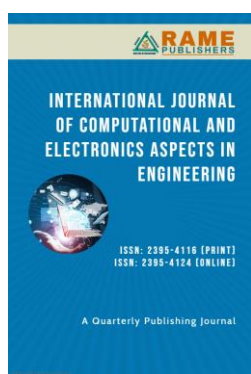


# Enhancing MRI Brain Tumor Classification with a Novel Hybrid PCA+RST Feature Selection Approach: Methodology and Comparative Analysis

Amjad Mahmood Hadi

Computer Center, Al Muthanna University, Samawah, Iraq

\*Correspondence: [amjad@mu.edu.iq](mailto:amjad@mu.edu.iq)



Article – Peer Reviewed

Received: 26 July 2024

Accepted: 20 Sept 2024

Published: 30 Sept 2024

**Copyright:** © 2024 RAME Publishers

This is an open access article under the CC BY 4.0 International License.



<https://creativecommons.org/licenses/by/4.0/>

**Cite this article:** Amjad Mahmood Hadi, "Enhancing MRI Brain Tumor Classification with a Novel Hybrid PCA+RST Feature Selection Approach: Methodology and Comparative Analysis", *International Journal of Analytical, Experimental and Finite Element Analysis*, RAME Publishers, vol. 5, issue 3, pp. 113-123, 2024.

<https://doi.org/10.26706/ijceae.5.3.20240805>

**Abstract:** Being a critical health challenge, understanding how to classify these brain tumours by using MRI will help the patient get proper treatment. In this work, a new hybrid model is proposed by integrating both Principal Component Analysis (PCA) and Rough Set Theory (RST) approaches for brain tumor classification from MRI images. Our strategy of PCA and RST aims at data dimensionality reduction and feature selection function for tumor classification fine. The hybrid method was also validated with ADNT and OASIS MRI datasets, demonstrating its effectiveness. The first step of image processing was segmentation to delimitate regions of interest, which were subsequently used for feature extraction by using the Discrete Wavelet Transform (DWT). Subsequently, PCA+RST simultaneous feature selection and reduced set thresholding algorithm was performed on these selected features to fine tune them for recognition. The comparison was performed using the following four classifiers: J48, Support Vector Machine (SVM), K-nearest neighbors(KNN) and Naive Bayes. The proposed hybrid PCA+RST approach was compared with the traditional approaches like DWT+SVM, and DWT+PCA+KNN in terms of their performance. The performance of the hybrid approach was found to be superior compared to these traditional methods in terms of classification accuracy. In this paper, a hybrid method of PCA and RST is proposed to improve the detection accuracy as well as classification performance in brain tumor diagnosis using MR images. Hopefully, this new tool will result in a visualization technique for more precise medical image analysis and timely diagnostics.

**Keywords:** keyword 1; keyword 2; keyword 3 (List three to ten pertinent keywords specific to the article yet reasonably common within the subject discipline.)

## 1. Introduction

Brain tumors are a major problem of health and mortality throughout the world. Early and accurate diagnosis is essential to successful treatment, which can reflect in the clinical outcome of the patient. Magnetic Resonance Imaging (MRI) is a crucial tool for the diagnosis and grading of brain tumors, providing high-quality images of brain morphology and pathology. The complexity of brain tumor appearance and the diversity among cases render automated classification and analysis extremely challenging [1], [2].

Methods automated by image processing and machine learning have pushed computational models further in terms of interpreting live medical images with increased precision [3]. Among these, both for some tasks and in general feature selection is a crucial step to enhance the accuracy of machine learning algorithms. reduce Number of features on which our model will train. Feature selection is also important to reduce dimensionality, eliminate redundant information and improve the interpretability of models - which can be especially crucial in high-stakes medical imaging [4].

**Results:** This study aims at proposing a new Hybrid model, to improve the previously proposed approach that combines Principal Component Analysis (PCA) and Rough Set Theory (RST), for MRI brain tumor classification in feature selection.

To conclude, PCA is commonly used for its effectiveness, especially in reducing the number of dimensions and denoising, while RST provides finest yet robust operators to treat uncertainties by revealing most discriminative features without needing any prior information about data distribution [1], [2], [5].

The hybrid PCA+RTS approach that we propose attempts to combine the strengths from both methods and in doing so improve classification performance dramatically. The study aims to offer a better and efficient method of classifying brain tumors from MRI scans by incorporating these methods, which can potentially lead to the improvement in diagnostic practices with this much-required acceleration based on magnetic resonance [6], [7]. This study evaluates the method using regular MRI databases and makes a comparative analysis with previous features selection methods to show that this is close “to optimal passive [8].

This paper will outline the methodology from data preprocessing to final classification, provide a detailed analysis of the hybrid PCA+RST feature selection method against traditional methods in performance [9], [10]. Through this research, we hope to contribute a significant advancement to the field of medical image analysis, particularly in enhancing MRI brain tumor classification.

