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Brain Tumor Detection Based on A Combination of GLCM and LBP Features with PCA and IG

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Abstract

Cellular abnormality leads to brain tumor development. It is one of the main causes of mortality worldwide for adults and children. Early tumor discovery can avert millions of mortalities. Magnetic Resonance Imaging (MRI) is one of the most popular imaging techniques that can be used for the earlier detection of brain tumors, so that may improve the survival of patients. Tumor visibility is improved in MRI, which facilitates subsequent treatment. This research tries to detect brain tumors early on. The suggested CAD system that uses MRIs has the potential to help doctors and other specialists to find the existence of brain tumors. This work makes use of machine learning to enhance classification accuracy. This work is carried out in many sequential steps that include preprocessing using the median filter for MRIs noise removal, feature extraction using Grey Level Co-occurrence Matrix (GLCM) and Local Binary Pattern (LBP) for extracting the features of tumors, then Principal Component Analysis (PCA) and Information Gain (IG) are used as Feature selection algorithms, finally, the classification step is performed using different types of machine learning classifiers to determine and classify the MRIs as tumorous or non-tumorous. The experimental results of the proposed method, which uses a combined feature vector of GLCM and LBP features, show 98% accuracy using IG and 97% accuracy using PCA.

Keywords: Brain tumor; MRI; Grey Level Co-occurrence Matrix GLCM; Local Binary Pattern LBP; Feature Selection.

1. Introduction

It is well recognized that brain tumors play a significant role in the sharp rise in death rates among children, adults, and particularly the elderly. The brain is a sophisticated part of the body of a human that is made up of billions of cells. Uncontrolled cell expansion is a factor in the growth of brain tumors. These cells and their uncontrolled growth may interfere with typical brain functions and can damage normal tissue [1], [2].

Brain cells can particularly be destroyed by tumors. They can cause cell damage by increasing pressure inside the skull [3]. When this foreign tissue or population of tumor cells continues to expand at an uncontrolled rate, it starts to interfere with regular brain function, so there may be a lot of problems for the person that has a brain tumor. One of the brain's most crucial jobs is controlling all of the body's actions and processes, including behavior, movement, and homeostatic processes like blood pressure, heart rate, body temperature, and the balancing of fluid in the body [4].

There are two different types of tumors: benign and malignant. Benign tumors are cancer cells and are less dangerous since they do not spread to other cells. Malignant tumors, on the other hand, are collections of cancerous cells that are dangerous and more prone to invade nearby tissues and cells. Brain tumors are typically graded from 1 to 4 according to their behavior. Less dangerous tumors in grade 1 are typically associated with longer survival. When observed under a microscope, they almost appear to have a normal texture and grow steadily. Surgery may be an effective option for this grade of the tumor. Under a microscope, grade 2 grows slowly and exhibits abnormal characteristics. A few recur and expand to nearby tissues, occasionally as grade-high tumors [5]. Although a grade 3 tumor is malignant, there isn't usually much of a difference between grade

2 and grade 3 tumors. This tumor typically recurs as a grade 4 tumor. The most malignant tumor is grade 4. It swiftly grows, has an abnormal appearance when viewed through a microscope, and successfully invades nearby brain tissues, causing the development of new vessels. Zones of dead cells can be found in the center of these tumor cells [6]. Fig. 1 shows an example of normal and abnormal MRIs.

