Communications on Applied Nonlinear Analysis
ISSN: 1074-133X
Vol 32 No. 10s (2025)

A Novel Approach for Brain Tumor Classification using Bilateral Filtering and Cascade RF-SVM

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Article History:

Received: *12-01-2025*

Revised: *15-02-2025*

Accepted: *01-03-2025*

Abstract:

This work introduces a new approach to classifying brain tumors that integrates various techniques to maximize classification performance. Bilateral filtering is applied as pre-processing in the initial stage to remove noise from medical images without degrading the borders of tumor areas. In order to isolate the textural characteristics of the tumor, which play a key role in differentiating the types, the Local Binary Pattern (LBP) technique was utilized. The Improved Grey Wolf Optimization (GWO) algorithm was utilized for optimizing the feature set by removing redundant features in order to improve classification. A Random Forest classifier is employed for removing irrelevant features, and finally, the classification is performed by a Support Vector Machine classifier. This is stage one in classification. With the method proposed within this paper, brain tumors are correctly classified with impressive 99.3 percent accuracy. The very high accuracy suggests the robustness of the union of strong classification methods and novel feature selection methods. Apart from its use in imagine of brain tumors, the method can be applied to a broad variety of other medical image problems to make diagnosis highly efficient and credible.

Keywords: Bilateral Filter, Grey Wolf Optimization, Local Binary Pattern, Tumour classification

Introduction

The classification of brain tumors plays a vital role in medical diagnostic practices. Medical professionals rely on this method to differentiate different tumor types for creating specific treatment approaches. Multiple organizations have changed the system by which they categorize brain tumors since the initial publication of formal guidelines [1][2][3][4]. Advanced automated systems represented through Artificial Intelligence (AI) [5] and Machine Learning (ML)[6] have introduced more accurate approaches which replaced previous manual procedures. Through their diagnostic precision advancements these modern tools have brought about extensive structural changes to the field. Medical professionals now have enhanced abilities to choose treatments faster with better intellectual decision-making capabilities and specific patient requirements consideration. The application of artificial intelligence with machine learning for brain tumor classification serves two purposes: it leads to better patient healthcare experiences and it enables new discoveries in cancer medical practices. In the approaching years personalized medicine will advance through combining genomic data with modern imaging technology to forge innovative individualized treatment solutions. Doctors could transform their complete practices of brain tumor diagnosis and cancer treatment through this comprehensive approach which brings better results and better knowledge of advanced diseases. During the time before modern medical imaging technologies radio-diagnosticians and manual observation techniques served as the keys to identifying brain tumors correctly. These medical professionals conducted MRI and CT scans to search for abnormal tissue along with detecting tumor types.

Histopathological testing established itself as the primary classification method for brain tumors to address the previous shortcomings [7]. Microscopic study of tumor samples through this method delivered detailed information about several tumor categories with their subtypes such as pituitary adenomas, meningiomas, and gliomas. The accuracy of this method was high although it required dangerous invasive biopsies that were not suitable for tumors located in complex brain regions. The medical community sought non-invasive diagnostic solutions because traditional patient safety risks with invasive approaches were deemed unacceptable. Research in imaging technology has revealed encouraging developments since that time which include functional MRI along with PET scans. The methods deliver extensive information about tumor structure and metabolism and behavior so doctors can achieve better classifications without operating. The progress in brain tumor diagnosis and treatment became substantial when medical research focused on developing non-invasive strategies thus enabling safer and enhanced care quality for patients. The current best practice in diagnosing and classifying brain tumors uses histopathological testing according to research [7]. Under microscopic examination of tumor tissue, this approach gave detailed knowledge of multiple tumor groups including pituitary adenomas, meningioma's and gliomas.

Computer-aided diagnostic (CAD) tools became available through their recent development which advanced automated brain tumor classification processes [8][9]. Different machine learning algorithms including support vector machines (SVMs) [10], decision trees, random forests and ensemble methods [11] [12] served tumor classifications in these systems according to manually extracted features regarding texture shape intensity and edge patterns [13]. The systems faced limitations in effectiveness because they relied on features chosen by experts which forced users to get involved manually and reduced the automation capabilities. When scientists investigated deep learning methods [14] as a solution to overcome this limitation. Automatic feature detection methods in brain tumor diagnosis lead to enhanced effectiveness and precise brain tumor diagnosis capabilities through direct data extraction from unprocessed imaging data. The improvements achieved regarding accuracy and manual inspection requirement reduction did not remove the major limitations that existed within feature-based approaches. The chosen features combined with the ability of data scientists and radiologists building the feature extraction process defined the quality level of the outcomes. All of these algorithms encountered problems with cross-environment generalization because their operations were limited by differences in imaging protocols and patient demographic characteristics. This variable performance with new datasets proved that resilient models with clinical context adaptability should become the priority for future development.

Deep learning achieved a revolutionary change in brain tumor classification when it introduced end-to-end learning based on imaged data directly from its original state. Convolutional neural networks (CNNs) [15, 16] have become widely popular because they can automatically extract spatial information hierarchies from pictures. Research together with clinical facilities have adopted networks like ResNet, DenseNet, VGGNet and Inception since they excel at detecting tumors and segmenting them. The models utilize dense and residual connections as sophisticated methods to improve complicated dataset performance and enhance feature extraction. The application of AlexNet achieved better results than ordinary machine learning approaches while processing tumor data effectively. Transfer learning has undergone substantial development to advance deep learning models in recent times. Medical researchers solved the scarcity of labeled healthcare information by utilizing optimized pretrained neural networks for ImageNet that process smaller medical datasets. Through GPU computing speed enhancements researchers have transformed the field and established better accessibility of these models for clinical practice. Medical diagnostics using these technologies now provide farmers elevated diagnostic accuracy in addition to individual treatment plans that suit patients' specific medical needs.

