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FCM and CBAC based Brain Tumor Identification and Segmentation

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Abstract

A brain tumor are an abnormal growth of cells within the brain, forming a mass that can be either cancerous (malignant) or non-cancerous (benign). Despite their differences, both types of tumors can pose serious health risks. As these tumors grow, they can increase intracranial pressure, leading to potential brain damage. This increased pressure can result in various symptoms such as headaches, seizures, vision problems, and changes in cognitive function. The potential for life-threatening consequences makes early detection and treatment crucial. The objective of the research is to develop a system or algorithm capable of accurately identifying the presence of brain tumors within medical imaging data (CT or MRI scans) and subsequently segmenting the tumor regions from the surrounding healthy brain tissue. This research aims at building an automated multi stage reliable system for classifying MRI images as tumor or non-tumor images. However, the research aims to diagnose brain tumor by extracting the tumor region accurately. The main contribution of this work is to automatically segment the tumor region from the MRI brain images, using Fuzzy C-Means (FCM) Clustering and the Content-Based Active Contour (CBAC) method. The CBAC method helps to resolve the issues of saddle points and broken edges in the extracted tumor region.

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1. Introduction

Brain tumors have become a leading cause of increased mortality among both children and adults globally. These tumors consist of abnormal cell growths within or around the brain. They can be broadly categorized into two types: noncancerous (benign) as well as cancerous (malignant). The diversity in types of brain tumors necessitates accurate diagnosis and treatment. Magnetic Resonance Imaging (MRI) is a crucial diagnostic tool for brain tumors, providing detailed images of the brain's structure[3-7]. This imaging method is extensively used to identify and evaluate brain tumors. Furthermore, the segmentation of brain tumors from MR images plays a vital role in enhancing diagnostics, predicting tumor growth rates, and planning appropriate treatments. Effective segmentation can significantly impact patient outcomes by allowing for more precise and individualized treatment strategies [8].

The system proposed integrates feature extraction, classification, as well as the segmentation methods to diagnose images of brain as either tumorous or normal and to isolate the tumor regions in tumorous brain images. The process begins with noise removal from the brain MRI images to enhance image quality. Following this, texture feature extraction techniques are employed to derive texture features from the images. These features extracted are given as input into a Support Vector Machine (SVM) classifier, which categorizes the MRI images of brain as either tumorous or normal [9-12].

Brain tumor identification and segmentation are critical components in medical imaging and healthcare. The primary motivation behind these efforts is to achieve early as well as precise diagnosis [13]. Early detection is crucial as it allows for timely medical intervention, which can significantly improve patient outcomes and potentially save lives. Advancements in MRI and CT technologies offer non-invasive methods for detecting and segmenting brain tumors, enhancing patient assessment and monitoring [14,15].

2. Related Work

In reference [1], a technique is proposed that does not rely on prior information about the image's type, content, or model. The system achieves over 99% accuracy by only segmenting images classified as tumorous, saving time by avoiding the segmentation of normal brain images. However, its heuristic threshold estimation often leads to inaccurate results and is computationally expensive.

In [2], the authors introduced a system called FVF, which performs effectively on postcontrast T1-weighted images. It's especially good at identifying brain hemorrhages and tumors, particularly those regions with high intensity. However, they haven't yet tested the method on T1-weighted and T2-weighted brain tumor MR images, nor with different types of tumors like isointense and heterogeneous ones.

3. Proposed Work

The Figure 2 illustrates the work flow of the proposed. The input image is fed into the pre-processing stage where noise removal is done using three wavelets. Then the noise free images are given as input into the feature extraction phase. Two feature extraction techniques have been used. The total features extracted from the brain MRI image are 13. Features are given as input for the classification process and it uses SVM algorithm for classifying the image as non-tumor or tumor. If MRI image is non-tumorous, there is no segmentation. Otherwise, the tumorous image is fed into the segmentation process which is done using FCM clustering algorithm. Finally, the segmented tumor region is given into the refining stage for accurately segmenting the tumor region using CBAC Method.

