making them hydrogen-rich and thus more visible in the MRI images.A wide range of noises, such as salt and pepper, Gaussian, Rician, and speckle noise, can significantly affect the quality of brain MRI scans, presenting a challenge for machine learning-based applications. Consequently, pre-processing stage deals with a crucial step of acquiring high-quality denoised images. However, each denoising method used in MRI has its own set of pros and cons. To reduce noise, various techniques have been developed that rely on statistical properties and frequency spectrum distribution [4]. Apart from denoising, pre-processing may involve a range of other tasks, such as eliminating tags, smoothing the foreground area, correcting intensity in homogeneity, preserving related edges, resizing, cropping, and skull stripping.

Segmentation is a crucial task in MRI brain scans, which focuses on label each voxel's tissue type and anatomical formation. The detection of Regions of Interest (ROI) is vital in tumor classification, as it enables the precise localization of the tumor region, enhances visualization, and enables quantitative measurements of image structures during feature extraction. Manual segmentation, semi-automatic segmentation, and fully automatic segmentation are the three basic methods to accomplish brain tumor segmentation. Region-based segmentation is a frequently employed technique in automated image processing approaches [5]. Region-based segmentation is a technique that divides an image into connected groups of pixels that share common characteristics, such as intensity values, texture, and shape. This segmentation method partitions an image into distinct regions to accurately identify the desired area.

When using region-based segmentation, the algorithm considers various factors, including the pixel values, such as differences in gray levels and variances, as well as the spatial relationship between pixels, such as Euclidean distance and the region thickness in collective grouping of pixels.

The most frequently utilized region-based segmentation methods for segmenting brain tumor include region growing and clustering algorithms. Clustering-based segmentation is a robust region-based segmentation technique where an image is partitioned into numerous separate groups [6], based on the degree of similarity between the pixels. Clustering techniques are unsupervised learning methods and have been extensively studied in medical image segmentation. Clustering-based segmentation is a robust region-based technique that partitions an image into several separate and distinct groups. The technique sorts similar pixels into a designated region and segregates dissimilar pixels into different regions. Clustering methods are unsupervised in nature and have been extensively studied to segment clinical imagery.

Feature extraction approaches involve mathematical models that use several image features such as texture, intensity, contrast, shape, and more to extract features. Commonly used feature extraction methods include Gabor transforms, GLCM, wavelet-based features, and histogram of local binary patterns (LBP). In addition, deep features obtained from CNNs have recently gained popularity as input for SVM classifiers in brain tumor classification tasks.

To enhance the ability of the machine learning model to classify different types of brain tumors, it is common to combine various features extracted from different models. In addition, dimensionality reduction is often applied through feature selection [7]. The final step of this process involves using a classifier to diagnose the tumor based on the extracted features. In general, a classifier analyzes the input data to identify patterns that can be utilized to assign it to a specific class, such as meningioma, glioma, or pituitary. To assess the performance of the classifier, three fundamental metrics known as accuracy, specificity, and sensitivity are used.

B. Brain Tumor Classification Techniques

Machine learning is a field that enables machines to improve their performance on tasks by gaining experience. There are three major types of machine learning techniques: supervised, unsupervised, and reinforcement learning. In supervised learning, the machine is trained on a data sample that has already been labeled by domain experts. In contrast, unsupervised learning aims to uncover patterns and structures from unlabeled data. Reinforcement learning involves making a sequence of decisions based on reward signals, which means that the machine learns through receiving either rewards or penalties for its actions. In this way, the machine learning algorithm is able to improve its performance over time [8].The application of machine learning in the classification of brain tumors using MRI images has shown promising results. Many researchers have proposed different classification techniques to identify different types of brain tumors from images. In the field of brain tumor classification, several commonly used classifiers have been discussed here:

1) *Support Vector Machine (SVM):* Support Vector Machine (SVM) uses a hyperplane to split data into two distinctspaces. The primary objective of SVM in classification is to locate a hyperplane that maximizes the margin between data points in different classes, as shown in Figure 2. Support vectors are the data points that underpin the location of the hyperplane.To decide these points, Quadratic Programming is often employed.

