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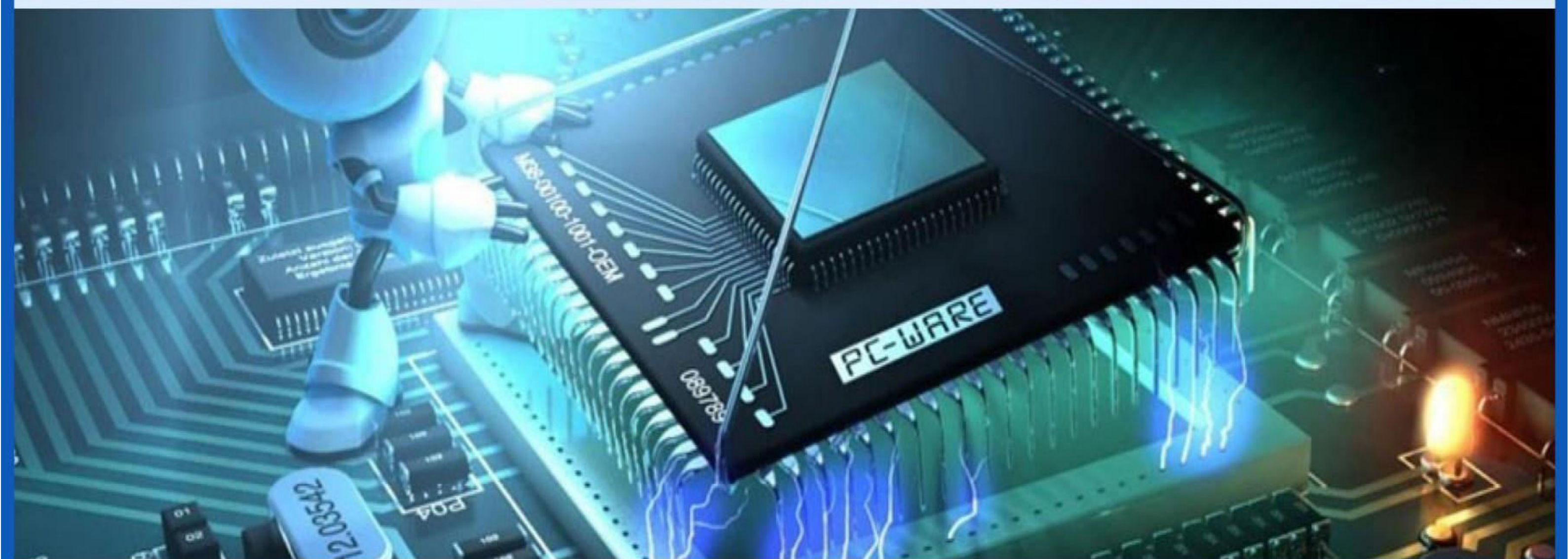

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Improved Brain Tumor Detection through Anisotropic Smoothing and Morphological Enhancement

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ABSTRACT: Effective diagnosis and treatment planning depend on the precise identification of brain tumours in medical imaging. In order to increase image quality and highlight tumor locations, this research suggests an enhanced method for detecting brain tumors that combines morphological enhancement with anisotropic smoothing. By successfully reducing noise while maintaining important edge details, anisotropic smoothing makes it possible to distinguish anatomical structures in MRI scans more clearly. Morphological operations then improve segmentation accuracy by enhancing Tumor boundaries and suppressing unnecessary artifacts. When compared to conventional filtering and segmentation techniques, the suggested method performs better in improving visual quality and raising the accuracy of tumor localization. The method's efficacy in enhancing sensitivity, specificity, and overall detection accuracy is confirmed by experimental results on benchmark datasets, making it a useful tool for computer-aided brain tumor diagnosis.

