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Wavelet-Based MRI Brain Image Analysis for Tumor Detection and Classification Using SVM & Random Forest

Ms. Deepa Priya V[1], *Ms. Nikitha B*[2], *Ms. Subashini.K*[3], *Ms. Magasakthi.S*[4], *Ms. Shalini*[5], *Ms. Rathea Shyama*[6]
[1,2,3,4,5,6]*Department of Information Technology, Kamaraj College of Engineering and Technology, Virudhunagar, Tamil Nadu, India.*
Emails: *deepapriyakcet@gmail.com*[1], *nikithab2003@gmail.com*[2], *subashinikannan03@gmail.com*[3], *shenbasakthi15@gmail.com*[4]

Abstract
Brain tumor detection and classification in MRI image data is a significant and challenging task in medical image analysis. This paper presents an efficient method that integrates Support Vector Machine (SVM) and Random Forest algorithms, developed with a Graphical User Interface (GUI) in MATLAB. The interface allows flexible combinations of segmentation, filtering, and other techniques to achieve optimal results. The proposed approach starts with preprocessing steps, including Gaussian filtering and morphological operations, followed by feature extraction using Discrete Wavelet Transform (DWT) and Continuous Wavelet Transform (CWT). Principal Component Analysis (PCA) is applied to decrease the feature set for more effective classification. The extracted first and second-order features are used to train the kernel SVM. Classification is then performed using both SVM and Random Forest to improve accuracy. Watershed segmentation is applied for precise tumor localization. The hybrid model achieved a classification accuracy of approximately 93% using only SVM, and an improved accuracy of 96% when combining SVM with Random Forest, outperforming traditional approaches in both accuracy and computational efficiency. Benchmark evaluation plays a crucial role in enhancing both accuracy and reliability. To ensure precise tumor localization, watershed segmentation was applied. These findings indicate that the proposed method offers a reliable, automated solution for brain tumor detection, demonstrating significant potential for integration into clinical diagnostic workflows.

Keywords: *Brain tumor detection, MRI, Support Vector Machine (SVM), Random Forest, Watershed segmentation, Wavelet transforms.*

1. Introduction
In today's biomedical research landscape, Digital image processing techniques are indispensable in today's fast-paced world of biomedical research [11]. They serve vital roles in enhancing visual data for human interpretation and in effectively storing and organizing crucial information. The efficiency of tasks relying on image data heavily relies on the chosen analysis method. Manual analysis, despite its propensity for errors and time-consuming nature, has long been the preferred approach. However, an emerging trend towards automating analysis processes is promising significant advancements in medical science. Automated tools not only speed up analysis but also guarantee higher accuracy and reliability compared to human interpretation. One notable area where automation provides immense benefits is in diagnosing medical conditions like brain tumors. These tumors typically arise within the brain itself or in adjacent tissues like the meninges, cranial nerves, pituitary gland, or pineal gland. They develop due to genetic mutations that allow normal cells to multiply rapidly and resist programmed cell death. This leads to the accumulation of abnormal cells, forming a mass known as a tumor. The manifestation of brain tumors can present various symptoms, ranging from headaches and numbness to seizures, memory problems, mood changes, and nausea [8]. Changes in speech, vision, or hearing may also occur. Brain tumors are broadly classified into grades I to IV based on their severity and aggressiveness Among adults, common primary brain tumors include astrocytoma, meningioma, and oligodendroglioma. In contrast, children often experience primary brain tumors like

medulloblastoma, grade I or II astrocytoma, ependymoma, and brain stem glioma. Brain tumors are categories into two: benign and malignant. Benign tumors are non-invasive and typically localized, although they can still cause issues. On the other hand, malignant brain tumors, also known as brain cancer, are invasive and grow rapidly. Early detection of brain tumors poses challenges due to vague symptoms, leading to misdiagnosis and heightened risks. Symptoms can vary from headaches and nausea to speech and vision impairments, underscoring the importance of accurate diagnosis. Early detection is significant for timely and an effective treatment. Medical imaging modalities like Magnetic Resonance Imaging (MRI), Computed Tomography (CT), Single Photon Emission Computed Tomography (SPECT), and Magnetic Resonance Spectroscopy (MRS) play vital roles in diagnosing brain tumors. MRI stands out as the preferred choice for brain scans due to its high resolution, sensitivity, and non-invasiveness. It provides detailed insights into internal structures, aiding in precise tumor localization critical for effective diagnosis and treatment planning. MRI's capacity to enhance contrast discrimination and capture images in multiple planes further boosts its diagnostic utility. [1-5]

