An Automated Brain Tumor Detection Framework using Hybrid GWO-SVM and MRI Image Analysis

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Abstract**—** Accurate detection of brain tumors from medical images plays a crucial role in clinical diagnosis and treatment planning. Magnetic Resonance Imaging (MRI) provides high-resolution visualization of brain tissues; however, the presence of noise, intensity variations, and complex anatomical structures makes automated tumor detection challenging.

In this work, a hybrid framework is proposed for the automated detection and classification of brain tumors using MRI images. The framework consists of multiple stages including image preprocessing, segmentation, feature extraction, feature optimization, and classification. Initially, MRI images are enhanced using a combination of bilateral filtering and wavelet-based denoising techniques to improve image clarity while preserving structural information. The enhanced images are then segmented to identify potential tumor regions.

Texture features are extracted using the Gray Level Co-occurrence Matrix (GLCM), which effectively captures spatial relationships within the tumor region. Grey Wolf Optimization (GWO) is applied to select the most informative features, thereby reducing redundancy and improving computational efficiency. Finally, a Support Vector Machine (SVM) classifier is employed to categorize tumors as benign or malignant.

Experimental results demonstrate that the proposed approach achieves an accuracy of 97.92%, highlighting its effectiveness and reliability. The integration of hybrid preprocessing and optimized feature selection significantly improves tumor detection performance. The proposed system can serve as an efficient computer-aided diagnostic tool for early detection and clinical decision support.

Keywords**—***Brain Tumor Detection, Magnetic Resonance Imaging (MRI), Hybrid Image Processing, Gray Level Co-occurrence Matrix (GLCM), Grey Wolf Optimization (GWO), Support Vector Machine (SVM), Feature Selection, Medical Image Analysis.*

I. INTRODUCTION

The detection and classification of brain tumors remain critical challenges in the field of medical image analysis due to the complexity of brain structures and the variability in tumor characteristics. Brain tumors are abnormal growths of cells that can disrupt normal brain function and are generally categorized as benign or malignant. Early and accurate identification of these tumors is essential for effective treatment planning and improving patient survival rates.

Magnetic Resonance Imaging (MRI) is widely used for brain analysis because it provides high-resolution images of soft tissues without exposing patients to harmful radiation. Despite its advantages, MRI images often contain noise, intensity inhomogeneity, and complex structural details that make manual analysis difficult and time-consuming. The reliability of diagnosis may also depend on the expertise of medical professionals, leading to variability in interpretation.

To overcome these challenges, computer-aided diagnosis (CAD) systems have been developed to automate the process of tumor detection and classification. These systems typically involve several stages, including image preprocessing, segmentation, feature extraction, feature selection, and classification. Effective preprocessing is crucial to enhance image quality and remove noise, while segmentation helps in accurately isolating tumor regions. Feature extraction techniques are then used to capture meaningful information from the segmented region, which is further optimized using feature selection methods to improve classification performance.

In this work, a hybrid framework is proposed for automated brain tumor detection using MRI images. The proposed method combines hybrid image preprocessing techniques with Gray Level Co-occurrence Matrix (GLCM) based feature extraction, Grey Wolf Optimization (GWO) for feature selection, and Support Vector Machine (SVM) for classification. The integration of these techniques improves the accuracy and efficiency of tumor detection.

The main contribution of this research lies in the combination of hybrid filtering methods and optimization-based feature selection, which enhances classification performance while reducing computational complexity. The proposed system aims to provide a reliable and efficient solution for automated brain tumor detection, assisting medical professionals in early diagnosis and treatment planning.

II. RELATED WORK

A large number of studies have been carried out in automated brain tumor detection using Magnetic Resonance Imaging (MRI) with image processing, machine learning, and deep learning techniques. Texture-based feature extraction methods are widely used in medical image analysis. Haralick et al. [1] introduced the Gray Level Co-occurrence Matrix (GLCM), which extracts features such as contrast, correlation, energy, and homogeneity to represent spatial information in MRI images.