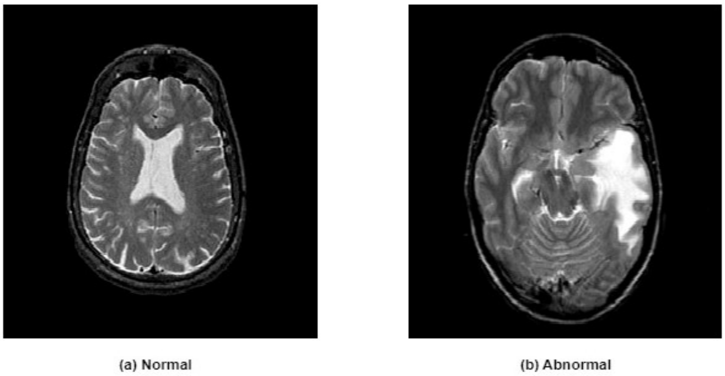


Fig. 1 Example of brain MRI

Tumors are found using imaging techniques including magnetic resonance imaging (MRI) and computed tomography (CT). The human inspection of CT and MRIs becomes challenging due to high resolution and numerous slices, including redundant ones. But MR imaging makes the abnormal brain tissue threads more obvious and hence it is preferred to use these scans [7]. MRIs are utilized to detect brain tumors because they have various morphological traits and characteristics depending on how they present on scans [8–10]. Radiologists may be helped by the proper interpretation of these abnormalities using a Computer Aided Diagnosis (CAD) system to aid in early and preoperative treatment planning and diagnosis.

The core contributions of this work are:

- Presenting a method for enhancing the accuracy of brain tumor detection.
- Utilizing a feature vector that combines two useful texture features LBP and GLCM.
- Using the feature-selection algorithms PCA and IG for selecting the most crucial features.

The organization of this paper is as follows: After this introduction, The previously related work is presented in Section 2. The proposed approach is presented in Section 3. Section 4 presents a discussion of the experimental results. This paper is concluded in Section 5.

2. **Related Work**

A crucial prerequisite is the early discovery of brain tumors. As a result, numerous researchers created methods for detecting brain tumors. Many methods have already been presented for brain tumor detection, among these, a few of the research papers are discussed here.

In [11], the authors introduced an approach for detecting brain tumors in brain magnetic resonance imaging (MRIs) utilizing a support vector machine (SVM) classifier and by applying GLCM and discrete wavelet transform (DWT) as two feature extraction techniques, they classified the test images into normal and tumorous brain MRIs over the dataset achieving 93% accuracy with GLCM and 97% accuracy with DWT. In [12], the authors fused the texture features of the GLCM, LBP, and GLRL, and by using a variety of machine-learning classification algorithms for the classification process to detect brain tumors to categorize the MR images into normal and abnormal, their suggested model reports average accuracy of 97.13%. In [13], the authors used a fusion feature vector containing two features, Gabor wavelet transform GWT and Local binary pattern LBP, then they applied many machine learning classifiers to perform the detection process of normal and abnormal MRIs and They achieved an accuracy of 97% on the Brats 2015 dataset using LBP and 98% using the combination of GWT and LBP. In [14], a variety of textural features were used, they employed the superpixel approach to differentiate between images with and without tumors on BRATS dataset, and they recorded a 98.28% accuracy rate. In [15], the authors used the Complex Wavelet Transform (CWT) and statistical characteristic features along with the skippy greedy snake technique for classification, and the detection result of the brain tumor on a simulated images dataset reported 96.80% accuracy. In [16], the authors classified the brain MRIs into two categories: normal and diseased. They applied GLCM to extract the features, and they used a probabilistic neural network (PNN) classification algorithm to achieve 95% accuracy in their classification process. In [17], A hybrid energy-efficient technique for automated tumor segmentation and identification was presented. Their suggested approach involves seven long steps and they have achieved 98% accuracy. They achieved a good performance, but their suggested model's main disadvantage was its lengthy computation time caused by the employment of various approaches. In [18], the authors proposed a model using image processing techniques and machine learning algorithms for tumor detection, in which the GLCM is used for extracting the features, and the AdaBoost algorithm is used for the classification of the tumor, their suggestion indicated an accuracy of 89.90% in classifying the tumor. In [19], the authors characterized tissue using GLCMs with feed-forward neural networks, which finally resulted in tumor diagnosis with 97.50% accuracy. In [20], the authors suggested a new, highly accurate, and optimized approach for detecting brain tumors. Preprocessing, segmentation, feature extraction, optimization, and detection processes are all included in this system. GLCM has been used to extract features. CNN classifiers are used for detecting brain tumors. This system's accuracy was measured to be 98.9%. In [21], the authors proposed a novel brain tumour detection approach by using a convolutional neural network with a transfer learning strategy in conjunction with the dimensionality reduction methodology. EfficientNetB7 models for transfer learning are used to extract features, and the PCA approach is used to reduce the number of features. Accuracy is increased by combining features from PCA and the CNN EfficientNet model. 80% accuracy was attained. In [22], the authors suggested a hybrid model based on a convolutional neural network (CNN) and SVM to identify brain tumours in MRI images,. Additionally, they used a pre-processing method on the MRI pictures, which significantly improved their accuracy, they achieved an accuracy of hybrid CNN-SVM in overall comes 98.495%.

