INDIAN JOURNAL OF SCIENCE AND TECHNOLOGY

ORIGINAL ARTICLE

OPEN ACCESS

Received: 07/06/2024

Accepted: 04/04/2025

Published: 11/05/2025

Citation: Srivaishnavi KR, Pramananda Perumal T, Anishiya P (2025) Feature Extraction from Segmented Brain MRI Images using Traditional Methods and Classification Analysis of Brain Tumor using Machine Learning Classifiers. Indian Journal of Science and Technology 18(17): 1309-1320. https://doi.org/10.17485/IJST/v18i17.1902

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Funding: None

Competing Interests: None

Published By Indian Society for Education and Environment (iSee)

ISSN
Print: 0974-6846
Electronic: 0974-5645

Feature Extraction from Segmented Brain MRI Images using Traditional Methods and Classification Analysis of Brain Tumor using Machine Learning Classifiers

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Abstract

Objectives: To determine the most effective traditional method for feature extraction and Machine Learning (ML) classifier for classification of segmented brain MRI images. **Methods:** The dataset of brain MRI images are segmented using the Morphological Active Contour Boltzmann Monte Carlo Method (MACB) model from our previous work. The feature extraction analysis of the segmented brain MRI images is done using the traditional feature extraction methods viz. shape, Gray Level Co-occurrence Matrix (GLCM), wavelet, Local Binary Pattern (LBP) and intensity. After feature extraction, the classification of brain tumor using the ML classifiers such as Support Vector Machine, Logistic Regression, Linear Discriminant Analysis, Decision Tree (DT), Random Forest, AdaBoost, K-Nearest Neighbours and Naive-Bayes are carried out in the segmented brain MRI images. An extensive classification analysis is made to find the best feature extraction method and best ML classifier for segmented brain MRI images. The public multi-class dataset of brain MRI images available in Kaggle website are used in this work, it contains 7023 images (5712 training and 1311 testing images). **Findings:** The 31 features, extracted using various combinations of 5 traditional feature extraction methods, are inputted to 8 ML classifiers and performance analysis is done. It is found from the analysis that the DT classifier achieves the highest classification accuracy of 96.05%. **Novelty:** The key novelty of the proposed approach depends on the tumor segmentation technique using our MACB model for segmenting brain tumors in MRI images, since the MACB model has itself demonstrated better performance in providing better quality tumor delineation, as compared to traditional segmentation methods. From the dataset of MACB segmented brain MRI images, 31 features, extracted using various combinations of 5 traditional feature extraction methods, are inputted to 8 ML classifiers and a performance analysis is done. It is concluded that the DT classifier achieves higher accuracy.

Keywords: Image segmentation; Feature extraction; Machine Learning classifiers; Brain tumor classification

1 Introduction

The brain tumor is an unexpected growth of brain cells which are classified according to the tumor location [1]. The brain tumors of grades I and II categories are rated as slow growing and less aggressive while the tumors of grades III and IV categories are malignant and harmful [2]. The most frequent type of brain tumor in adults is glioma (arises from glial cells) which may be classified into LGG (Low Grade Glioma) and HGG (High Grade Glioma) [3]. The WHO further categorized LGG into Grade I and Grade II tumors. The Grade I tumors are basically regular in shape and they develop slowly, the Grade II tumors appear strange to view and grow more slowly [4]. Even certain tumor types are rated with Grade I; they are being the least malignant viz. meningioma and pituitary tumors. The HGG is categorized into Grade III and Grade IV tumors. The Grade III tumors grow more quickly than Grade II cancerous tumors and Grade IV tumors are reproduced with greater rate [1].

One of the most critical tasks of radiologists and neurologists is early brain tumor detection. However, manually detecting and segmenting brain tumors from **MRI** scans are challenging and are susceptible to errors. Hence, an automated brain tumor detection and classification system is required for early diagnosis of the brain tumor [5].

In recent years, several research works and studies have been carried out for classification of brain tumor MRI images. Song Jiang et al. have employed a range of Machine Learning (ML) classifiers /algorithms such as K-Nearest Neighbours (KNN), Decision tree (DT), Support Vector Machine (SVM), Logistic Regression (LR) and Stochastic Gradient Descent (SGD) to classify brain MRI images. It is shown that KNN works most efficiently among all those classifiers [6].

R. H. Ramdlon *et al*. have performed basic image processing techniques, comprising of image enhancement, image binarization, morphological image and watershed methods. Tumor classification is applied after the segmentation process by extracting shape features and achieved an accuracy of 89.5% for tumor classification using KNN classifier [7].

L. Chato and S. Latify have employed pre-trained models such as AlexNet, VGG16 and VGG19 for feature extraction and Machine Learning (ML) algorithms such as SVM, KNN, Linear Discriminant Analysis (LDA), Ensemble and Logistic Regression for classification. The best classification accuracy, achieved by using pre-trained AlexNet model for feature extraction and LDA algorithm for classification, is 73% [8].