Support Vector Machine (SVM), proposed by Cortes and Vapnik [2], is a widely used classification algorithm due to its ability to handle high-dimensional data and provide accurate results. It has been successfully applied in brain tumor classification.

Optimization techniques are used to improve feature selection. Grey Wolf Optimization (GWO), introduced by Mirjalili et al. [3], is a nature-inspired algorithm that helps in selecting the most relevant features, improving accuracy and reducing complexity.

Wavelet-based methods are used for image enhancement and feature extraction. Bahadure et al. [4] combined Biologically Inspired Wavelet Transform (BWT) with SVM for better tumor detection. Similarly, Varuna Shree and Kumar [5] used Discrete Wavelet Transform (DWT) with Probabilistic Neural Network (PNN) for classification.

GLCM-based texture features with SVM have also been used for tumor detection, as shown by Kavin Kumar et al. [6], highlighting the importance of texture information.

Hybrid approaches combining deep learning and machine learning have shown improved performance. Özyurt et al. [7] proposed a CNN–SVM model where CNN is used for feature extraction and SVM for classification.

Deep learning methods, especially Convolutional Neural Networks (CNN), have gained popularity in recent years. Sultan et al. [8] developed a deep CNN model for tumor classification, while Çinar and Yıldırım [9] proposed a hybrid CNN approach. Huang et al. [10] also demonstrated CNN-based tumor detection methods.

III. PROPOSED METHODOLOGY

The proposed system is designed to automatically detect and classify brain tumors from MRI images using a combination of advanced image processing and machine learning techniques. The framework integrates hybrid preprocessing, clustering-based segmentation, texture feature extraction, optimization-based feature selection, and classification. The overall architecture of the system is illustrated in Fig. 1.

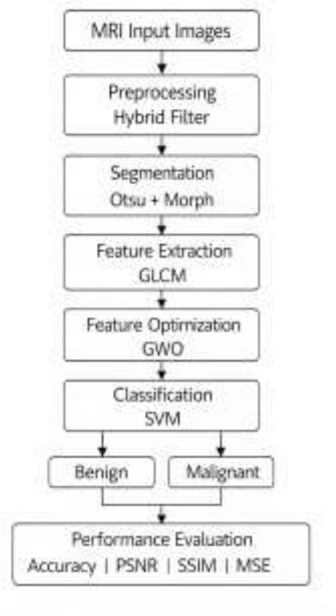

Fig. 1. Block diagram of the proposed hybrid GWO–SVM framework for brain tumor detection and classification using MRI images.

A. System Overview

The proposed methodology consists of the following sequential stages:

1. MRI Image Acquisition
2. Image Preprocessing
3. Tumor Segmentation
4. Feature Extraction using GLCM
5. Feature Selection using Grey Wolf Optimization (GWO)
6. Tumor Classification using Support Vector Machine (SVM)
7. Performance Evaluation

B. Image Preprocessing

MRI images are often affected by various types of noise such as Gaussian noise, salt-and-pepper noise, and speckle noise, which degrade image quality and hinder accurate tumor detection. Therefore, preprocessing is essential to enhance image clarity and preserve important structural information.

In this work, a hybrid filtering approach is proposed by combining multiple filtering techniques. Initially, median filtering is applied to eliminate impulse noise. Wavelet-based denoising is then used for multi-resolution noise reduction. Wiener filtering is employed for adaptive noise suppression, followed by non-local means filtering to preserve texture details. Bilateral filtering is applied to maintain edge information, and finally, image sharpening is performed to enhance important features.

This hybrid preprocessing approach effectively improves image quality and facilitates accurate tumor segmentation. The performance of the preprocessing stage is evaluated using PSNR, SSIM, and MSE metrics, as shown in Figs. 2–4.