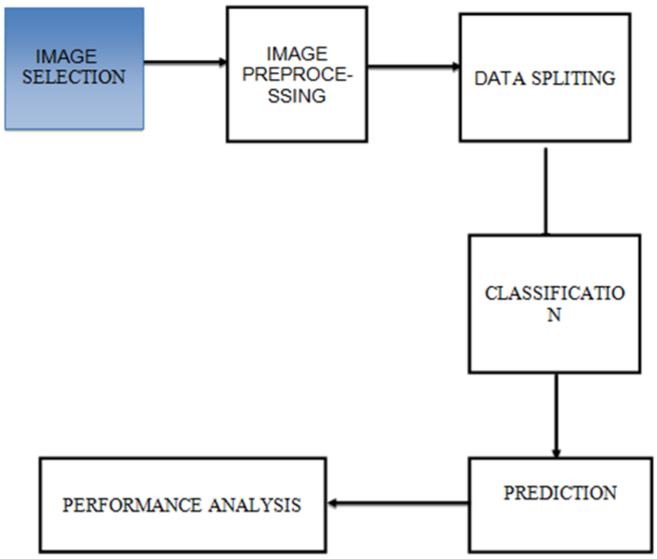

Figure 1. Flow Diagram

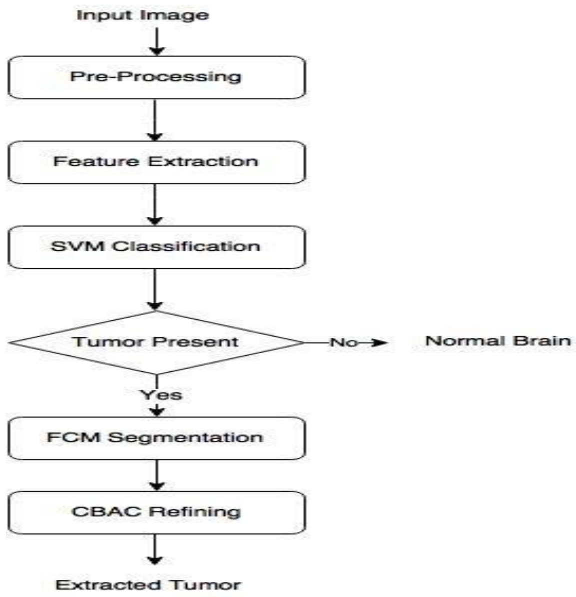

Figure 2. Data Flow diagram

FCM: The most widely used technique for segmenting images is the fuzzy c-means (FCM) algorithm, which may preserve far more information than hard segmentation techniques and has resilient properties for ambiguity. The traditional FCM algorithm has a significant drawback that prevents it from being effective for most noise-free images: it ignores spatial context, which results in noise and imaging distortions. The apparent solution is to smooth the image before segmentation in order to balance this inadequacy of FCM. Nevertheless, the use of traditional smoothing filters may cause the loss of crucial visual information, such as edges or boundaries.

Two feature extraction techniques have been used. Totally 13 extracted features from the brain MRI image from Kaggle and BRATS dataset are used in the proposed work. Features are used as input for classification process and it uses SVM algorithm for classifying the image as tumor or non-tumor. If the brain MRI image is non-tumorous, there is no segmentation. Otherwise, the tumorous image is fed into the segmentation process which is done using FCM clustering algorithm.

4. Result and Discussion

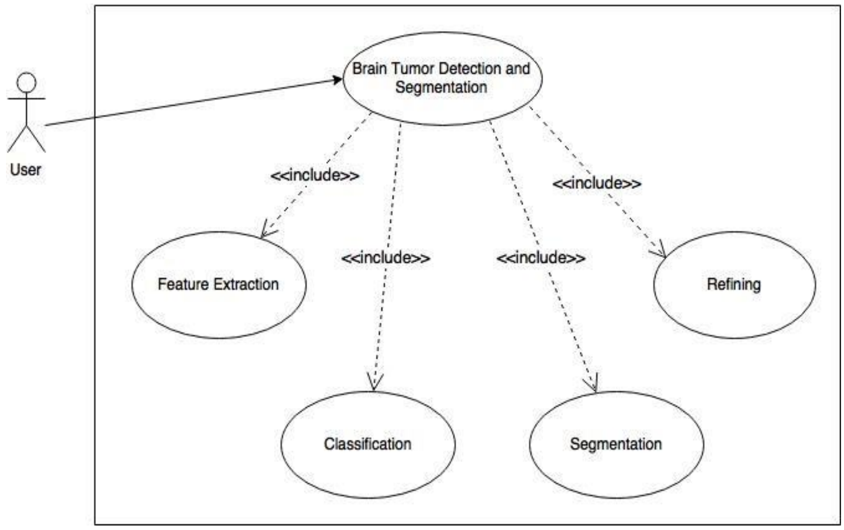

Figure 3. Use Case Diagram

The overall use case diagram of the entire system is shown in the Figure 3. It consists of brain tumor detection and segmentation process. Pre-condition:An input brain MRI image is given as input by the user.Post condition:The refined brain tumor region is generated.The extracted feature set will be the input into the classification process. The classification is done using SVM algorithm.

