A COMPREHENSIVE STUDY ON BRAIN TUMOR DETECTION TECHNIQUES FROM MRI SCANS

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ABSTRACT

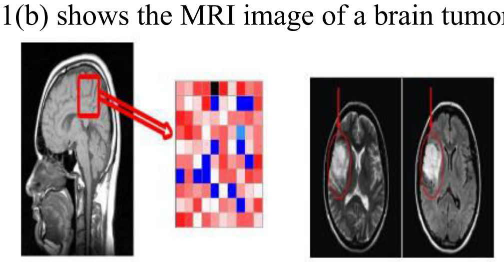
Brain tumors are among the most life-threatening neurological disorders, and early detection plays a crucial role in improving patient outcomes. Magnetic Resonance Imaging (MRI) is widely recognized as the most reliable non-invasive imaging modality for brain tumor diagnosis due to its high-resolution visualization of soft tissues. This paper presents a comprehensive study of various techniques used for brain tumor detection and segmentation from MRI scans. The research covers traditional image processing methods, machine learning algorithms, and advanced deep learning models such as Convolutional Neural Networks (CNNs) and U-Net architectures. Comparative analysis of these approaches highlights their respective strengths, limitations, and suitability for different clinical and research scenarios. Furthermore, the study explores the integration of AI-assisted diagnostic tools into clinical practice, focusing on their accuracy, robustness, and computational efficiency. This review aims to guide future developments in automated brain tumor detection systems and support radiologists in making faster and more reliable diagnoses.

I. INTRODUCTION

Brain tumors represent a significant health challenge, with increasing incidence worldwide and high mortality rates if not diagnosed early. These abnormal growths within the brain can be malignant or benign and often require complex, timely medical intervention. Among the imaging modalities used for diagnosis, Magnetic Resonance Imaging (MRI) stands out for its ability to produce detailed anatomical representations of brain structures, making it indispensable in detecting tumors, determining their size and location, and planning surgical or therapeutic procedures.

Despite MRI's effectiveness, manual interpretation of MRI scans by radiologists is time-consuming, subjective, and prone to variability, especially when tumors exhibit irregular shapes or low contrast with surrounding tissues. To address these challenges, researchers have developed a wide range of computational techniques aimed at automating the detection, segmentation, and classification of brain tumors from MRI images. These techniques range from classical image processing and feature extraction to modern AI-powered approaches, including machine learning and deep learning models trained on annotated datasets.

This paper offers a detailed review of these brain tumor detection techniques, emphasizing their methodological foundations, performance metrics, and real-world applicability. The goal is to provide a unified understanding of how these technologies contribute to early diagnosis, reduce diagnostic errors, and support clinicians in delivering more effective treatment strategies. To overcome all these challenges, a new methodology that has been developed and it's clinically focused and takes advantage not only of advanced imaging technologies takes into account the type of information that is typically available for patient and large-scale clinical therapy plans [17]. Figure 1 (a)shows the 2D model of brain tumor detection, and 1(b) shows the MRI image of a brain tumor



1(a) 1(b)

Figure 1: (a) 2D Model of Brain Tumor Detection
(b) MRI image of a brain tumor [18]

This work focuses on the automated segmentation of meningioma from MR imaging in multi-spectral brain datasets. One of the few benign tumors determined in the brain region is a meningioma [19]. Accurate tumor identification leads to the development of surgical indications in elderly persons who are carrying intracranial meningioma [20]. In recent years, Support Vector Machine (SVM) methods in MRI segmentation aimed at determining a range of neurological conditions have demonstrated excellent performance [21]. Segmentation is used for the identification of contaminated tumor tissues from modes of medical imaging [22]. In image analysis, segmentation is necessary and essential; it is a procedure of dividing an image into various blocks or regions which share common and identical characteristics like gray level, texture, color, contrast, boundaries, and brightness [23].

The significant contribution of this paper is:

- To propose Fully Automated Heterogeneous Segmentation using Support Vector Machine (FAHSSVM) for brain tumor detection and segmentation.
- To design an Extreme learning machine algorithm for the classification and feature extraction of MRI images.
- The experimental results show high accuracy in detecting brain tumors with the help of datasets.