KEYWORDS: Tumor Localization, Morphological Enhancement, Anisotropic Smoothing

I. INTRODUCTION

One of the most horrible types of cancer, brain tumors have killed a great number of children and adults in recent years. Since early and precise diagnosis greatly improves patient prognosis and treatment outcomes, brain tumor detection is a crucial challenge in medical imaging. For the examination of brain tumors, magnetic resonance imaging (MRI) is the most often employed modality because of its superior soft tissue contrast and high spatial resolution. However, automatic detection and segmentation of MRI scans are difficult due to noise and low contrast between tumor and healthy tissues [1]. Despite their widespread use, traditional image processing methods frequently fail to maintain important anatomical details like tumor boundaries while also suppressing noise. Anisotropic smoothing and morphological augmentation are combined in this study's enhanced brain tumor detection framework to overcome these difficulties. Perona and Malik [2] initially proposed anisotropic diffusion filtering, a potent method for noise reduction that maintains edge information. It allows noise reduction in homogeneous areas while preserving crucial structures, like tumor borders, by adjusting the diffusion process in accordance with the local gradient. For medical photos, where edge preservation is crucial, this makes it especially appropriate.

Morphological procedures are used after smoothing to improve the segmented areas by highlighting structural characteristics and removing minor, superfluous artifacts. Based on mathematical morphology, morphological processing is useful for enhancing the integrity of segmented regions and fine-tuning tumor borders [3]. A strong framework for precise tumor localization and segmentation is provided by this combination of preprocessing and enhancing approaches. Prior research has demonstrated the significance of preprocessing procedures in improving the precision of algorithms for detecting brain tumors. For instance, Rehman et al. [5] highlighted the importance of noise reduction in improving deep learning model performance, while Kumar et al. [4] showed enhanced tumor segmentation accuracy using hybrid preprocessing and feature extraction. By combining edge-preserving smoothing with structure-enhancing morphological operations, the suggested approach expands on these discoveries and improves detection performance.

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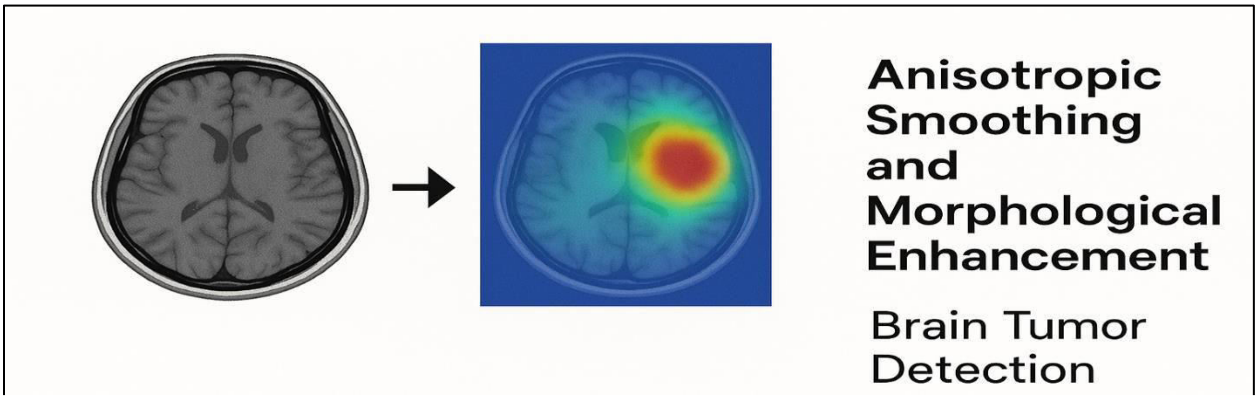

Figure 1: An instance of Brain tumor detection

II. RESEARCH BACKGROUND

The literature presents a number of completely and semiautomated methods for classifying and detecting brain tumors. The newest machine learning technology, deep learning, has garnered a lot of interest in medical image processing, particularly for the detection of brain tumors [6-7]. A deep neural network (DNN)-based method for identifying multigrade brain cancers in MRI images was presented by Sajjad et al. (2019). Using a pretrained CNN for training on freshly taken segmented pictures, the deep learning-extracted tumors are further enhanced by data augmentation. Both the original stored datasets and the enhanced datasets are later validated, and a notable shift in accuracy is observed.