3. Proposed work

The primary outcome of the suggested approach is the detection of a tumor in a brain MRI. In the present work, a Computer Aided Diagnosis (CAD) system using normal and abnormal MRI brain imaging is presented, based on effective feature extraction techniques and classification algorithms to improve the accuracy of classification results.

The noisy contents in the input MRI dataset are first eliminated from the images using the median filter in the pre-processing stage. The desired features are then obtained from the previously pre-processed MRI images. After that, the feature selection process is performed by applying two feature selection techniques to the previously extracted features. Finally, the classification process is applied to classify the brain MR images as normal or abnormal. The suggested method for tumor detection is shown in Fig. 2. The details of the proposed method will be explained in the following subsections.

3.1 *Dataset*

The necessary data for distinguishing brain tissues are contained in MR images. This makes the detection of brain tumors from brain MR images is popular study topic for both medical and image-processing experts. The MRI scan does not cause any harm to the human body and it is also non-invasive, radiation-damage-free, multi-directional, and multi-dimensional identification, it is better than those of other imaging techniques like CT and X-ray, among others, in the medical field [23].

The brain MRI dataset used for our research is Brain MRI Images for Brain Tumor Detection [24]. The dataset is divided into two classes of images: tumorous and non-tumorous images. There are 253 total images: 155 images with tumors, and 98 images without tumors.

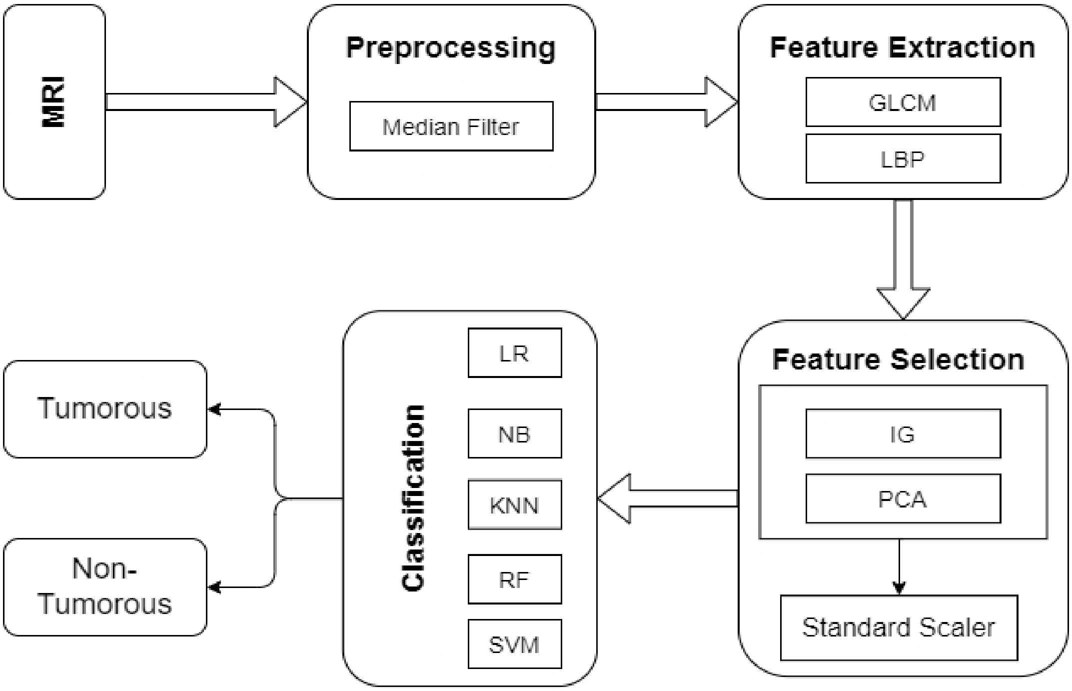


Fig. 2 Proposed method block diagram.