Pronab Kumar et al. have combined K-means and fuzzy C-means (FCM) clustering for brain tumor segmentation, GLCM methods for feature extraction and SVM algorithm for classification of brain MRI images and have achieved a classification accuracy of 94.37% [9].

Islam R. et al. have combined methods viz. optimal thresholding, watershed segmentation technique and morphological operation in order to separate the tumor region. Then, Convolutional Neural Network (CNN) is used for feature extraction and finally Kernel Support Vector Machine (KSVM) is used for classification. This proposed method has effectively achieved a classification accuracy of 87.4% [10].

Ansari A.S. has suggested the system which has 3 stages: (1) Fuzzy C-means and K-means methods are used for picture segmentation, (2) Gray Level Co-occurrence Matrix (GLCM) and Discrete Wavelet Transform (DWT), followed by Principal Component Analysis(PCA), are used for feature extraction and selection and (3) SVM classifier is used for classification of benign and malignant tumor types. This process has achieved a classification accuracy of 88% as compared to the RBF kernel's accuracy and the polynomial kernel's accuracy [11].

M.O. Khairandish et al. have proposed a threshold-based segmentation in terms of detection and a hybrid model (combined CNN and SVM algorithms) for classification of benign and malignant tumor. The proposed CNN-SVM hybrid model has achieved an overall classification accuracy of 98.50% [12].

Zobia Suhail et al. have carried out a comprehensive analysis to find out the optimal feature extraction technique. For this, several experiments have been done by using Principal Component Analysis (PCA), Independent Component Analysis (ICA), Factor Analysis (FA) and Linear Discriminant Analysis (LDA) methods. Further, various ML classifiers viz. Logistic Regression (LR), Gaussian Naive Bayes (GNB), Support Vector Machine (SVM), K-Nearest Neighbours (KNN) and Decision Tree (DT) are used for classification. This study shows that the proposed LDA technique has achieved higher classification accuracy of 92.84% for brain tumor in MRI images [13].

Ramdas Vankdothu et al. have proposed a novel automated scheme by using Improved K-Means Clustering (IKMC) algorithm for segmentation. GLCM method is used to extract features and Recurrent Convolutional Neural Networks (RCNN) for classification of the brain MRI images such as gliomas, meningiomas, non-tumors and pituitary tumors. In this scheme, they have obtained an accuracy of 95.17% [14].

The literature survey shows that most of the existing approaches have used a comprehensive scheme for brain tumor detection and classification of brain MRI images. That is, image pre-processing, image segmentation, feature extraction using traditional methods or Deep Learning (DL) methods and classification using Machine Learning (ML) classifiers are combined here.

In the existing approaches, there are limitations in improving classification accuracy of segmented brain MRI images, since only two or three traditional feature extraction methods have been combined together in the existing research works.

In order to overcome these limitations, in the proposed approach, all the five traditional feature extraction methods such as shape, GLCM, wavelet, Local Binary Patterns (LBP) and intensity will be combined together.

Further, the MRI brain tumor segmentation using the proposed MACB model in our previous study[15] has significantly enhanced the classification accuracy, as we have compared with the existing segmentation methods.

The proposed approach outperforms the existing approaches with respect to classification accuracy through its synergistic use of MACB segmentation model, proposed combination of 5 traditional feature extraction methods and 8 ML classifiers. This new approach addresses the limitations of the existing approaches which depend on the combination of only two or three traditional feature extraction methods for feature extraction.

Further, in our proposed approach, the 31 features, extracted using various combinations of 5 traditional feature extraction methods viz. shape, GLCM, wavelet, LBP and intensity, from the segmented brain MRI images are inputted to the 8 popular ML classifiers viz. SVM, LR, LDA, DT, RF, AdaBoost, KNN and NB.

The main objectives of our proposed approach are as follows.

By using the segmented dataset available from the proposed Morphological Active Contour Boltzmann Monte Carlo method (MACB) model from our previous research work[15], the following are to be implemented.

1. To carry out the feature extraction by integrating the geometry (shape)[7], texture (GLCM, wavelet, LBP)[11],[14],[16],[17] and statistical (intensity)[16] features.
2. To classify the above extracted features, using ML classifiers such as SVM, LR, LDA, DT, RF, AdaBoost, KNN and Naive-Bayes (NB) [6-14] and to do performance metrics analysis for classification.

This paper is organized as follows. In Section 2, we briefly describe the details of the work such as dataset for brain tumor classification and performance analysis, flow diagram of our proposed approach, feature extraction from segmented brain MRI images using traditional methods and classification of brain tumor using Machine Learning classifiers and its implementation. In Section 3, we present our results and discussion on- a) feature extraction from segmented brain MRI images using traditional methods and performance metrics (accuracy) for classification of brain tumor using various ML classifiers, b) confusion matrices with highest accuracy for the classification of brain tumor in segmented MRI images for each of the eight combinations, c) performance metrics analysis of brain tumor classification both in the existing methods and our proposed approach and, d) research findings. In Section 4, we discuss about the principal outcome of the work.