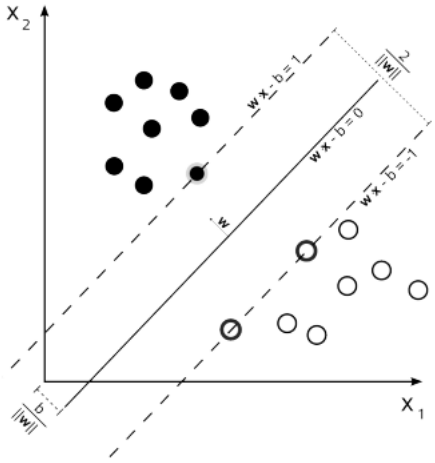

Figure2: Support Vector Machine

This image depicts a hyperplane (black line) that has been calculated to separate the data points, with a soft margin indicated by the area between dotted lines.Linear classifiers, like SVMs, cannot deal with overlapping class data. To solve this problem, Cortes and Vapnik put forth a Soft-Margin Hyperplane that enables class overlapping by penalizing data points that breach the hyperplane into the other class's feature space [9]. This penalty is expressed mathematically using a slack variable in the Quadratic Programming formulation. To tackle non-linearly separable issues, the "kernel trick" can be used.This technique involves transforming the data into a higher dimensional space, allowing for the separation of non-linearly separable data.Most research in this field utilizes a radial basis function as the kernel, which is the most common selection of kernel for SVMs.

2) *K-Nearest Neighbor:* K-Nearest Neighbor (k-NN) is a lazy learning algorithm that does not require a formal training phase. Instead, the algorithm constructs a model by adding training cases. At any stage during the inclusion of the training cases, the model can be used for testing cases. Computing the distance between the test point and all other points in the dataset is first step for classification. While any distance metric can be utilized for k-Nearest Neighbor (k-NN) algorithm, Euclidean distance is frequently employed in various domains [10]. The next step is to select k nearest neighbouring points to the test point. Finally, the class is determined by the most common class among the selected set of neighbouring points.Figure 3illustrates an example of how k-NN works.

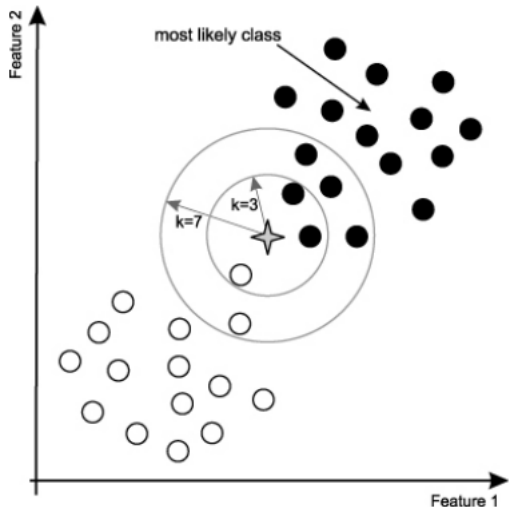

Figure 3: Use of k = 3 and k = 7 for the data point symbolized by a star in the Nearest Neighbor building process

There are several ways to implement a k-NN algorithm. The kd-tree is the most widely used data structure for classification. A kd-tree divides the space into a d-dimensional tree [11].If a point, x_i, occurs within the separated space of another point, x_j, then the two points, $x_i$and x_j, can be considered close to each other when traversing a kd-tree. This approach is not only efficient but also offers fast processing speed. It is as compared to brute force techniques. In contrary to brute force, a kd-tree can be traversed more quickly. However, when it comes to classification, kd-tree may be less efficient in higher dimensions of the feature-space.

3) *Artificial Neural Networks (ANN):* Artificial Neural Networks (ANN) are a class of AI algorithms used for classification in various domains. These algorithms, inspired by the brain, store knowledge obtained from input data via a training process. An ANN follows a three-layer structure, comprising the input, hidden, and output layers, as shown in Figure 4.