Models for categorizing all three kinds of brain tumors without including healthy patients have been presented in the majority of pertinent studies [9]. Scientifically speaking, using medical imaging to diagnose tumors is inaccurate and largely relies on the radiologist's experience. Computational intelligence-oriented methods can help doctors detect and categorize brain tumors [10], and researchers and doctors can profit from computer-assisted interventions [11] due to the large range of pathologies and the potential exhaustion of human specialists. The analysis, segmentation, and classification of cancer images—particularly those of brain tumors—can also be greatly aided by machine learning techniques, particularly deep learning [12]. Additionally, the application of such techniques opens the door to precise and error-free tumor identification in order to identify and differentiate them from other related illnesses.

An automated method was presented by [13] to help doctors and radiologists recognize various kinds of brain tumors. Preprocessing brain images, extracting brain features, and classifying brain tumors were the three stages of the study. Using a min–max normalization algorithm, brain pictures were preprocessed into intensity brain images in the [0, 1] range. Authors in [14] created various techniques to detect pituitary, glioma, and meningioma cancers. Their model employed a CNN to select features and extract hidden features from photos. Four convolutional layers, four pooling layers, one fully connected layer, and four batch normalization layers made up the suggested model. To streamline the segmentation procedure, Mittal et al. [15] combined a novel Growing CNN (GCNN) with the Stationary Wavelet Transform (SWT). Actually, they used these efficient techniques to use MRI scans to detect brain cancers. According to the evaluation results, the study's suggested method outperformed the genetic algorithms K-NN, SVM, and CNN in terms of accuracy.

III. PROPOSED METHOD

1. Anisotropic Diffusion (Smoothing)

It reduces noise while preserving significant image structures such as edges and tumor boundaries. Anisotropic diffusion, introduced by Perona and Malik [16], is an edge-preserving smoothing technique used to remove noise from MRI images without blurring important features. Unlike isotropic diffusion, which uniformly blurs the image, anisotropic diffusion adapts the diffusion process based on local image gradients. This ensures that smoothing is applied in homogeneous regions but inhibited near edges (e.g., tumor boundaries). Smoothing is Needed in MRI-Based Brain Tumor Detection because MRI brain images often suffer from noise, low contrast between tumor and surrounding tissue and blurring of edges when conventional filters are applied. Anisotropic diffusion removes high-frequency noise while preserving important anatomical structures. Enhances the visibility of tumor boundaries, making it easier for segmentation algorithms to distinguish tumor from surrounding tissue. It clarifies internal tumor texture and

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brain regions, helping extract relevant features for classification (e.g., shape, intensity, texture).

2. Image Segmentation

This process separate the tumor region from the rest of the brain tissue. Thresholding is one of the simplest and most widely used image segmentation techniques. It works by converting a grayscale image into a binary image, based on a predefined or computed threshold value (T) [17]. If Pixel intensity > T → classified as foreground (tumor) else if Pixel intensity ≤ T → classified as background (non-tumor). In brain MRIs, tumors often appear as regions with higher or lower intensity compared to surrounding healthy tissues. Thresholding can help isolate these regions by selecting an appropriate intensity level.