3.2 *Preprocessing*

For image processing techniques, pre-processing is a crucial step. Pre-processing will be done to remove contaminants or unwanted noisy elements from the image to simplify processing while enhancing picture quality. Since multiple types of noise can damage or affect the MRI brain images, many types of filters may be employed in this case to enhance the MRI quality, however, a non-linear filter is suggested for the proposed method which is the median filter, that is selected for its efficiency. More information about the median filter is provided in the next subsection.

3.2.1 *Median filter*

The median filter is employed to reduce noise without affecting the quality of input brain MRI dataset images. In general, the median filter is a non-linear filter in which the idea depends on finding the median of the pixel set entering the filter mask. Each pixel is addressed, and it is then replaced by the median value of brightness of its immediate surroundings. The edge blur and loss of picture details are prevented because the median value, which is determined from the nearby pixels is extremely resistant to outliers and does not produce a new realistic pixel value. Additionally, it maintains fine high-frequency details [25]. The median filter equation as shown in Equation (1)

$$Z(i,j) = \underset{(s,t)\in S_{ij}}{median}\{\, g(s,t)\} \tag{1}$$

where, $Z(i, j)$ is the median filter at a given coordinate, and Sij is the coordinate of the sub-image window of size $m \times n$.

3.3 *Feature Extraction*

The process of feature extraction is essential for representing an image. It is the process of converting data (images) into meaningful characteristics for the classification task. Finding the most significant characteristics that can fully describe an image is called extracting features. The feature set that is extracted determines how accurate the categorization will be, making feature extraction an important and difficult process.

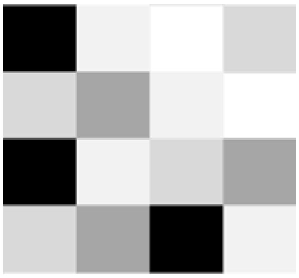
Understanding how different features are used to categorize brain MR images into tumorous and non-tumorous image categories is made easier by understanding their physical relevance. Significantly texture feature characteristics can distinguish brain tissues, therefore, the suggested method depends on a combined feature vector of two separate texture feature techniques: Gray Level Co-occurrence Matrix GLCM [26] and Local Binary Pattern LBP [27]. A more detailed description of the two types of features that are being used is provided in the next two subsections.

3.3.1 *Gray Level Co-occurrence Matrix (GLCM)*

Gray Level Co-occurrence Matrix GLCM is commonly employed statistical textural characteristics that describe the association and recurrence of pixel pairs with certain values. GLCM is calculated for different angle relations and distances between adjacent pixels carrying a particular set of grey levels. For the construction of the GLCM matrix for texture representation, three key inputs were required: the measurements of the image's grey levels, the displacement, and the orientation [28]. In Fig. 3. a sample of the GLCM structure is shown, where P (i, j) is the likelihood of finding a pixel with the gray-level value i together with a pixel with the gray-level value j, and N is the total number of grey levels found in the image. Fig. 4. provides an illustration of a gray-level image and the related computed GLCM.

$$\begin{bmatrix} \boldsymbol{P(1,1)\ P(1,2)\ P(1,3)\ \dots\ \dots\ \dots\ \dots\ P(1,N)} \\ \boldsymbol{P(2,1)\ P(2,2)\ P(2,3)\ \dots\ \dots\ \dots\ \dots\ P(2,N)} \\ \boldsymbol{P(3,1)\ P(3,2)\ P(3,3)\ \dots\ \dots\ \dots\ \dots\ P(3,N)} \\ \boldsymbol{P(4,1)\ P(4,2)\ P(4,3)\ \dots\ \dots\ \dots\ \dots\ P(4,N)} \\ . \\ . \\ . \\ \boldsymbol{P(N,1)\ P(N,2)\ P(N,3)\ \dots\dots\dots\dots\ P(N,N)} \end{bmatrix}$$

Fig. 3 Format of GLCM matrix



sample image

	0	1	2	3
0	0	3	4	2
1	2	1	3	4
2	0	3	2	1
3	2	1	0	3

gray intensity values

	0	1	2	3	4
0	0	1	0	3	0
1	1	0	3	1	0
2	0	3	0	1	1
3	3	1	1	0	2
4	0	0	1	2	0

angle 0 GLCM

Fig. 4 GLCM calculation example

Although GLCM may be considered time-consuming, it provides spatial information and recurrence details among traditional textural features [29]. GLCMs may be used to identify the precise textural properties that a tumor may have in a certain direction due to its dependencies in specific directions while the matrix computation. Out of all the features in the GLCM matrix, only 5 of them are sufficient [30]. So, six of the GLCM features are used in our work, namely contrast, dissimilarity, homogeneity, energy, correlation, and ASM. The four possible orientations for the used features are taken into consideration to make the GLCM features more effective. The used features are as follows.