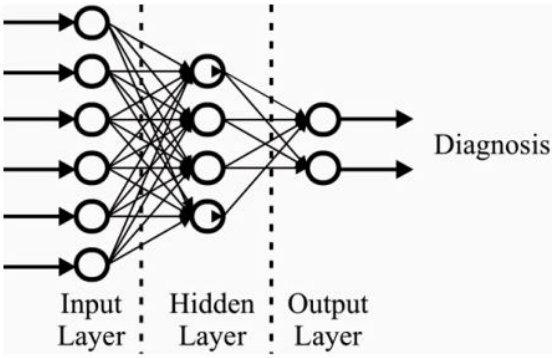

Figure 4: Artificial Neural Network

During the training process of Artificial Neural Networks, the weights (variables) that connect all the layers are adjusted to match the input with its corresponding class [12]. This allows the detection and storage of hidden patterns that are shared by all the inputs and their respective classes. Therefore, a sufficient database with representative scenarios is necessary to train the ANN effectively.

4) *Deep Neural Networks:* The design of an ANN serves as the foundation for deep neural networks (DNN).This type of network stores knowledge in multiple layers, similar to how the brain does, to solve complex tasks. One specific type of DNN is the Convolutional Neural Network (CNN), which is modeled after the visual processing cortex and is used to classify images. The architecture of a typical CNN is shown in Figure 4. It is important to note that the use of DNNs requires significant amounts of data to train the network effectively.

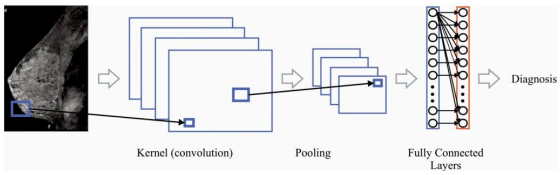

Figure 6. Convolutional Neural Network

A CNN is composed of a kernel, pooling layers, and fully connected layers, as can be seen in the figure. The convolution operator is typically used in the kernel layer to determine and obtain spatial characteristics from the image [13]. The feature map output by this layer may contain negative values, which could lead to numerical instability during training; as a result, the feature map is treated using a function to prevent the negative values. The output of the pooling layer is then sent to the fully connected layer to be classified after the feature map has been processed, where it is reduced in size to get rid of unnecessary data. In this regard, CNN has been used in a number of studies to identify benign and malignant regions in mammography or MRI images. It should be mentioned that the performance of the classifier is influenced by the depth of the network, or the number of layers, the fine-tuning of certain of the kernel or pooling layers, as well as the quantity of images.

II. LITERATURE REVIEW

G. Raut, et.al (2020) investigated a Convolutional Neural Network (CNN) algorithm to detect the brain tumor [14]. The initial objective of this algorithm was to augment the brain Magnetic Resonance Imaging (MRI) images for generating the sufficient data. The next task was to pre-process the images for eliminating the noise, and making the images appropriate for further stages. The pre-processed images were considered to train this algorithm while classifying the images as tumorous and healthy. The error was diminished, and more precise outcomes were obtained using Back Propagation (BP) model. Autoencoders were deployed on the generated image for eliminating the inappropriate features, and the K-Means algorithm was implemented for segmenting the tumorous area. The investigated algorithm yielded an accuracy up to 0.955 to diagnose the brain tumor. Furthermore, this algorithm assisted in saving human efforts and time.

S. Sangui, et.al (2023) suggested a modified U-Net model in a deep-learning (DL) method to diagnose and segment the brain tumors from Magnetic Resonance Imaging (MRI) images [15]. Primarily, U-Net model was deployed to outline the tumor, and detect the tumorous region in MRI images. This work made the implementation of diverse techniques which assisted in detecting the brain tumor. The median filtering method was adopted in the first pre-processed segment so that the MRI images were pre-processed. The images taken from BRATS 2020 datasets were applied in the experimentation. The results validated that the accuracy of the suggested model was calculated 99.4% as compared to the traditional methods. This model consumed lower time in training and computing.

O. Turk, et.al (2022) projected a method in which ensemble deep learning (DL) methods known as ResNet50, InceptionV3, MobileNet and VGG19 were exploited for the purpose of diagnosing the brain tumors in an automatic way [16]. Moreover, Class Activation Maps (CAMs) indicators were also employed based on Magnetic Resonance Imaging (MRI) images [16]. This method was executed in 3 phases. First of all, the binary approach was implemented for determining that the images had tumor or not. After that, this method helped in classifying diverse tumor kinds such as healthy, Glioma, Meningioma, and Pituitary Tumor from MR images (Multi-class Approach). In the end, the formation of CAMs of every tumor group was done as an alternative tool for assisting the doctors in detecting the brain tumor. The projected method offered an accuracy of 100% on first 3 algorithms and 99.71% on the VGG19 for tackling binary classification issue. Moreover, the accuracy of first algorithm was counted 96.45%, 85.03% for second, 89.34% for third and 93.40% for the last algorithm in the multi-class approach.