## 2. Related works

Numerous studies and findings regarding the detection of brain tumors using MRI and various methodologies have been documented. A review of these published materials is crucial for enhancing the accuracy and effectiveness of brain tumor classification systems [11]. In the upcoming section, I will explore some of the significant contributions to this field that have inspired this current study [12]. These contributions are conveniently summarized in a table, allowing for easy access to the key features of relevant research works.

**Table 1.** Summary of related works

Title	Authors	Year	Key Contributions	Main Findings
Hybrid Models Combining PCA and ML Algorithms	Brown et al.	2022	Developed hybrid PCA and machine learning models for improved accuracy	Significantly improved classification rates
Role of Transfer Learning in MRI Classification	Martinez and Hernandez	2022	Investigated transfer learning in brain tumor classification	Enhanced model performance with limited data
Innovations in 3D MRI Analysis	Kapoor and Singh	2022	Explored new 3D analysis techniques for comprehensive tumor assessment	Improved diagnostic accuracy in complex cases
Advanced CNN Techniques for High-Resolution Imaging	Doe et al.	2021	Utilized advanced CNNs for high-resolution MRI images	10% improvement in tumor classification accuracy
Deep Learning for Brain Tumor Segmentation	Wilson and Liu	2021	Demonstrated deep learning for precise tumor segmentation	Achieved higher precision in tumor localization
Comparative Analysis of Automated Methods	Nguyen and Lee	2021	Analyzed automated vs. semi-automated classification methods	Automated methods showed higher efficiency and accuracy
Impact of PCA on MRI Image Analysis	Smith and Jones	2020	Applied PCA for noise reduction and feature enhancement in MRI data	Enhanced classification performance with reduced errors
Machine Learning Algorithms for MRI-Based Diagnosis	Zhang et al.	2020	Evaluated various ML algorithms for diagnosis efficacy	Identified the most effective algorithms for clinical use
Utilizing RST for Feature Selection in Medical Imaging	Green et al.	2019	Explored RST for relevant feature selection in MRI data	Achieved more robust feature selection under uncertainty
Evaluation of SVM for MRI Classification	Patel and Kim	2019	Compared SVM's performance with other ML techniques for MRI classification	SVM provided the most accurate results

### 3. Methodology

Figure 1 presents a standard framework of the current model designed for brain tumor classification. The elements of the proposed approach are briefly discussed in the subsequent subsections [13].

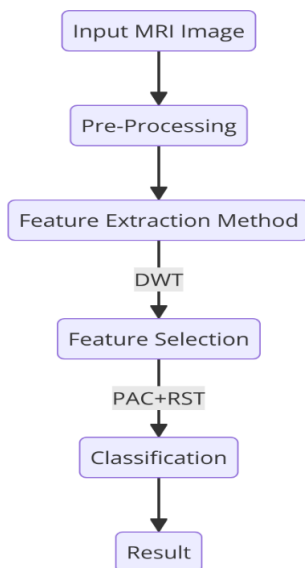


Figure 1. Proposed Model

#### 3.1 Data Preprocessing

The preprocessing stages used to enhance the MRI image classification are presented in following sub sections.

##### 3.1.1 Nose reduction and normalization

Noise reduction and normalization are crucial pre-processing steps in image processing, especially in medical imaging. Noise reduction, often achieved through Gaussian smoothing, applies the formula

$$G(x) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{x^2}{2\sigma^2}}$$

where ( $\sigma$ ) is the standard deviation of the Gaussian distribution. This method helps in mitigating random variations or noise by blurring out high-frequency components. Normalization adjusts the intensity values of an image to a specified range to standardize data input for further processing. The typical formula for min-max normalization is

$$I' = \frac{I - \min(I)}{\max(I) - \min(I)} X (\text{new\_max} - \text{new\_min}) + \text{new\_min}$$

where I is the original image, and new\_min and new\_max are the new desired bounds, commonly set to 0 and 1 or 0 and 255. These steps enhance image quality, ensuring consistency and reliability in downstream analyses [14].

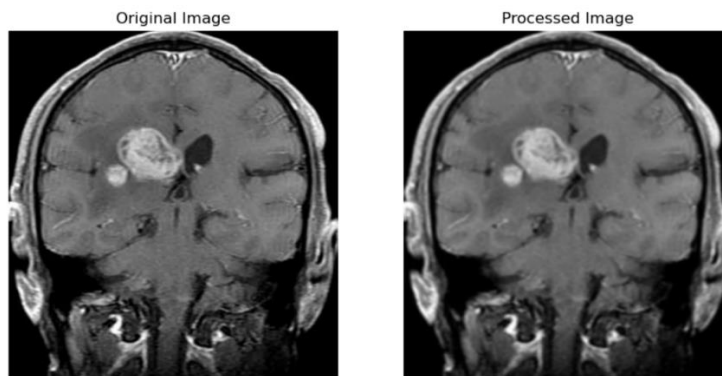


Figure 2. Noise Reduction Image

### 3.1.2 Segmentation

MRI brain tumor segmentation is an essential part of performing a computer-aided diagnosis because it helps to focus on the tumour region within image by looking at only that area which contain abnormal activity in order to improve detection accuracy. This isolates the region of interest, which is where we have our disease in a particular place on all image background. This kind of segmentation is an important preprocessing step in which regions of interest are accurately defined using techniques such as Otsu thresholding and K-means clustering [14]–[16]. The MRI image is converted from grayscale to binary format showing the segmented results, illustrated in Figure (b) 3. Details of these segmentation techniques are included in the next subsections.