- Contrast: It measures the local differences in intensity between a pixel and its neighbor in the image.
- Dissimilarity: It is a measurement of the distance between two pixels in an image.
- Homogeneity: It shows how similar pixels are. The homogenous image's GLCM matrix indicates that its value is 1.
- Energy: It gives information on the homogeneity of the image; its values are low when the probability of the grey-level pairings is similar, and high when they are not.
- Correlation: It measures the pixels' linear dependency on the grey level (compared to one another) at the predefined positions.
- ASM: It is the sum of the squares of the entries in the GLCM.

3.3.2 *Local Binary Pattern (LBP)*

LBP describes a local image texture pattern's spatial organization. A local binary pattern LBP is created by thresholding a 3x3 neighborhood using the value of the center pixel [31]. LBP is obtained from Ig(x,y), where a window is slid through all slices to compare the neighborhood with the threshold values of the center pixels. If the value of the nearby pixel is greater than or equal to the value of the center pixel, the neighboring pixel is decided as 1, otherwise, the neighboring intensity value is chosen as 0 [13]. This is given in Equation (2) and Fig. 5. shows an example of LBP calculation.

$$LBP_{P,R} = \sum_{i=0}^{P-1} S(g_i - g_c)2^i \quad S(X) = \begin{cases} 1 & x \geq 0 \\ 0 & x < 0 \end{cases} \tag{2}$$

where P is the surrounding pixels, R denotes the neighborhood's radius, g_i is the intensity of the surrounding pixels, and g_c is the value of the center pixel.

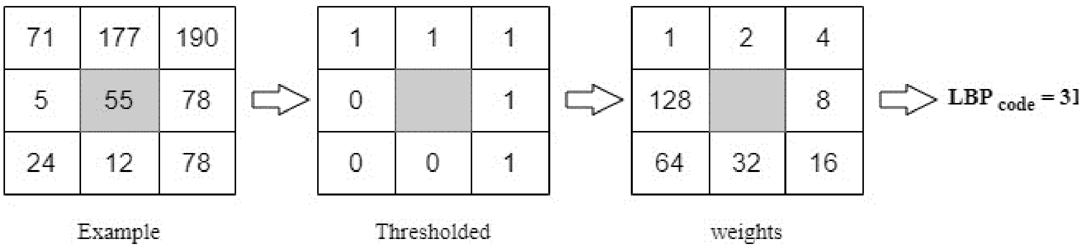


Fig. 5 LBP calculation example

3.4 *Feature Selection*

While features are crucial for obtaining high accuracy, having too many features can complicate computations, waste a lot of memory, and also sometimes it may make classification harder. This is known as the dimensionality curse [32]. An overfitting issue may be caused by an increase in features that may reduce the generality of the system and also decrease the accuracy. Therefore, it is necessary to design feature selection strategies, which choose the ideal subset of characteristics or features. The original set and the selected set of features both include the same information [33]. So, it is considered to be one of the most common and significant data preparation approaches. Feature selection has become a crucial step in the machine learning process because this step can accelerate algorithms, enhances prediction accuracy, and makes algorithms more understandable [34]. Two feature selection algorithms are used to choose the most useful and important subset of features. The two used feature reduction techniques are briefly described in the following. A standard scalar is also applied to the selected features for reducing the processing overhead in the next steps. Because it scales the data within a specific range, it can help make the data more suitable to accelerate the algorithm's calculations and produces better results [35]. The next two subsections present a more detailed explanation of the two feature selection algorithms that are being used.