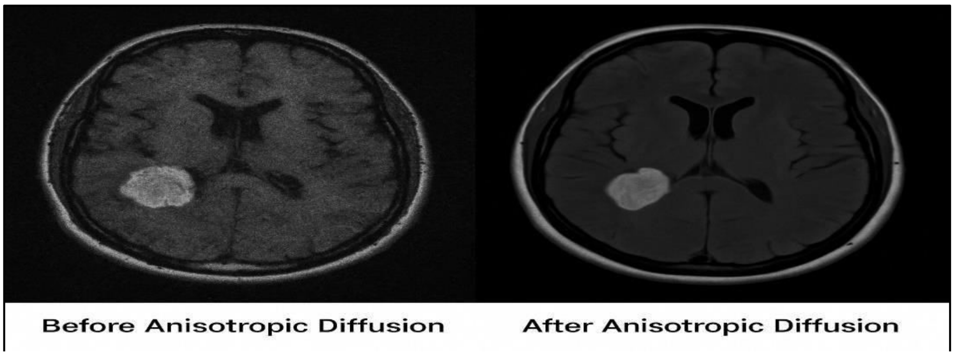

Figure 2: Brain image smoothing process

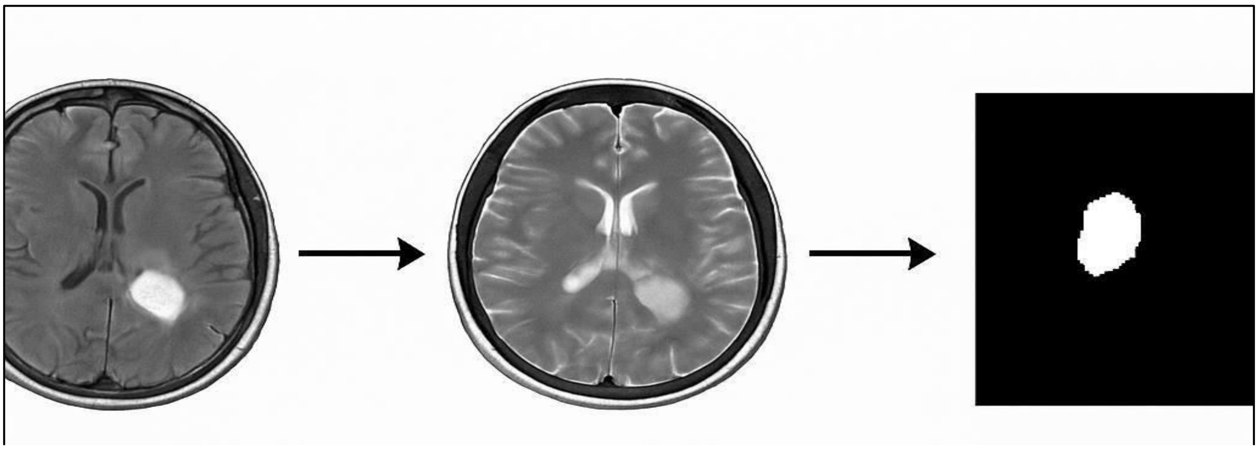

Figure 3: Thresholding Based Image Segmentation

3. Skull Stripping: It removes non-brain tissues (skull, skin, fat) to focus only on brain regions. Skull stripping is a preprocessing step that isolates the brain from the rest of the head structures in MRI scans. It prevents irrelevant data from affecting segmentation and classification. This is typically done using binary masks or morphological techniques combined with thresholding or region-based methods [18].