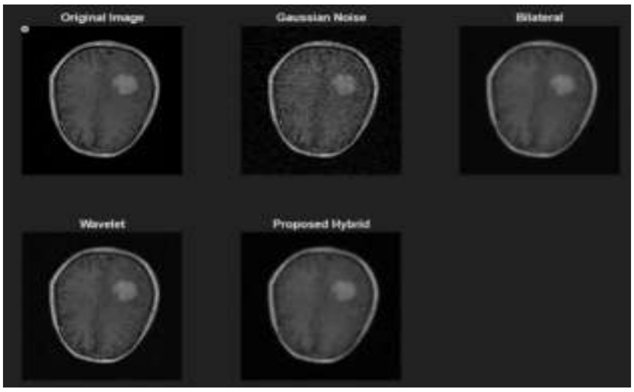

Fig. 2. Preprocessing results for MRI image corrupted with Gaussian noise: (a) Original MRI image, (b) Gaussian noise image, (c) Bilateral filter output, (d) Wavelet filter output, and (e) Proposed hybrid filter output.

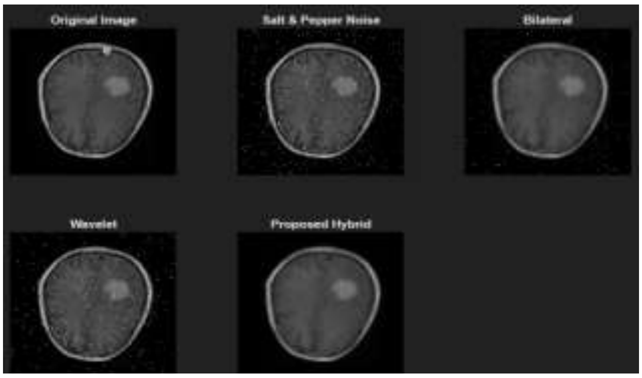

Fig. 3. Preprocessing results for MRI image corrupted with Salt-and-Pepper noise: (a) Original MRI image, (b) Salt-and-Pepper noise image, (c) Bilateral filter output, (d) Wavelet filter output, and (e) Proposed hybrid filter output.

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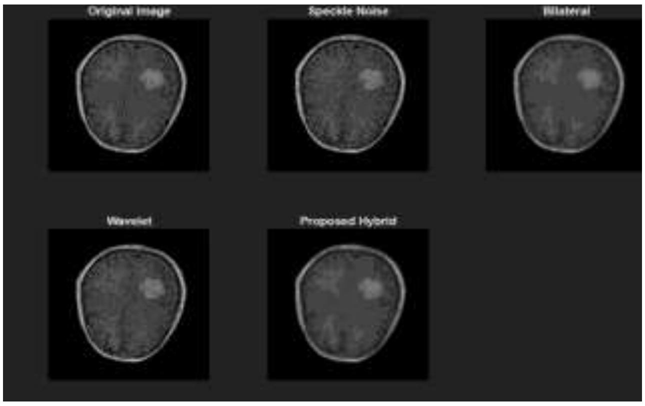

Fig. 4. Preprocessing results for MRI image corrupted with Speckle noise: (a) Original MRI image, (b) Speckle noise image, (c) Bilateral filter output, (d) Wavelet filter output, and (e) Proposed hybrid filter output.

C. Tumor Segmentation

After preprocessing, tumor segmentation is performed to isolate abnormal regions from normal brain tissues. In this study, K-means clustering is employed due to its simplicity and computational efficiency.

The algorithm partitions the image into k clusters by minimizing the intra-cluster variance:

$$J = \sum_{i=1}^{k} \sum_{x \in C_i} || x - \mu_i ||^2$$

where C_i represents the set of pixels in the i^{th}cluster and $\mu_i$is the centroid.

Among the generated clusters, the region with higher intensity is identified as the tumor region, as tumor tissues typically appear brighter in MRI images.

To enhance segmentation accuracy, morphological operations such as opening, closing, and hole filling are applied. These operations remove noise, smooth the tumor boundaries, and improve region continuity. The largest connected component is selected as the final tumor mask to eliminate irrelevant regions.