3.4.1 *Principal Component Analysis (PCA)*

The principal component analysis is a common method for reducing the number of dimensions in large data by reducing a large group of correlated variables into a smaller set of uncorrelated variables named principal components, which nevertheless retains the majority of the variability. The purpose of PCA is to replace highly correlated variables with linear combinations of the original variables that are not highly correlated. The first principal component contains the most differences in the data, the second principal component has the most differences in the other remaining variations, etc. Therefore, following the feature extraction phase, PCA is applied to our feature set to get the most highly uncorrelated and beneficial features for the classification process.

3.4.2 *Information Gain (IG)*

There are several methods for ranking features like Information Gain. Information gain may be used to estimate the information impurity and the degree of prediction uncertainty for the objective variable. It's specifying the range within which a certain feature provides information about a category. Each attribute is given a ranking, and the highest score is selected, ignoring the lower ratings. To obtain the most informative and highly ranked features, the IG is additionally used in our feature set.

3.5 *Evaluation Metrics*

For the evaluation process of the suggested method, several measures are recommended such as accuracy, precision, recall, and F1 score [36]. It depends on the confusion matrix that contains the prediction result information. Let us denote the number of true negatives, false negatives, true positives, and false positives by TN, FN, TP, and FP respectively.

- Accuracy (ACC): it is a metric that evaluates a model's probability to identify correctly categorized data. It computes several accurately categorized negative and positive samples as in Equation (3).

$$Acc = \frac{\mathrm{TP+TN}}{TP+TN+FP+FN} \tag{3}$$

- Precision (P): it is a metric that evaluates how well a model can predict data samples that fall into the positive category. It determines the percentage of positive samples that were accurately predicted as in Equation (4).

$$Precision\ (P) = \frac{\mathrm{TP}}{TP+FP} \tag{4}$$

- Recall (R): it is a metric that is also known as Sensitivity. It determines the percentage of positive samples whose predictions were accurately predicted to all samples in the actual class as in Equation (5).

$$Recall\ (R) = \frac{\mathrm{TP}}{TP+FN} \tag{5}$$

- F1 Score (F1): it is the function of Precision and Recall's weighted average. Both false negative and false positive results are considered as in Equation (6).

$$F1 = 2\,.\,\frac{P\,.\,R}{P+R} \tag{6}$$

4. Experimental Results and Discussion

In this section, the results of our proposed method will be presented. After performing the MRI preprocessing phase to remove unwanted noise from the images, the preprocessed images are used for the feature extraction process to extract the GLCM features as well as the LBP features. The feature selection phase is then carried out to select the most useful features from the extracted features. In an extra step trying to speed up the processing in the following phases, the standard scalar is applied to the features data that is being used. The classification/detection phase then comes in to classify the images into normal and abnormal categories. In the classification phase, five different machine learning classifiers are used: Logistic Regression (LR), Naïve Bayes (NB), K-Nearest Neighbor (KNN), Random Forest (RF), and Support Vector Machine (SVM). The classification phase is applied three times, for the extracted features without feature selection, for the selected features using PCA, and for the selected features using IG. Table 1 shows the result in terms of evaluation metrics of the proposed method without applying feature selection, Table 2 shows the result in terms of evaluation metrics of the proposed method with feature selection. Based on table 1 and table 2, it is noted that the classifiers' accuracies are improved and achieved better accuracies after performing the feature selection step than without doing it. For example, it observed that Random Forest (RF) achieved the highest accuracy of 98% with the IG. And it achieved an accuracy of 95% using PCA, and in both, the accuracies are higher than the same classifiers' accuracies without using feature selection. It also clearly observed that the other classifiers' accuracies increased with the use of feature selection than without using it. For example, as shown in table 2 LR, NB, KNN, and SVM achieved accuracies of 97%, 75%, 84%, and 90% respectively without feature selection, and also achieved 97%, 96%, 93%, and 94% respectively using PCA, and 97%, 88%, 88%, and 93% respectively by using IG.

Table 1 Results of the proposed method without feature selection

	Accuracy	Precision	Recall	F1-Score
LR	0.970	1.0	0.951	0.975
NB	0.754	0.746	0.903	0.817
KNN	0.843	0.859	0.887	0.873
RF	0.813	0.877	0.806	0.840
SVM	0.901	0.964	0.870	0.915

For comparison purposes and because of the difficult challenge of obtaining a public dataset containing brain MRIs for normal and abnormal cases, the suggested method of [12] for their suggestion of texture features in the level of detection of brain tumors, and the suggested method of [13] for the detection of the Brain tumor are performed on the same dataset that is used. Table 3 and Fig. 6 show the comparison results of the proposed method with [12] and [13] methods after applying both in the same dataset. It observed that the proposed method has improved the accuracy than the other works, which means that our proposed method works better when compared with others.