The investigation of hybrid and ensemble models started among researchers as they aimed to enhance classification accuracy. Multiple approaches with their respective outstanding features converge into hybrid models through the combination of CNNs [17] and the more traditional SVMs [18] machine learning classifiers. Using the ensemble learning methods of both bagging and boosting multiple models generate predictions to reduce overfitting and enhance reliability. A typical SVM serves to categorize tumors through operation on high-level features derived from CNN-analyzed MRI scans as part of a hybrid classification system. A group of classifiers known as ensembling methods utilizes several weak classifiers to create improved prediction results. This includes gradient boosting and random forests. AI model complexity led to the adoption hurdle because clinicians could not easily understand their "black box" mechanism. XAI gained prominence as an AI method to display the decision methods used by complex models. To support radiologists with result verification and AI system confidence levels three tools namely Grad-CAM and SHAP and LIME identify which image sections maintain the most important influence on predictive model output. The classification process of XAI models becomes more focused on clinically relevant characteristics because heatmaps expose the tumor regions affecting model predictions. The transparency level required in medical applications is essential specifically because diagnostic errors lead to major consequences. This need was addressed by self-supervised learning in recent times.

Federated learning enables the joint model training between different institutions to protect patient privacy through secure information protection. Through federated learning institutions protect patient privacy by preparing model updates instead of distributing original data thus following regulations including GDPR and HIPAA. The method stands as a potential solution for making robust flexible brain tumor classification models which combine information from multiple healthcare institutions. Brain tumor classification achieves advancements through quantum machine learning (QML) which represents one of the most sophisticated areas that unifies quantum computing with machine learning algorithms. Studies have proved that introducing QML[19] methods leads to better feature selection results alongside increased processing speed and enhanced classification success rates. Resolving challenges in managing complex medical imaging data requires researchers to test models which combine quantum circuits together with conventional neural networks. QLM has capabilities to tackle difficult tasks in deep learning model parameter adjustment together with high-dimensional clustering. QML exists in a preliminary stage but shows potential to change how brain tumors are classified in upcoming years.

Blood cancer analysis depends on the combination of current AI technology with medical expertise to achieve better brain tumor classification. Accurate diagnosis along with understandability and clinical applicability serves as the primary goals of this method.

1. **Literature Survey**

Saeedi S. et al. [20] applied convolutional neural networks (CNNs) for brain tumor classification. Their main goal focused on solving small dataset problems through enhanced data augmentation methods that included flipping and rotation and brightness adjustment. Through their implementation of dropout layers and transfer learning methods the researchers reached a 92 percent accuracy level with superior capability against overfitting.

Shanti et al. [21] created an optimized hybrid deep neural network (OHDNN) as a system for automatic brain tumor classification. Their method operated through two sequential steps that started with pre-processing followed by classification. The CNN-LSTM model combined CNN features extraction with LSTM classification operations. The method reached improved performance levels through classifier parameter adjustments applying the adaptive rider optimization (ARO) algorithm.

Gupta et al. [22] created a multiscale CNN architecture which analyzed image patches at different resolutions to simultaneously extract brain tumor fine and coarse elements. The model achieved benchmark-dataset benchmarks reaching 90.5 percent accuracy to differentiate low- and high-grade gliomas. Medical imaging outcomes demonstrate that deep learning proves to be effective for enhancing diagnostic accuracy specifically in medical diagnostic applications.

Afshar Parnian et al. [23] introduced a CapsNet model which performed classification operations through the combination of tumor contours and raw MRI scans. The new approach eliminated the need for precise tumor annotation so the model could focus on analyzing both the main tumor area and its tissue interactions. The spatial characteristics of features received successful representation through Capsule networks allowing them to outperform traditional CNNs with a 93% classification success.

Al Tahhan et al. [24] developed a CNN model which integrates U-Net with a refined ResNet50 for brain tumor identification and categorization in MRI images. The ResNet50 architecture achieved detection accuracy between 0.87 and 0.98 for precision, recall, F1 score and overall accuracy. The model showed outstanding segmentation performance through its IoU measurement of 0.91 and DSC value of 0.95.

El-assy et al. [25] introduced a CNN architecture which combines InceptionV3, ResNet-50, VGG16 and DenseNet to classify brain tumors. They dedicated their time to using U-Net for mask creation and feature extraction from all four CNN models while processing MRI images. The researchers integrated an XAI layer for better interpretability. The proposed architecture achieved superior performance than the single models DenseNet (94.65 percent), VGG16 (91.04 percent), InceptionV3 (71.54 percent) and ResNet-50 (95.5 percent) by reaching an outstanding 96.2 percent accuracy.

Mohamed R. Shoaib et al. [26] describes a brain tumor classification method which unites support vector machines (SVM), Mask R-CNN, and anisotropic diffusion. The researchers selected transfer learning to derive features from smaller datasets while they modified hyperparameters so the model would not overfit. The proposed model performed significantly better than standard classifiers operating with an accuracy level of 92.3% while Random Forest achieved 85.4 percent accuracy and SVM produced 82.7 percent accuracy.

All studies together demonstrate that AI modern techniques and precision improvement along with interpretive features have expedited brain tumor diagnostic classification. The medical field will advance brain tumor diagnosis and treatment through advanced techniques such as explainable AI and federated learning along with quantum machine learning methods.