D. Feature Extraction using GLCM

Feature extraction is performed to obtain meaningful descriptors from the segmented tumor region. In this work, texture features are extracted using the Gray Level Co-occurrence Matrix (GLCM), which captures spatial relationships between neighboring pixels.

The GLCM is computed in four directions (0°, 45°, 90°, and 135°) to analyze texture variations in multiple orientations. From the GLCM matrix, the following features are extracted:

- Contrast
- Correlation
- Energy
- Homogeneity

These features effectively characterize the texture of tumor regions and assist in distinguishing between normal and abnormal tissues.

The average values of these features across all directions are computed to obtain stable and reliable descriptors for classification.

The mathematical formulations of GLCM features are given as:

$$\text{Contrast} = \sum_{i,j} (i-j)^2 P(i,j)$$

$$\text{Correlation} = \sum_{i,j} \frac{(i-\mu_i)(j-\mu_j)P(i,j)}{\sigma_i \sigma_j}$$

$$\text{Energy} = \sum_{i,j} P(i,j)^2$$

$$\text{Homogeneity} = \sum_{i,j} \frac{P(i,j)}{1+| i-j |}$$

where $P(i,j)$represents the probability value of the GLCM matrix.

GLCM Feature Values in Different Directions

S.No	Texture Feature	0°	45°	90°	135°
1	Contrast	4.12	3.98	4.05	3.87
2	Correlation	0.62	0.64	0.63	0.65
3	Energy	0.29	0.31	0.30	0.32
4	Homogeneity	0.51	0.53	0.52	0.54

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Average Feature Values

Feature	Average Value
Contrast	4.00
Correlation	0.635
Energy	0.305
Homogeneity	0.525

These averaged values provide a stable representation of tumor texture.

E. Feature Selection using Grey Wolf Optimization (GWO)

Not all extracted features contribute equally to classification performance. Therefore, feature selection is performed to identify the most relevant features and eliminate redundant ones.

Grey Wolf Optimization (GWO) is a nature-inspired optimization algorithm based on the hunting behavior and leadership hierarchy of grey wolves. It categorizes candidate solutions into alpha, beta, delta, and omega wolves and iteratively updates their positions to search for the optimal feature subset.

By selecting the most informative features, GWO improves classification accuracy while reducing computational complexity.

F. Tumor Classification using SVM

The selected optimal features are used to train a Support Vector Machine (SVM) classifier. SVM is a supervised learning algorithm that determines an optimal hyperplane to separate data into different classes:

$$w \cdot x + b = 0$$

Based on this decision boundary, the classifier categorizes tumors into two classes:

- Benign Tumor
- Malignant Tumor

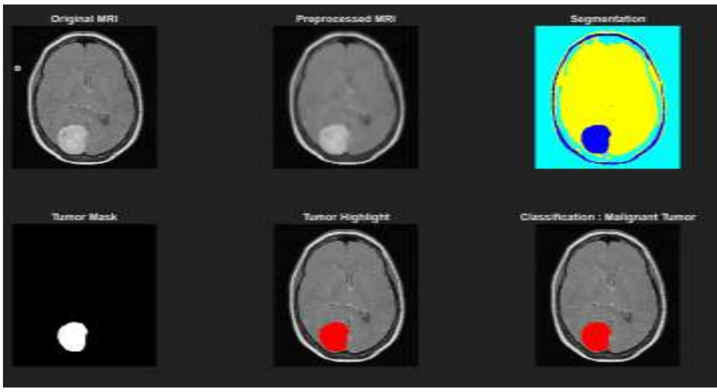

Fig. 5: Malignant brain tumor detection results.