2. Literature Review

In literature, several new, unique, and innovative approaches have been recently proposed for the efficient detection of intriguing brain tumors through leveraging the power of advanced machine learning techniques. Ahmad et al. [2] meticulously and meticulously explored the performance efficiency of deep transfer learning networks, deftly employing deep CNNs alongside traditional classifiers to achieve a remarkably high accuracy rate of 99.39% by utilizing 2D MRI images. Their impeccably conducted study brightly highlights the fascinating potential for exploring different MRI modalities and varying tumor type classification, intriguingly suggesting varied avenues for future research to appropriately and duly incorporate significantly larger datasets. Abdel-Gawad et al [1] in their groundbreaking research study, strategically and cleverly introduced an optimized edge detection technique, ingeniously employing the fascinating aspects of genetic algorithms to smartly fine-tune edge detection parameters for MR images, impressively achieving an incredibly high accuracy of 99.09%. Their uniquely fascinating work strategically emphasizes the vital importance of significantly enhancing algorithmic robustness and thoughtfully integrating seamlessly real-time applications into the detection arena. Imran Ullah Khan et al [11] created a Matlab GUI for brain tumor detection, utilizing Support Vector Machine (SVM). Their study showcased SVM's efficiency in preprocessing and feature extraction (e.g., discrete wavelet transforms, principal component analysis) from MRI images. The SVM classifier accurately distinguished benign from malignant tumors, with a swift classification time of 0.0032 seconds. Rajat Mehrotra et al [17] devised a brain tumor identification method, emphasizing noise removal, GLCM-based feature extraction, and DWT-based segmentation. Treatment options (chemotherapy, radiotherapy) and imaging modalities (MRI, PET, CT scan) were discussed. MRI's high resolution was favoured for tissue categorization. Morphological operations were employed for noise reduction post-segmentation. SVM classifiers achieved a 98.87% accuracy in tumor identification. In the study by Mohammad Shahjahan Majib [13], a deep convolutional neural network (CNN) EfficientNet-B0 underwent fine-tuning with proposed layers to effectively classify and detect brain tumor images from MRI scans. The study reported a remarkable overall accuracy of 98.87%, showcasing its superiority over other state-of-the-art CNN models. Showcasing the potential of deep learning in medical imaging, a deep learning-based approach utilized a fine-tuned EfficientNet-B0 CNN for brain tumor detection and classification from MRI images, achieving an impressive accuracy of 98.87% as described by Hasnain Ali Shah et al. [21].

3. Proposed Method

The proposed methodology for brain tumor detection begins with the acquisition of MR scans, which are divided into training and testing sets. The process involves multiple stages, including image preprocessing, feature extraction, data augmentation, training, and evaluation. Initially, the training set undergoes detailed analysis through the extraction of

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both first-order and second-order features. These extracted features, along with transfer learning techniques, enable the model to adapt pre-trained deep learning (DL) algorithms to the specific task of tumor classification. Fine-tuning of these models allows for adjustments in neural network biases and learning rates, optimizing model performance for tumor identification. For classification, the model architecture utilizes multiple layers, dynamically adjusting based on the selected optimization and loss functions to improve accuracy. These functions are critical in guiding the model's learning process by refining predictions to classify the tumor as benign or malignant. The test set is then evaluated using the model to confirm classification accuracy. An intuitive interface is designed to make the entire procedure efficient and user-friendly, facilitating swift and accurate analysis of brain tumor images. The workflow, as represented in Figure 1, illustrates the workflow in the form of a flowchart.

