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Brain Tumor Detection and Classification from T2-weighted MRI Images using Cuckoo Search Optimization and SVM Classifier

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Abstract: Brain tumor detection is one of the critical and time utilizing tasks. Manual detection of tumor needs experts in the radiological medical filed, in addition, it took more time. In such cases the false findings are high and accuracy of tumor detection system is less. Hence, we need to reduce the false finding rates and increase the accuracy. The automatic brain tumor detection techniques can make it possible. In this article we propose automatic brain tumor detection and classification technique using cuckoo search optimization technique and support vector machine classifier. The proposed system consists of four stages such as preprocessing, segmentation, feature extraction and classification. The median filter in the preprocessing enhances the quality of the input image, the cuckoo search optimization technique (CSO) makes the pre-processed image into different segments in the second stage, the features of the segmented image are extracted in stage three using gray level co-occurrence matrix (GLCM) and local binary pattern (LBP). The tested images are classified using support vector machine (SVM) classifier in fourth stage. The performance parameters such as sensitivity, specificity and accuracy of the proposed technique are determined and compared with existing techniques.
Keywords: Brain tumor detection, Cuckoo Search Optimization, GLCM, Local Binary Pattern, Support Vector Machine, T2-Weighted Brain MRI.

Introduction

The tumor is basically an abnormal or uncontrolled growth of cancerous cells in the body, whereas brain tumor is classified as abnormal growth of cancerous cells in the brain. A brain tumor can be benign or malignant. A brain tumor can be benign or malignant. A benign brain tumor has similarity in a structure called homogeneous structure and does not contain cancer cells, whereas malignant brain tumor has a non-similarity in a structure called heterogeneous structure and contains cancerous cells. The World Health Organization and American Brain Tumor Association have initiated grading mechanism for tumor stages into grade I to grade IV to classify benign and malignant tumor types. On that scale, grades I and II are also called low-grade brain tumors and classified as benign tumor types, whereas grades III and IV are called high grade brain tumors and classified as malignant brain tumors [1]. As per the estimation of American Brain Tumor Association (ABTA) in the year 2017, in United States only, there are almost 80,000 new patient cases are diagnosed with a primary brain tumor and a total of over 700,000 living with the brain tumor out of them 28,000 kids fighting with brain tumors. Approximately there are 32 percent (one-third) of brain tumors are malignant. The national brain tumor foundation (NBTF) estimated that the growth of brain tumors among people and people expire out with brain tumor raising every year [2].

Different screening modalities available such as Computed tomography (CT), Positron emission tomography (PET), Single positron emission computed tomography (SPECT) and MRI. Compare to all other imaging modalities, MRI provides excellent contrast for different brain tissues. For the applications of detection and identification of brain tumor, MRI is very efficient due to high contrast for soft tissues; its spatial resolution is high. MRI doesn’t produce radiation, not harmful to brain and its tissues. It is non-invasive technique and more comfortable than CT scan for diagnosis which produces more radiation, harmful to brain. An MRI screening modality is cable of producing different imaging pulse sequences such as T1-W (T1 weighted), T2-W (T2-weighted) and PD (proton density). Early detection and screening of brain tumor increases the longer life of patients as possible in terms of quality. The digital screening systems assist greatly in diagnosis of brain cancer. These systems also used to provide second opinion by radiologists for the confirmation of diagnostic outcomes. It is advantage in terms of tumor area quantification, speed, accuracy, reduces the miss rate, and reduces the burden. A minor incorrect treatment or artificial miss can guide to wrong and poor treatment. So, to analyse the tumor area, digital imaging and its processing techniques can help greatly [3].