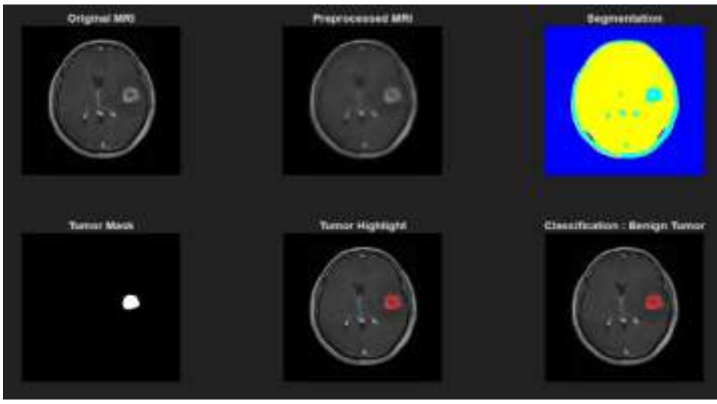

Fig. 6: Benign brain tumor detection results.

SVM is chosen due to its strong generalization capability and effectiveness in handling high-dimensional data, resulting in accurate classification performance.

G. Performance Evaluation

The performance of the proposed system is evaluated using both image quality and classification metrics.

- **Image Quality Metrics:**
- Peak Signal-to-Noise Ratio (PSNR)
- Structural Similarity Index (SSIM)
- Mean Squared Error (MSE)

Classification Metrics:

- Accuracy
- Sensitivity
- Specificity
- Precision
- F1 Score

These metrics demonstrate the effectiveness and reliability of the proposed hybrid GWO–SVM framework in accurately detecting and classifying brain tumors.

IV. RESULTS AND DISCUSSION

A. Dataset

The proposed system was evaluated using a dataset of MRI brain images consisting of both benign and malignant tumor cases. The dataset was divided into training and testing subsets to validate the performance of the model under different conditions.

B. Confusion Matrix Analysis

The classification performance of the system is analyzed using a confusion matrix, as shown below:

Class	Benign	Malignant
Benign	116	4
Malignant	5	115

The results indicate that the majority of tumor samples were correctly classified. A total of 116 benign and 115 malignant images were accurately identified, while only a few cases were misclassified. This demonstrates that the proposed approach provides reliable classification with minimal error.

C. Performance Metrics

The effectiveness of the proposed model is further validated using standard evaluation metrics, as presented in Table below:

Parameter	Value (%)
Accuracy	97.92
Sensitivity	97.50
Precision	98.33
Specificity	98.33
F1 Score	97.90
False Discovery Rate	1.67
False Negative Rate	2.50
Negative Predictive Value	97.50
False Positive Rate	1.67

The system achieved an overall accuracy of 97.92%, indicating high reliability in tumor detection. The high precision and specificity values confirm that the model effectively reduces false positives, while strong sensitivity ensures correct identification of tumor cases. These results highlight the robustness of the proposed method.

D. Image Quality Analysis

The effectiveness of the proposed hybrid preprocessing technique is evaluated using standard image quality metrics such as Peak Signal-to-Noise Ratio (PSNR), Mean Squared Error (MSE), and Structural Similarity Index (SSIM). These metrics are used to assess noise reduction capability, reconstruction accuracy, and structural preservation of MRI images.

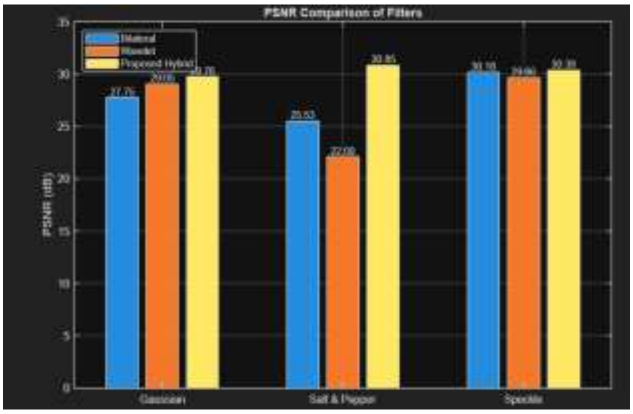

Fig.7. PSNR comparison of bilateral, wavelet, and proposed hybrid filters for different noise types.