5. Conclusion

In this research paper, a method for detecting brain tumor from MR images is presented depending on combining the texture features of GLCM and LBP, as well as by using PCA and IG as feature selection techniques and different classification algorithms are used for the classification process to categorize the MRIs into tumorous and non-tumorous images, it demonstrated that the random forest classifier achieved an accuracy of 98% when using the IG which is the highest among them. These results prove that the combination of GLCM and LBP features together with PCA and IG feature selection techniques could give a more effective and accurate technique for detecting brain tumor from MRIs. These results also represent a significant improvement over earlier approaches and demonstrate the potential of the suggested method for enhancing brain tumor detection. Despite the major obstacle we encountered which was obtaining a public dataset with both normal and abnormal MR images, finally, a good and satisfactory outcome is achieved. The main advantage of the suggested method is enhancing the performance of brain tumor detection by combining two important and useful texture features with feature selection algorithms to use only the most important features. However, the main limitation was obtaining public datasets that contained infected and non-infected MRI images for the use of brain tumor detection. For future work, combining texture and shape features with feature selection techniques like IG and PCA could lead to better outcomes, moreover, employing recent techniques and methodologies could enhance the outcomes.

Table 2 Results of the proposed method PCA and IG feature selection

	Selection Method	Accuracy	Precision	Recall	F1-Score
LR	PCA	0.970	1.0	0.951	0.975
	IG	0.970	1.0	0.951	0.975
NB	PCA	0.960	0.967	0.967	0.967
	IG	0.882	0.867	0.951	0.907
KNN	PCA	0.931	0.923	0.967	0.944
	IG	0.882	0.903	0.903	0.903
RF	PCA	0.950	0.967	0.951	0.959
	IG	0.980	0.983	0.983	0.983
SVM	PCA	0.941	0.951	0.951	0.951
	IG	0.931	0.982	0.903	0.941

Table 3 Results Comparison

	Feature set	Accuracy
[12]	GLRL, GLCM, LBP	0.941
[13]	Gabor, LBP	0.951
Proposed method	GLCM, LBP	0.980

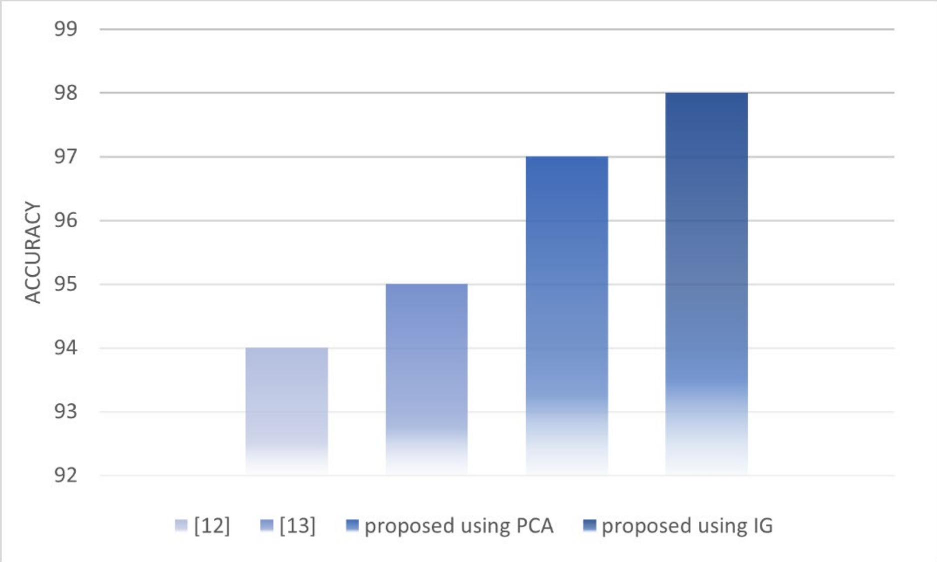


Fig. 6 Results comparison

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