2 Methodology

2.1 Dataset for brain tumor classification and performance analysis

Magnetic Resonance Imaging (MRI) is the most common method for differential diagnosis of various types of tumors[18]. The public dataset of brain tumor MRI images is created by MsoudNickparvar and retrieved from Kaggle website[19]. This dataset contains 7023 images of human brain MRI images which are categorized into 4 classes: glioma, meningioma, no tumor and pituitary. Also, this dataset is a combination of figshare and Br35H datasets. The summary of the dataset is given in Table 1.

Table 1. Summary of the dataset of brain tumor MRI images

Tumor type	No. of samples in training dataset	No. of samples in testing dataset
Glioma	1321	300
Meningioma	1339	306
No tumor	1595	405
Pituitary	1457	300
Total	5712	1311

The segmentation of the above dataset of brain MRI images is done by the proposed MACB model from our previous research work[15]. The sample from each class of the segmented dataset is as shown in Figure 1.

2.2 Feature extraction from segmented brain MRI images using traditional methods and Classification of brain tumors using Machine Learning classifiers

The segmented brain MRI images are once again pre-processed for both training and testing dataset. As an initial step, Gaussian filtering is carried out in the images for noise reduction. Then, the images are resized into 227 x 227 pixels. Further, these

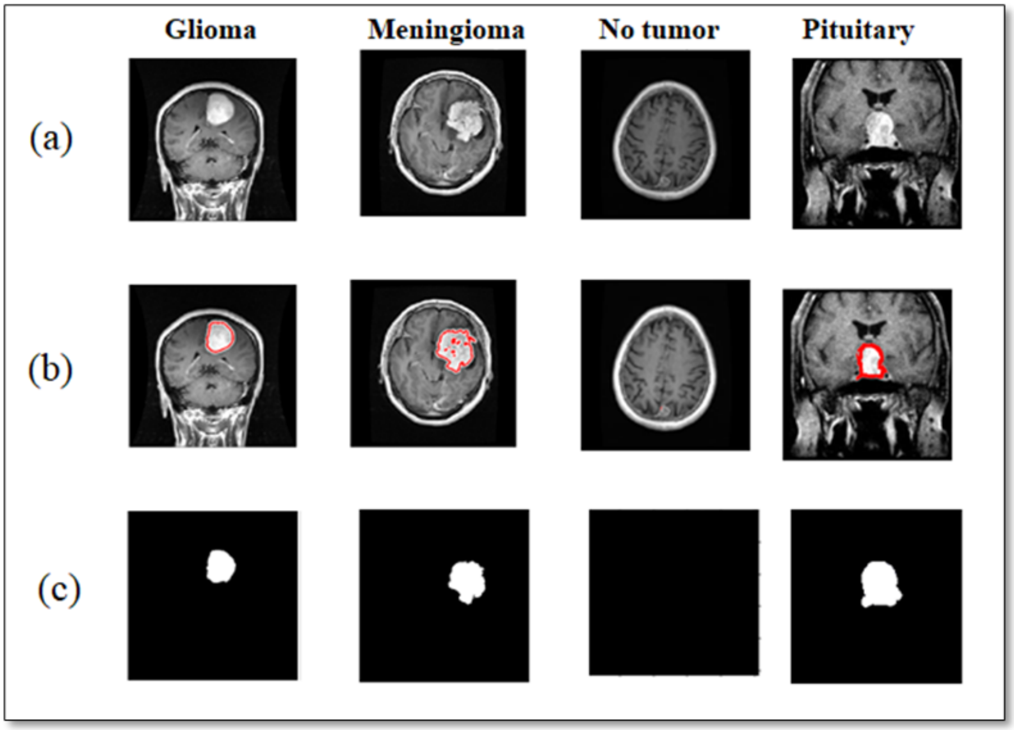

Fig 1. Multi-class brain tumor detection and segmentation using MACB model in MRI images. (a) Sample brain MRI images of 4 classes: glioma, meningioma, no tumor and pituitary; (b) Tumor outline (red colour) marked in the brain MRI images using MACB model; (c) Tumor segmented using MACB model

images are normalized by using min-max normalization technique [20]. After pre-processing, our proposed approach starts and combines as follows.

1. Feature extraction from segmented brain MRI images using traditional methods and
2. Classification of brain tumors using Machine Learning (ML) classifiers.

The flow diagram of our proposed approach is as shown in Figure 2.

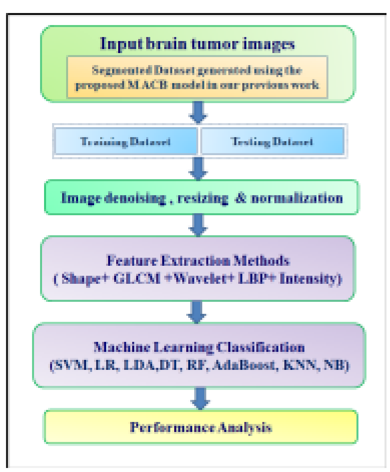

Fig 2. Flow diagram of our proposed approach

2.2.1. Feature extraction from segmented brain MRI images using traditional methods

The traditional features such as volumetric, geometric, statistical, intensity, texture, histograms and deep features are available for feature extraction [8]. In our proposed research work, the possible combinations of geometric, texture and statistical features are used. The following feature extraction methods in each traditional feature are used for feature extraction from the segmented brain MRI images.