Segmentation is a process of separating an image into the similar class of properties such as color, contrast, brightness, and gray level into blocks or regions. Brain tumor segmentation is employed in medical imaging such as magnetic resonance (MR) images or other modern imaging modalities in order to separate the tumor tissues such as edema and necrosis (dead cells) from normal brain tissues, such as WM, GM, and CSF. To detect tumor tissues from medical imaging modalities, segmentation is employed and depending on the evaluations performed using advanced medical imaging modalities; specialized patient care is provided to patients with a brain tumor. The detection of a brain tumor at an early stage is a key issue for providing improved treatment to the patient. Once a brain tumor is clinically suspected, radiological evaluation is required to determine its location, size, and impact on the surrounding areas. Past few years, many types of research on brain tumor diagnosis has been evolved highly for different imaging modalities but not fully imperative. Many researchers investigating for advanced diagnosis systems. Segmentation is a vital and fundamental process and is one of the difficult tasks in image processing [4].

Lakshmi Narayana et al. [5] proposed a system for brain tumor detection using DWT and K-means clustering from MRI images. The proposed method produces larger value of MSE, smaller value of MSE and the time taking for decision and computing is more. The results show that there is improvement in above mentioned parameters. El Syed et al [6] proposed a new algorithm for brain tumor detection and classification. Initially the author surveyed different research work on tumor detection and then projected a new system using median filter, feedback pulse coded neural network (FPCNN) based segmentation and DWT for feature extraction and principal component analysis (PCA) for dimension reduction and artificial neural network (ANN) for classification. This hybrid intelligence method carried on few images and resulted low specificity. Varuna Shree et al [7] projected region growing based segmentation and neural network based classification. In this approach of detection and classification, initially trained some images and then tested different images. The MSE and PSNR are not good. The accuracy obtained in the classification is also poor. Need to improve the PSNR, MSE and classification rates.

Guptha N et al [8] have authored a research paper, to detect brain tumor from T2-W brain MRI images with customised Otsu's thresholding method. The same work includes different features extraction techniques and SVM classifier for prominent feature selection and classification. The classification results are not in the satisfying range. B.S.Babu et al [9] recommended a brain tumor detection approach using tetrolet and SVM classifier from MRI images. The proposed work carried Haar transform tetrolet with level 4, level 5 and level 6 decompositions and recommended level 5 as good decomposition for brain tumor detection. Classification accuracy is needed to improvement. Lakshmi Narayana et al proposed optimization techniques such as genetic algorithm (GA) [10], particle swarm optimization (PSO) [11] for brain tumor detection and classification from T2-W MRI images. The GA based segmentation resulted poor results compared with PSO based segmentation. In these papers the segmentation parameters are determined such as PSNR, MSE, segmentation accuracy etc. Need to determine the classifier performance parameters. Lakshmi Narayana et al [12] extended the research work and proposed cuckoo search optimization (CSO) and compared the segmentation results and extracted features with PSO algorithm. The binary classifier SVM is proposed to decide the input T2-W MRI image is normal or abnormal. The classifier performance is not determined.

Therefore, this paper introduces a very powerful optimization method in terms of speed (computational time), PSNR, MSE, segmentation accuracy and computational time. This paper presents an automatic brain tumor detection approach based on soft computing and cuckoo search optimization algorithm. The steps in this work are: 1) initially read the input MR images, 2) to enhance the contrast of brain MR images the median filter technique is used to adjust intensity levels and eliminate high frequencies and improve the visual quality of input image, 3) CSO algorithm to segment or cluster and optimize the results with lesser time consumption and higher accuracy, 4) the morphological open operation elements the edges and skull if any around the brain and convert into binary from, 5) the prominent features are extracted using feature extraction techniques such as GLCM and LBP, 5) SVM classifier make a decision the scanned image is abnormal or not.

The structure of this article has arranged as follows. In section II, the methods and materials are presented. The performance evaluation parameters of proposed work have been explained in section III. In section IV the results are presented and discussed. Finally, the conclusion and scope for future are presented in section V.