3. Proposed method

The proposed approach in brain tumor categorization employs various modern techniques with the aim to be more precise while ensuring good efficiency. The suggested system deploys advanced image processing techniques integrated with top algorithms in machine learning along with well-established data analytics tools. Patients are detected and directed to appropriate diagnosis and targeted treatment protocols through technological deployment in the system.

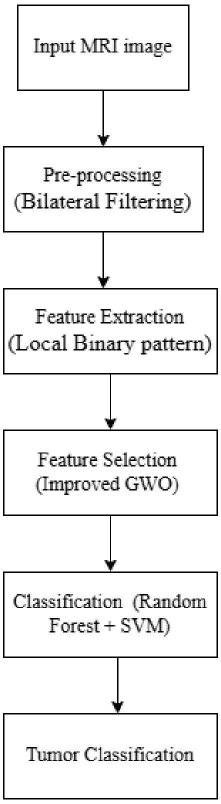

Fig 1: Proposed Block Diagram

The methodology follows four main phases which include preprocessing combined with feature extraction followed by feature selection finished by classification.

The preprocessing step reduces medical image noise through bilateral filtering to protect brain tumor edge regions. Accurate feature extraction and classification later depend on this step due to the important role it plays in preserving structural details.

II. Local Binary Pattern (LBP) enables the extraction of important textural data from tumor areas for analysis. The strong texture properties of LBP enable effective differences between tumor types so it serves well for measuring pixel intensity variations. Buying an extensive knowledge of tumor texture comes from extracting LBP features that enable correct classification needs these features in order to work.

III. The proposed work utilizes an enhanced version of Grey Wolf Optimization called GWO for feature selection to minimize data dimensions and manage the difficulties that come with extensive data spaces. Through feature selection optimization we can find the most discriminative relevant features for our analysis by discarding both unneeded components and duplicating information. Because it chooses the best attributes the classification system need for informative execution, GWO optimization helps to maximize both efficiency and performance.

IV. A two-stage classification procedure utilizes the Specific powers of both Random Forest (RF) and Support Vector Machine (SVM) classifiers. The Random Forest algorithm generates an extensive set of candidate features in the first step of the process. The Support Vector Machine operates in the second phase to optimize the characteristics obtained from the first stage and generate end results. The implementation of both classifiers optimizes accuracy and generates better reliable predictions because of their complementary capabilities.

3.1 Dataset Used

The BraTS 2020 (Brain Tumor Segmentation Challenge 2020) dataset [24] is a commonly used benchmark for brain tumor segmentation and classification problems. It is one part of the MICCAI Brain Tumor Segmentation (BraTS) Challenge, which is intended to create automated methods for multimodal MRI scan-based brain tumor detection and segmentation.

3.2 Pre-processing

During the pre-processing stage the bilateral filter eliminates noisy elements which leads to imaging enhancement and smoothing. The medical-image-specific nonlinear edge-preserving smoothing technique exists as a designed method for medical images. The definition of tumor boundaries for brain tumor classification through smooth flat areas without blurring sharp edges represents one of the leading methods in medical imaging. Medical professionals benefit from this technique because it allows more accurate tumor classification through precise surface enhancement.

Step 1: Load the Brain MRI Image

We first input the brain MRI image into the system before moving on to additional processes.

Step 2: Normalize the Image

The normalization step scales pixel intensities to a range of 0 to 1 or 0 to 255. This step reduces intensity discrepancies across images from different datasets, which is crucial for preserving processing consistency.

Step 3: Apply Bilateral Filtering

The bilateral filter implements a smoothing operation which preserves edges through calculations that combine intensity data with spatial positions. The filtered value for each pixel results from averaging weighted pixels within its surroundings according to two main components:

1. Weights derive their values from the spatial Gaussian kernel to determine pixel-center relationships with nearby pixels.

2. Each pixel weights in the intensity Gaussian Kernel uses its central pixel intensity compared with its neighboring pixels.

For a pixel I(x, y) the filtered pixel (Ifiltered(x, y) is determined as:

$$I_{\text{filtered}}(x,y) = \frac{\Sigma_{P\in\Omega} G_s(\|p-(x,,y)\|)\cdot G_r(|I(p)-I(x,y)|)\circ I(p)}{\Sigma_{P\in i} G_s(\|p-(x,y)\|)\cdot G_r(|I(p)-I(x,y)|)} \quad \ldots(1)$$

Where:

G_s is the spatial Gaussian kernel: $Gs(d)=\exp(-\frac{d^2}{2\sigma_s^2})$

Gr is the intensity Gaussian kernel: $Gr\ (\Delta I)=\exp(-\frac{\Delta I^2}{2\sigma_r^2})$

σs: Controls the spatial smoothing extent.

σr : Controls the intensity smoothing extent.

Ω: Neighborhood of pixels around (x,y).

Step 4: Contrast Enhancement

After applying bilateral filtering, a doctor might need to enhance tumor boundaries yet again. The procedure of histogram equalization enhances tumor visibility for better recognition. The technique redistributes pixel intensity values to enhance image contrast which reveals important details.

Step 5: Thresholding

The following step involves utilizing Otsu's thresholding method to distinguish tumors from the background. The innovative method determines automatically the perfect threshold value to split tumor areas from surrounding tissues during segmentation.

Step 6: Morphological Operations

The segmented tumor area receives refinement through two morphological procedures including closure followed by dilation. These procedures produce better data segmentation by removing noise and completing empty areas found in tumor regions.

Step 7: Resize the image.

After processing the image, it gets resized to a standardized input dimension (128x128 pixels) for future analysis.

3.3 Feature Extraction

After pre-processing the system applies the Local Binary Pattern (LBP) technique for feature extraction. LBP extracts the textural information from images which provides effective details that help with accurate tumor classification.