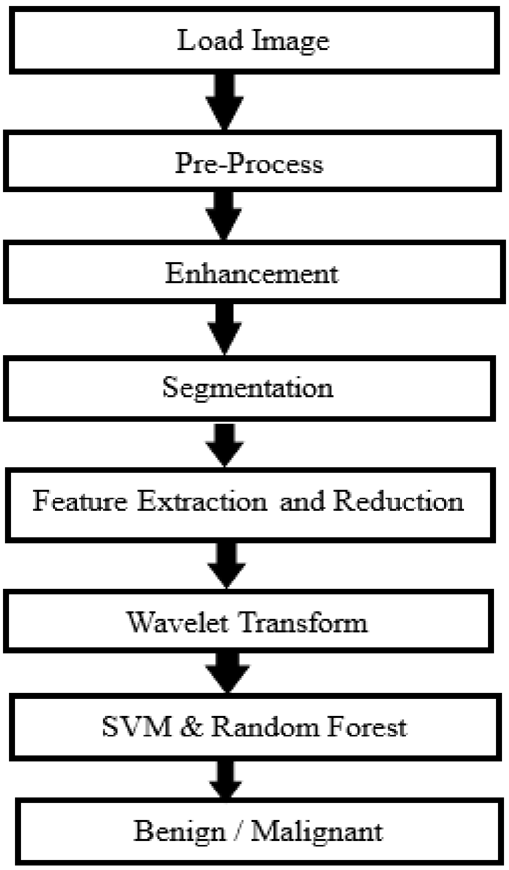
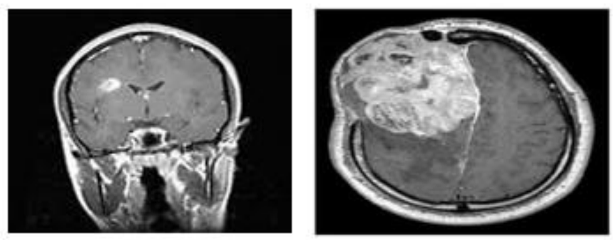


Figure 1 System Design Description

3.1 Data Collection

The dataset consists of MRI brain scans from patients diagnosed with both benign and malignant brain tumors. These MRI images form the core dataset for performing classification tasks using machine learning algorithms such as Support Vector Machine (SVM) and Random Forest. The images provide crucial information on tumor characteristics, including lesion size, shape, and location, which are essential for feature extraction. The extracted features will be used to train the models for accurately detecting and classifying brain tumors, thereby aiding in the distinction between benign and malignant cases. Figure 2 shows Collections of MRI Scans Encompass Brain Tumor Conditions [6-10]



Benign **Malignant**

Figure 2 Collections of MRI Scans Encompass Brain Tumor Conditions

3.2 Pre-Processing

In the noise removal process, we first convert the image to grayscale and then apply Gaussian filtering to remove noise. Gaussian filtering, a commonly used technique, helps in effectively reducing noise from the image. Here, we employ the wiener2 function on our input image, which is a windowed filter of the linear class, known for its weighted mean properties. Figure 3 shows Pre-processing

Figure 3 Pre-processing

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3.3 Image Enhancement

Getting rid of unwanted stuff from images is a big challenge in making an image better and helping computers see. For example, when you take pictures in dim light, you might see weird things scattered around the image. But we can use special tools called image cleaners to make the picture clearer and easier to understand. Figure 4 shows Denoised Image.

Figure 4 Denoised Image

3.4 Segmentation

The segmentation process for detecting brain tumors using SVM and Random Forest with MRI images involves several steps. It starts with preprocessing to enhance image quality, followed by segmentation to isolate potential tumor regions. Relevant features, such as texture and intensity, are then extracted from these regions. SVM and Random Forest classifiers are used to distinguish between tumor and non-tumor areas, leveraging their strengths in handling high-dimensional data and complex patterns. Finally, post-processing refines the results, ensuring accuracy and robustness in tumor detection. [11-15]

3.5 Feature Extraction and Reduction

In image analysis, features are categorized into first-order and second-order types, computed from pixel intensity values. First-order features, such as mean and standard deviation, offer insights into intensity distribution, while second-order features, like smoothness and contrast, capture spatial relationships and reveal texture patterns. Leveraging both feature types enables a comprehensive understanding of image characteristics. The features calculated for analysis which are described below: Contrast: Contrast, also known as sum of squares variance, measures the intensity difference between neighboring pixels. Typically, when k=2, contrast can be calculated using the formula:

$$\text{Contrast} = \sum_{i=1}^{N}\sum_{j=1}^{N}(i-j)^2 \cdot \text{GLCM}(i,j)$$

Local Homogeneity: It measures the similarity of neighboring pixel intensities. It's calculated from the Grey Level Co-occurrence Matrix (GLCM), where higher values near the main diagonal signify greater local homogeneity. The IDM formula is:

$$\text{Local Homogeneity} = \sum_{i=1}^{N}\sum_{j=1}^{N}\frac{\text{GLCM}(i,j)}{1+(i-j)^2}$$