Materials and Methods

In this section, we present the materials and the methodology which is used to detect brain tumor from T2-W brain MRI images using cuckoo search optimization. The block diagram as shown in figure 1 gives the process flow and different stages of identification, extraction and classification of tumor from brain MRI images. The more details about the steps and various algorithms involved in the proposed methodology have been discussed in the following subsections.

A. Image Acquisition

To overcome the privacy issues, the MRI brain image data has obtained from websites which publically available datasets such as BrainWeb [13], Harvard Medical School [14]. These datasets provides different

MRI images such as T1-W, T2-W, PD, and FLAIR etc with different thickness, noise levels and formats. We considered T2-W brain MRI because the visual quality is good and perfectly suitable for separating the tissues in the images. The acquired images are in gif format, they are converted to jpeg format.

B. Preprocessing

In the preprocessing stage, the input acquired images are resized into 256x256 size, then converted into gray scale if it in color form. The median filter is used to enhance the quality of the image by removing the noise and clearout the undesired parts in background and makes more reliable without persevering the edges of image.

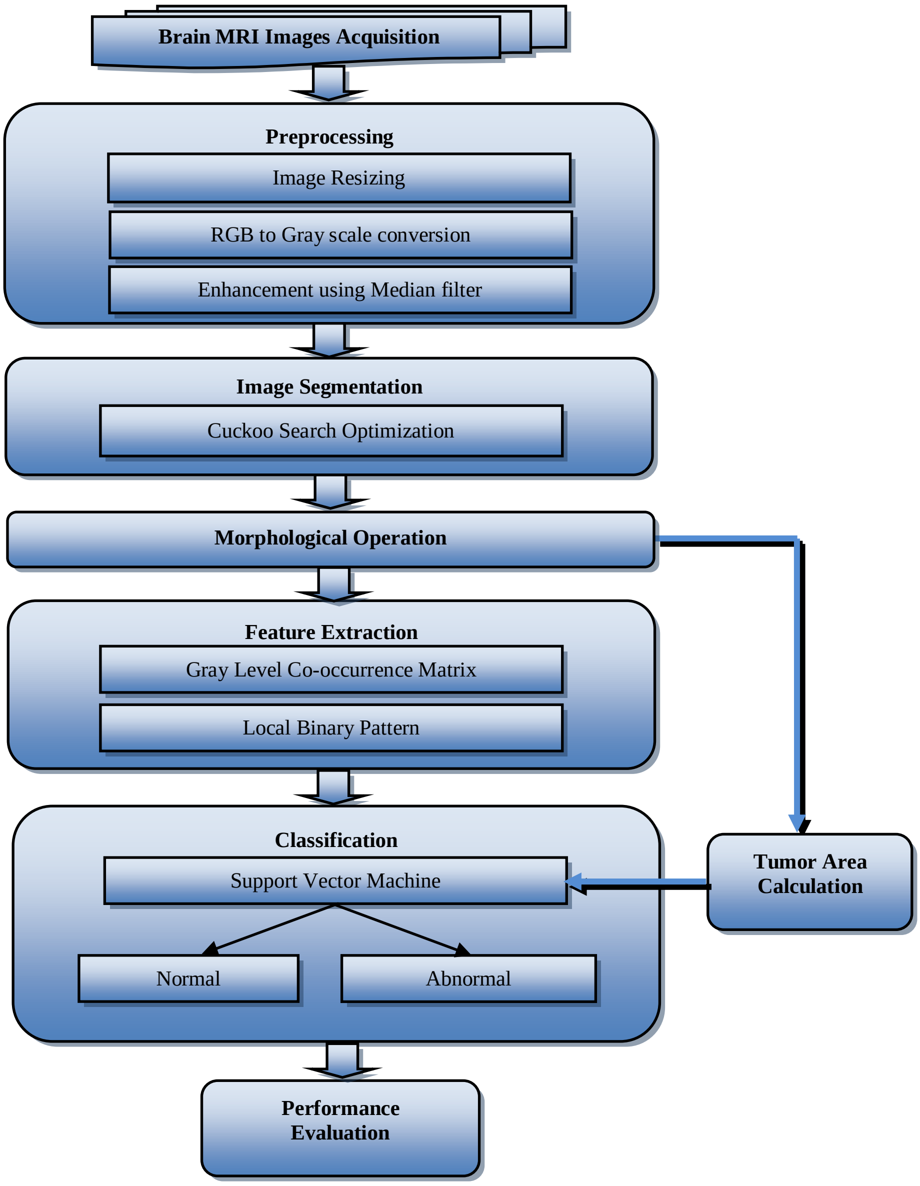

Fig 1. Block diagram of proposed methodology

Most of the noise fading filters blur the boundaries. The median filter is used to remove the noise and preserves the edges of the image. It is a non-linear filtering technique that removes the high frequency components in MRI images without disturbing the edges. The median filter works based on the arrangement of the required pixel values in terms of increment order and considered the most mid pixel value as a result of median filter.

C. Segmentation

The technique which is used to segregate the specific suspicious region from an image is called segmentation; it plays a vital role in medical imaging processing such as brain lesion detection from the

MRI images. The CSO algorithm is best technique to segment and detect the T2-W brain images. The more details about the CSO is explained in the following subsection.