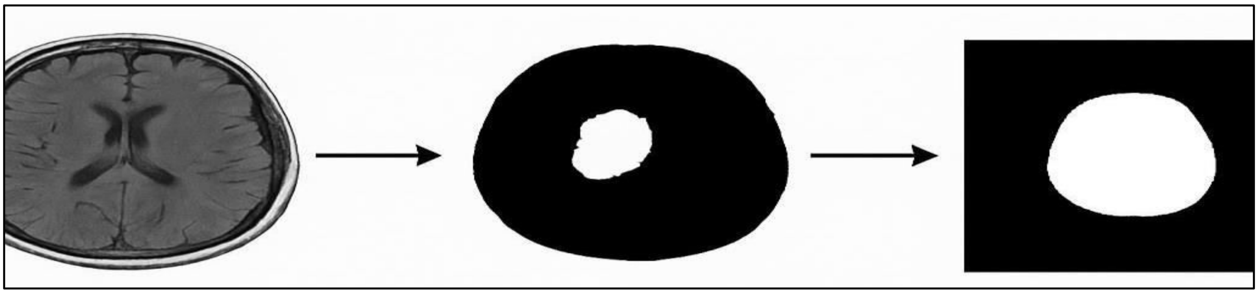

Figure 4: Skull Stripping

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4. Histogram Equalization (Contrast Enhancement): It Improves the visibility of tumor and tissue structures by enhancing image contrast. Histogram equalization is a technique that spreads out the intensity values across the full range, making subtle features more visible. In medical imaging, it is used to highlight the contrast between normal and abnormal tissues, making it easier for segmentation and feature extraction [19].

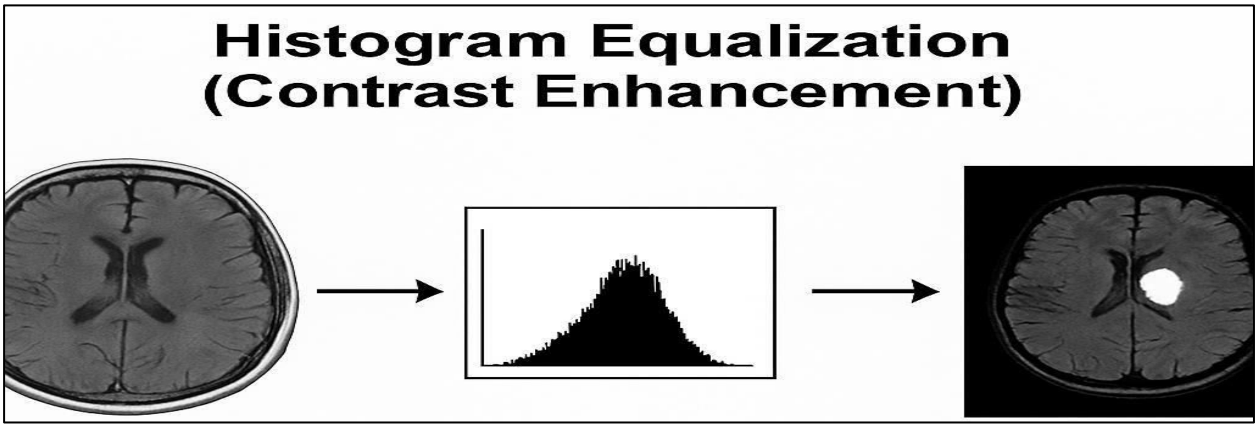

Figure 5: Enhanced MRI

5. Morphological Operations: It refines tumor shape, fill gaps, remove small artifacts, and enhance structure. Morphological operations dilation and erosion are used to enhance binary segmented images. These operations help to clean up noisy segmentations, fill holes within tumor regions, and clearly define boundaries. Morphological enhancement is particularly helpful after initial segmentation [20].