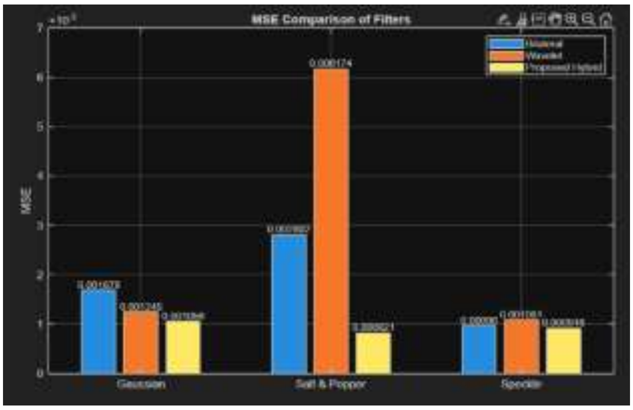

Fig. 8. MSE comparison of bilateral, wavelet, and proposed hybrid filters for different noise types.

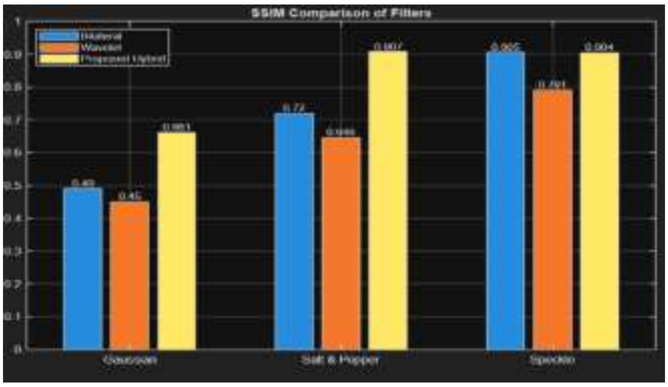

Fig. 9. SSIM comparison of bilateral, wavelet, and proposed hybrid filters for different noise types.

As shown in Figs. 7–9, the proposed hybrid filter consistently outperforms bilateral and wavelet filters under Gaussian, Salt-and-Pepper, and speckle noise conditions. The proposed method achieves higher PSNR values, indicating better image quality, and lower MSE values, reflecting reduced reconstruction error. Additionally, higher SSIM values demonstrate improved preservation of structural information. These results confirm the effectiveness of the hybrid preprocessing approach in enhancing MRI images for accurate tumor detection.

The performance of the proposed hybrid preprocessing method is evaluated using image quality metrics such as Peak Signal-to-Noise Ratio (PSNR), Mean Squared Error (MSE), and Structural Similarity Index (SSIM). These metrics are used to measure noise reduction, reconstruction accuracy, and structural preservation of MRI images.

From Fig. 7, it is observed that the proposed hybrid filter achieves higher PSNR values compared to bilateral and wavelet filters for Gaussian, Salt-and-Pepper, and speckle noise, indicating better image quality.

Fig. 8 shows that the proposed method produces lower MSE values, which means the reconstruction error is minimized and noise is effectively removed.

Fig. 9 illustrates that the proposed hybrid filter provides higher SSIM values, demonstrating improved preservation of structural information and visual quality of the MRI images.

Overall, the proposed hybrid preprocessing approach outperforms existing filtering techniques across all evaluation metrics, confirming its effectiveness in enhancing MRI images for accurate brain tumor detection.

E. Discussion

The performance improvements can be attributed to the integration of multiple techniques within the proposed framework. The hybrid preprocessing stage effectively reduces noise while preserving important structural details, which enhances segmentation quality. The use of K-means clustering enables efficient separation of tumor regions from normal tissues.

Additionally, GLCM-based feature extraction captures significant texture information from the tumor region, improving feature representation. The application of Grey Wolf Optimization (GWO) further enhances performance by selecting the most relevant features and eliminating redundancy. Finally, the SVM classifier provides accurate decision boundaries, leading to improved classification results.