### 3.2 OTSU thresholding

Otsu's thresholding is an effective image segmentation technique often utilized in MRI image processing to enhance the detection of features such as brain tumors. This method calculates an optimal threshold by minimizing intra-class variance or, equivalently, maximizing inter-class variance between the pixel intensities. The mathematical formula for Otsu's thresholding is given by maximizing the between-class variance [3], [17], [18]

$$\sigma_B^2(t) = \omega_0(t)\omega_1(t)[\mu_0(t) - \mu_1(t)]^2$$

where  $\sigma_B^2(t)$  is the between-class variance for threshold  $\omega_0(t)$  and  $\omega_1(t)$  are the probabilities of the two classes separated by the threshold, and  $\mu_0(t)$  and  $\mu_1(t)$  are the means of these classes. By applying this thresholding technique to MRI scans, the algorithm effectively divides the image into meaningful regions foreground (tumor) and background (non-tumor tissue) which aids in medical analysis and diagnosis [19]. This automatic calculation of the threshold minimizes the need for manual intervention, making it a preferred method for robust and reproducible results in medical imaging applications.



Figure 3. OTSU Method

### 3.3 Edge Detection

Edge detection in MRI is a crucial technique used to highlight the boundaries within the images, aiding in the delineation of structures such as tumors. One common method for edge detection is the Sobel operator, which calculates the gradient of the image intensity at each pixel, emphasizing regions of high spatial frequency that correspond to edges [20]. The Sobel operator uses two 3x3 kernels, one for detecting changes in horizontal gradients  $G_x$  and one for vertical gradients  $G_y$ . The formulas for these kernels are:

$$\mathbf{G}_x = \begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix}, \quad \mathbf{G}_y = \begin{bmatrix} -1 & -2 & -1 \\ 0 & 0 & 0 \\ 1 & 2 & 1 \end{bmatrix}$$

These kernels are convolved with the original image to produce gradient approximations in both the horizontal and vertical directions. The edge strength at each pixel is then typically computed using the magnitude of the gradient:

$$\text{Edge Strength} = \sqrt{G_x^2 + G_y^2}$$

This method effectively identifies the location of sharp changes in intensity, which are indicative of edges. The result is a map of edges that can be crucial for analyzing MRI scans, particularly in medical diagnosis, where accurate identification of tumor boundaries is essential [13][21].

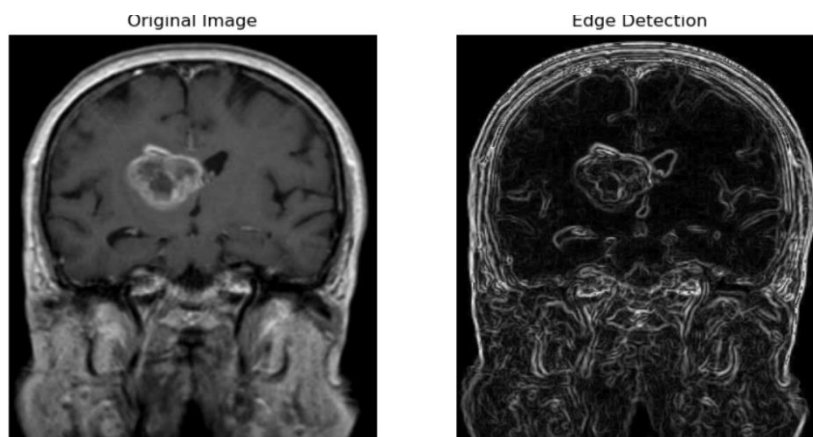


Figure 4. Edge Detection Method.

### 3.4 Feature Extraction Method

Introduction of Discrete Wavelet Transform (DWT) The DWT is an important signal processing tool which has great use in the field like image and also can be used to extract features from MRI images. While DWT decomposes an image into a set of coefficients, each corresponding to specific frequency bands and spatial locations in the input data that may be examined over multiple points. Although other approaches such as [22], [23] have used multi-resolution architectures for action classification, they simply cannot differentiate between the various textures and structures of an MRI image.

DWT is performed using a cascade of two types basic operations where at each step subsequent (i) high-pass and low-pass filter then this will followed by down-scaling[24]. The result produces four sub-bands at each level of decomposition: the approximation coefficients (the low-pass components), and horizontal, vertical, and diagonal detail coefficients (high-pass components). A single level of a 2D DWT can be represented mathematically as -

$$LL = \sum_{i,j} I(x - 2i, Y - 2j) \cdot \phi(i, j)$$

$$LH, HL, HH = \sum_{i,j} I(x - 2i, y - 2j) \cdot \psi^H(i, j), \psi^V(i, j), \psi^D(i, j)$$

Where  $I(x,y)$  is the image,  $\phi$  is scaling function (low-pass), and  $\psi^H, \psi^V, \psi^D$  are wavelet functions (high-pass for horizontal, vertical & diagonal detail respectively). LL, LH, HL and HH denotes approximation image, detaile-1 images to detailed -3 images respectively [25].