Segmentation using Cuckoo Search Optimization Techniques: Cuckoo search algorithm was first proposed by Yang and Deb (2009). The algorithm was one of the most recent swarm intelligent-based algorithms that were inspired by the obligate brood parasitism of some cuckoo species by laying their eggs in the nests of other host birds. Cuckoo search is based on three idealized rules, i) each cuckoo bird lays an egg at a time and abandons its egg in random chosen nest, ii) the nests that have preeminent qualities of eggs will carry over to next generation, iii) the number of host nests available is fixed and the probability in which the host bird discovers the egg laid by the cuckoo is $Pa\in(0,1)$. Discovering of the egg is operated on some set of worst nests and discovers solutions dumped from further solutions.

The algorithm for CSO based segmentation is shown below:

Step 1: Initialize the Cuckoo and initialization of nests and random initial
and fitness calculation
Step 2: Fitness solutions are evaluated;
While (t < Max Generation)
Place a cuckoo randomly by Levy flights;
Check the quality/fitness Ft;
For maximization $F\alpha f(x_i)$
Randomly choose a nest among n (say, j);
If $F_i < F_j$
Replace i by the new solution j;
End if
Step 3: If the nest is not good, then cuckoo will abandon the nest or build the
new nest.
Step 4: Rank the solution/nests and find the current best
Step: pass these to the next generations.
Step 5: Reproduction and mutation to update the position of cuckoos, i.e.,
nest is updated. Thus, new nest is generated.
Step 6: Find the fitness for new nest.

D. Morphological Operation

The morphological operation is used for the extraction of the boundary areas of the brain images. In the morphological operation, the pixel values greater than the selected threshold is mapped to white, while others are marked as black, due to this two different regions are formed around the infected tumor tissues, which is to be cropped out. Then, in order to eliminate white pixel, a morphological open operation is executed. Finally, the opened region and the original image are both divided into two equal regions and the black pixel region extracted from the open operation are counted as a brain MR image mask

E. Feature Extraction

Feature extraction is the process of conveying and mining the quantitative information like color features, texture, shape and contrast. In this research work, the features are extracted using local binary patterns (LBP) and gray level co-occurrence matrix (GLCM) for statistical feature extraction.

LBP: Local binary pattern is a gray scale local texture and spatial structure; implementation is very easy, computationally light weight features, derived from the local neighborhood of each pixel in the image. LBP parameters are robust in case of change of image illumination. The mean of the histogram is measured as feature.

