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Robust classification of Multi Class brain Tumor in MRI images using Hybrid Descriptor and Pair of RBF Kernel – SVM

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Abstract

In medical imaging, detecting and classifying the brain tumors in Magnetic Resonance Image (MRI) is a demanding and critical task. MRI gives anatomical structure's information, and the potential abnormal tissues' information. Thus, this paper proposes a new system for MRI brain tumor segmentation and classification. This work includes the following stages: preprocessing, segmentation, extraction of feature, selection of a feature, and classifying the images. Removing of Speckle and white Gaussian noise in the given MRI images is done in the preprocessing stage, by using the Distribution based Adaptive Filtering (DAF) technique. It smoothens the image by removing the noise and enhancing the intensity of the image. In segmentation stage, the clustering and label formation processes are performed to predict the tumor part. Here, the Neighboring Cellular Automata (NCA) model is proposed for clustering. Then, the labels such as Back Ground (BG), border area, Gray Matter (GM) and White Matter (WM) are formed for the clustered image. Hence, the features of the segmented image are extracted by using the Differential Binary Pattern (DBP) technique. After extracting the feature vectors, the firefly optimization technique is employed to select the best features. After selecting the set of features, the Pointing Kernel Classifier (PKC) is employed to classify both the abnormal and normal brain images and the type of brain tumors. The performance of the proposed method is evaluated using sensitivity, specificity, accuracy, correction rate, positive likelihood and negative likelihood.

Keywords: Brain Tumor; Distribution based Adaptive Filtering (DAF);Magnetic Resonance Image (MRI);Differential Binary Pattern (DBP); Gray Matter (GM); White Matter (WM) and Pointing Kernel Classifier (PKC).

INTRODUCTION

Brain is an important organ in the human body that contains different parts such as Gray Matter (GM), White Matter (WM), Cerebrospinal Fluid (CSF) and background. The cells in the human body have the property to multiply them, due to this property, the overall operations of the brain is in a controlled manner. When the multiplicity of the cells gets out of control, the growth cells became abnormal and known as a brain tumor. A brain tumor sometimes may prove fatal due to abnormal growth of the tissues. In which, the cells grow, multiply uncontrollably and controls the normal cells. The brain tumor is classified into the following types:

- Benign
- Malignant

A benign tumor is non-cancerous, so it is rarely life threatening, in which the tumor does not occupy the nearby tissues and other body parts. Due to their position, it is can cause some complications, so the radiation and surgery can be useful. Malignant is also known as brain cancer that can be extended outside of the brain. Moreover, the brain malignancies are categorized into two types such as,

- Primary brain cancer
- Secondary brain cancer or Metastatic

The primary brain cancer can originate from the brain, and metastatic cancer can spread from the body to the brain. In medical image processing, Magnetic Resonance Imaging (MRI) plays an essential role that provides the detailed anatomical information of any part of the body. It is an important diagnostic tool for tumor, cancer, and other dangerous diseases. The normal and abnormal brain images are shown in Fig 1(a) and (b).

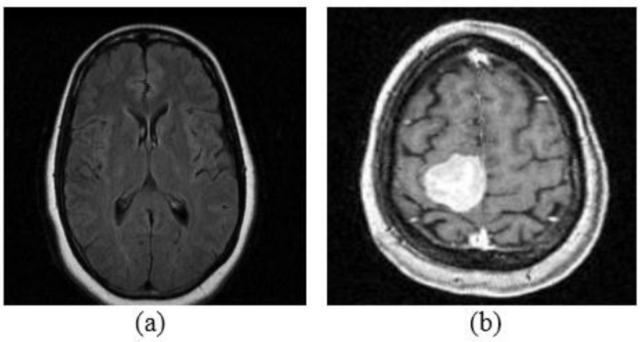


Figure 1 (a). Normal MRI brain image and **(b).** Abnormal MRI brain image

Under certain conditions, brain cells grow and multiply uncontrollably because for some reasons. The mechanism that controls normal cell is unable to regulate the growth of the brain cells. In the skull space is occupied by the abnormal mass of brain tissue called the brain tumor. Normal functioning of the brain is interrupted, and an enhancing pressure in the brain is created. Its threat level depends on a combination of factors like the type of tumor, size, location and state of development. This paper introduces an effectual brain tumor detection technique from MR images. At first, the given MRI is preprocessed by using the Distribution based Adaptive Filtering (DAF) technique, which effectively removes the noise in the image. Then, the preprocessed image is segmented by performing the clustering and label formation processes. Hence, the features of the segmented image are extracted by using the Differential Binary Pattern (DBP) technique. After that, the best features are selected from the extracted features with the help of Firefly optimization technique. Finally, the proposed Pointing Kernel Classifier (PKC) is employed to classify the normal and abnormal brain image. It also classifies the type of tumors such as benign, malignant and metastatic.