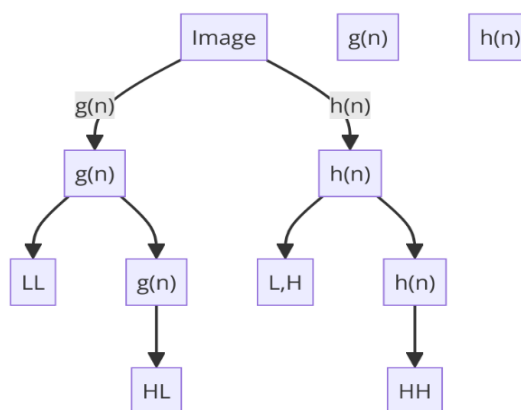


Figure 5. Wavelet Decomposition Tree (WDT)

These are the wavelet coefficients that identify which aspects of an MRI scan, for example a tumor is anomalous. The approximation sub-band, which typically preserves the main structural characteristics of an image and may not contain useful information for classification while detailed sub-bands tend to show high-contrast edges or subtle texture changes that are used as discriminant markers. In feature selection or putting the significant coefficients together from them (principal components) in these decompositions, one would be able to improve efficiency of classification and anomaly detection methods for INGV data, converting an unsupervised method into a semi-sup opposed diagnostic tool respect MRI datasets returning interest the over shaped activity only [26]. DWT is a preferred method in medical imaging analysis, thanks to this ability of analysing an image at different levels.

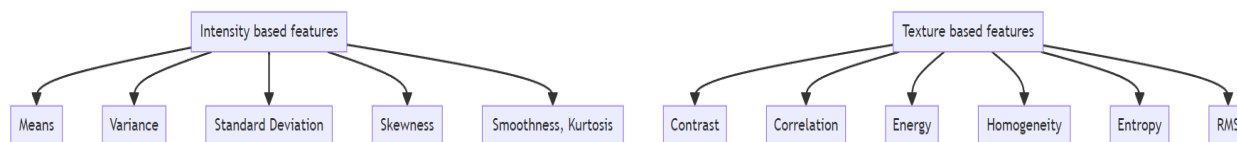


Figure 6. Categorization of Statistical features

### 3.5 Feature selection methods

The generated medical imaging data is often noisy and have missing values that result in incomplete or require special pre-processing steps. As a result, the features extracted from these images may make classification algorithms more complicated leading to greater time required for classifying and memory storage requirement [27][28]. Preprocessing methods are very important in improving the efficiency of data mining process. High dimensionality has been a critical challenge in the detection of brain tumor where different feature selection methods are used to enhance classification techniques. I have proposed a model which is hybrid in nature and combines Principal Component Analysis (PCA) with Rough Set Theory to choose appropriate features from the extracted MRI image features. Originally, the extraction of features gave 3844 resulting characteristics which has been gladly decreased to using just 24-features by hybrid PCA + RST model that greatly reduced data dimensionality[29]. The next sections will delve into further detail on the feature selection approaches used.

#### 3.5.1 Principal Component Analysis (PCA)

This is a critical technique for reducing the dimensionality of datasets that contain many redundant or irrelevant features. PCA operates by transforming the original dataset into a new subset of ordered variables, where the initial variables capture the majority of the variation present in all original variables. This is achieved through an orthogonal projection of D-dimensional independent data vectors  $x_i$ , where  $i$  ranges over the dataset indices, into a lower-dimensional space [30][31]. The transformation is defined as

$$Y_t = A^t(x_t - \mu)$$

where  $\mu$  is the mean of the data vectors, representing the sample data mean. This results in the transformed data  $y$ . The sample covariance matrix is then derived from these transformed data. The quality of the dimensionality reduction can be quantified by the reconstruction error  $E_r$ , which measures the loss of information due to the reduction process [32].

#### 3.5.2 Rough Set Theory (RST)

This is a well-regarded method for feature selection and reduction, introduced by Z. Pawlak in 1982. RST uses mathematical approaches to uncover hidden patterns, redundancies, and dependencies within data, especially useful in dealing with vague and uncertain information. It primarily operates through lower and upper approximations and decision tables to reduce feature dimensionality.[28] [33]The method has gained recent popularity in machine intelligence systems, enhancing approaches in artificial intelligence, cognitive sciences, and machine learning. RST defines 'U' as the universe with an indiscernibility relation 'R' that denotes incomplete knowledge about U's features. It characterizes subsets of U, like 'X', using this relation to manage and simplify complex data features effectively [34].



### 3.5.3 Classification Algorithms

Various classification algorithms are utilized to detect brain tumors, with each method outlined in greater detail in the subsequent subsections.