The remainder of the paper discussed as follows: Section 1 and Section 2 discussed the importance of detecting brain tumor and background review. In section 3, a Fully Automated Heterogeneous Segmentation using Support Vector Machine (FAHS-SVM) has been proposed for brain tumor segmentation based on deep learning techniques. In section 4, the experimental results have been demonstrated. Finally, section 5 concludes the research article.

II. Background Review and Features of this Research Paper

P.Mohamed Shakeel et al. [24] proposed the machine learningbased Back propagation neural network (MLBPNN) method for brain tumor classification systems. Besides, the system can help doctors utilizing order and package calculations to scan the picture cell by coloring telephone qualities. The various steps needed in the preparation of the images from biopsy pictures to locate a disease include acquisition, upgrading and division, extraction, picture representation, characterization, and essentialmanagement. MLBPNN is analyzed using infrared sensorimaging technology in this study. Instead, when the entirestructure is degraded in some subsystems, the multidimensionalmachine existence of distinguishing neural proof unbelievablydecreases. This image sensor is integrated via a WirelessInfrared Imaging Sensor that transfers the warm tumor data to amedical specialist to screen the well-being situation and tousefully control the level of ultrasound measurement, especiallyif elderly patients in remote areas are present.

Ali ARI et al. [25] introduced the Extreme learning machinelocal receptive fields (ELM-LRF) for brain tumor classificationand detection. First of all, non-local means and methods of localsmoothing have been utilized to neglect noises. In the secondstep, the use of ELM-LRF identified cranial magnetic resonance(MR) images as malignant or benign. The tumors weresegmented in the third phase. The purpose of this study wasonly to use cranial MR images that have mass. Theclassification exactness of cranial MR images is 96.2 % in theexperimental studies. The findings analyzed showed that theefficiency of the suggested approach was higher than that ofother recent literature studies. Experimental results have shownthat it is an effective method that can be used to diagnosecomputer-aided brain tumors.

Nilesh Bhaskarrao Bahadur et al. [26] initialized the BerkeleyWavelet Transformation and Support Vector Machine (BWTSVM) for image analysis for Magnetic Resonance images basedBrain Tumor identification and feature extraction. Theyexplored histogram-based and texture-based features with anapproved MR brain tumor classification classifier. The tests forbrain tumor diagnosis can be seen quickly and accurately fromthe experimental results in the various images in contrast withmanual identification by clinical experts or radiologists. Thedifferent performance variables show a better result with theproposed algorithm by enhancing other parameters such asPSNR, mean, MSE, precision, specificity, sensitivity,coefficient of dice.

Jason J. Corso et al. [27] introduced the MultilevelSegmentation by Weighted Aggregation (MSWA) for braintumor segmentation. A new way of automatically segmentingheterogeneous imaging data is to bridge the gap betweenaffinity-based, bottom-up, and top-down model-based methods.The paper's significant contribution is a Bayesian algorithm forintegrating soft model tasks in the measurement of affinities thatare usually free of models. The effective computationalapproach exceeds current techniques in order of magnitude thatoffers comparable or enhanced results. Their quantitative outcomes show that model affinities are integrated into the segmentation procedures for the hard case of brain tumors. This approach blends the essential section of each voxel with the essential part of the graph hierarchy. The system is independent of each voxel, and the neighborhood data is integrated implicitly because the graphical hierarchy is agglomerated.

Pradeep Kumar Mallick et al. [28] suggested the Deep wavelet Auto Encoder and Deep Neural Network (DWA-DNN) for Brain Magnetic Resonance image classification for cancer recognition. This paper proposes a Deep Wavelet Auto Encoder (DWA) image compression technique, which combines the Auto Encoder essential feature extraction function with the transform wavelet image decomposition method. The mixture of both has a tremendous impact on the reduction of the feature set to continue to identify with DNN. The suggested DWA-DNN image classifier was reviewed, and a brain picture dataset was taken. In comparison to other classifiers like Auto Encoder - DNN or DNN, the efficient criterion for the DWA-DNN was compared, and the approach suggested summarizes the methods that exist. The tests of the DWA-DNN approach proposed to show that it is much more accurate and predictive than any other deep learning methodology. Further finding a way to combine DNN with many other improvements in the Auto Encoder would be far more interesting to see the impact or results within the brain MRI dataset [29-33].