1. **Geometric feature**:
   - Shape method: The segmented image serves as the input for this process, where the detected tumor region is white in colour and the background image is black in colour [7]. The 8 shape features viz. area, eccentricity, perimeter, centroid, irregularity index, equivalent diameter, convex area and solidity are available. In this research work, the following features such as area, perimeter and eccentricity are used.
2. **Texture feature**: It is important in medical images as it refers the surface characteristics of the image. In this research work, 3 texture feature methods viz. GLCM, wavelet and Local Binary pattern are used.
   - GLCM method: The Gray Level Co-occurrence Matrix (GLCM) is used to extract texture features for classification of brain MRI images and captures spatial pixel intensity relationships [8]. The texture analysis facilitates the differentiation between cancerous and non–cancerous tissues [17].
     In this research work, the texture features such as contrast, correlation, energy and homogeneity are used.
   - Wavelet method: The two-dimensional (2D) wavelet is used for image applications in general. This 2D wavelet decomposes a segmented brain MRI image into four components viz. approximation (cA), Vertical (cV), horizontal (cH) and diagonal (cD) [8]. In this research work, the features such as mean, standard deviation, skewness and kurtosis are extracted for the above four wavelet components.
   - LBP method: The Local Binary Patterns (LBP) technique is used to identify the local texture patterns, and it is a widely employed texture descriptor in image processing. In this research work, a circle of radius, R is fixed around the centre pixel and it is compared with its neighbouring pixels [17].
3. **Statistical feature**:
   - Intensity method: It extracts information from the intensity values of the pixels in an image. In this research work, 4 intensity features such as mean, SD (Standard Deviation), skewness of intensity distribution and kurtosis are used [13], [17].

Hence, in this research work, totally 29 types in the above 5 traditional feature extraction methods are used in order to study the essential characteristics of the images. Later, to investigate the efficacy of the extracted features for all possible combinations of above 5 methods viz. geometric + texture features, geometric + statistical features, texture + statistical features and geometric + texture + statistical features are experimented.

2.2.2. Classification of brain tumor in MRI images using Machine Learning classifiers

Based on a thorough literature study, we have chosen the 8 ML classifiers which indicate their extensive use and success in brain tumor image classification tasks, esp. in medical imaging. Also, it is shown that these models are frequently used without significant parameter modifications and highlighting their strong performance and adaptability across brain tumor MRI image datasets [21].

In this research work, 31 features, extracted using various combinations of 5 traditional feature extraction methods, from the MACB segmented brain MRI images, are sent to the eight popular ML classifiers viz. SVM, LR, LDA, DT, RF, AdaBoost, KNN and NB. The flow diagram of the classification analysis using traditional feature extraction methods and ML classifiers is as shown in Figure 2.

These classifiers are trained using the training dataset and the predictions are made on the 31 features, extracted from the testing dataset.

2.3 Implementation

This research work is implemented using MATLAB R2024b in the Lenovo LAPTOP-8T6ALGF9 which is equipped with Intel(R) Core (TM) i3-8145U CPU @ 2.10GHz and 36.0 GB RAM. The device runs a 64-bit version of Windows 11 Home Edition for segmented (using proposed MACB model) brain tumor MRI images. The performance metrics evaluation for classification of