S. Patil, et.al (2023) introduced an Ensemble Deep Convolutional Neural Network Model (EDCNN) framework for detecting the brain tumor [17]. At first, this model employed Shallow Convolutional Neural Network (SCNN) and VGG16 network with 1C modality Magnetic Resonance Imaging (MRI) image. At second, an analysis was conducted on loss and accuracy [17]. The accuracy was enhanced after fusing the extracted features from utilized models for enhancing the accuracy to classify 3 kinds of brain tumors. The experimental results revealed that the introduced framework was adaptable for enhancing the accuracy while tackling multiclass classification issue and overfitting for imbalance dataset. Furthermore, this framework yielded an accuracy of 97.77% for diagnosing the brain tumor.

L. Ma, et.al (2021) presented a Deep Learning (DL) and Predictive Intelligence model [18]. Initially, a new lightweight neural network (LNN) based end-to-end (E2E) model was developed for detecting the brain tumor accurately and efficiently. Subsequently, edge intelligence was put forward for making the model effective to process the data in medical data center in hospital and for balancing various resources. The developed model was computed in a series of experiments. The experimental results depicted that the developed model outperformed the existing methods and its practicality was proved for detecting the brain tumor.

M. Gupta, et.al (2020) constructed an effective approach in which a novel non-invasive quantitative feature set (NQFS) was implemented on the basis of Magnetic Resonance Imaging (MRI) to diagnose the brain tumor, and classify their grade [19]. The segmentation-based fractal texture analysis (SFTA) model was utilized for extracting the texture attributes. The extraction of selected shape measures was done from the segmented tumor volume for differentiating the low-grade (LG) tumor from the high-grade (HG) one. Support Vector Machine (SVM) algorithm was put forward for classifying the tumor grade. The constructed approach offered an accuracy of 87%, specificity of 86% and sensitivity of 88% to classify LG and HG brain tumor.

M. V. S. Ramprasad, et.al (2022) established an Artificial Intelligence (AI)-based tool recognized as BTFSC-Net to detect the brain tumor [20]. A hybrid probabilistic wiener filter (HPWF) was adopted to pre-process the clinical images. Magnetic Resonance Imaging (MRI) and CT images were fused with robust edge analysis (REA) properties through deep learning convolutional neural network (DLCNN) algorithm for recognizing the slopes and edges of source images. Afterward, a hybrid fuzzy c-means integrated k-means (HFCMIK) algorithm was presented for segmenting the disease affected region from the fused image. Additionally, Gray-Level Co-occurrence Matrix (GLCM) and Redundant Discrete Wavelet Transform (RDWT) descriptors were executed for extracting the hybrid features such as texture, color, and low-level attributes.

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At last, a Deep Learning Based Probabilistic Neural Network (DLPNN) was assisted in classifying the tumors as malignant and benign. The established model offered an accuracy of 99.21% to segment the brain tumor and 99.46% to classify the tumor. The experimental results depicted the supremacy of this model over the traditional techniques.

M. Rizwan, et.al (2022) presented a Computer Aided Diagnosis (CAD) method in order to detect and classify the radiological images of brain tumor (BT) into 3 classes: pituitary-tumor, glioma-tumor, and meningioma-tumor [21]. Moreover, a technique based on Gaussian Convolutional Neural Network (GCNN) was implemented for diagnosing distinctive BT types on 2 datasets. At first, a Gaussian imaging filter was employed to pre-process the image. At second, this method emphasized on creating 16-layers based network. The process of augmenting the data was proved effective to generate promising results. According to the experimental results, the presented method provided an accuracy of 97.14% on initial dataset and 99.8% on second one.

A. Hossain, et.al (2021) recommended a Deep Neural Network (DNN) algorithm called You Only Look Once-version 3 (YOLOv3) for detecting the brain tumors in a portable electromagnetic (EM) imaging system [22]. The major task was to gather the scattering metrics from the nine-antenna array setup in which 1 antenna was employed as a transmitter and rest were utilized as receivers. The modification of delay-multiply-and-sum algorithm was implemented for re-constructing the images from the post-processed scattering metrics. The EM imaging system was utilized to gather 50 sample images from diverse head areas. Various image datasets were executed to conduct the simulation. The recommended algorithm attained an accuracy of 95.62%, and F1 scores of 94.50%. Additionally, this algorithm was applicable in the portable electromagnetic (EM) head imaging system.