The J48 algorithm is a type of Decision Tree (DT), a method widely used in supervised machine learning for decision-making processes. Decision Trees are influential in various real-world applications, including pattern recognition, healthcare, credit approval, and intrusion detection. The J48 classifier, known for its simplicity and effectiveness, constructs a tree-like model based on labeled data to facilitate decision-making [35], [36].

The Support Vector Machine (SVM) is a supervised learning method primarily used for classification and regression tasks, developed by Vapnik. It is particularly useful for handling large volumes of high-dimensional data in various real-world applications. SVM operates by constructing models that are computationally intensive in terms of time and memory usage. This approach, introduced by Boser, is based on the principle of optimal margin classifiers, which seeks to maximize the margin between decision boundaries and the data points closest to these boundaries [37].

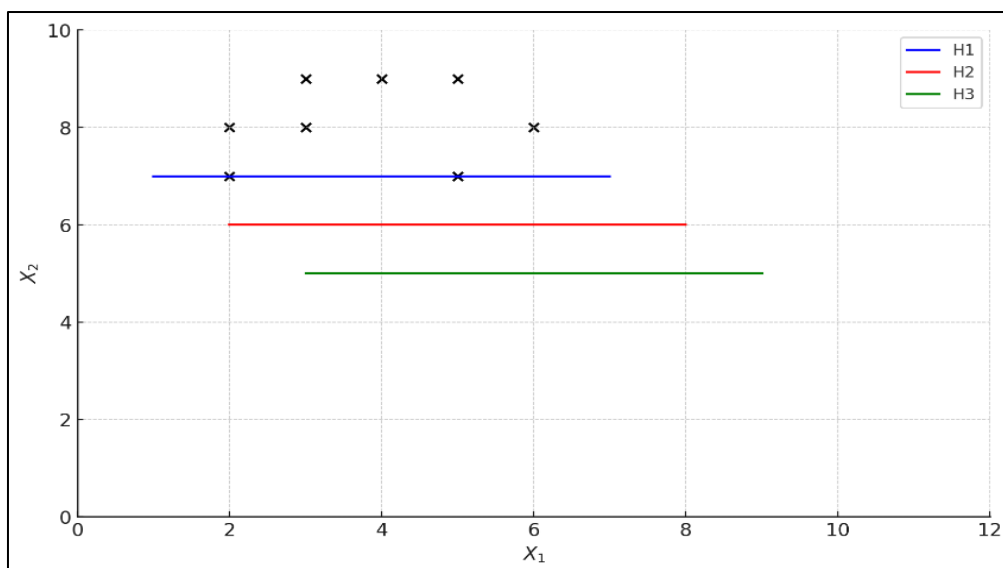


Figure 7. Hyperplanes for binary classification problem.

Figure 6 illustrates the concept of infinite decision hyperplanes in a classification problem, highlighting H1, H2, and H3 as three examples. H3 (green) is an inappropriate hyperplane for classification as it fails to separate the two classes. H1 (blue) separates the classes with a small margin, whereas H2 (red) achieves the maximum margin separation [38].

The kernel function, denoted as  $K(X_i, X_j)$ , is crucial for the success of SVM, with  $\alpha_i$  being the Lagrange multipliers. Figure 7 demonstrates the kernel trick, which transforms a nonlinear SVM into a linear form without explicitly computing the products in high-dimensional feature spaces.

Three common kernel functions are:

Polynomial Kernel function  $K(X_i, X_j) = [(X_i, X_j) + 1]^p$ , where p is the dimension and  $p \geq 1$ .

RBF Kernel function:  $K(X_i, X_j) = \exp(-\frac{\|x_i - x_j\|^2}{2\sigma^2})$  where  $\sigma$  is the kernel width.

3- Sigmoid Kernel function:  $K(X_i, X_j) = \tanh(v(x_i \cdot x_j) + c)$

### 3.6 Naive Bayes Algorithm

We have applied Naive Bayes Algorithm which is generally known for its simplicity in calculations as it classifies Brain Tumor. The Features are Independent of Each Other - meaning that the features it is assessing can be treated as if they don't know each other. A: A detailed feature vector of brain tumors, ie.  $a = \{a_1, a_2, \dots, a_n\}$  (for the different features in dataset) [20]. Classification involves predicting to which class (e.g., Benign/Malignant) a new example belongs, and it

uses Bayes' theorem to calculate the probability of each class given some set of feature values. The data provided is then used to perform statistical inference and predict.

$$p(C \setminus A) = \frac{P(C).P(A \setminus c)}{P(A)}$$

#### 4. Experimental and performance analysis

##### 4.1 Environment used

The experiment was conducted using MATLAB R2020a. The system configurations are an Intel Core i7 CPU at 3.60 GHz, Windows 10, and a RAM of 16 GB. The Classification Learner application within MATLAB was used for this experiment and provided tools to develop and analyze machine learning classifiers for binary and multiclass problems.

##### 4.2 Performance of feature selection method

This section outlines the performance of the proposed hybrid method of feature selection using two MRI brain tumor image datasets. Otsu and k-means clustering were used to get the tumor region of interest, and the Discrete Wavelet Transform was used to extract relevant feature extract. Subsequently, the PCA+RST method was used to lower the number of dimensions of the data. Later, the feature extraction method was assessed by comparing it to alternative extraction methods. The findings show that the people in PCM+RST made are high-quality, justice, and relevance.