Table 2. List of five traditional feature extraction methods with their types

Traditional feature extraction methods	Types/parameters in each method	Feature description
1. Shape [7] (Geometric)	Area	Total area of the brain tumor region in the MRI image
	Perimeter	Total perimeter of the brain tumor in the MRI image
	Eccentricity	Total eccentricity of the brain tumor in the MRI image
	Area-Perimeter ratio	The area to perimeter ratio provides information about the image shape and complexity
2. GLCM [8], [17] (Texture)	Contrast	The amount of changes that can affect the way to measure the intensity value among whole image pixels and neighbour pixels.
	Correlation	The average degree to which each pixel in the image is connected with its neighbours.
	Energy	The similarity or uniformity of an image and it is defined as angular second moment.
	Homogeneity	The closeness of distribution of elements in GLCM to the diagonal of GLCM.
3. Wavelet [8] (Texture)	cA -Approximation Coefficients details	Mean: Measure of average intensity value of the cA. Standard Deviation: Measure of dispersion of cA from its mean value(or) spread of gray level around the mean value of cA. Skewness: Measure of asymmetry of the distribution of cA. Kurtosis: Measure of peakedness of the distribution of cA.
	cH-Horizontal Coefficients details	Mean: Measure of average intensity value of the cH. Standard Deviation: Measure of dispersion of cH from its mean value. Skewness: Measure of asymmetry in the distribution of cH. Kurtosis: Measure of peakedness of the distribution of cH.
	cV-Vertical Coefficients details	Mean: Measure of average intensity value of the cV. Standard Deviation: Measure of dispersion of cV from its mean value. Skewness: Measure of asymmetry in the distribution of cV. Kurtosis: Measure of peakedness of the distribution of cV.
	cD- Diagonal Coefficients	Mean: Measure of average intensity value of the cD. Standard Deviation: Measure of dispersion of cD from its mean value. Skewness: Measure of asymmetry in the distribution of cD. Kurtosis: Measure of peakedness of the distribution of cD.
4. Linear Binary Pattern (LBP) [17] (Texture)	Neighbouring pixels, Radius (parameters)	It measures texture characteristics of the image. Each pixel is compared with its neighbouring pixels of the centre pixel.
5. Intensity [13], [17] (Statistical)	Mean	The mean intensity value of the image pixels which may be calculated by adding all pixel values of an image and this value is divided by the total number of pixels in the image
	Standard Deviation (SD)	The SD of the pixel intensities provides information about texture variation and describes probability distribution of an observed population and can serve as measure of inhomogeneity.
	Skewness	Measure of deviation of asymmetry in the intensity distribution.
	Kurtosis [13]	Measure of peakedness of the probability distribution.

segmented images is studied. The various metrics such as accuracy, precision, sensitivity, specificity and F1-score are calculated by finding the number of True Positives (TP), True Negatives (TN) False Positives (FP) and False Negatives (FN) from the confusion matrices. The analysis is made between all possible combinations of traditional feature extraction methods and Machine Learning classifiers to find which classifier exhibits better performance metrics.

2.4 Results and discussion

This section presents the experimental results on feature extraction using traditional methods, classification and performance metrics evaluation and analysis of brain tumor classification. The performance metrics analysis of brain tumor classification both in the existing methods and our proposed approach are compared.

2.5 Feature extraction using traditional methods, classification and performance metrics evaluation and analysis

The feature extraction from the segmented brain MRI images using traditional methods viz. shape, GLCM, wavelet, LBP, intensity and performance metrics (esp. accuracy) of classification of brain tumors using eight ML classifiers are given in Table 3. This table gives all possible combinations of methods viz. geometric + texture features, geometric + statistical features, texture + statistical features and geometric + texture + statistical features.

Further, Table 3 shows that the features, extracted using geometric + texture + statistical methods, have achieved better accuracy among all classifiers. However, the efficacy of each feature extraction method varies with respect to each classifier[7]. For instance, the SVM classifier has exhibited better accuracy (**92%**) when it is combined with GLCM, whereas it has yielded the poorest result (**59.72%**) when the same classifier is combined with Shape + GLCM + wavelet. In other instance, the KNN classifier has exhibited better accuracy (**88.8%**) when it is combined with Shape. Generally, it is found that Decision Tree (DT) consistently achieves the highest classification accuracy levels (i.e., **above 90%**) when it is combined with most of the feature extraction methods.

From Table 3, it is observed that among using all the feature extraction methods and ML classifiers, the features, extracted using shape + GLCM + wavelet + LBP + intensity, along with Decision Tree (DT) classifier has achieved highest classification accuracy of **96.05**%. In addition, precision (96.88%), sensitivity (95.22%), specificity (96.09%) and F1-score (96%) metrics for the segmented multi-class dataset using the MACB model are found. From Table 3, it is also observed that whenever **GLCM** type is combined with other methods such as shape, wavelet, LBP, wavelet + LBP, shape + LBP, shape + intensity, shape + wavelet + intensity and shape + wavelet + LBP, along with DT classifier gives higher classification accuracies of **94.05%, 94.01%, 94.11%, 94.43%, 94.89%, 94.69%, 95.41% and 95.85%** respectively. This indicates that the glioma, meningioma, no tumor and pituitary tumor are classified with minimum false positives and negatives.

2.6 Confusion matrices with highest accuracy for the classification of brain tumors in MACB segmented MRI images for each of the eight combinations

The confusion matrices are as shown in Figure 3 for the 3 features (viz. geometric, texture, statistical) and their 5 combinations along with ML classifiers, exhibiting highest accuracy within each of the 8 combinations for the classification of brain tumors in the MACB segmented MRI images.

The confusion matrices show that our proposed MACB model for segmentation and our novel approach of combining the 5 traditional feature extraction methods viz. shape, GLCM, wavelet, LBP and intensity along with DT classifier achieves highest classification accuracy of **96.05 %**. Also, the confusion matrices indicate that the meningioma, no tumor and pituitary tumor are classified with minimum false positives and negatives.