T. Rahman, et.al (2023) designed a new Parallel Deep Convolutional Neural Network (PDCNN) model for extracting global and local features from 2 parallel stages and tackling over-fitting issue with dropout regularizer (DR) and batch normalization (BN) [23]. This model aimed to resize the input image and transform the grayscale image. Thereafter, the process of augmenting the data was employed for increasing the number of datasets. Two deep convolutional neural networks (DCNNs) were integrated with 2 different window sizes for learning local and global information. The designed model yielded an 97.33% accuracy on dataset-I, 97.60% on Figshare dataset, and 98.12% on Kaggle dataset. The results exhibited the robustness as well as effectiveness of the designed model.

A. Comparison Table

Author	Year	Techniques Used	Results	Limitations
G. Raut, et.al	2020	Convolutional Neural Network (CNN) algorithm	The investigated algorithm yielded an accuracy up to 0.955 to diagnose the brain tumor. Furthermore, this algorithm assisted in saving human efforts and time.	The size of dataset employed in this work was restricted and the images of this dataset were related to few subjects only.
M. Gupta, et.al	2020	An effective approach	The constructed approach offered an accuracy of 87%, specificity of 86% and sensitivity of 88% to classify LG and HG brain tumor.	This approach was not able to compute the percentage area of the tumor having brain tumor.
L. Ma, et.al	2021	A new lightweight neural network (LNN) based end-to-end (E2E) model	The experimental results depicted that the developed model outperformed the existing methods, and its practicality was proved for detecting the brain tumor.	The accuracy of this model was mitigated in case the images contained noise.

A. Hossain, et.al	2021	You Only Look Once-version 3 (YOLOv3)	The recommended algorithm attained an accuracy of 95.62%, and F1 scores of 94.50%. Additionally, this algorithm was applicable in the portable electromagnetic (EM) head imaging system.	The efficacy of the recommended algorithm was alleviated in the presence of images of higher dimensionality.
O. Turk, et.al	2022	Ensemble deep learning (DL) methods	The accuracy of first algorithm was counted 96.45%, 85.03% for second, 89.34% for third and93.40% for the last algorithm in the multi-class approach.	These methods consumed higher time in recognizing the tumor.
M. V. S. Ramprasad, et.al	2022	BTFSC-Net	The established model offered an accuracy of 99.21% to segment the brain tumor and 99.46% to classify the tumor. The experimental results depicted the supremacy of this model over the traditional techniques.	This model was not localized the tumorous area precisely.
M. Rizwan, et.al	2022	Computer Aided Diagnosis (CAD) method	According to the experimental results, the presented method provided an accuracy of 97.14% on initial dataset and 99.8% on second one.	It was not possible to reutilize this method for detect the modest number of images.
S. Sangui, et.al	2023	modified U-Net model	The accuracy of the suggested model was calculated 99.4% as compared to the traditional methods. This model consumed lower time in training and computing.	This model was not effective for detecting the survivability of patients suffered from brain tumors. Moreover, it was unsuitable to larger and varied datasets.
S. Patil, et.al	2023	Ensemble Deep Convolutional Neural Network Model (EDCNN) framework	The introduced framework was adaptable for enhancing the accuracy while tackling multiclass classification issue and overfitting for imbalance dataset. Furthermore, this framework yielded an accuracy of 97.77% for diagnosing the brain tumor.	The hyper-parameter obtained in this approach was not optimal and this work did not focus on selecting attributes.
T. Rahman, et.al	2023	Parallel Deep	The designed model	This technique

		Convolutional Neural Network (PDCNN)	yielded an 97.33% accuracy on dataset-I, 97.60% on Figshare dataset, and 98.12% on Kaggle dataset. The results exhibited the robustness as well as effectiveness of the designed model	offered lower efficiency on 3D structure to recognize brain tumor from 3D brain MRI images.