To overcome these issues, in this paper, a Fully Automatic Heterogeneous Segmentation using Support Vector Machine (FAHS-SVM) has been proposed for brain tumor segmentation based on deep learning techniques. A supervised method for the segmentation of the brain image, which is the Support Vector Machines (SVM) classification process, has been utilized. To use the support vector machine (SVM) can identify brain tumors in many MRI modalities. The proposed system reviews segmentation as a classification issue. More accurately, because it is crucially faster than other classification techniques, because of its robustness in generalization precipitation and its capacity to manage volume information, the SVM classification method ensures segmentation.

III. A Fully Automatic Heterogeneous Segmentation using Support Vector Machine (FAHS-SVM):

In this study, a Fully Automatic Heterogeneous Segmentation using Support vector machine (FAHS-SVM) for brain tumor detection and segmentation. Figure 2 describes the proposed FAHS-SVM method architecture. Magnetic Resonance Imaging is a diagnostic tool for human anatomy study and testing. Increased tumor vascularity leads to preferential uptake of thecontrasting agent and can be utilized better to view the tumorsof the normal tissue around them. When the contrast injectionsare performed repeatedly, the dynamic nature of contrast uptakecan be tested, which can increase the distinction betweenmalignant or benign diseases.

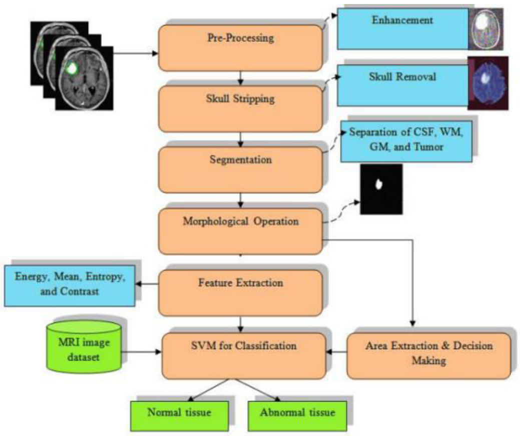


Figure 2: The proposed FAHS-SVM method architecture

i) Pre-Processing:

The primary operation of pre-processing is to enhance the quality of the Magnetic Resonance images and to make them suitable for further processing via a human visual for people or computers. Pre-processing leads to improving specific Magnetic Resonance image parameters like the enhanced SNR ratio, the improvement of the visual look of the Magnetic Resonance Image, the elimination of unnecessary noise, and the underseen parts from the picture, smoothing the region's inner part and retaining its edges. To apply adaptive contrast improvement based on a changed sigmoid feature to enhance the SNR ratio and, therefore, the quality of the raw Magnetic Resonance images.

ii) Skull Stripping:

Skull stripping is a major biomedical image analysis procedure. It is essential for a practical test of brain tumors from MR images, in which all non-brain tissue in brain imaging is removed. Skull stripping enables additional brain tissues like skull, skin, and fat to be extracted in brain images. There are a variety of skull stripping techniques available, some of which are common include the use of an automated skull stripping by image contour, segmentation-and morphological stripping of the skull, and hector graphic analysis or threshold-based skull stripping.

iii) Morphological Operation and Segmentation:

In the first stage, the pre-processed brain Magnetic Resonance image will be transformed into a binary image with a threshold of 128 for the cutoff. Pixel values higher than the specified thresholds are mapped as white, with other regions marked as black; these two allow various regions to be generated around the disease. In the second stage, an erosion process of morphology is used to extract white pixels. Eventually, the eroded area and the original image are separated into two equal areas, and the region with black pixels from the eroding is counted as a mask of brain Magnetic Resonance image. In this paper, wavelet transformation is used for the efficient segmentation of the brain Magnetic Resonance image. Figure 3 shows the fully automatic heterogeneous segmentation. Figure 3(a) shows the axial image and its segmentation figure 3(b) Coronal image and its segmentation figure 3 (c) Sagittal images and its segmentation.