The remaining sections of this paper are organized as follows: Section II reviews some of the existing works related to brain tumor segmentation and classification. Section III gives the detailed description of the proposed system. Section IV presents the performance and comparison results of both existing and proposed brain tumor classification systems. Finally, the paper is concluded, and the future work to be carried out is stated in Section V.

RELATED WORK

This section presents some of the existing works related to brain tumor segmentation and classification in medical image processing.

Kong, et al. [1] suggested a discriminative clustering method for segmenting the MRI brain tumor. In this paper, an Information Theoretic Discriminative Segmentation (ITDS) method was proposed for selecting the feature and clustering of data at the super voxel level. The major objectives the work were listed as follows:

- For brain tumor segmentation, the informative features were selected, and the uncertainties of super voxel assignment were reduced simultaneously.
- The mutual information of super-voxels was maximized with the help of ITDS.
- Moreover, a logistic-like probabilistic classifier was employed to maximize the latent clustering labels of the super-voxels.

Roy and Bandyopadhyay [2] suggested a fully automatic system for brain tumor detection and quantification. The proposed interactive segmentation method was used efficiently to segment the tumor portion in the MRI brain region. This method combined the region and edge information, so it provides the advantages of both approaches. Azhari, et al. [3] developed an automatic brain tumor detection and localization framework to detect and localize the tumor in MRI brain image. This work includes the following stages:

- Noise elimination
- Edge detection for region identification
- Modified histogram clustering and morphological operations

Roy, et al. [4] studied various automated brain tumor detection and segmentation techniques for the MRI brain images. Here, different types of filtering techniques were reviewed such as,

- Min-max median filter
- Center-weighted median filter
- Adaptive median filter
- Progressive switching median filter

In this work, the advantages and disadvantages of these techniques were also discussed. Tamil selvy, et al. [5] analyzed different clustering techniques to track the tumor objects in the MRI brain image. The algorithms reviewed in this paper were listed as follows:

- K-means
- Self-Organizing Map (SOM)
- Hierarchical clustering
- Fuzzy C-Means (FCM)

This work includes the following stages:

- Pseudo color translation
- Color space translation
- Implementation of clustering algorithms
- Cluster selection
- Histogram Clustering
- Region elimination

Malathi and Kamal [6] proposed an efficient K-Means clustering technique for MRI brain tumor identification and detection. This work includes the following stages:

- Image acquisition for quality enhancement
- Segmentation using k-means clustering
- Tumor detection

Fernandez and Simon [7] proposed Model of Population and Subject (MOPS) for detecting lesions. Local signal intensity characteristics were considered for this purpose. This approach was a combination of global intensity model and local intensity model. Local intensity model was derived from an aligned set of healthy reference subjects. Zhan, et al. [8] suggested a fast and effective method for automatic segmentation of white matter lesions with the help of T1 and Fluid Attenuated Inversion Recovery (FLAIR) image modalities. This work includes the following stages:

- In the initial stage, the z-score of the image pixels were calculated to distinguish the abnormalities from the brain tissues.

- In the second stage, the level set was initialized, and the prior knowledge was generated by using the preliminary lesion segmentation method.

Demirhan, et al. [9] proposed a "robust segmentation method" for segmenting brain MRI's into a tumor, edema, White Matter (WM), Gray Matter (GM) and Cerebro Spinal Fluid (CSF). In this paper, the threshold and morphological operations were combined to strip the skull. Here, Stationary Wavelet Transform (SWT) decomposed the images into sub-bands. Hence, to obtain the feature vector, spatial filtering methods were applied, and segmentation operation was performed using an unsupervised Self-Organizing Map (SOM) framework. Roy, et al. [10] presented a "patch based sparse dictionary learning" method for MR brain segmentation. Here, the patches of single voxel intensities were used to improve the discrimination of anatomical structures. Datteri, et al. [11] proposed a new algorithm, namely, Assessing Quality Using Image Registration Circuits (AQUIRC) for the identification of non-rigid registration errors. Here, the Local Normalized Correlation Coefficient (LNCC) was used for evaluating the performance of the system. The registration error between two images cannot be predicted with a single circuit; thus, this work focused on predicting the error by using the multiple circuits. Van Opbroek [12] suggested four different transfer classifiers. These, with a small amount of training data, were used for training a classification scheme. Here, a new machine learning approach, namely, transfer learning was proposed to perform the segmentation process. This learning approach identified the similarities between different classification problems for facilitating the construction of a new classification model. Mustaqeem, et al. [13] proposed a new watershed and thresholding based segmentation technique for efficient brain tumor detection. This system includes the following stages:

- Image acquisition for quality enhancement
- Post processing
- Segmentation

Here, the quality of the given MRI image was enhanced at the initial stage, and then tumor detection was done by applying morphological operators. Jain [14] suggested a Gray Level Co-occurrence Matrix (GLCM) technique for feature extraction to classify brain cancer. This work includes the following stages:

- Noise removal
- Morphological operations
- Region isolation
- GLCM based feature extraction
- Back Propagation Learning Network (BPN) based classification

Bron, et al. [15] improved the Support Vector Machine (SVM) technique with feature selection for Dementia classification. Moreover, two novel feature selection methods were introduced in this paper such as direct approach (filtering) and an iterative approach (wrapper). Afshin, et al. [16] developed a flexible hybrid model to improve the prediction power and reproducibility of the functional MRI (fMRI) data classification and visualization system. Here Linear Discriminative Analysis (LDA)'s optimization functions were added along with weights and a Generalized Canonical Correlation (gCCA) model was also considered. Song, et al. [17] suggested a "Large Margin Local Estimate (LMLE)" method based on the sparse representation for medical image classification. Here, by using the large margin aggregation, the authors calculate how far the test image from the local estimate is. In this paper, the pipeline of image classification contains two stages, which includes: feature extraction and classification. In feature extraction stage, the enhancement of descriptiveness and discriminative power of features were concentrated with the help of feature descriptors. In the classification stage, a scheme that would efficiently classify feature was designed to include the complexity of feature space.

Harmouche, et al. [18] proposed a new automatic probabilistic method for the classification of Multiple Sclerosis (MS) lesion in the brain image. Here, the authors aimed to classify both the T1-hypointense and the T2-hyperintense lesions in the brain image. In this work, the false positives in the classification result were eliminated by using the posterior probability distribution and entropy. Kharat, et al. [19] suggested the neural network based method for brain tumor classification. This work includes the following stages:

- In the initial stage, the features related to the MRI image were obtained with the help of Discrete Wavelet Transformation (DWT).
- In the next stage, the features of MRI were reduced to the more important features by using the Principle Component Analysis (PCA) approach.
- In the classification stage, there were two different classifiers such as Feed Forward Artificial Neural Network (FF-ANN) and the Back Propagation Neural Network (BPNN) were used for tumor classification.

Sangeetha [20] developed the Probabilistic Neural Network (PNN) based classification technique to classify the types of brain tumors such as benign and malignant accurately. In this work, the Discrete Cosine Transformation (DCT) technique was utilized for feature selection. This system includes the following stages:

- Image decomposition
- Feature extraction and selection for region identification
- Training and classification for tumor detection

PROPOSED METHOD

This section presents the detailed description of the proposed PKC based MRI brain tumor detection and classification system. The main intention of this work is to detect the portion of the tumor and to classify the type of tumor. For this purpose, the Differential Binary Pattern (DBP) based feature extraction technique and the PKC based classification techniques are proposed in this paper. The overall flow of the proposed system is shown in Fig 2.

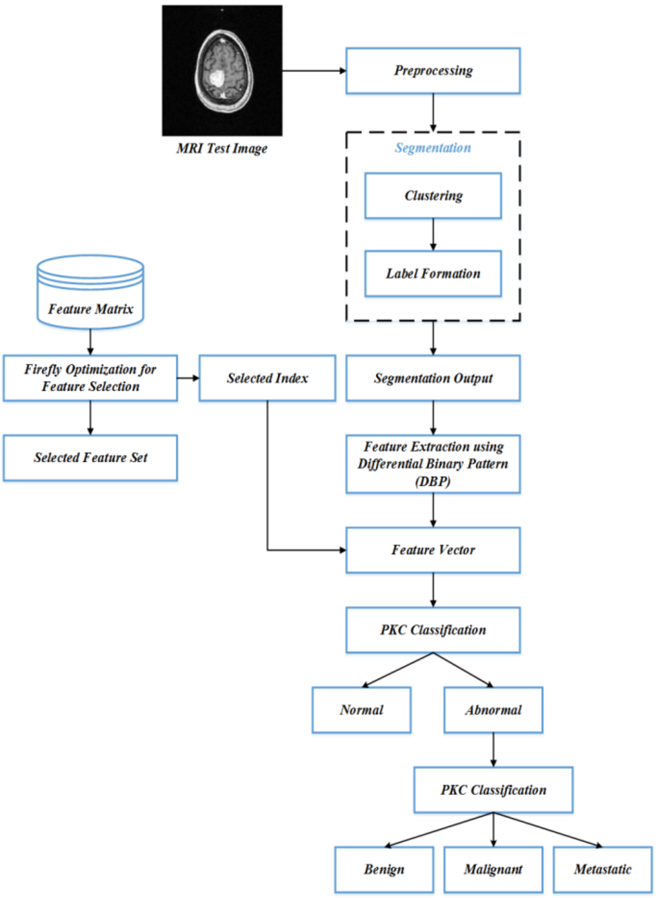


Figure 2. Overall flow of the proposed system

The proposed work includes the following stages:

- Preprocessing
- Segmentation
- Feature extraction
- Feature selection
- Classification

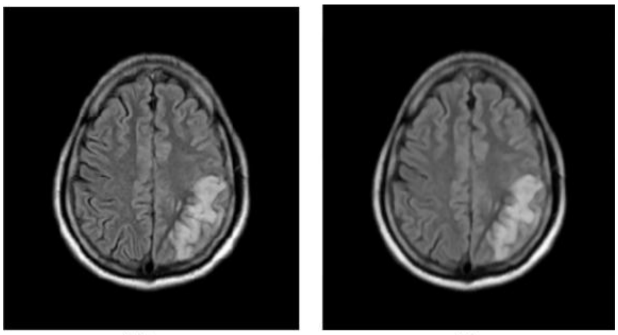
A. Preprocessing

Preprocessing is an important and initial step in any image processing applications. It is defined as the process of removing noise and enhancing the quality of the image. Due to a diagnostic and therapeutic application, noise cannot be easily removed. So, it is a critical process specifically in MRI due to the external noise, inhomogeneous magnetic field, and patient motion. These are all the artifacts that cause the computational errors. Therefore, it is important to remove the noise in the image during preprocessing. In this work, a novel filtering technique, namely, Differential based Adaptive Filtering (DAF) technique is proposed to preprocess the given MRI image. It comprises the following steps:

- Noise Removal
- Background Normalization

1) Noise Removal

Different types of noises corrupt the medical images, so it is very important to obtain precise images to simplify the correct observation. In this work, the noise removal is done by the DAF technique. Using the median filtering noise is minimized and also useful details of the image is preserved. The drawback of the existing median filter is, it is useful for non-linear image smoothing, but it does not state the difference between the noise and fine details. Thus, this work proposed a DAF technique to determine the image pixel that affected by the impulse noise. In this technique, each pixel in the image is compared to its surrounding neighbor pixels by classifying the pixels as noise. Then, these pixels are substituted by the value of the median pixel by neighbor pixel. Image smoothening is a necessary functional module that improve the quality of the image by removing the noise. The input MRI image is shown in Fig 3 (a), and the preprocessed image is shown in Fig 3 (b).



(a) (b)

Figure 3 (a). Input MRI image and **(b).** Filtered MRI image

Algorithm I – Distribution based Adaptive Filtering

Input: *Input MRI brain image B;*
Output: *Preprocessed image P;*
// Where, a and b are the row and column iteration respectively;
Step 1: Initialize window size(3 ×3);
Step 2: Project window over image matrix as,
Temp = M (a-1: a+1, b-1: b+1);
Step 3: Check neighboring pixel variation;
Step 4: S = sort (Temp);
// Where, s indicates the sorted neighboring borders;
Step 5: If S(1) < median (S) && median (S) < S (9) && 0 < median (S) && median (S) < 255
P (a, b) = median (S);
End if;
Step 6: If S(1) >= median (S) || median (S) >= S(9) || median (S) == 255 && median (S) == 0
P (a, b) = P (a, b-1)
End if;

2) Background Normalization

In background normalization, the following processes are performed:

- Edge detection
- Skull area removal

a) Edge Detection

Here, the Canny edge detector is used to detect the edges of the MRI brain image. It is also known as the optimal edge detector that detects the edges based on certain criteria. It includes the following processes:

- It finds the edges by reducing the error rate
- It maximizes the localization by marking the edges as closely as possible to the actual edges
- When a single edge exists for a minimal response, it marks the edges only once.

Moreover, this detector smoothens the given image by removing the noise for detecting the edges of the brain. For this purpose, it computes the gradient of the image through convolution in the horizontal and vertical directions. The main intention of edge detection is to convert the blurred edges of the gradient magnitude to the sharp edges. The detected edge for the given image is shown in Fig 3(c).

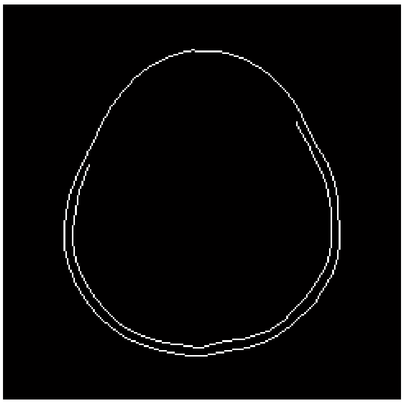


Figure 3(c). Edge detection

The advantages of DAF are listed as follows:

- It effectively removes the impulse noise
- It smoothens the other noise
- Moreover, it eliminates the distortions such as, excessive thinning and thickening of objects

b) Skull Removal

After detecting the edges, the morphological operations such as erosion and dilation are applied to remove the skull in the MRI brain image. In this stage, the acquired MRI is taken into consideration, where the outer part of the brain is known as a skull that must be removed. Because, it affects the result of seed point selection. The skull removal is also defined as the removal of the non-cerebral brain tissues. In brain imaging applications, it has been one of the major key processing phases. Due to the homogeneity nature of skull, segmentation of non-cerebral and the intracranial tissues are the main problems in skull removal. Moreover, the skull is defined as an unused part of the brain for abnormality detection, and it does not contain any soft tissues. So, the removal of the skull from the brain image avoids the chances of erroneous results. The erosion and dilation are the two main operators in the mathematical morphology. An erosion is a technique that uses both the foreground and background for skull removal. During erosion, some cerebral tissues are distorted due to the presence of false background, thus, the dilation process is applied for restoration. These operations make the skull removal as more efficient by differentiating the false background with the original background.

B. Segmentation

After that, the preprocessed image is segmented to identify the region of the tumor. In medical image processing, segmentation is an essential process that extracts the information from complex medical images. It is defined as a process of partitioning a set of pixels to simplify the representation of an image. The main intention of segmenting the images is to segregate the given image into exhausted and commonly exclusive regions. Here, the segmentation process is done in two stages such as:

- Clustering
- Label formation

1) Clustering

Clustering is one of the most widely used segmentation technique in medical image processing. It is a tool that divides the data into the groups of similar objects. It is defined as the form of data compression that converts a large number of samples into a small number of representative prototypes or clusters. The cluster is defined as a collection of objects that similar between them and dissimilar to the other clusters. In this paper, a new clustering technique, namely, Neighboring Cellular Automata (NCA) model is proposed for identifying the neighbor's pixel intensity variation. This most widely used model for parallel computation, which contains a grid of cells that are uniformly connected with each other.

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Algorithm II – Neighboring Cellular Automata (NCA) for segmentation

Input: *Filtered image P;*
Output: *Segmented image Y;*
Step 1: *Initialize mapping value of image cluster by estimating maximum and standard deviation of image pixel intensity as,*

$$Mp = \{\max(P), std\ (P)\}$$

Step 2: $Mw = RAnd\ (8,8)$ *// Initialize random Map window for clustering.*

Step 3: $[Wx, Wy] = \begin{cases}(i,j) & \sum\sqrt{Mw\ (i,j) - Mp^2} \\ 0 & Otherwise\end{cases}$

// Where, i and j are row and column size of Map window
Step 4: *Initialize Radius R = rand; // This radius limit of moving window for updating cluster weight;*
Step 5: *Cluster weight extraction*

$$Cw = R * e^{-\sqrt{\frac{(x-Wx)^2+(y-Wy)^2}{(2*R)}}}$$

Step 6: *Update mapping window by,*

$$Mw_{i,j} = Mw_{i,j} + (Cw * Mw_{Wx,Wy}) - Mw_{x,y}$$

Step 7: *Update the radius according to cluster weight as,*

$$R = 1 + \left(\frac{0.99}{0.99+(0.01*t)} - 1\right) * 0.1$$

// Where, t represents the number of iteration. Since the radius value was
Step 8: *Difference in cluster weight extraction as,*

$$D = Mw_i - Mw_j$$

Step 9: *Extract minimum cluster index of D*

$$[a, b] = \min(D)$$

Step 10: *Extract index of cluster from mapping matrix*
For i=1 to size (Mw)
If (a > 0 && a < R)

$$Cent\ (i) = \frac{Mw\ (i) + Mw\ (b)}{2}$$

Idx (b) =0;
D (b, i) = 0;
[a, b] = min (D);
End if;
End i loop;
Step 11: *Project the indexed cluster over image and find the best matching of image pixel with clustering matrix as,*

$$[Vec, Index] = \min((P - Cent_i)^2$$

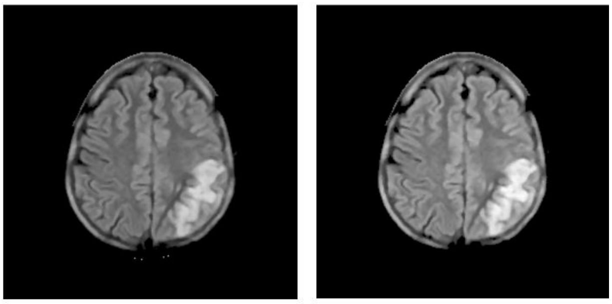
Step 12: *Segmented indexed image* $Y = \sum P\ (Index)$

2) Label Formation

After clustering, the labels of the brain image are formed, which includes:

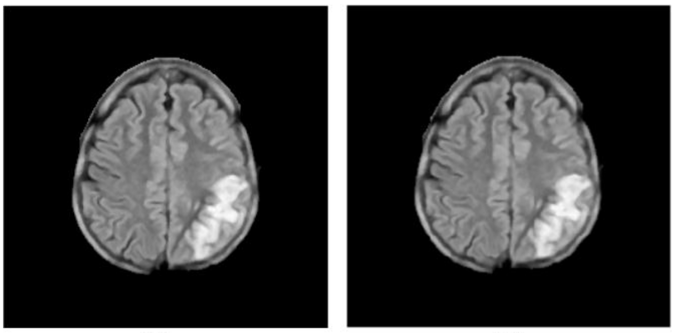
- Back Ground (BG)
- Boundary detection
- Gray Matter (GM)
- White Matter (WM)

Here, the exact boundary portion is detected by segmenting the enhanced cells for the proper treatment. Moreover, the functionality of the brain is studied by segmenting the WM from the GM. It helps to identify, disparate activities of the active part of the brain at a particular time. The GM and WM both are important components of the brain, where the GM is made up of neural cell bodies. It has a gray-brown color that comes from the neuron cell bodies and the capillary blood vessels. The main function of GM is to create a response to the stimulus through chemical synapse activity. Hence, the WM is composed of bundles of nerve cell processes that connect various gray matter areas of the brain. Because of the fatty substance, the WM is white that surrounds the nerve fibers. It is the tissue that pass the messages between the areas of GM within the nervous system. Thus, the GM and WM are detected for segmenting the tumor portion. The boundary region of the image is shown in Fig 4 (a), and the removal unwanted boundary is depicted is shown in Fig 4 (b). The normalized background image and the enhanced original brain image are shown in Fig 4 (c) and (d). The clustered output and the labeled output are shown in Fig 4 (e) and (f). Finally, the segmented area of the given MRI brain image is shown in Fig 4 (g).



(a) (b)

Figure 4 (a). Boundary region of the image and **(b).** Unwanted boundary removal



(c) (d)

Figure 4 (c). Background normalization and **(d).** Enhanced image

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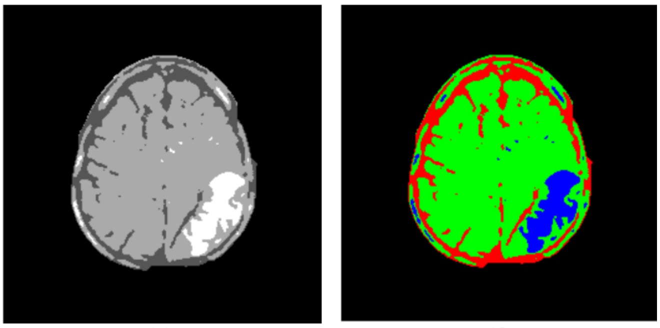

(e) (f)

Figure 4 (e). Clustered output and **(f).** Labeled output

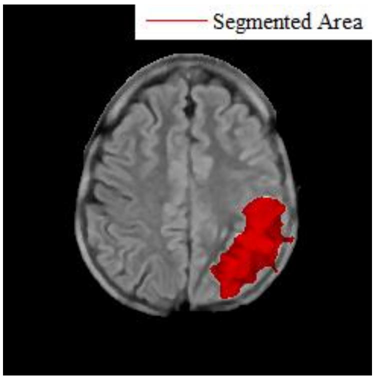

Figure 4 (g). Segmented area

C. Feature Extraction

Feature extraction is defined as a form of dimensionality reduction that transforms the input data into a reduced representation set of features. The main objective extracting the features of the image is, to reduce the original data set by measuring the properties. It provides the characteristics of the image by considering the description of relevant properties to the classifier. Here, the feature extraction process is used to estimate the brain parameters such as entropy, energy, contrast and correlation. In this work, a new technique, namely, Differential Binary Pattern (DBP) is used to extract the features of the segmented MRI image. DBP is a local texture operator that has low computational complexity and low sensitivity. Furthermore, it is invariant to monotonic gray scale transformation, because it is less sensitive to changes in illumination. In this method, the number of neighboring sample points is not limited. The example of DBP feature extraction process is shown in Fig 5(a). Here, each pixel of the image is labeled with a DBP code. The major advantages of this work are, it is more accurate, sparse and easy to compute. The resultant image after extracting the features is shown in Fig 5 (b).

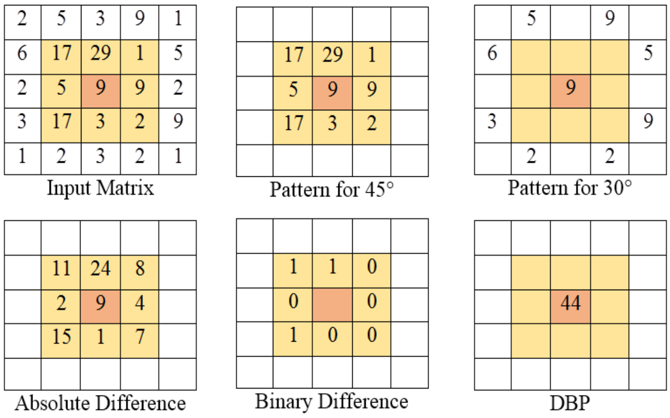

Figure 5 (a). Example for DBP feature extraction

Algorithm III – Differential Binary Pattern (DBP) for feature extraction

Input: *Filtered image P;*

Output: *Dataset feature Lt;*

Step 1: *Initialize* 5×5 *window and project it on the input image.*

Step 2: *Choose 8 neighboring pixels* I_n *around the central pixel* I_c *for each* 45°.