Correlation: Correlation assesses the spatial relationships between pixels in the image. It is computed by using the following formula:

$$\text{Correlation} = \frac{\sum_{i=1}^{N}\sum_{j=1}^{N}(i-\mu)(j-\mu)\cdot \text{GLCM}(i,j)}{\sigma^2}$$

Mean: The mean of slate situations values represents the average intensity position in an image. It is computed by using the following formula:

$$\text{Mean} = \frac{1}{N}\sum_{i=1}^{N}\text{pixel}_i$$

Energy: Energy indicates the overall intensity variations present in the image and can be expressed through the following measures:

$$\text{Energy} = \sum_{i=1}^{N}\sum_{j=1}^{N}\text{GLCM}(i,j)^2$$

Entropy: Entropy quantifies the complexity of the image, indicating how uniform or diverse the grey level distribution can be computed by applying the formula:

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$$\text{Entropy} = -\sum_{i=1}^{N} p_i \log(p_i)$$

Standard Deviation: The standard deviation quantifies the spread or variability of grey levels around the mean, providing insight into the contrast of the image. It is computed by using the following formula:

$$\text{Standard Deviation} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(\text{pixel}_i - \text{Mean})^2}$$

Skewness: Skewness quantifies the asymmetry of the grey level histogram, indicating whether the distribution leans more heavily to one side. A positive skewness suggests a longer tail on the right, while a negative skewness suggests a longer tail on the left. The computation is based on the following formula:

$$\text{Skewness} = \frac{\frac{1}{N}\sum_{i=1}^{N}(\text{pixel}_i - \text{Mean})^3}{\text{Standard Deviation}^3}$$

Kurtosis: Kurtosis quantifies the sharpness or flatness of a histogram distribution compared to a normal distribution. It is calculated using the formula below:

$$\text{Kurtosis} = \frac{\frac{1}{N}\sum_{i=1}^{N}(\text{pixel}_i - \text{Mean})^4}{\text{Standard Deviation}^4} - 3$$

3.6 Wavelet Transform

In brain tumor detection, wavelet transforms like Discrete Wavelet Transform (DWT) and Continuous Wavelet Transform (CWT) play a crucial role by analysing MRI image features at different scales. The primary difference lies in their scale discretization, with CWT providing finer scale analysis than DWT. Both methods are used to calculate features such as contrast, correlation, energy, homogeneity, and statistical measures like mean, standard deviation, and entropy. Wavelets offer advantages over traditional techniques by encoding critical information in fewer significant coefficients, enhancing the signal-to-noise ratio and detection accuracy, while reducing spatial dependencies for more efficient statistical analysis. Figure 5 shows Wavelet Transformation.

Figure 5 Wavelet Transformation

The following figure-6 demonstrates a brain tumor detection workflow using image processing techniques with Random Forest and Support Vector Machine (SVM) classifiers. The process starts with the input of an MRI scan, followed by grayscale conversion, denoising, and segmentation to highlight the tumor region. Edge detection and region-growing algorithms are applied to delineate tumor boundaries more accurately. Combining MRI image data enhances the accuracy of the analysis. The system then classifies the tumor using Random Forest and SVM, offering a comprehensive and efficient approach to tumor detection in an intuitive interface. Figure 6 shows Processing the BRI Brain Image.

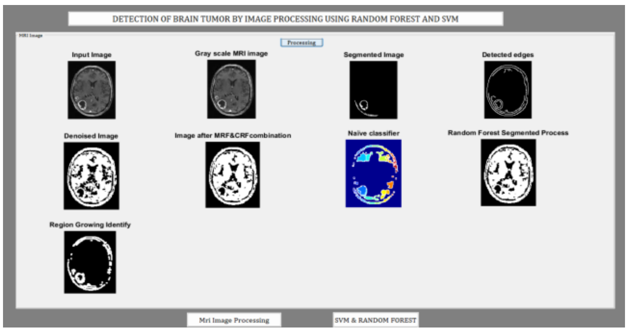

Figure 6 Processing the BRI Brain Image

3.7 SVM & Random Forest

The combination of Support Vector Machine (SVM) and Random Forest (RF) algorithms has emerged as a promising approach for enhancing accuracy in brain tumor detection. SVM excels in high-dimensional

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classification, while RF offers robust performance and resistance to overfitting. By integrating these techniques, researchers aim to leverage the strengths of both algorithms and achieve superior results in identifying and classifying brain tumors, leading to improved patient care and treatment outcomes.