This technique classifies the image into tumor or non-tumor. The tumorous image is further segmented using FCM clustering algorithm in the segmentation process. To reduce the saddle points in the segmented region, it is further refined using CBAC method in the refining process.

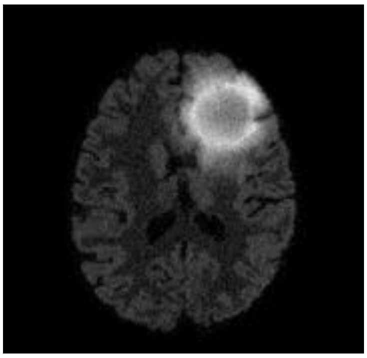

Figure 4. Sample Input Brain MRI Image

Input brain MRI image is given to the system which detects the tumor in the image and segments the tumor from the image if any. The extracted tumor is further refined using the CBAC method. The Figure 4 is an example of input brain MRI image with tumor. The input and output to each module of the system along with the algorithms used and example test cases are described in this section. The pre-processing step involves the noise removal process.

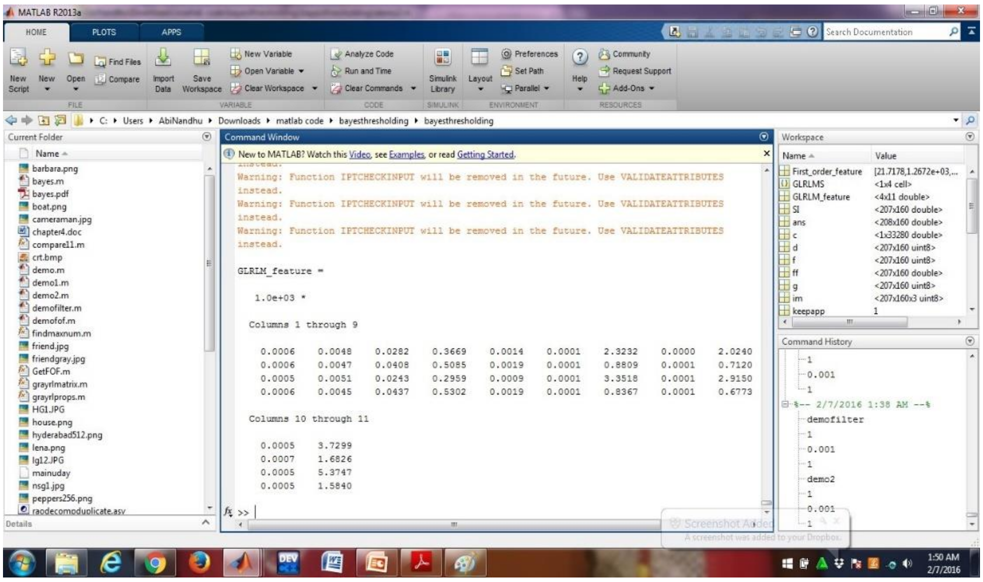

Figure 5. Noise Removal

Medical images are prone to be affected by noise, which affects the clarity of images. Hence noise removal is mandatory for further processing. The input to this module is the noisy brain MRI images and the output is the noise free brain MRI images. The Noise removal process is presented in Figure 5 and 6.