Step 3: $I_{d1} = (I_c - I_n)$ *// Compare center pixel value* I_c *with its neighbor* I_n *for angle* 45°.

Step 4: *Choose 8 neighboring pixels* I_g *around the central pixel* I_c *for the set of,*

$$\theta = \{30°, 60°, 120°, 150°, 210°, 240°, 300°, 330°\}$$

Step 5: $I_{d2} = (I_c - I_g)$ *// Compare center pixel value* I_c *with its neighbor* I_g*;*

Step 6: $I_b = \begin{cases} 1, & (I_{d1} - I_{d2}) \geq 0 \\ & 0, else \end{cases}$ *// Extract binary pattern*

Step 7: $I_{dec} = Decimal\ (I_b)$ *// Convert binary to decimal*

Step 8: *Lt = Histogram* (I_{dec}) *// Histogram feature vector of image pattern*

D. Feature Selection

After extracting the features of the segmented MRI brain image, the best features are selected by using the firefly optimization technique.

Figure 5 (b). Texture pattern extraction

Feature selection is defined as a process of subset selection that is widely used in machine learning applications. It is a meta-heuristic, nature-inspired optimization technique, which is based on the social behavior of fireflies. To attract the fireflies, it uses the flashing as a signal. Moreover, it contains three idealized rules based on the major characteristics of fireflies, which are listed as follows:

All fireflies are unisex so that every firefly will be attracting each other fireflies irrespective of gender.

The degree of a firefly is proportional to its brightness that decreases the distance.

The brightness of a firefly is determined by the value of the objective function.

In this analysis, the firefly optimization technique is used to select the reduced set of features based on the intensity value. Using Firefly optimization problems are solved since it is a swarm-based algorithm.

Algorithm III – Firefly optimization

Input: *Feature matrix Tf;*

Output: *Selected Training feature Tr;*

Step 1: *Initialize* α *= 0.2,* γ *= 1.0,* β *= 1.0; //* α *,* β *and* γ *are the firefly light intensity;*

Number of particles n = size of Tr;

Number of grids m = 100;

Step 2: *Initialize population of fireflies,*

$X = x_{(i=1,2,\dots,n)};$

Step 3: *Initialize light intensity* $I = rand\ (Tf);$

Step 4: *Extract observation coefficient* γ_1

Step 5: *Update coefficient as,*

$\gamma_1 = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2};$ *// Where, i =1, 2, 3 … n; // Where, i = 1, 2, 3 … n and j = 1, 2, 3 … m;*

Step 6: $If\ (I\ (i) < I\ (j))$ *then // Check best light intensity;*

Step 7: $\beta = 1 * e^{(-\gamma * \gamma_1^2)}$*;* *// Update beta value;*

Step 8*:* *Update coordinates;*

x position, $x_n = x_n(i) * (1 - \beta) + x_n(j) * \beta + \alpha * (rand - 0.5)$

y position, $y_n = y_n(i) * (1 - \beta) + y(n) * \beta + \alpha * (rand - 0.5)$

Step 9: *Update light intensity I;*

Step 10: *ft = I (x, y);* *// Extract fitness value;*

Step 11: $idx = \min(ft);$ *// Extract best fitness value;*

Step 12: $Tr = Tf\ (idx)$*;* *// Selected best feature*

E. Classification

Due to the complexity and variance of tumors, classification of MRI brain tumor is a demanding task. Thus, this work proposes a novel technique, namely, Pointing Kernel Classification (PKC) to classify the normal and abnormal brain images. It is also used to classify the tumor and multi-sclerosis images.