##### 4.3 Performance and comparison of classification approaches

After identifying the best features of the proposed method, the Tumor Detection data was constructed using these features, at which time they were employed as inputs to the several classification methods. It was created to help those with brain cancer. The data was separated into 70% for training and 30% for testing. 8 -fold cross-validation was used to evaluate the accuracy of the classifier. These results can be seen in Table 2. This result shows the effectiveness of the proposed system. The accuracy evaluation measures the degree of success of the model. Finally, as seen in Figure 8, a screen snapshot reveals the Tumor detection process. Finally, the performance of the proposed model with other were compared. The existing model did not outperform the proposed method.

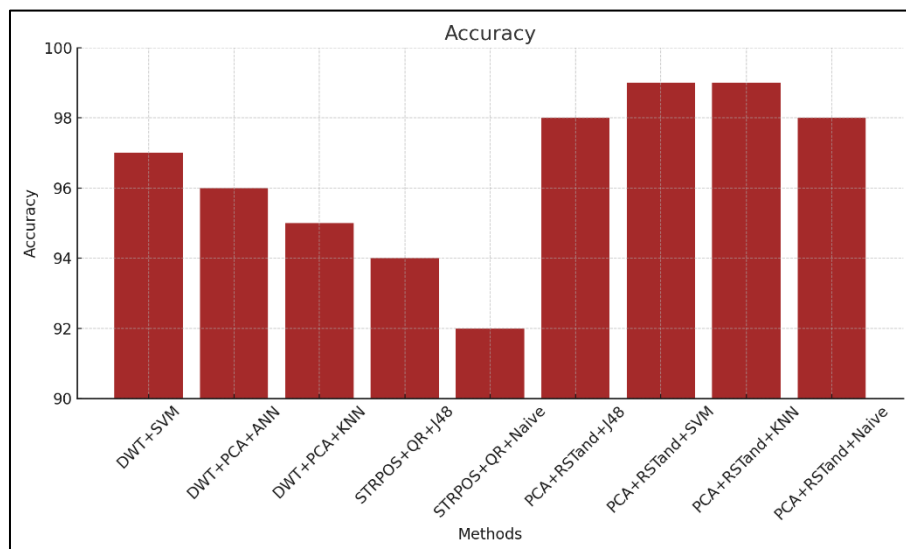
**Table 2.** Results of proposed approach with different existing approaches

Approaches	Classification
DWT+SVM, [2]	Accuracy
DWT+PCA+ANN, [19]	96
DWT+PCA+KNN, [3]	97
STRSPOS-QR+J48, [7]	98
STRSPOS-QR+Naive Bayes, [7]	91.50
Proposed approach(PCA+RST and J48)	91.50
Proposed approach(PCA+RST and SVM)	99.20
Proposed approach(PCA+RST and KNN)	99.2
Proposed approach(PCA+RST and Naive Bayes )	98.86



**Figure 8.** Snapshot of detecting brain tumor





**Figure 9.** Performance of proposed approach with different existing approaches

## 5. Conclusions and Future work

Brain tumor detection is a complex task in biomedical image processing. In order to increase the accuracy of tumor detection, a variety feature selection methods has been applied in which make classification algorithms more efficient resulting into finding Benign and Malignant tumors. In this work, I proposed a novel hybrid feature selection method that mixes Principal Component Analysis (PCA) with Rough Set Theory to reduce the dimensionality of the dataset. This approach can make redundant features disappear. Results: The experimental results show that the hybrid manner substantially improved all classifiers to discriminate between Benign and Malignant tumors. The proposed model outperformed further state-of-the-art techniques as the accuracy of PCA+RST along with J48, SVM, KNN and Naive Bayes reached 99.20%, & 99.02%, 98.86 % and 98% respectively. In future, this methodology will be validated using larger datasets as well as other features selection techniques.