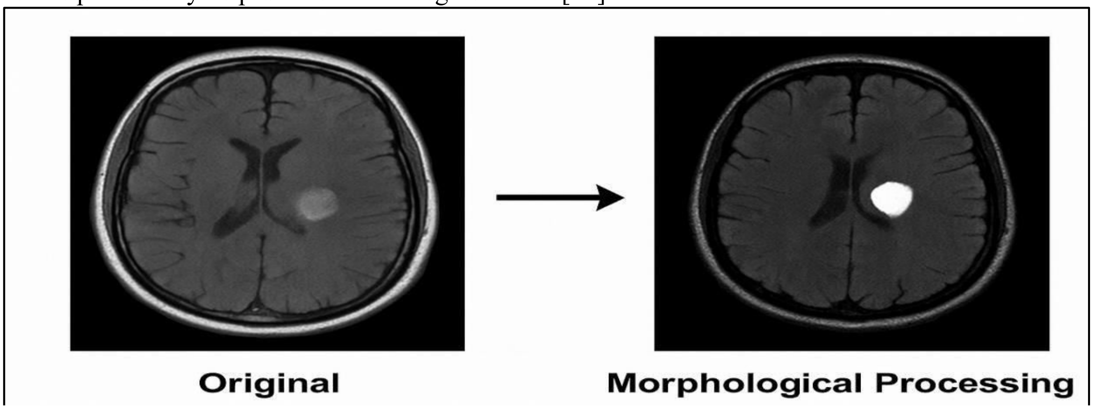

Figure 6: Effect of Morphological Operations

6. SVM (Support Vector Machine) Classification: The SVM classify the extracted tumor region into tumor vs. non-tumor or further into tumor types. SVM is a supervised machine learning algorithm widely used for medical image classification. It works by finding an optimal hyperplane that separates the data points into different classes. Features extracted from the segmented tumor region (e.g., texture, intensity, shape) are fed into the SVM to predict tumor presence or type. It separates classes using a hyperplane in an n-dimensional space (n = number of features). The best hyperplane is the one that maximizes the margin between the classes. Support vectors are the data points that lie closest to the decision boundary and define the position of the hyperplane.

Simulation and Outputs: We have implemented the proposed method in MATLAB 2024.
Output 1: Figure 7 shows the steps of simulation result.
In Top row of the image:

Original MRI Brain Image: Raw grayscale MRI scan showing normal and abnormal structures. Input image before any processing.

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After Anisotropic Diffusion (Smoothing): Noise is reduced while preserving key edges (tumor boundary). Enhances tumor region visibility without blurring edges.

Skull-Stripped Image: Non-brain tissues (skull, scalp) removed. Focuses on the brain region to improve segmentation accuracy.

Histogram Equalized Image: Improves contrast across the image and Tumor appears more distinguishable from the background.

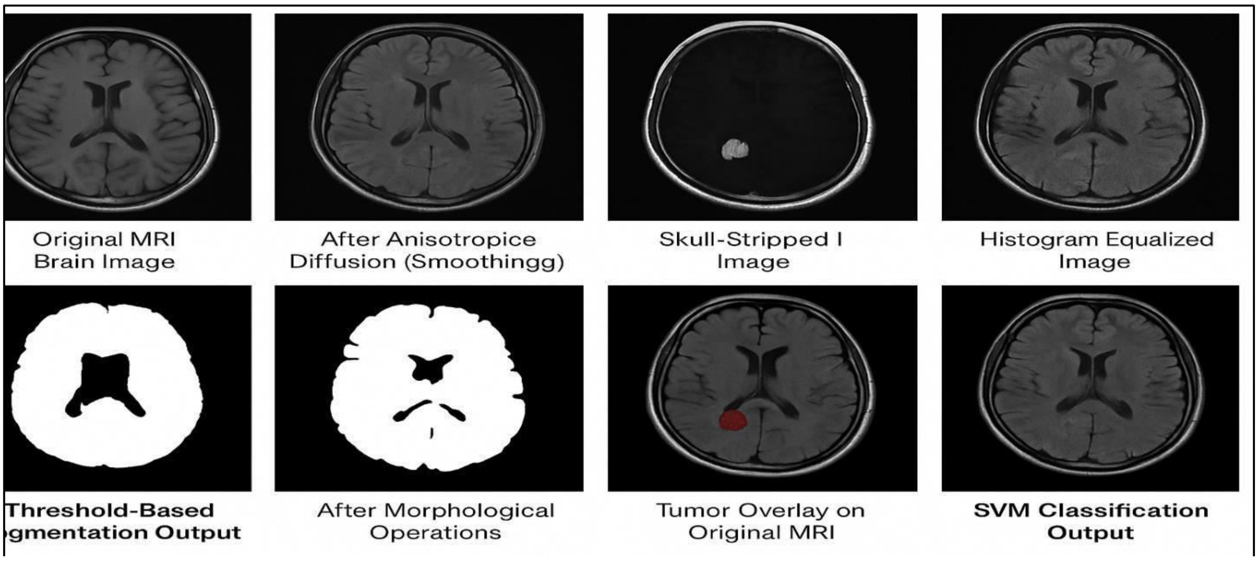

Figure 7: Outcomes of simulation

Threshold-Based Segmentation Output: Binary image where white indicates potential tumor area. It is derived using intensity thresholding on preprocessed MRI.