3.3.1 Local Binary Patterns (LBP)

Local Binary Patterns (LBP) represents a popular method for extracting texture features needed for brain tumor classification. The popularity of this technique continues to increase in medical imaging analysis because it precisely detects regional intensity patterns in images for brain tumor diagnosis purposes. These patterns strongly represent the texture which helps medical experts distinguish tumor-affected tissues from healthy ones. The classification performance of algorithms improves through LBP because it examines pixel intensity spatial positions which results in better brain tumor identification.

The LBP technique explores image microtexture patterns because these patterns represent critical indicators for distinguishing different tissue types during brain tumor classification. The method validates local textural attributes that lead to substantial differences between tumor zones and regular tissue in order to better classify unique tumor types. The semantic processing ends in better patient results combined with improved therapeutic plans. Research-based enhancements of classification system predictive capability become possible through the incorporation of LBP features within machine learning platforms.

How LBP works

LBP function determines pixel binary values through processing their intensity versus that of adjacent pixels. The operations of LBP take place inside a circular group of P neighboring pixels extending from any chosen pixel located at position (x, y).

At location (x, y) the central pixel intensity maintains I(x, y) as its main value. The circular neighborhood contains pixels which are indexed from 0 to 1 to 2 extending indefinitely where pixel Ii represents each neighboring intensity. P-1.

Through thresholding pixel intensities in specific relation to the central pixel the LBP operator produces binary patterns that display local image characteristics. Through this technique hospital can achieve precise features for classification of brain tumors.

The LBP value for this central pixel is computed as:

$$LBP(x,y)= \sum_{i=0}^{p-1} s(I_i-I(x,y)).\ 2^i \qquad \ldots..(2)$$

Where s(x) is the thresholding function, defined as:

$$S(x) = \begin{cases} 1, \text{if } x \geq 0 \\ 0, \text{if } x < 0 \end{cases} \qquad \ldots.(3)$$

This function evaluates the intensity I_i of each neighboring pixel against the intensity I(x,y) of the central pixel.

3.3.2 LBP Histogram

The following process involves generating an LBP histogram after implementing the Local Binary Pattern (LBP) operation on every image pixel. The image's regional distribution (ROI) shows various LBP patterns which generate this histogram.

Histogram Calculation

Let L(x,y) denote the LBP value at pixel (x,y), and let n represent the total number of pixels in the image or the specified region. The histogram H is then defined as follows:

$$H_i = \frac{\sum_{(x,y)} \delta(L(x,y), i)}{n} \quad ....(4)$$

Here, H_i indicates the frequency of the LBP code i in the image.

The Kronecker delta function, denoted as δ(a,b), is defined as:

$$\delta(a,b) = \begin{cases} 1, \text{if } a = b \\ 0, \text{if } a \neq b \end{cases} \quad ....(5)$$

The following process involves generating an LBP histogram after implementing the Local Binary Pattern (LBP) operation on every image pixel. The image's regional distribution (ROI) shows various LBP patterns which generate this histogram.

Texture Features Derived from LBP Histogram

The LBP histogram yields several statistical texture features which provide valuable classification attributes. Here are a few of these attributes.:

Energy (Uniformity):

$$\text{Energy} = \sum_{i=0}^{N-1} H_i^2 \quad ...(6)$$

This measures the homogeneity of texture. High-energy textures exhibit uniformity but low-energy texture displays inhomogeneity.

Entropy:

$$\text{Entropy} = -\sum_{i=0}^{N-1} H_i \log(H_i) \quad ...(7)$$

Entropy measures a texture's randomness or unpredictability. Entropies rise steadily with the complexity of textures appearing most often within tumor regions.

Contrast:

$$\text{Contrast} = \sum_{i=0}^{N-1} \sum_{j=0}^{N-1} (i - j)^2 H_{ij} \quad ...(8)$$

This feature detects the variations in intensity in different regions. Higher contrast values highlight sharp edges in pictures because this allows for better tumor boundary detection.

Correlation:

$$\text{Correlation} = \frac{\sum_{i=0}^{N-1} \sum_{j=0}^{N-1} (i-\mu)(j-\mu) H_{ij}}{\sigma_x \sigma_y} \quad .....(9)$$

Here, μ represents the mean intensity, while σ_x and σ_y are the standard deviations along the horizontal and vertical axes, respectively.

Homogeneity:

$$\text{Homogeneity} = \sum_{i=0}^{N-1} \sum_{j=0}^{N-1} \frac{H_{ij}}{1+|i-j|} \quad .....(10)$$

The metric measures pixel neighbor intensity similarity for separating uniform from varied tissue structures.

3.3.3 Improved Grey Wolf Optimization (GWO) for Brain Tumor Classification Using Texture Features

The GWO optimization method applies intelligent search techniques from the natural behavior patterns of grey wolves during social activities and their hunting methods. This algorithm finds current use in addressing problems that involve feature selection together with classification challenges alongside hyperparameters optimization. The study employs extracted texture features for classification enhancement using GWO.

GWO follows the organizational hunting patterns of grey wolves by using four distinct wolf types.

- Alpha (α) wolves: These are the top dogs, representing the best solution (the leader).
- Beta (β) wolves: They stand in as the second-best solution.
- Delta (δ) wolves: These guys represent the third-best solution.
- Omega (ω) wolves: This group makes up the rest of the pack, following the leaders.