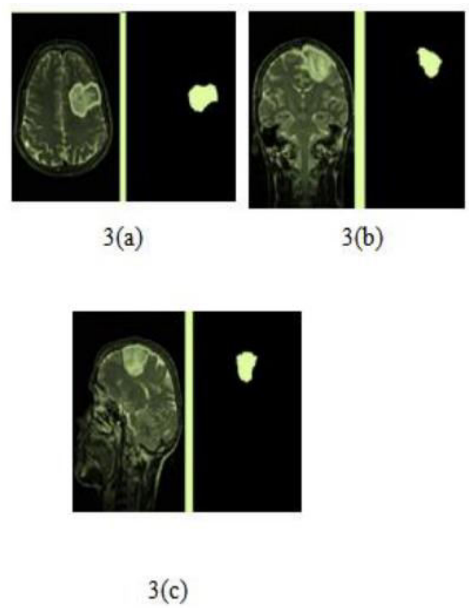


Figure 3: Fully Automatic Heterogeneous segmentation (a) Axial image and its segmentation (b) Coronal image and its segmentation (c) Sagittal image and its segmentation

A wavelet is a function stated over a limited time interval with an average value of null. The transformation wavelet method is used to create features, operators, and data into different frequency components, which allows every component to bediscretely studied. All wavelets are produced from a basic wavelet utilizing the translation and scaling procedure stated by equation (1); A simple wavelet is called a mother wavelet due to the other wavelets it is the point of origin.

$$\varphi_{w,\tau} = \frac{1}{\sqrt{w}}\varphi\left(\frac{r-\tau}{w}\right) \qquad (1)$$

As shown in equation (1), where w and are the translation and scale factors correspondingly.

The efficient way of the depiction of image transformation and is a piecewise constant function and it generates a different pixel position in the 2D plane via translation and scaling of wavelet and expressed as,

$$\alpha_\theta^\varphi(\tau,w) = \frac{1}{w^2}\alpha_y^\varphi(3^w(y-j),3^w(x-i)), \qquad (2)$$

As shown in equation (2), where and w are translation and scale variable of the wavelet transformation. The only constant term sufficiently depicts an image mean value; in the single term, the coefficient value is shown

$$\alpha_0 = \frac{1}{\sqrt{9}}\left[v\left(\frac{y}{3},\frac{x}{3}\right)\right] \qquad (3)$$

The morphological procedure is used for extracting the limits of the brain images. Conceptually, only the relative order of the pixel values is restructured in morphological operation, not their mathematical values, and only binary images can, therefore, be processed. Dilatation operations are intended to insert pixels into an object's boundary area and to delete pixels from the object boundary zone. Addition and pixel removal operations depend on the structuring aspect of the selected picture from or to the boundary region of objects. The results of the experiment provided by the proposed procedure are shown for the segmented results of the CSF, GM, and WM, classes, and the tumor region extracted.

iv) Feature Extraction:

It is the set of superior-level image details, including contrast, shape, color, and texture. In reality, texture analysis is a crucial attribute for the vision and machine learning systems of humans. It is utilized efficiently by choosing prominent features to maximize the precision of the diagnostic system. Due to the complex structure of different tissues like CSF, WM, and GM in the brain images MR, it's a crucial challenge to obtain relevant features. The diagnosis of the tumor (tumor stage) could be enhanced by textual observations and analyses, as well as the therapy response assessment. Some of the useful features can be found below in the mathematical formula.

A. Mean: The mean of an image is determined by summing up an image total pixel values divided by the total pixel value of an image.

$$N = \left(\frac{1}{n\times m}\right)\sum_{y=0}^{n-1}\sum_{x=0}^{m-1} f(y,x) \qquad (4)$$

B. Standard Deviation: The SD is the second central moment in which an observed population can be described as the probability distribution and to calculate of inhomogeneity. A better value shows a good level of intensity and great contrast between the edges of an image.

$$SD(\rho) = \sqrt{\left(\frac{1}{n\times m}\right)\sum_{y=0}^{n-1}\sum_{x=0}^{m-1}(f(y,x)-N)^2} \qquad (5)$$

C. Entropy: Entropy is measured to characterize the textured image randomness and is defined as

$$D = -\sum_{y=0}^{n-1}\sum_{x=0}^{m-1} f(y,x)\log_2 f(y,x) \qquad (6)$$

D. Skewness: Skewness is a symmetry attribute or symmetry absence. The Skewness is called and defined as a random variable Y.

$$W_l(Y) = \left(\frac{1}{n\times m}\right)\frac{\sum (f(y,x)-N)^3}{SD^3} \qquad (7)$$