V. COMPARISON WITH EXISTING METHODS

Authors	Year	Method	Accuracy
Zhiguan Huang et al.	2020	CNNBCN	95.49%
Fatih Özyurt et al.	2019	CNN-SVM	95.62%
Sultan et al.	2019	16-Layer CNN	96.13%
Bahadure N. et al.	2017	BWT + SVM	96.51%
Ahmet Çinar et al.	2020	Hybrid CNN	97.20%
Proposed Method	-	Hybrid GLCM + GWO + SVM	97.92%

The proposed method outperforms several existing brain tumor detection approaches.

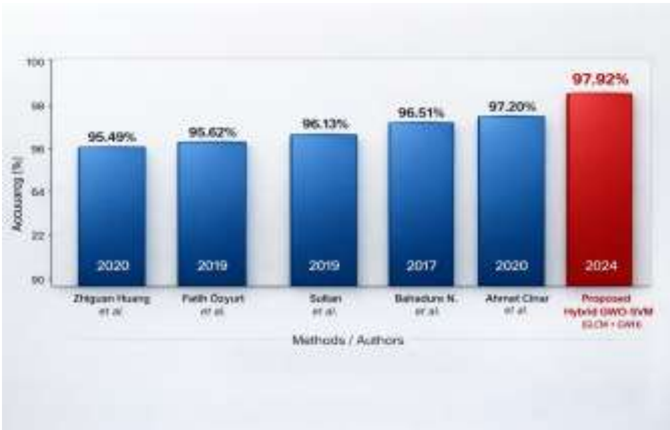

Fig 10: Comparison of the proposed brain tumor detection method with existing methods based on classification accuracy.

The proposed approach achieves higher accuracy compared to existing methods. This improvement is mainly due to the effective combination of hybrid preprocessing, optimized feature selection, and efficient classification.

VI. CONCLUSION

This study presents an automated framework for brain tumor detection using MRI images. The proposed system integrates hybrid preprocessing, K-means-based segmentation, GLCM feature extraction, Grey Wolf Optimization for feature selection, and SVM classification.

The hybrid preprocessing technique enhances image quality by effectively reducing noise while preserving important features, leading to improved segmentation accuracy. Texture features extracted using GLCM provide meaningful information about tumor characteristics, and GWO helps in selecting the most relevant features for classification.

The experimental results demonstrate that the proposed system achieves a classification accuracy of 97.92%, outperforming several existing approaches. Therefore, the developed framework can serve as a reliable computer-aided diagnostic tool for assisting medical professionals in early detection and classification of brain tumors.

VII. FUTURE SCOPE

Future enhancements of the proposed system can focus on improving generalization and clinical applicability. The use of larger and more diverse MRI datasets can further increase model robustness.

Advanced deep learning techniques such as Convolutional Neural Networks (CNN), ResNet, or hybrid deep learning models can be incorporated to automatically learn complex features and improve classification performance. Additionally, the system can be extended to perform multi-class tumor classification, including different tumor grades and types.

Integration of the proposed method into real-time clinical decision support systems can further assist radiologists in accurate and faster diagnosis.

Furthermore, a comparison with existing methods shows that the proposed Hybrid GLCM + GWO + SVM framework outperforms several previously reported techniques, including CNN-based and hybrid deep learning models. The improved performance is mainly due to the effective combination of hybrid preprocessing, optimized feature selection using GWO, and accurate classification using SVM.

Overall, the experimental results demonstrate that the proposed method provides an efficient and accurate solution for automated brain tumor detection using MRI images. The system can potentially assist medical professionals in early diagnosis and decision-making in clinical environments.

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Cheng et al. [18] proposed a brain tumor classification approach using tumor region augmentation techniques, which improved classification accuracy by enhancing relevant tumor features. Menze et al.

[19] introduced the BRATS benchmark dataset, which has become a standard dataset for evaluating brain tumor segmentation and classification methods. Kamnitsas et al. [20] developed a multi-scale 3D Convolutional Neural Network combined with Conditional Random Fields (CRF) for accurate brain lesion segmentation, demonstrating the effectiveness of deep learning models in medical image analysis.