GLCM: Gray level co-occurrence matrix (GLCM) is most classical texture based feature extraction technique. It determines the textural relationship between pixels by performing an operation according to second order statics in the image. The second ordered gray level probability distribution of a texture image can be calculated by considering they gray levels of pixels in pairs at a time. So it is called as co-occurrence distribution. Texture feature calculations use contents of GLCM to give a measure of the variation in the intensity at the pixel of interest. The co-occurrence matrix is computed based on two parameters, which are the relative distance between the pixel pair d measured in pixel number and their relative orientation. Single GLCM might not sufficient to describe all texture features; therefore there are four possible directions. i.e., one horizontal, one vertical and other two are diagonals arranged in 0°, 90°, 45° and 135° respectively. To increase the accuracy of GLCM features, the values of four directions are averaged. Various features that can be calculated from the co-occurrence matrices are contrast, correlation, energy, entropy, homogeneity etc.

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F. Classification

Classification using SVM: Support vector machine is a most effective supervised learning and pattern classification technique, determined by Vapnik & Cortes. In this research work, the support vector machine (SVM) classifier used to classify brain MRI image is cancerous (tumor present) or noncancerous (tumor absent). SVM is a binary classifier, takes set of input data and classifies them into one of the two distinct classes. The power of SVM lies in its ability to transform data to a high dimensional space where the data can be separated using hyper plane and distinct two classes by maximizing the distance or margin between two classes.

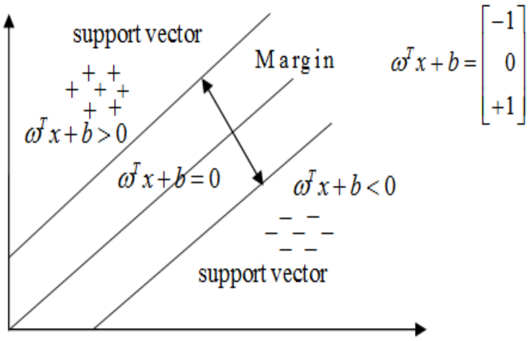


Fig 2. Representation of SVM

The hyper plane is defined as $\omega^T x+b=0$, where ω^T is normal to hyper plane and b is the bias of the hyper plane from the origin. The training set contains pairs of (X_i, Y_i), where i=1,2,…,n feature vector and y=+1 are class labels. They must satisfy $(\omega^T x+b)>0$ if $Y_i=+1$ and $(\omega^T x+b)>0$ if $Y_i=-1$. The optimization process reduces the margin i.e., minimizes the distance. The decision function for input pattern x with binary classifier is $f(x)=\sin(\omega^T x+b)$. The distance between the margin $\omega^T x+b=1$ and $\omega^T x+b=-1$ is $(2/||\omega||)$. The optimization process to create SVM is defined as $((1/2)||\omega^2||-(\omega^T x+b)$. SVM has the special property of simultaneously minimizing classification error and maximizing the geometric margin, classified both linear and non-linear type of data.

Performance evaluation and Metrics

Feature extraction is a key area used to classify the characteristics of an image. Some of the useful features under the classification of GLCM, intensity based features and segmentation based fractal texture analysis are listed below:

$$MSE=(1/p*q)\Sigma\Sigma(f(i,j)-f'(i,j))^2 \quad (1)$$

$$PSNR=20\log_{10}(max_I/\sqrt{(MSE)}) \quad (2)$$

Calculation of the area of the tumor: Tumor area is also one of the features used to classify the tumor type. Hence, create superior conclusion and opinion on the tumor kind, area calculation is one of the feature. To estimate the size of the tumor, the extracted image is converted to binary image. The tumor region identified with white pixels and considered as tumor area, used to compute the size of the tumor. The method to compute the area of the tumor is illustrated as follows: W is number of white pixels, where 1pixel=0.264 mm^2. The size of the tumor = $\sqrt{(W)}*0.264\ mm^2$. Unit of tumor size is mm^2. If the area of the tumor is less than 8 mm^2, then it is called as benign or no tumor otherwise called as malignant [15].