III. CONCLUSIONS

In this paper, it is concluded that brain tumor detection has the three major phases which are segmentation, feature extraction and classification. Detecting Similarities intend to partition an image into regions that are comparable as indicated by an arrangement of predefined criterion; this incorporates image segmentation calculations like thresholding, region growing, region splitting and merging. The region based segmentation approach, textual based feature analysis and classification give maximum accuracy for brain tumor detection. In the future novel hybrid classification method will be designed for the brain tumor detection.

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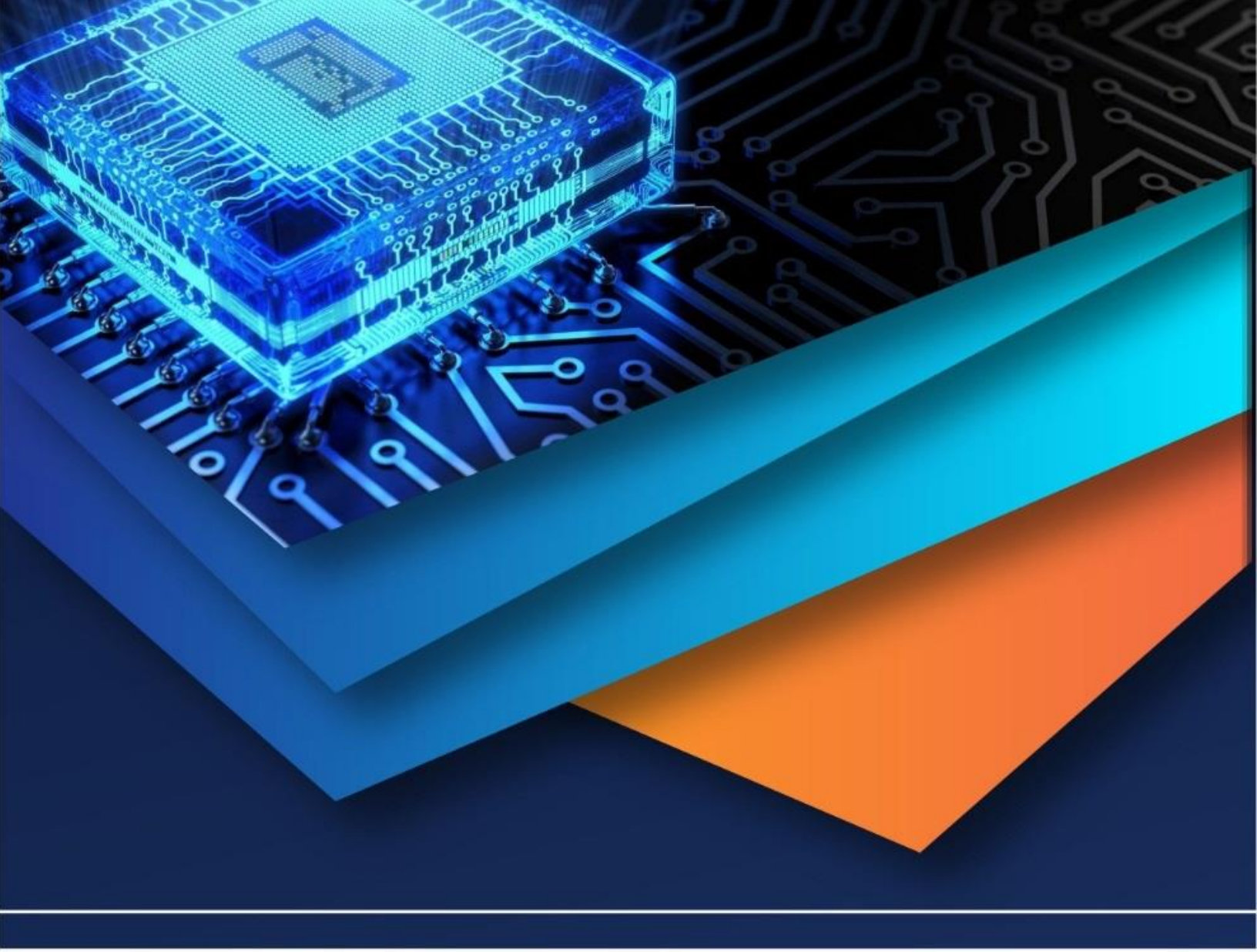

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