IV. Experimental Result Analysis

(i) Dice Similarity Coefficient

The Dice similarity coefficient is utilized to assess the results quantitatively. In a manual segmentation, the ground truth has been established. The manual segmentation of the tumor tissues has not available for healthy tissues, however. Therefore, it can be assessed quantitatively only the exactness of the tumor segmentation. Only visual inspection has necessary to determine the accuracy of the segmentation of healthy tissues qualitatively. Dice similarity coefficient is an overlap measure between two images and defined as,

$$Dice(B,A) = 2\times\frac{|B_1 \wedge A_1|}{(|B_1|+|A_1|)}$$

As shown in equation where e is the expert's ground truth and is a tumor region extracted fromal gorithmic predictions. The dice coefficient, the maximumvalue 1, and the minimum value are 0, while the higher value means a good overlap between the two images. Figure 5 shows the Dice similarity coefficient for the proposed FAHS-SVM method.

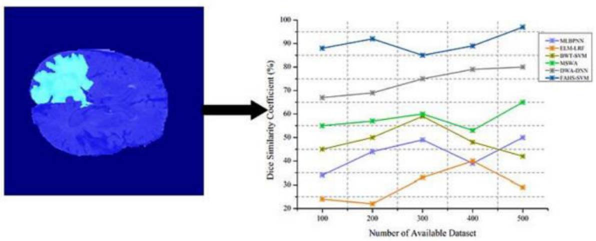


Figure 5: Dice Similarity Coefficient

Table 1 demonstrates the dice similarity coefficient of the proposed FAHS-SVM method (Mean and Standard Deviation).

The gross tumor region, including active, necrotic, and edema parts, comprises a gross tumor volume (GTV). The findings are provided with and without regularization for intra-and interpatient (leave-one-out cross-validation). The dice coefficients for each sub-region of the tumor are lower. The results, however, show once again that if no hierarchical regulation is applied, the Dice coefficient is worse.

Table 1: Dice Similarity Coefficient

Number of Available Datasets	MLBPNN	ELM-LRF	BWT-SVM	MSWA	DWA-DNN	FAHS-SVM
100	34.5	24.4	45.6	55.7	66.1	89.3
200	42.1	21.6	50.9	56.3	74.4	92.4
300	48.2	32.5	56.4	57.3	75.8	85.6
400	39.6	40.4	48.7	54.2	83.4	91.2
500	50.4	29.8	43.6	65.1	85.6	97.6

(ii) Segmentation Accuracy Analysis

The accuracy of our automated system is similar to the valuesrecorded for manual segmental inter-observer variability.Finally, a robust initialization of labeling is created, taking bothSVM and high-profile candidate regions into account. Results ofthe validation experiment on multi-parametric images showedthat increased accuracy in tumor segmentation relative to stateof-the-art methods could be achieved. Tissues with brainstructures are complex, and their intensity features are notsufficient to precisely segment the tumor. To improve theaccuracy of segmentation, texture features are used. The texturalfeatures are evaluated based on texture analysis in this review.Textons are small image elements generated by an imageconvolution with a particular filter bank. The accuracy ofsegmentation is high when compared to other existing methods.Figure 6 demonstrates the segmentation accuracy analysis of thesuggested FAHS-SVM approaches.

V. CONCLUSION

The detection of brain tumors from MRI scans has evolved significantly with the advancement of computational imaging and artificial intelligence. This paper has presented a comprehensive overview of various detection and segmentation techniques, highlighting the shift from traditional manual methods to automated, AI-driven systems that offer greater precision, speed, and consistency in medical diagnostics.

While traditional techniques such as thresholding and region-based segmentation still hold value in specific scenarios, the integration of machine learning and deep learning, especially architectures like CNNs and U-Nets, has greatly enhanced tumor localization and classification. These models not only improve detection accuracy but also reduce the workload of medical professionals, offering scalable solutions for clinical environments.

In conclusion, continued innovation in MRI-based brain tumor detection will rely on combining high-quality datasets, robust algorithms, and clinical validation. Future research should focus on building interpretable models, improving generalization across diverse patient groups, and ensuring real-time deployment in hospitals. These efforts will accelerate the adoption of intelligent diagnostic systems, ultimately leading to better patient care and outcomes in neuro-oncology.

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