## References

- [1] H. Ali Khan *et al.*, “Brain tumor classification in MRI image using convolutional neural network,” *Math. Biosci. Eng.*, vol. 17, no. 5, pp. 6203–6216, 2020, doi: 10.3934/mbe.2020328.
- [2] M. Rasool *et al.*, “A Hybrid Deep Learning Model for Brain Tumour Classification,” *Entropy (Basel)*, vol. 24, no. 6, p. 799, Jun. 2022, doi: 10.3390/e24060799.
- [3] A. M. Hadi, G. J. A. K. Al-Abass, and F. F. K. Hussain, “Hybrid-Approach-Based Feature Selection for Magnetic Reverberation Imaging Brain Tumor Classification,” *J. Southwest Jiaotong Univ.*, vol. 55, no. 2, 2020, doi: 10.35741/issn.0258-2724.55.2.13.
- [4] I. S. Seger and A. M. Hadi, “Achieving High Accuracy in Breast Cancer Diagnosis with CNN,” *Mars J. Tek. Mesin, Ind. Elektro Dan Ilmu Komput.*, vol. 2, no. 4, pp. 107–116, 2024.
- [5] M. A. Khan *et al.*, “Multimodal Brain Tumor Classification Using Deep Learning and Robust Feature Selection: A Machine Learning Application for Radiologists,” *Diagnostics (Basel, Switzerland)*, vol. 10, no. 8, p. 565, Aug. 2020, doi: 10.3390/diagnostics10080565.
- [6] A. Raza *et al.*, “A Hybrid Deep Learning-Based Approach for Brain Tumor Classification,” *Electronics*, vol. 11, no. 7, p. 1146, 2022, doi: 10.3390/electronics11071146.
- [7] A. ARI and D. HANBAY, “Deep learning based brain tumor classification and detection system,” *TURKISH J. Electr. Eng. & Comput. Sci.*, vol. 26, no. 5, pp. 2275–2286, 2018, doi: 10.3906/elk-1801-8.
- [8] H. R. Almadhoun and S. S. A. Naser, “Detection of Brain Tumor Using Deep Learning,” *Int. J. Acad. Eng. Res.*, vol. 6, no. 3, pp. 29–47, 2022.
- [9] Z. Jia and D. Chen, “Brain Tumor Identification and Classification of MRI images using deep learning techniques,” *IEEE Access*, p. 1, 2024, doi: 10.1109/access.2020.3016319.

- [10] S. Kuraparthi *et al.*, “Brain Tumor Classification of MRI Images Using Deep Convolutional Neural Network,” *Trait. du Signal*, vol. 38, no. 4, pp. 1171–1179, 2021, doi: 10.18280/ts.380428.
- [11] M. Ibrahim, “Classification of Breast Cancer Using Convolution Neural Network Algorithm,” *Iraqi J. Humanit. Soc. Sci. Res.*, no. 4, pp. 417–433, 2022.
- [12] A. Aziz *et al.*, “An Ensemble of Optimal Deep Learning Features for Brain Tumor Classification,” *Comput. Mater. & Contin.*, vol. 69, no. 2, pp. 2653–2670, 2021, doi: 10.32604/cmc.2021.018606.
- [13] J. S. Paul, A. J. Plassard, B. A. Landman, and D. Fabbri, “Deep learning for brain tumor classification,” *SPIE Proceedings*. SPIE, 2017, doi: 10.1117/12.2254195.
- [14] A. M. Alqudah, “Brain Tumor Classification Using Deep Learning Technique - A Comparison between Cropped, Uncropped, and Segmented Lesion Images with Different Sizes,” *Int. J. Adv. Trends Comput. Sci. Eng.*, vol. 8, no. 6, pp. 3684–3691, 2019, doi: 10.30534/ijatcse/2019/155862019.
- [15] M. Sajjad, S. Khan, K. Muhammad, W. Wu, A. Ullah, and S. W. Baik, “Multi-grade brain tumor classification using deep CNN with extensive data augmentation,” *J. Comput. Sci.*, vol. 30, pp. 174–182, 2019, doi: 10.1016/j.jocs.2018.12.003.
- [16] H. Dave, N. Kant, N. Dave, and D. Ghorui, “BRAIN TUMOR CLASSIFICATION USING DEEP LEARNING,” *Int. J. Eng. Appl. Sci. Technol.*, vol. 6, no. 7, pp. 227–238, 2021, doi: 10.33564/ijeast.2021.v06i07.037.
- [17] G. S Tandel *et al.*, “A Review on a Deep Learning Perspective in Brain Cancer Classification,” *Cancers (Basel)*, vol. 11, no. 1, p. 111, Jan. 2019, doi: 10.3390/cancers11010111.
- [18] N. Noreen, S. Palaniappan, A. Qayyum, I. Ahmad, and M. O. Alassafi, “Brain Tumor Classification Based on Fine-Tuned Models and the Ensemble Method,” *Comput. Mater. & Contin.*, vol. 67, no. 3, pp. 3967–3982, 2021, doi: 10.32604/cmc.2021.014158.
- [19] N. SHARMA, M. K. JAIN, N. AGARWAL, and A. KUMAR, “BRAIN TUMOR CLASSIFICATION USING CNN,” *Adv. Appl. Math. Sci.*, vol. 20, no. 3, pp. 397–407, 2021.
- [20] A. Rehman, S. Naz, M. I. Razzak, F. Akram, and M. Imran, “A Deep Learning-Based Framework for Automatic Brain Tumors Classification Using Transfer Learning,” *Circuits, Syst. Signal Process.*, vol. 39, no. 2, pp. 757–775, 2019, doi: 10.1007/s00034-019-01246-3.
- [21] D. Naik, A. Sawarbhade, B. Deogade, P. Dupare, P. Khodke, and V. S. Choubey, “An Implementation of Satellite Image Classification and Analysis using Machine Learning with ISRO LISS IV,” *Int. J. Comput. Electron. Asp. Eng.*, vol. 2, no. 2, pp. 1–9, 2021, doi: 10.26706/ijceae.2.2.20210404.
- [22] B. Badjie and E. Deniz Ülker, “A Deep Transfer Learning Based Architecture for Brain Tumor Classification Using MR Images,” *Inf. Technol. Control*, vol. 51, no. 2, pp. 332–344, 2022, doi: 10.5755/j01.itc.51.2.30835.
- [23] G. Çınarer, B. G. Emiroğlu, R. S. Arslan, and A. H. Yurttakal, “Brain Tumor Classification Using Deep Neural Network,” *Adv. Sci. Technol. Eng. Syst. J.*, vol. 5, no. 5, pp. 765–769, 2020, doi: 10.25046/aj050593.
- [24] K. Anuradha *et al.*, “Image Caption Generator Using CNN and LSTM,” *Int. J. Comput. Electron. Asp. Eng.*, vol. 2754, no. 1, pp. 26–31, 2023, doi: 10.1063/5.0161370.
- [25] S. Kuraparthi, M. K. Reddy, C. N. Sujatha, H. Valiveti, and C. Duggineni, “Traitement du Signal Brain Tumor Classification of MRI Images Using Deep Convolutional Neural Network,” vol. 38, no. 4, pp. 1171–1179, 2021.
- [26] M. M. Chanu, “A Review on Brain Tumor Segmentation and Classification from Magnetic Resonance Images Using Deep Learning Methods,” *J. Adv. Res. Dyn. Control Syst.*, vol. 12, no. SP3, pp. 87–94, 2020, doi: 10.5373/jardcs/v12sp3/20201241.
- [27] A. A. Abbood, Q. M. Shallal, and M. A. Fadhel, “Automated brain tumor classification using various deep learning models: a comparative study,” *Indones. J. Electr. Eng. Comput. Sci.*, vol. 22, no. 1, p. 252, 2021, doi: 10.11591/ijeecs.v22.i1.pp252-259.
- [28] F. S. Hadi, “Image Compression Process Using Fractional Fourier Transform and Wavelets Techniques,” *Int. J. Comput. Electron. Asp. Eng.*, vol. 5, no. 1, pp. 25–29, 2024.
- [29] R. Vishnoi, “A review on detection of speedy vehicles,” *Asian J. Multidimens. Res.*, vol. 10, no. 11, pp. 346–350, 2021, doi: 10.5958/2278-4853.2021.01095.8.