2.7 Performance metrics analysis of brain tumor classification both in the existing methods and our proposed approach

Table 4 presents a comprehensive comparison of various existing methods in the field of image segmentation and classification of brain tumor in MRI images and their corresponding performance metrics (esp. accuracy) with our proposed research work. Each existing method is associated with a reference dataset used, segmentation method, feature extraction method, classification method and performance metrics (esp. accuracy). These performance metrics values provide insights into the efficacy of each method in segmenting and classifying tumors in segmented brain MRI images.

As given in Table 4, our proposed approach shows the highest classification accuracy while using traditional feature extraction methods along with ML classifiers. It highlights that the image segmentation using our proposed MACB model[15] and features, extracted using shape + GLCM + wavelet + LBP + intensity along with Decision Tree ML classifier has achieved highest classification accuracy of 96.05%.

2.8 Research findings

In this proposed research work, we use and analyze five traditional feature extraction methods viz. shape, GLCM, wavelet, LBP and intensity and evaluate their performance with eight popular ML classifiers to determine the best combination to achieve the highest classification accuracy. The findings of our proposed approach are as follows.

- The combination of feature extraction methods esp. shape + GLCM + wavelet + LBP + intensity shows highest classification accuracy, but the efficacy of each feature extraction method depends on the choice of ML classifiers. For

Table 3. Feature extraction from MACB segmented brain MRI images using traditional methods and performance metrics (esp. accuracy) for the classification of brain tumor using various ML classifiers

S. No.	Features and their combinations	Feature extraction methods and their combinations	Accuracy for the classification of brain tumor using various ML classifiers							
			SVM	LR	LDA	DT	RF	AB	KNN	NB
1.	Geometric feature	Shape	81.75	50.58	76.14	86.53	79.44	72.76	**88.8**	69.91
2.	Texture feature	GLCM	**92**	91.32	84.03	91.76	83.3	84.66	86.46	84.18
		Wavelet	84.54	64.22	81.69	**88.63**	79.02	82.42	87.82	79.7
		LBP	79.56	58.27	78.51	**90.47**	78.22	82.07	83.98	69.91
3.	Statistical feature	Intensity	85.78	70.4	83.57	**88.33**	72.63	82.8	85.45	82.25
4.	Texture feature combinations	GLCM + wavelet	87.59	67.95	81.12	**94.01**	79.16	84.34	87.82	84.62
		GLCM + LBP	65.14	84.19	81.76	**94.11**	80.66	84.66	86.6	73.04
		Wavelet + LBP	89.32	60.94	81.14	**92.14**	79.23	84.42	87.82	79.96
		GLCM + wavelet + LBP	89.85	48.15	81.14	**94.43**	80.38	85.34	87.84	79.96
5.	Geometric feature + texture feature combinations	Shape + GLCM	84.07	77.94	81.3	**94.05**	78.66	84.66	86.72	81.7
		Shape + wavelet	77.5	67.25	81.68	**92.23**	79.65	88,80	89.14	84.35
		Shape + LBP	74.54	50.27	81.74	**92.96**	80.43	82.8	88.21	72.3
		Shape + GLCM + wavelet	59.72	73.09	81.91	**93.88**	79.65	85.31	86.72	79.62
		Shape + GLCM + LBP	71.38	38.69	84.94	**94.89**	80.04	85.31	89.91	74.82
		Shape + wavelet + LBP	83.84	47.17	81.3	**95.02**	80.46	82.8	89.91	80.22
		Shape + GLCM + wavelet + LBP	87.15	63.61	85.12	**95.85**	80.84	85.31	89.91	83.62
6.	Geometric feature + statistical feature combinations	Shape + intensity	81.07	45.79	83.07	**91.28**	86.65	82.8	89.91	84.93
7.	Texture feature + statistical feature combinations	GLCM + intensity	87.15	73.27	81.96	**92.88**	81.29	82.8	89.91	82.13
		Wavelet + intensity	85.16	67.31	82.63	**88.48**	75.83	82.61	86.64	80.98
		LBP + intensity	82.67	64.34	81.04	**89.40**	75.43	82.44	84.72	76.08
		GLCM + wavelet + intensity	83.3	53.16	81.52	**91.38**	80.19	82.8	88.71	81.61
		GLCM + LBP + intensity	85.78	73.33	82.04	**90.19**	78.05	83.18	85.30	78.78
		Wavelet + LBP + intensity	83.29	64.30	81.26	**89.14**	76.62	82.43	85.75	77.29
		GLCM + wavelet + LBP + intensity	83.8	56.14	81.52	**91.99**	79.69	85.34	89.01	82
8.	Geometric feature + texture feature + statistical feature combinations	Shape + GLCM + intensity	87.65	69.71	81.96	**94.69**	78.29	85.34	86.58	85.58
		Shape + wavelet + intensity	88.68	60.62	82.07	**92.29**	79.76	82.8	89.91	84.88
		Shape + LBP + intensity	79.61	79.59	83.3	**94.95**	81.47	82.8	86.6	76.62
		Shape + GLCM + wavelet + intensity	82.63	62.72	82.43	**95.41**	79.64	85.34	89.91	84.97
		Shape + GLCM + LBP + intensity	80.32	56.14	84.07	**92.07**	81.2	85.34	86.58	76.85
		Shape + wavelet + LBP + intensity	87.15	73.27	81.96	**95.03**	81.29	82.8	89.91	82.13
		Shape + GLCM + wavelet + LBP + intensity	92.94	79.52	83.17	**96.05**	80.61	85.84	89.91	86.99