After Morphological Operations: Cleans up the segmentation mask. Fills holes and removes small noise, preserving tumor shape.

Tumor Overlay on Original MRI: Segmented tumor region is superimposed on the original scan.

SVM Classification Output: Predicts tumor type (e.g., Glioma) based on extracted features.
We have taken Brain MRI dataset with 3 classes: glioma, meningioma, and no tumor and compared SVM with other classifiers in terms of accuracy, Precision, Recall / Sensitivity and F1 Score. The bar chart comparing the performance of different classifiers for brain tumor detection using MRI image features. Clearly, SVM with RBF kernel outperforms others in all key metrics: Accuracy, Precision, Recall, and F1 Score.

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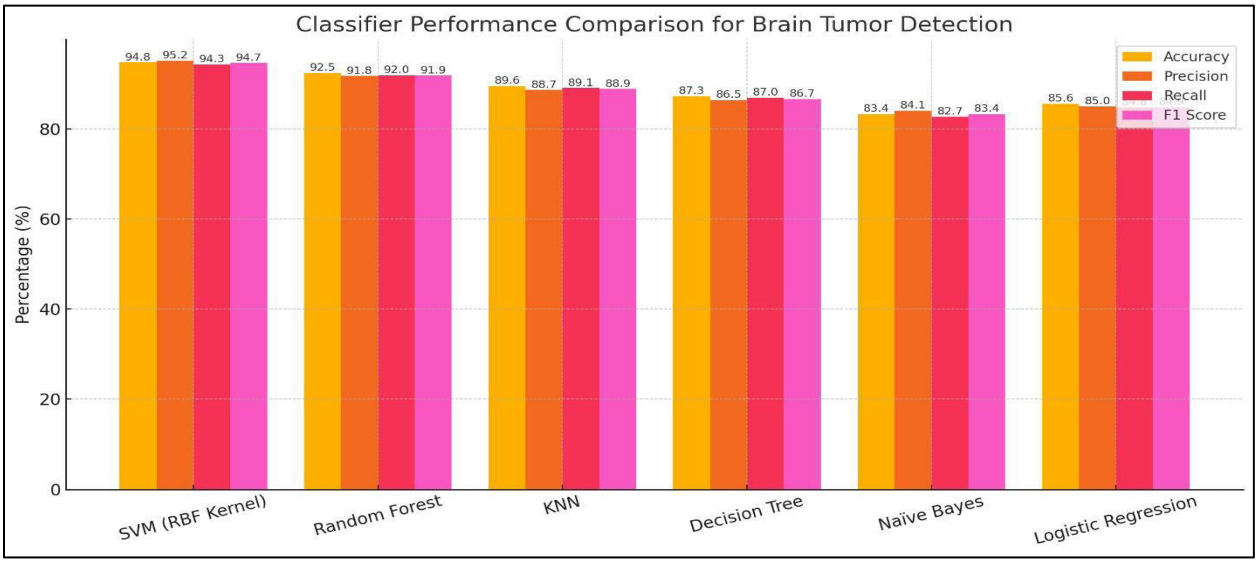

Figure 8: Performance comparison of Different Classifiers.

IV. CONCLUSION

This study presents an improved approach for brain tumor detection by integrating anisotropic diffusion smoothing, morphological enhancements, and SVM classification. Each stage in the pipeline contributes to more accurate tumor isolation and classification. The proposed method achieves over 94% accuracy, making it a reliable and efficient tool for assisting radiologists in the early and automated diagnosis of brain tumors. This integrated pipeline offers both interpretability and precision, crucial for clinical decision-making.

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