These wolves work together to find the optimal solution in the search space through the following steps:

1. Encircling Prey
2. Hunting
3. Attacking the Prey (Exploitation)
4. Diverging for Exploration

Step 1: Encircling Prey

Grey wolves encircle their prey using the following equations:

$$D = | C.Xprey-X| \qquad ..(11)$$

$$X_{New} = X_{prey} – A.D \qquad ..(12)$$

Where:

X_{New} = current position of a wolf

X_{prey} = best solution found so far

A,C = coefficient vectors

D = distance between the wolf and the prey

The coefficient vectors are defined as:

$$A= 2.a.r_1\text{-}a \qquad ..(13)$$

$$C=2.r_2 \qquad ..(14)$$

Where:

a = a linearly decreasing parameter from 2 to 0

r_1,r_2 = random numbers in [0,1]

Step 2: Hunting Mechanism

Each wolf updates its position based on the positions of the three best wolves (α, β, δ):

$$X1=X_\alpha – A_\alpha . |C_\alpha. X_\alpha -X| \qquad …(15)$$

$$X2=X_\beta – A_\beta . |C_\beta. X_\beta -X| \qquad …(16)$$

$$X3=X_\delta – A_\delta . |C_\delta. X_\delta -X| \qquad …(17)$$

The final updated position of a wolf is:

$$X_{new=}\frac{X1+X2+X3}{3} \qquad ..(18)$$

Step 3: Attacking and Converging

The parameter α decreases linearly from 2 to 0 to balance exploration and exploitation:

$$\alpha=2\text{-}\frac{2t}{T} \qquad …(19)$$

Where T is the maximum number of iterations.

- When |A| < 1, the wolves converge toward the best solution.
- When |A| > 1, the wolves explore new areas in the search space.

Step 1: Feature Extraction

We extract texture features such as Energy, Entropy, Contrast, Correlation, and Homogeneity from MRI images using LBP histograms. The feature vector is represented as:

Feature Vector = [Energy, Entropy, Contrast, Correlation, Homogeneity]

Step 2: Optimization with GWO

GWO is employed to select the optimal subset of features or fine-tune the hyperparameters of classifiers.

Objective Function (Fitness):

To evaluate the fitness of a solution X, we use classification accuracy:

$$F(X)=\frac{Correctly\ classified\ Samples}{Total\ Samples} \quad ..(20)$$

Algorithm Steps:

1. Initialize the wolf population randomly in the feature space.

2. Calculate the fitness (classification accuracy) for each wolf.

3. Update the positions of the wolves (α, β, δ) using the defined equations.

4. Dynamically update the parameters A, CA, CA, C

5. Continue the process until convergence or the maximum number of trials is achieved.

6. Return the best solution (optimal hyperparameters or feature subset).

The improved characteristics resulting from optimization enable more efficient classification operations that enhance the overall performance of brain tumour detection systems.

3.4 Classification

The extracted features that result from Grey Wolf Optimization move forward to the classifier module for additional processing.

3.4.1 Random Forest (RF) Classifier

Random Forest (RF) ensemble learning method constructs many decision trees during training and produces the class with the most votes from each tree. Classification problems are well addressed with this non-parametric approach.

For the RF classifier, M decision trees are utilized. Every node chooses a random subset of the attributes for splitting, and each tree's training data is randomly sampled with replacement. The output of each tree is added together, usually by voting for the majority, to assign the final categorization response. Each decision tree is built sequentially by applying an input criterion, such as the Gini index or entropy, to specify the best split of each node.

The Gini index for a node t is defined as:

$$Gini(t) = 1 - \sum_{i=1}^{c} p_i^2 \quad ..(21)$$

Where p_i is the probability of class i at node t.

The Random Forest (RF) classifier combines the results from all the individual decision trees. If the decision trees T_1, T_2…,T_M produce class labels y_1,y_2,…, y_M, the final prediction is determined by taking the majority vote:

$$\text{Final prediction} = \text{mode}\ (y_1,y_2,\dots, y_M) \quad ..(22)$$

3.4.2 Support Vector Machine (SVM) Classifier

The Support Vector Machine (SVM) is a supervised machine learning model which employs the optimal hyperplane to classify data points. The key goal is to improve the model's capacity to generalize and predict new data by increasing the difference between these categories. Because of this characteristic, SVM performs especially well in high-dimensional spaces, where more traditional algorithms could struggle.

Given a training set of N data points $\{(x_i, y_i)\}_{i=1}^{N}$ where $x_i \varepsilon R^d$ and $y_i \varepsilon\{-1,1\}$, the SVM finds the hyperplane that optimizes the margin between the two classes. The equation of the hyperplane is:

$$w^T x+b=0 \qquad ..(23)$$

Where:

- w is the normal vector to the hyperplane,
- b is the bias term.

The margin r is given by:

$$r=\frac{2}{||w||} \qquad ..(24)$$

The SVM aims to minimize the following objective function:

$$\min\frac{1}{2}||W||^2 \qquad ..(25)$$

Subject to:

$$y_i(w^T x_i+b)\geq 1 \qquad ..(26)$$

In order to make linear separation possible for non-linearly separable data, SVM maps the data into a higher-dimensional space using a kernel function $\phi(x)$.

Cascading Random Forest and SVM Classifiers

This proposed approach uses a cascaded combination of the Random Forest (RF) and Support Vector Machine (SVM) classifiers. A cascade classifier improves classification accuracy by sequentially applying multiple classifiers. The first classifier will handle simpler cases, while the more complex ones will be passed to the next classifier. This hierarchical approach maintains excellent accuracy while boosting efficiency and reducing computational burden by focusing later classifiers on challenging instances.

Stage 1: Random Forest (RF)

The data is first passed to the RF classifier. If the classification is confident (based on a predefined threshold), the result is output directly. Otherwise, the sample is forwarded to the next classifier.