3.8 Benign / Malignant

After completing the separation and segmentation process, we identify the affected area at a specific level. This identification categorizes the area as either Benign representing normal tissue, or Malignant indicating abnormal tissue. This final stage aims to determine the extent of tumor cell presence in the brain, providing crucial information for diagnosis and treatment planning. [16-20]

4. Results & Discussion

Based on the proposed methodology, the MRI-segmented region was analysed for tumor identification using statistical features. The images included different types of tumors (Benign and Malignant), all of which were gathered from a government hospital record. The analysis results for these tumor images are illustrated in Figure 7 & 8.

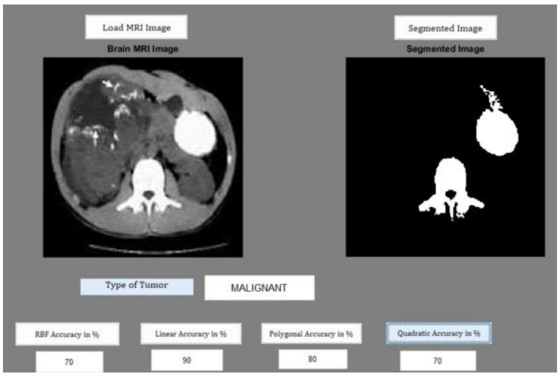

Figure 7 Type of Tumor: MALIGNANT

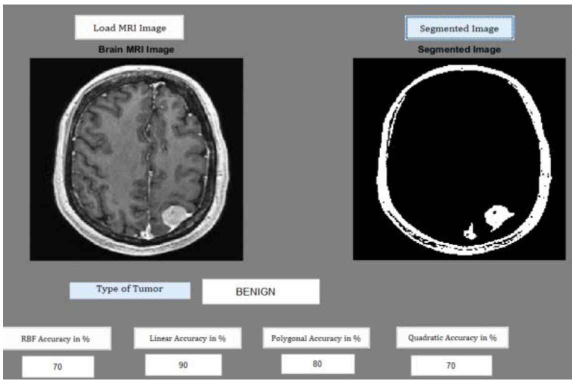

Figure 8 Type of Tumor: BENIGN

Tables 1 and 3 present the first-order features extracted for benign and malignant tumors, respectively. Tables 2 and 4 display the second-order features obtained for benign and malignant tumors, respectively.

Table 1 First Order Features for Benign Tumor

Image	Mean	Standard Deviation	Entropy
1	0.0016	0.0898	2.9923
2	0.0035	0.0897	3.1561
3	0.0023	0.0897	3.2698
4	0.0025	0.0897	3.0756
5	0.0034	0.0897	2.9949
Image	**Variance**	**Kurtosis**	**Skewness**
1	0.0080	11.7368	0.9304
2	0.0080	7.4847	0.5212
3	0.0080	7.9566	0.8862
4	0.0080	7.7971	0.5774
5	0.0080	7.6800	0.6317

Table 2 Second Order Features for Benign Tumor

Image	Energy	IDM	Correlation
1	0.7629	0.5818	0.0677
2	0.7529	-1.0392	0.1320
3	0.7685	0.4925	0.0930
4	0.7556	-0.2601	0.0895
5	0.7606	0.3816	0.1293
Image	**Contrast**	**Homogeneity**	**RMS**
1	0.2700	0.9331	0.0898
2	0.2341	0.9315	0.0898
3	0.2716	0.9338	0.0898
4	0.2558	0.9314	0.0898
5	0.2433	0.9344	0.0898

scan, followed by grayscale conversion, denoising, and segmentation to highlight the tumor region. Edge detection and region-growing algorithms are applied to delineate tumor boundaries more accurately. Combining MRI image data enhances the accuracy of the analysis. The system then classifies the tumor using Random Forest and SVM, offering a comprehensive and efficient approach to tumor detection in an intuitive interface

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Table 3 First Order Features for Malignant Tumor