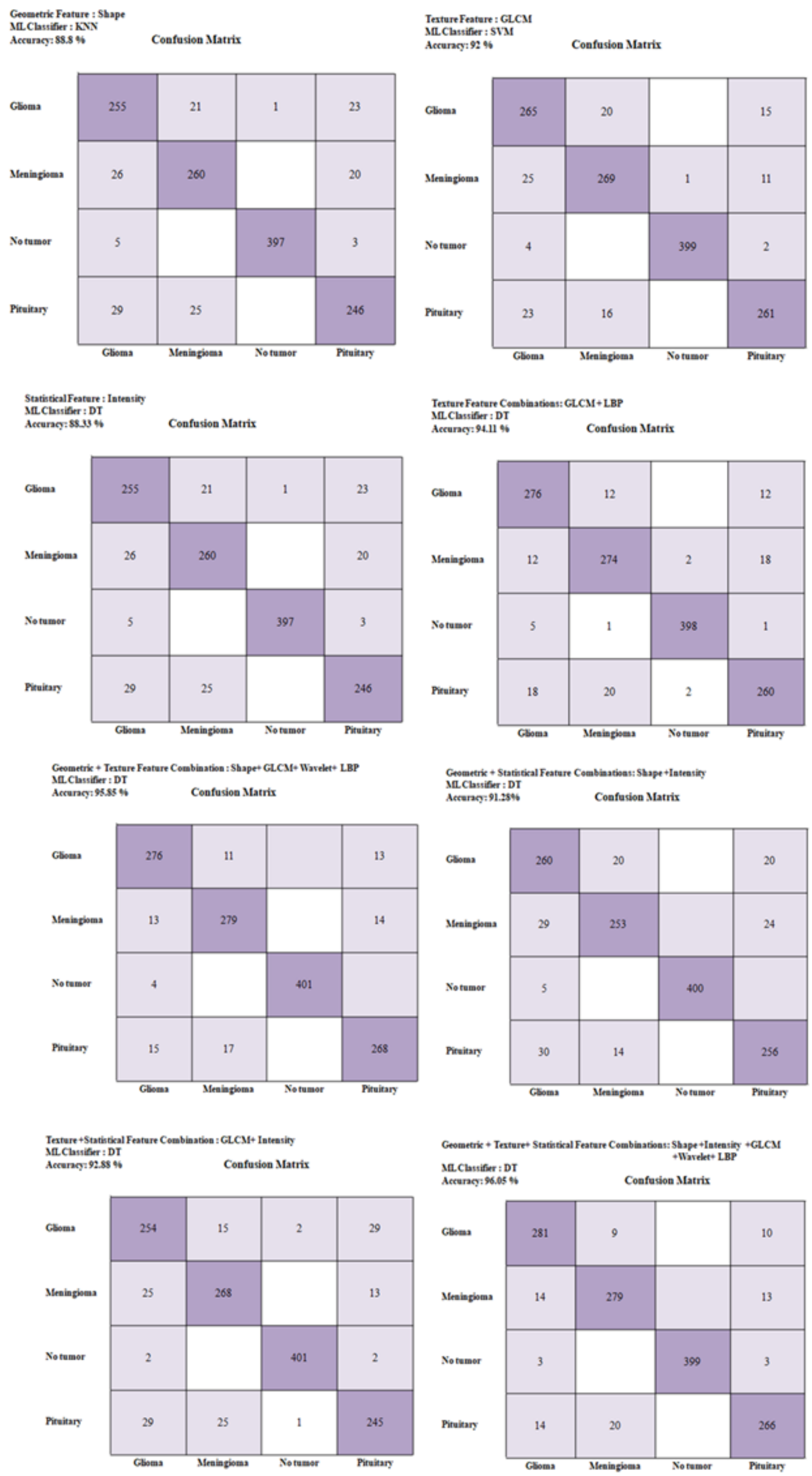

Fig 3. Confusion matrices of the ML classifiers with highest accuracy within each combination

Table 4. Performance metrics analysis of brain tumor classification both in the existing methods and our proposed approach