The proposed algorithm performance can be evaluated in terms of accuracy, sensitivity and specificity. The confusion matrix defining the terms TP, TN, FP and FN from the expected outcome and actual data result for the calculation of accuracy, sensitivity and specificity as shown in table 1.

- *TP*: True Positive - signifies the correct classification of tumor cases. Tumor from the test image is identified accurately classified as abnormal.
- *TN*: True Negative - indicates the correct classification of non-tumorous cases. Non-tumorous test image is identified and classified as non-tumorous i.e., the normal images is classified as normal.
- *FP*: False Positive - specifies non-tumorous test image is incorrectly classified as tumorous that is the normal test image is classified as abnormal image.
- *FN*: False Negative - denotes the tumorous test image is incorrectly classified as non-tumorous that is abnormal test image is classified as normal image.

The formulas for calculating the accuracy, sensitivity and specificity are shown in equations. Also the precision, recall, F-score and dice similarity index are shown in equations. A total images 155 images consisting of 60 normal brain images of one type and 95 abnormal brain images of different types.

$$\text{Sensitivity} = (TP)/(TP+FN) \tag{3}$$
$$\text{Specificity} = (TN)/(TN+FP) \tag{4}$$
$$\text{Accuracy} = (TP+TN)/(TP+TN+FP+FN) \tag{5}$$
$$\text{Precision} = (TP)/(TP+FP) \tag{6}$$
$$\text{Recall} = (TP)/(TP+FN) \tag{7}$$
$$\text{F1-score} = (2*\text{Precision}*\text{Recall})/(\text{Precision}+\text{Recall}) \tag{8}$$
$$\text{Dice Similarity Coefficient} = (2*TP)/(2*TP+FP+TN) \tag{9}$$

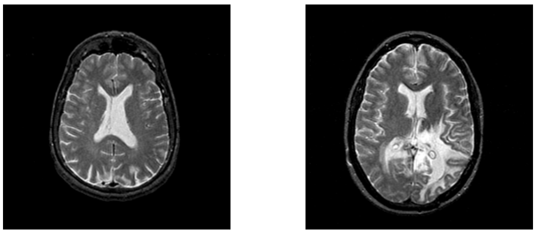
Table 1. Confusion matrix defining TP, TN, FP and FN.

Expected Outcome	**Actual Data**		**Row Total**
	Tumor	**Normal**	
Tumor	TP	FP	TP+FP
Normal	FN	TN	FN+TN
Column Total	TP+FN	FP+TN	TP+FP+FN+TN

Results and Discussion

The proposed work is carried out on MATLAB 2016a by using different image processing tool boxes and worked under Windows 8.1 with Intel Core i3 processor which having 2GHz speed and 4GB RAM. This research gives the results of each processing step involved in the detection and classification of brain tumor from T2-W MRI images using proposed techniques.

Initially the brain T2-W MRI images are acquired from publicly available databases such as BrainWeb and Harvard Medical School datasets. Note that there are no medical ethical issues by using publicly available datasets. The datasets contains normal and abnormal images in the form of different pulse sequences. Due better visual quality we considered T2-W images and acquired 155 slices of different types of brain images with different diseases along with normal images. The sample acquired images of T2-W brain MRI images are shown in figure 3. Fig 3(a) is normal brain sample and 3(b) is abnormal sample. In the preprocessing the input acquired image is resized into 256x256 and then converted into gray scale form if the input is in color forms. Later it is enhanced by removing the noise and different artefacts using the median filter as shown in figure 5(b), it makes easy the further processes involved here. The proposed cuckoo search optimization technique segmented the MRI images and separated the GM, WM, CSF, and tumor. The tumor appears very clear. Figure 4 gives the normal image segmentation results such as gray matter, white matter and CSF from fig 4(b) to (d) respectively. The sub-images obtained individually indicate the gray matter (GM), white matter (WM) and cerebrospinal fluid (CSF) respectively. In T2-W, the GM has darker pixel intensities, almost black pixel intensities for WM and brighter pixel intensities for CSF.



a). Normal Image b). Abnormal Image

Fig 3. Sample T2-W brain MRI images

In this research work cuckoo search optimization technique with multiple thresholding levels are used for segmenting the T2-W brain MR images.