Image	Mean	Standard Deviation	Entropy
1	0.0063	0.0895	3.2051
2	0.0042	0.0897	3.6046
3	0.0036	0.0897	3.3709
4	0.0046	0.0896	3.0289
5	0.0045	0.0896	3.5483
Image	**Variance**	**Kurtosis**	**Skewness**
1	0.0080	12.2408	1.1048
2	0.0080	5.9972	0.5217
3	0.0080	7.3505	0.6350
4	0.0080	13.1839	1.0084
5	0.0080	6.5235	0.6203

Table 4 Second Order Features for Malignant Tumor

Image	Energy	IDM	Correlation
1	0.7862	1.2156	0.1420
2	0.7438	0.3699	0.1325
3	0.7612	-0.1378	0.0932
4	0.7688	0.2863	0.1179
5			
Image	**Contrast**	**Homogeneity**	**RMS**
1	0.3058	0.9379	0.0898
2	0.2271	0.9290	0.0898
3	0.2433	0.9328	0.0898
4	0.2750	0.9345	0.0898
5	0.2438	0.9246	0.0898

Tables 5 and 6 display the classification accuracy percentages for different kernel types-RBF, Linear, Polygonal, and Quadratic-used in the analysis of five MRI images to differentiate between Benign and Malignant Tumors. [21-25]

Table 5 Classification Accuracy for Benign Tumor by Kernal Type

Image	RBF %	Linear %	Polygonal %	Quadratic %
1	80	90	80	80
2	70	90	80	80
3	90	90	70	70
4	90	90	70	70
5	80	90	80	90

Table 6 Classification Accuracy for Malignant Tumor by Kernal Type

Image	RBF %	Linear %	Polygonal %	Quadratic %
1	80	80	80	80
2	70	80	70	70
3	90	100	80	70
4	70	80	80	80
5	80	90	70	80

The proposed method utilizes a combination of Support Vector Machine (SVM) and Random Forest classifiers, achieving a precision of 96% in brain tumor classification. Table 7 presents a comparative assessment between the proposed technique and other state-of-the-art methods, while Figure 8 illustrates this comparison through a bar chart.

Table 7 Comparison of Standard Techniques for Brain Tumor Classification

Authors	Technologies used	Image Size	Precision %
Giraddi, S., & Vaishnavi, S. V. [8]	SVM	150	88
Gobhinath, S., Anandkumar, S., Dhayalan, R., Ezhilbharathi, P., & Haridharan, R. [9]	PCA+DWT+KSVM +GTB	250	92
Mathew, A. R., & Anto, P. B. [16]	Wavelet transform + SVM	200	92
Gupta, M. P., Shringirishi, M. M., & Singh, Y. [10]	K-means + fuzzy C-means	200	89
Naveen, A., & Velmurugan, T. [19]	K-means	80	88
Proposed Method	CWT+DWT+PCA+SVM+RF	247	96

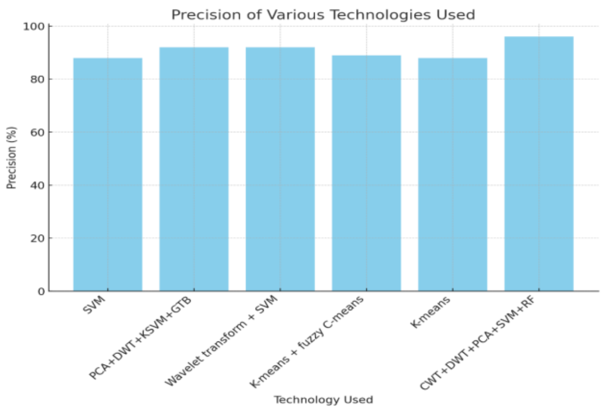

Figure 8 Comparison of Standard Techniques for Brain Tumor Classification

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Conclusion

In conclusion, the proposed brain tumor detection system, combining SVM and Random Forest algorithms, enhances classification accuracy and efficiency. The GUI simplifies the process by allowing parameter adjustments without reprogramming. Wavelet transforms (CWT and DWT) enable precise feature extraction, with CWT excelling in edge preservation and DWT in tasks like de-noising. The hybrid approach balances visualization needs and computational speed, achieving up to fivefold improvement. This solution effectively supports accurate diagnosis and treatment planning, providing a versatile and efficient tool for clinical use.

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