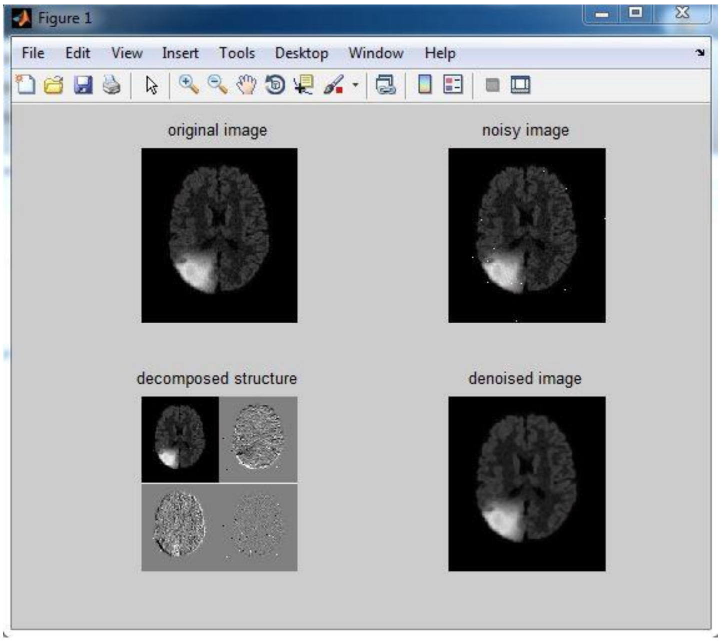

Figure 6. Noise Removal

Texture Feature Extraction: The input to this module is the noisy brain MRI images and the output is the noise free brain MRI images.

Input: Denoised brain images

Output: FOH and GLRLM features

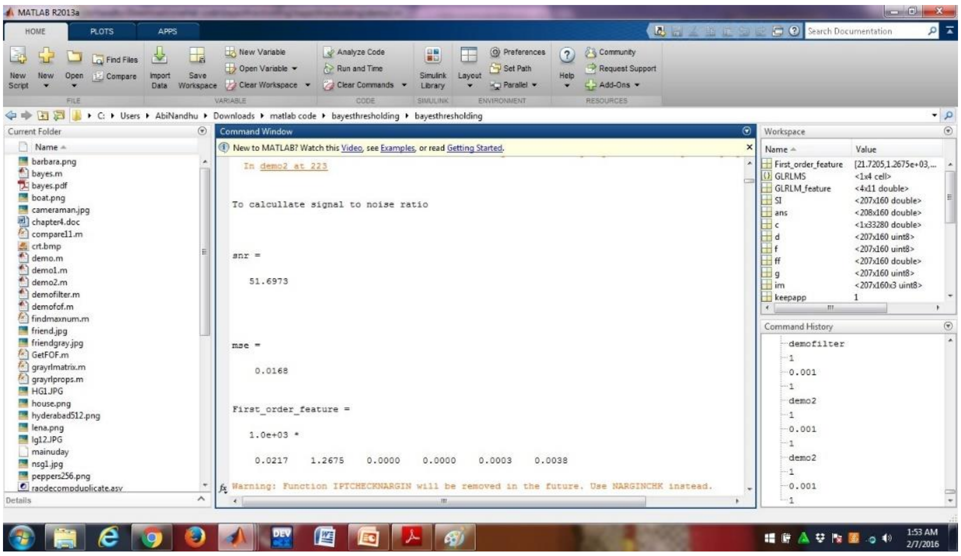

Figure 7. Feature Extraction (FOH)

Three independent classifiers have been used. They are SVM, K- NN and Backpropagation neural network. These classifiers are used to classify the images as tumorous or non-tumorous. The input to this module is the extracted texture features and the output of this module is the classification of the brain image as tumorous or non-tumorous.