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a). Normal T2-W brain MRI input b). Gray matter c). White matter d). CSF

Fig 4. Segmented results of normal T2-W brain MRI image such as GM, WM and CSF

a). Input T2-W brain MRI image b). Enhanced image using Median filter c)Segmented image by CSO d) Morphological processed image e) Extracted tumor

Fig 5. Results of various steps involved in the proposed system

As shown in figure 5, the abnormal is shown in (a) and from (b) to (e) gives the various results of different steps involved in the proposed tumor detection and classification algorithm such as enhanced image using median filter, CSO based segmented image, morphologically opened image and extracted tumor images respectively.

The tumor region is identified and extracted the relevant features. The area of the tumor is calculated and compared in terms of pixels and mm^2. The PSNR, MSE and computational time also determined. From the observation, a lower value of MSE and higher value of PSNR obtained using proposed technique, these matrices indicates good amount of noise elimination from the image and better signal to noise ratio in the extracted image. The computational time is also very less compared with existing techniques.

Table 2. Comparison of the performance metrics with existing techniques

Parameter / **Technique used**	**PSNR**	**MSE**	**Tumor area**	**No of defected pixels**	**Computational time (sec)**
Region Growing [7]	14.0110	6.1210	16.3786	3849	-
K- Means [5]	36.9922	12.9975	11.2750	1824	125.00
Genetic algorithm [10]	40.0310	6.4560	-	-	-
PSO [11]	60.0714	0.0640	14.3486	2954	7.2839
Proposed CSO	60.4546	0.0586	14.4068	2978	5.2519

The proposed SVM classifier classifies the normal and abnormal images very accurately. The performance parameters and classification rates of the SVM for selected 155 T2-W MRI images of brain are shown in table 2. The classification rates are obtained as TP is 95, TN is 59, FP is 1 and FN is 0. With that values the sensitivity, specificity and accuracy is 100, 98.3333 and 99.3548 respectively. Similarly the precision, recall, F1 score and dice coefficient is obtained as 98.9583, 100, 99.4764 and 99.4764. Here F1 score and dice coefficient obtained is same and recall and sensitivity also equal.

Table 3. Results of classification rates

Total number of brain images 155 (60 normal and 95 abnormal)	
TP	95
TN	59
FP	1
FN	0
Sensitivity	100
Specificity	98.3333
Accuracy	99.3548
Precision	98.9583
Recall	100
F1-score	99.4764
Dice Similarity Index	99.4764

Conclusion and Future scope

In this study we segmented brain tissues into normal tissues such as white matter, gray matter, CSF and tumor-infected tissues. We use preprocessing to reduce the effect of unwanted noise captured during the acquisition of MRI and improve the quality of raw MRI. The best possible segmentation results obtained based on various numbers of levels and various numbers of iterations. The global best solution while searching is considered as threshold level. Multi-level thresholding using CSO reduces the complexity in processing the data. GLCM features are determined and LBP operator converts the image into integer labels describing small-scale textures of the image. So reduces the dimensionality of the segmented image. Finally SVM classifier classifies the feature extracted image. The experimental results achieved 99.3548 % of accuracy, 100% of sensitivity and 98.3333% specificity using SVM classifier. Our experimental results show that proposed approach can aid in the accurate and timely detection of brain tumor along with identification of brain tumor. Thus proposed approach is significant, reliable and robust for brain tumor detection from MRI images. The future work is used to reduce the MSE, improve the PSNR, accuracy and sensitivity and specificity using hybridizing the advanced algorithms.

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