Reference	Tumor types in the dataset	Segmentation methods	Traditional Feature extraction methods	ML classifiers	Accuracy (%)
R. H. Ramdlon et al. [7]	Astrocytoma, glioblastoma, and oligodendroglioma	Watershed method	Shape	KNN	89.5%
Pronab et al. [9]	Benign, malignant	K-means and fuzzy C-means (FCM	GLCM	SVM	94.37%
Islam R. et.al [1], [10]	Tumor no tumor.	thresholding and watershed	CNN	SVM	87.4%
Ansari, A. S. [11]	Glioblastoma, sarcomaand metastatic bronchogenic carcinoma.	fuzzy clustering	GLCM, DWT, PCA	SVM	88%
Zobia Suhail et al. [13]	Gliomas, pituitary, Meningioma and Glioblastoma	-	LDA	LR	92.84
Ramdas Vankdothu et al. [14]	Glioma, meningioma, no tumors and pituitary	K-Means Clustering	GLCM method	RCNN	95.17%
Mst Sazia Tahosin et al. [16]	Benign Malignant	Morphological opening	Shape, Texture and Intensity	SVM KNN CNN	86% 88 % 89 %
A. Hussain et al. [22]	Benign Malignant	Watershed segmentation method	GLCM feature extraction	SVM	93.05%
Our proposed approach	Glioma, Meningioma, No tumor and Pituitary	Proposed MACB model in our previous work [15]	Shape + GLCM + Wavelet + LBP + Intensity	**DT**	**96.05%**

instance, the SVM classifier has exhibited better accuracy (**92%**) when it is combined with GLCM, whereas it has yielded the poorest result (**59.72%**) when the same classifier is combined with Shape + GLCM + wavelet. In other instance, the KNN classifier has exhibited better accuracy (**88.8%**) when it is combined with Shape. Generally, it is found that Decision Tree (DT) consistently achieves the highest classification accuracy levels (i.e., **above 90%**) when it is combined with most of the feature extraction methods. The SVM and KNN classifiers show better classification accuracies, followed by DT classifier.

- It is observed that whenever **GLCM** method is combined with other methods such as shape, wavelet, LBP, wavelet + LBP, shape + LBP, shape + intensity, shape + wavelet + intensity and shape + wavelet + LBP, along with DT classifier gives higher classification accuracies of **94.05%, 94.01%, 94.11%, 94.43%, 94.89%, 94.69%, 95.41% and 95.85%** respectively.
- It is observed that out of using all the 31 combinations of 5 feature extraction methods and 8 ML classifiers, the combination method viz. shape + GLCM + wavelet + LBP + intensity, along with Decision Tree (DT) ML classifier, has achieved highest classification accuracy of **96.05%** for multi-class MACB segmented brain MRI images dataset [15].
- The key novelty of the proposed approach depends on the tumor segmentation technique using our MACB model for segmenting brain tumors in MRI images, since the MACB model has itself demonstrated better performance in providing better quality tumor delineation, as compared to traditional segmentation methods.

3 Conclusion

This proposed research approach presents the feature extraction analysis by doing several experiments. This approach integrates the traditional feature extraction methods viz. geometry (shape), texture (GLCM, wavelet, LBP) and statistical (intensity) methods. This approach has used and analyzed five traditional feature extraction methods viz. shape, GLCM, wavelet, LBP and intensity and evaluated their performance with eight popular ML classifiers viz. SVM, LR, LDA, DT, RF, AdaBoost, KNN and Naive-Bayes (NB) to determine the best combination for achieving the highest classification accuracy.

It is found that the combination of feature extraction methods (shape + GLCM + wavelet + LBP + intensity) shows higher classification accuracy but the efficacy of each feature extraction method depends on the choice of ML classifiers. For instance, the SVM classifier has shown better accuracy (**92%**) when it is combined with GLCM, whereas it has given the poorest result

(**59.72%**) when the same classifier is combined with Shape + GLCM + wavelet. In other instance, the KNN classifier has shown better accuracy (**88.8%**) when it is combined with Shape. Generally, it is found that Decision Tree (DT) classifier has consistently achieved the highest classification accuracy levels (i.e., **above 90%**) when it is combined with most of the feature extraction methods. The SVM and KNN classifiers show good classification accuracy, followed by DT classifier.

It is also found that whenever **GLCM** method is combined with other methods such as shape, wavelet, LBP, wavelet + LBP, shape + LBP, shape + intensity, shape + wavelet + intensity and shape + wavelet + LBP, along with DT classifier gives higher classification accuracies of **94.05%, 94.01%, 94.11%, 94.43%, 94.89%, 94.69%, 95.41% and 95.85%** respectively.

It is found that the image segmentation using our proposed MACB model[15] and the combination method viz. shape + GLCM + wavelet + LBP + intensity, along with **Decision Tree ML classifier has achieved highest classification accuracy of 96.05%.**

Thus, for the future research work, we like to propose a performance analysis on brain tumor classification using CNN models and feature extraction using CNN models & classification using the popular ML classifiers on the dataset of MACB segmented MRI images, since the MACB model has itself demonstrated better performance in providing better quality tumor delineation, as compared to traditional segmentation methods.

4 Acknowledgments

The authors would like to express their special thanks to Dr. K. S. Easwarakumar, Professor, Department of Computer Science, Anna University CEG campus, Chennai for useful discussions, his interest and encouragement. The first author (KRS) is very grateful to "Baby-Perumal Research Institute" at Chennai for research guidance and supporting with computing facilities.

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