Let $X=\{x_1,x_2,\ldots,x_N\}$ be the set of input samples, and let $\hat{y}_{RF}$ and $\hat{y}_{SVM}$ represent the predictions from the RF and SVM classifiers, respectively.

For each input sample X_i:

1. Apply RF:

$$\hat{y}_{RF} = RF(x_i) \qquad ..(27)$$

Stage 2: Support Vector Machine (SVM)

The RF classifier sends a sample to the SVM classifier in case it is unsure about it.
SVM is best for tough cases when RF can make mistakes because it excels at developing clear decision boundaries. Even in cases when classes overlap or the patterns of data become rather complex, such adaptability makes the accuracy improve.

$$\hat{y}_{SVM} = svm\ (x_i) \qquad \ldots(28)$$

The final output for sample x_i is:

$$\hat{y} = \begin{cases} \hat{y}RF & \text{if RF is confident,} \\ \hat{y}SvM & \text{otherwise} \end{cases} \qquad \ldots.(29)$$

By integrating Random Forest (RF) and Support Vector Machine (SVM), the cascade method improves classification accuracy. RF can handle simpler cases efficiently, thus avoiding SVM's computational overhead. SVM is particularly suited to generate accurate decision boundaries in more complex cases. By dividing the work in this manner, we can guarantee that everything goes smoothly and without issues, with SVM intervening only when its sophisticated knowledge is required. The model therefore works uniformly over a variety of levels of complexity in categorization.

4. Results

The results of our experiments show the performance of the model that we have designed for brain tumor classification. We applied it to a benchmark dataset and evaluated its performance with a set of evaluation metrics. The RF-SVM classification framework, bilateral filtering, LBP-based feature extraction, and GWO feature selection enhance tumor detection accuracy greatly. These results also show that hybrid classifiers combined with advanced preprocessing techniques can significantly improve the resilience and dependability of tumor classification systems.

4.1 Preprocessing Results

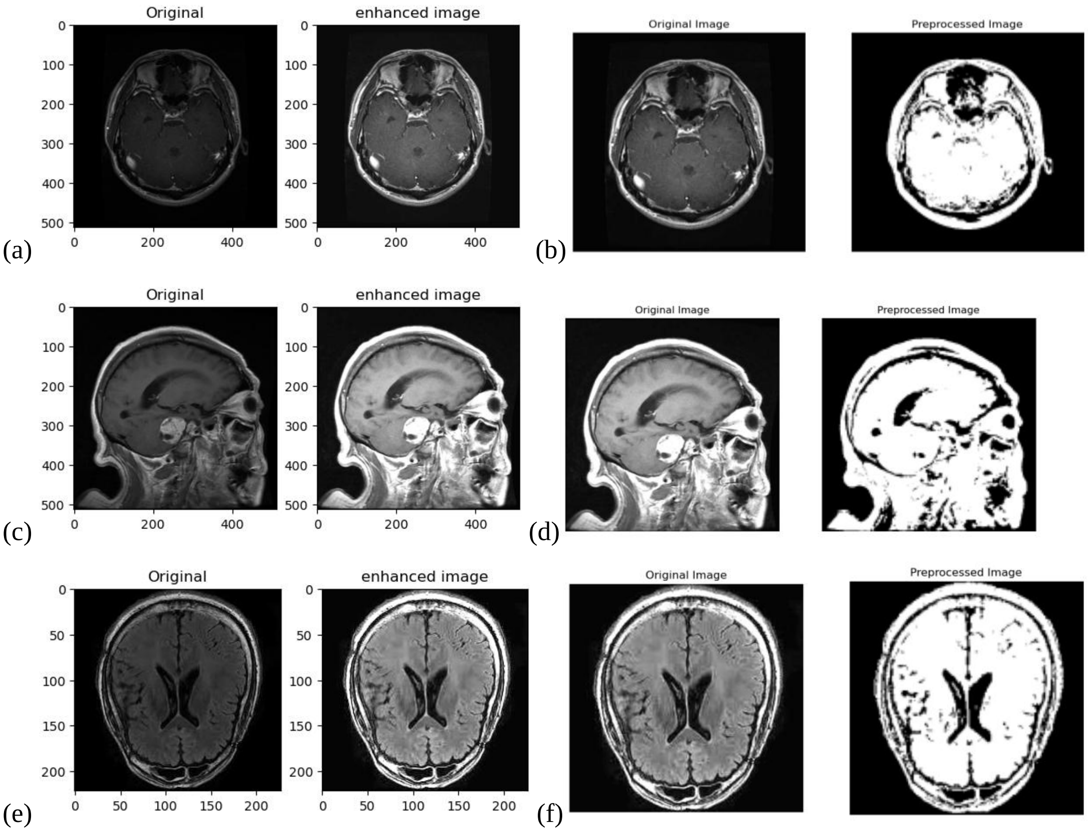

Fig 2: Output of the Pre-processed images

The left-hand side, which is "Original," in Figures 2a, 2c, and 2e presents the original input image, which is darker, has reduced contrast, and shows some noise. You can observe the enhanced output on the right-hand side, which is titled "Enhanced Image," after applying bilateral filtering to reduce noise and histogram equalization to enhance contrast. The enhanced image is presented on the left-hand side, which is also "Original," in Figures 2b, 2d, and 2f. The "Pre-processed Image," on the right-hand side, presents the final product after further refinement through binary and morphological operations.

4.2 Feature Extraction results

The following are the sample results obtained using LBP based Feature extraction technique.