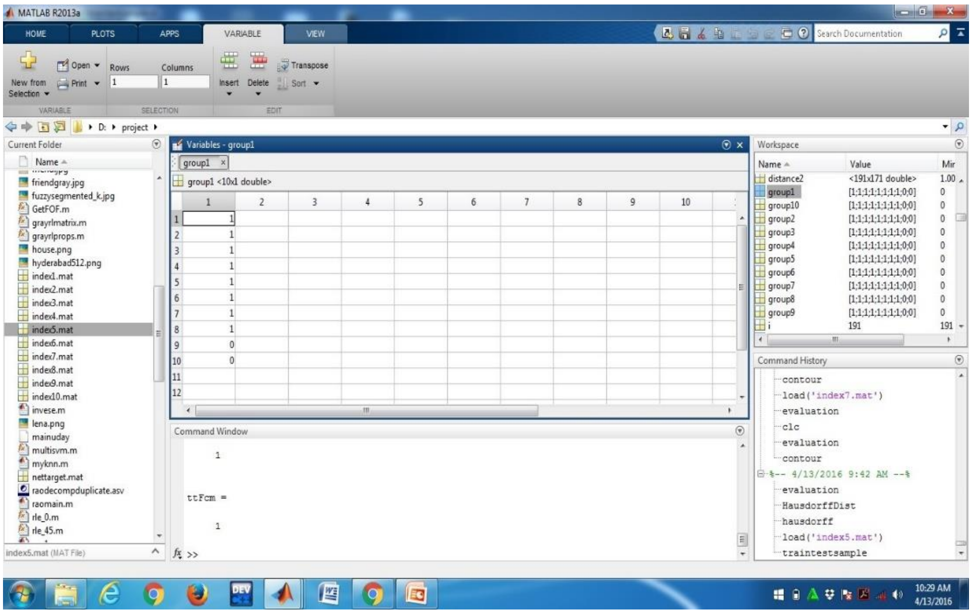

Figure 8. Classification using SVM Classifier

Here the input will be the extracted texture feature which is extracted from the brain MRI image and the corresponding output will be either normal or tumorous brain image. The figure 5,7 and 8 shows the implementation details about three classifiers, namely, SVM, Backpropagation Neural Network, K-NN. Here, we had conducted experiments with these three classifiers and calculated the accuracy, specificity and sensitivity values. By comparing these values, we have selected SVM classifier for classification of brain MRI images. Since it has the highest accuracy, specificity and sensitivity.

The FCM clustering algorithm is a robust method used for brain tumor segmentation in MRI images. It effectively handles the inherent uncertainty in medical images by using fuzzy membership values. The implementation steps involve careful preprocessing, iterative application of the FCM algorithm, and post-processing to refine the segmentation results. The performance of the algorithm can be validated using standard metrics to ensure accurate and reliable tumor detection.

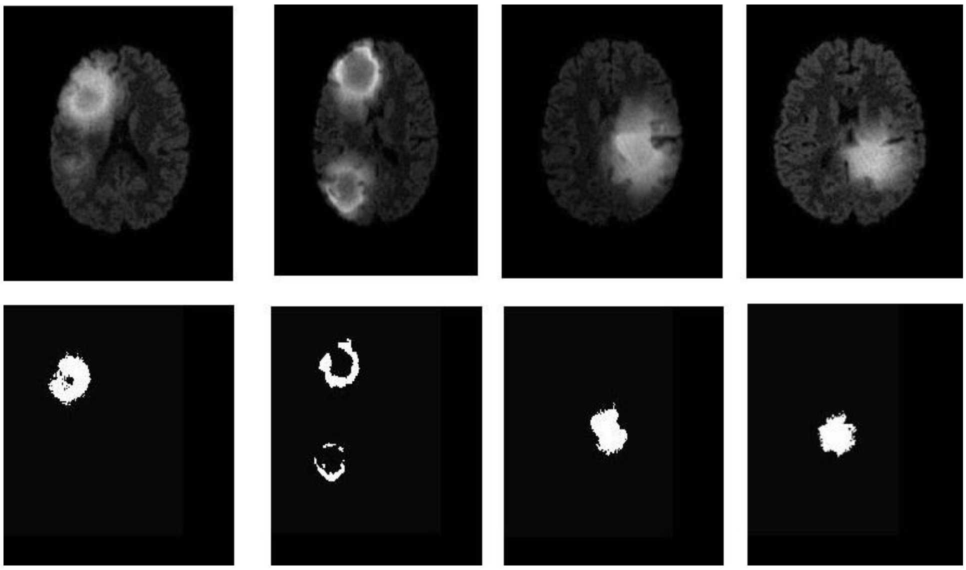

Figure 9. Segmentation

Initialization

- Define the number of clusters (e.g., 2 for tumor and non-tumor regions).
- Set the fuzziness parameter mmm (usually m=2m = 2m=2).
- Membership function. The proposed method uses Gaussian function.
- Set convergence criteria, such as a threshold for membership change and a maximum number of iterations.

FCM Functions

- **Initialize Membership Matrix**: Randomly initialize the membership matrix, ensuring the sum of memberships for each pixel equals 1.
- **Update Cluster Centers**: Compute cluster centers based on the membership values and the image intensity values.
- **Update Membership Matrix**: Recalculate the membership values based on the distance between each pixel and the cluster centers.