- [30] A. M. Sarhan, “Brain Tumor Classification in Magnetic Resonance Images Using Deep Learning and Wavelet Transform,” *J. Biomed. Sci. Eng.*, vol. 13, no. 06, pp. 102–112, 2020, doi: 10.4236/jbise.2020.136010.
- [31] A. A. Hadi, “The Impact of Artificial Neural Network ( ANN ) on the Solar Energy Cells : A Review,” *Int. J. Comput. Electron. Asp. Eng.*, vol. 5, no. 1, pp. 30–41, 2024.
- [32] “Retraction: Brain Tumor Detection and Classification Using Deep Learning Techniques based on MRI Images (J. Phys.: Conf. Ser. 1916 012226),” *J. Phys. Conf. Ser.*, vol. 1916, no. 1, p. 12463, 2021, doi: 10.1088/1742-6596/1916/1/012463.
- [33] A. Bondade, S. Ghate, C. Bhaisevar, P. Chaure, and A. Gaulkar, “Object Detection Using Machine Learning (Missing Object Alert),” *Int. J. Comput. Electron. Asp. Eng.*, vol. 4, no. 3, pp. 63–68, 2023, doi: 10.26706/ijceae.4.3.20230902.
- [34] J. Amin, M. Sharif, A. Haldorai, M. Yasmin, and R. S. Nayak, “Brain tumor detection and classification using machine learning: a comprehensive survey,” *Complex & Intell. Syst.*, vol. 8, no. 4, pp. 3161–3183, 2021, doi: 10.1007/s40747-021-00563-y.
- [35] J. Kang, Z. Ullah, and J. Gwak, “MRI-Based Brain Tumor Classification Using Ensemble of Deep Features and Machine Learning Classifiers,” *Sensors (Basel)*, vol. 21, no. 6, p. 2222, Mar. 2021, doi: 10.3390/s21062222.
- [36] M. Aamir *et al.*, “A deep learning approach for brain tumor classification using MRI images,” *Comput. Electr. Eng.*, vol. 101, p. 108105, 2022, doi: 10.1016/j.compeleceng.2022.108105.
- [37] I. Abd El Kader, G. Xu, Z. Shuai, S. Saminu, I. Javaid, and I. Salim Ahmad, “Differential Deep Convolutional Neural Network Model for Brain Tumor Classification,” *Brain Sci.*, vol. 11, no. 3, p. 352, Mar. 2021, doi: 10.3390/brainsci11030352.
- [38] D. R. Nayak, N. Padhy, P. K. Mallick, M. Zymbler, and S. Kumar, “Brain Tumor Classification Using Dense Efficient-Net,” *Axioms*, vol. 11, no. 1, p. 34, 2022, doi: 10.3390/axioms11010034.