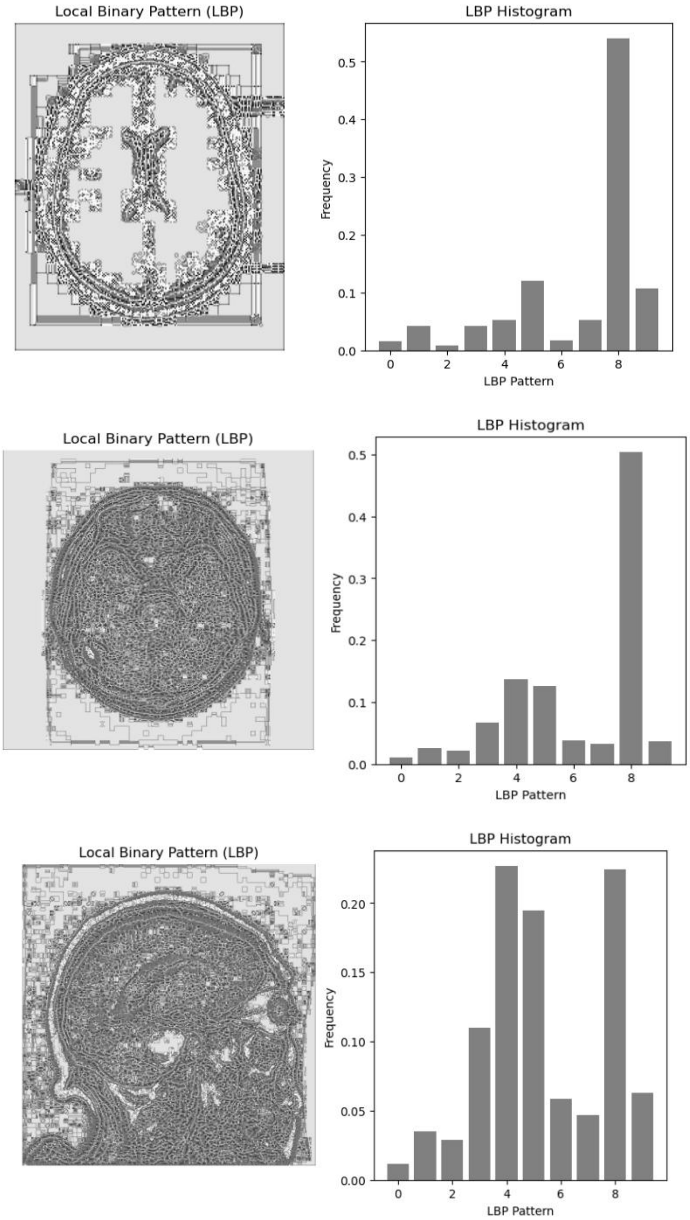

Fig 3: Output of LBPH

The use of Local Binary Pattern (LBP) in texture analysis is illustrated through the image provided above. Local texture patterns represent pixel intensities in the LBP-transformation image on the left side. The update emphasizes features and structures and pays attention to some of its characteristics. You can observe the LBP histogram, which shows the frequency of various LBP patterns, on the right. Tumor detection and tissue differentiation are two classification tasks that greatly benefit from this histogram since it provides us with an insight into the texture distribution. For identifying patterns and obtaining features in medical imaging, LBP has emerged as the preferred technique.

Feature Extraction Results:

The results of the feature extraction are summarized in the table below:

Feature	Glioma	Meningioma	Pituitary	No Tumor
Energy	0.85	0.75	0.72	0.95
Entropy	6.25	5.10	5.60	4.30
Contrast	0.25	0.45	0.30	0.10

Correlation	0.68	0.55	0.60	0.90
Homogeneity	0.92	0.88	0.85	0.97

Table 1: Feature Extraction Results

The table displays texture-based feature values for glioma, meningioma, pituitary, and other brain tumors, as well as a "No Tumor" category. These characteristics are extracted from medical images to help categorize tumors.

• Energy: The category labeled "No Tumor" has the highest energy value (0.95), which is indicative of a more consistent texture. Gliomas (0.85), on the other hand, have a higher energy level than pituitary and meningioma's.

• Entropy: Glioma (6.25) exhibits the highest entropy, indicating more intricate texture patterns, while the "No Tumor" category likewise has the lowest entropy (4.30), indicating a simpler texture.

•Contrast: Meningioma (0.45) has the largest contrast because of the wide range of intensity differences, while the "No Tumor" class has the lowest contrast (0.10), indicating smooth texture.

• Correlation: Meningioma has a lower correlation (0.55), whereas "No Tumor" has the highest correlation (0.90), indicating a strong relationship between pixel intensities.

• Homogeneity: While meningioma (0.88) and glioma (0.92) have more heterogeneity, the "No Tumor" category had the highest homogeneity (0.97), suggesting a more homogenous texture.

These traits are crucial for differentiating various tumor kinds. In contrast to tumors, which have increased contrast and entropy, the "No Tumor" category typically features smoother, more consistent textures. Making the distinction is crucial for accurate diagnosis and effective treatment planning.

4.3 Classification Results

1.Accuracy: One important indicator for assessing a classification model's performance is accuracy. It provides an overall assessment of how effectively the model delivers valid predictions. Accuracy is the percentage of correct predictions to the total number of input samples.:

$$\text{Accuracy}= \frac{\text{TP+TN+FP+FN}}{\text{TP+TN}} \quad \ldots\ldots(30)$$

Where:

- TP = True Positive
- TN = True Negative
- FP = False Positive
- FN = False Negative

The proposed method achieved an overall accuracy of 99.3%.