- **Convergence Check**: Iterate and update the steps until the change in membership values is less than a predefined threshold or the maximum number of iterations is reached.

The Content-Based Active Contour (CBAC) method is an image segmentation technique used in medical image analysis as well as computer vision. It's a variant of the traditional active contour model (also known as snakes) that incorporates content-based features into the energy functional to improve segmentation accuracy. Here's an overview of how the CBAC method works similar to traditional active contours, the CBAC method starts with an initial contour or curve that is placed close to the object boundary to be segmented. The CBAC method defines an energy functional that represents the trade-off between the smoothness of the contour and its adherence to image features. This energy functional typically consists of two terms:

- **Internal Energy**: Encourages smoothness of the contour and is typically based on the curvature of the contour.
- **External Energy**: Encodes image information to attract the contour towards object boundaries. Unlike traditional active contours, which often rely solely on edge-based features (e.g., gradient magnitude), the CBAC method incorporates additional content-based features such as texture, color, intensity, or even higher-level semantic information.

The proposed method obtains 98.8% accuracy using the FCM and CBAC method. Hence, the average detection rate for the proposed tumor detection and segmentation method is nearly 98.8%."

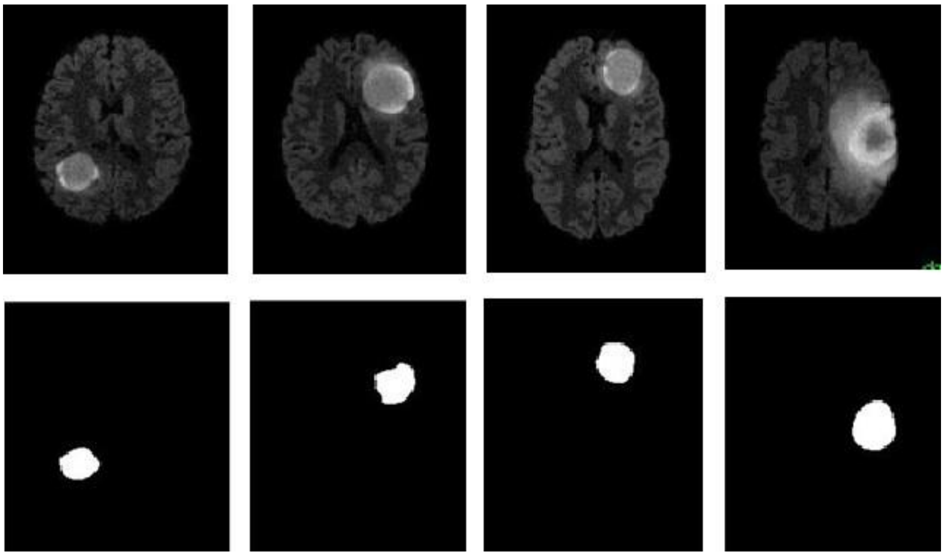

Figure 10. Tumor Extraction using CBAC

Table1 Performance of Algorithms

Methodologies	Se (%)	Sp (%)	Acc (%)	DR (%)
Proposed work	97.9	98.5	98.8	98
SVM	97.1	97.3	96.1	94
Backpropagation Neural Network	97.6	97.1	96.7	93
K-NN	96.8	97.3	97.6	95

Evaluating a machine learning model involves various tools, platforms, and libraries depending on the specific task and the technology stack used. Here's a generalized list of common one of the primary programming language Python- Spyder 3.9 . Software used.

Front End : Anaconda Navigator -Spyder

Back End : Anaconda Navigator -Spyder Console

5. Conclusion

The proposed method can be further extended by finding out the features again in the extracted tumor region. With the obtained features of tumor, the type of tumor can be determined. This would add additional functionality and efficiency of the project. The proposed system described in this paper achieves 98.8% accuracy using the FCM and CBAC method, compared to other methods such as SVM, Backpropagation Neural Network, and K-NN. Hence, the average detection rate for the proposed tumor detection and segmentation method is nearly 98.8%."Overall, the motivation behind brain tumor detection and segmentation lies in the collective effort to improve patient care, enhance clinical decision-making, and advance scientific understanding of brain cancer. Through interdisciplinary collaboration between healthcare professionals, engineers, and researchers, innovative solutions continue to emerge, driving progress in the field of medical imaging and oncology.

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