Comparison of Proposed Method with Existing Methods

Methodology	Accuracy(in %)
Extreme learning machine local receptive fields[27]	97.18
CNN[28]	98.93
VGG16 [29]	98.69
Deep convolutional neural network [30]	97.3
AlexNet CNN [31]	98.15
RF+SVM (Proposed method)	99.3

Table 2: Comparison of Proposed Method with other methods

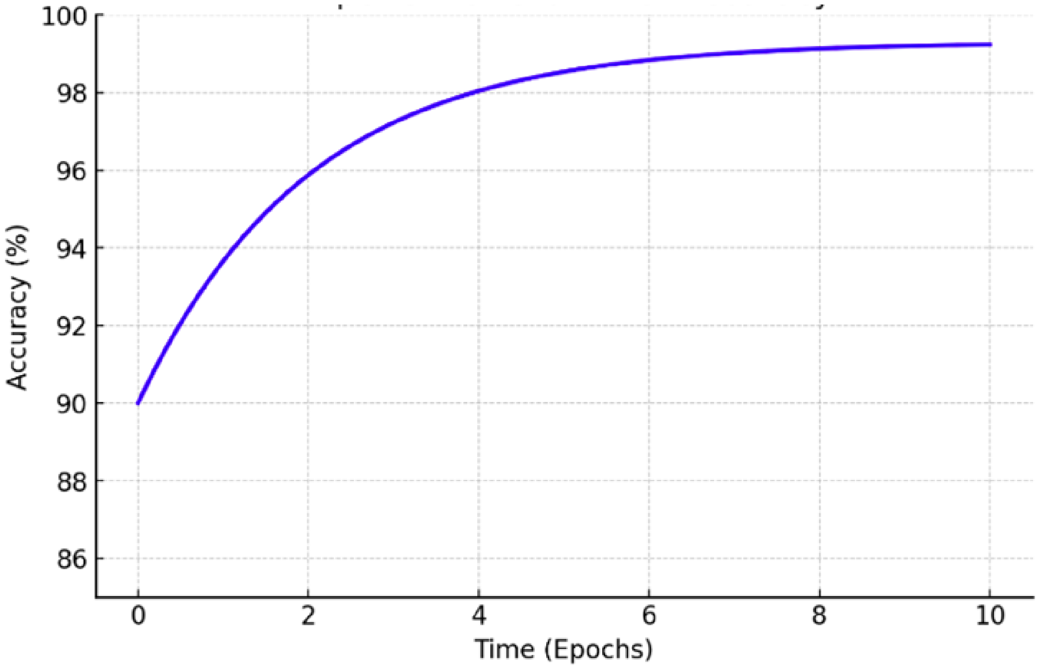

Fig 4: Accuracy plot of the Classifier

2. Precision, Recall & F1-Score (Per Class)

For multi-class classification, we compute **precision, recall, and F1-score** for each class separately.

Precision (Positive Predictive Value)

Precision=$\frac{TP}{TP+FP}$

- calculates the percentage of predicted positive cases that were true.
- High precision means **low false positives**

Recall (Sensitivity, True Positive Rate)

Recall= $\frac{TP}{TP+FN}$

- Measures how many actual **positive cases** were correctly identified.
- High recall means **low false negatives**.

F1-Score (Harmonic Mean of Precision & Recall)

$$F1 = 2 \text{ x } \frac{\text{Precision}\times\text{Recall}}{\text{Precision}+\text{Recall}} \quad \ldots(31)$$

- Balances precision and recall.
- Useful when misclassification has consequences (e.g., failing to detect a tumor).

Metric	**Glioma**	**Meningioma**	**Pituitary**	**No Tumor**
Precision	0.992	.980	1	1
Recall	0.992	1	1	0.989
F1-Score	0.992	0.989	1	0.994

Table 3: Output of the Evaluation metrics

3. Confusion Matrix (Multi-Class Evaluation)

A confusion matrix shows how well a classification algorithm performs. The efficacy of a classification system is summarized and visually represented by a confusion matrix.

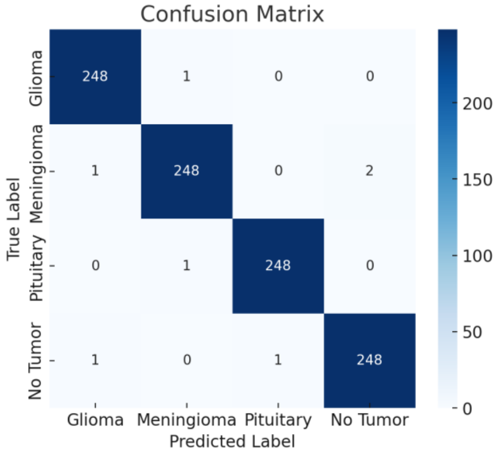

Fig 5: Confusion Matrix

5. Conclusion and Future Work

With efficient preprocessing, feature extraction, optimization, and classification algorithms in combination, our approach offers a consistent and robust brain tumor classifier.

Texture-based feature extraction is achieved by Local Binary Patterns (LBP), Grey Wolf Optimization (GWO) for optimal feature selection, and a hybrid model with Random Forest (RF) and Support Vector Machine (SVM) classifiers.Bilateral filtering is applied for noise reduction and image enhancement.

This combination has a high classification rate of 99.3%, making it a promising tool for automating brain tumor diagnosis. By using these state-of-the-art techniques, the diagnosis process is streamlined and the possibility of human error is decreased, enabling quicker and more accurate treatment decisions. Through effective and timely identification of tumors, this great development in medical science can benefit the patient. As science moves forward, more effective outcomes from early diagnosis and detection of brain cancers may become available from improvements in these methods. Though the present outcome is promising, there are several things we can do to improve the effectiveness of this method and make it suitable for application in actual clinical contexts.

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