Algorithm IV – Pointing Kernel Classification (PKC)

Input: *Dataset feature Lt, Label index Lb and Training data Tr;*
Output: *Classified results Rt;*
Step 1: **for** *(R =1 to size (Lt)) // Where, R represents the row size of the dataset feature;*
Step 2: **for** *(C =1 to size (Lt)) // Where, C represents the column size of the dataset feature*
Step 3: $L_1 = Tr^{-1}Lt(x,y) + O$ *// Where, O represents the offset parameter*
Step 4: $K = Tr^{-1}\emptyset(x)$ *// Kernel function for* $\emptyset(x)$ *linear to non-linear;*
Step 5: **for** *(i =1 to size (Lt))*
Step 6: **for** *(j=1 to size (Tr))*
Step 7: $Tr_{ij} = K_{ij} + \rho_{ij} = Tr^{-1}\emptyset(x) + \rho_{ij}$ *// Where, training feature with some neighboring link parameter* ρ_{ij}*;*
Step 8: ***end for*** *j*
Step 9: ***end for*** *i*
Step 10: $P_i(Tr) = \frac{1}{(2\pi)^{\frac{n}{2}}}\frac{1}{N_i}\sum_{i=1}^{N_i} e^{\left[-\frac{(Tr_i - Tr_j)^{-1}(Tr_i - Tr_j)}{2\sigma^2}\right]}$ *// Probability distribution on training set Tr with kernel for neighboring features*
Step 11: ***if*** $(I_{RC} > P(Tr))$ *// Estimate classified label*
Step 12: $Rt_{RC} = Lb(P(Tr));$
Step 13: ***end if***
Step 14: *End for C*
Step 15: *End for R*

PERFORMANCE ANALYSIS

This section presents the performance and comparison results of both existing and proposed techniques. Here, the performance of both existing and proposed techniques are evaluated regarding False Acceptance Rate (FAR), False Rejection Rate (FRR), Genuine Acceptance Rate (GAR), accuracy, sensitivity, specificity, precision, recall, Jaccard, and dice similarity. The datasets used in this work are Internet Brain Segmentation Repository_ Version 2 .0 (IBSR_V2.0) [21] and BrainWeb [22] has brain MRI data. It gives segmentation results just like experts and also are manually guided.

A. ROC for Classification

Receiver Operating Characteristics (ROCs) are produced by plotting the fraction of true positives out of the total actual positives (TPR) and the fraction of the false positives out of the total actual negatives (FPR) at different thresholds. TPR is defined as the True Positive Rate, and FPR is the False Positive Rate. Fig 6 shows the ROC curve, which is a plot of the true positive rate against false positive rate for all possible systems and calculates the entire performance of the system

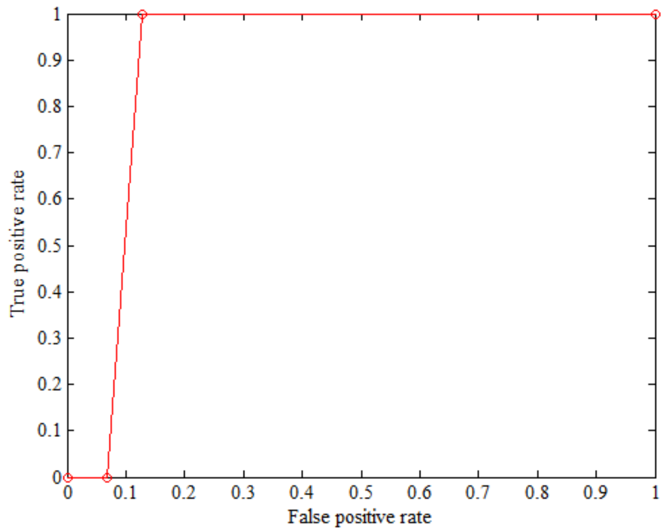

Figure 6. ROC for classification

B. False Rejection Rate

The False Rejection Rate (FRR) is defined as the measure of the probability that the PKC classification system will incorrectly reject the untruthful results and it is calculated as follows,

$$FRR = \frac{\text{The number of false rejections}}{\text{The number of identification items}} \quad (1)$$

The graphical representation of FRR with respect to number of image classes are shown in Fig 7.

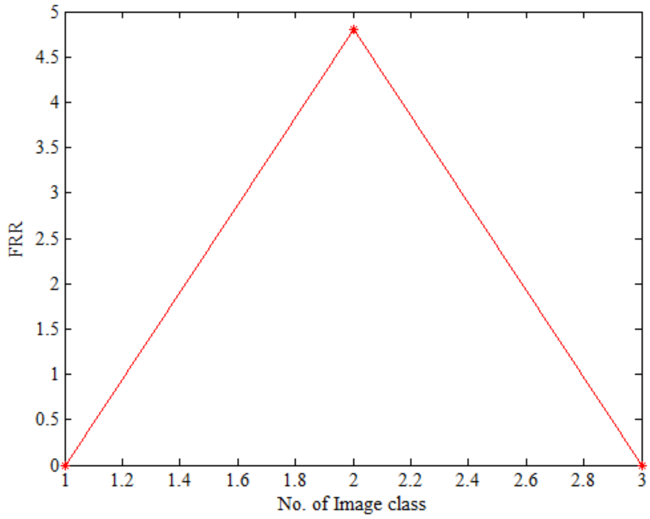

Figure 7. False Rejection Rate (FRR)

C. *False Acceptance Rate (FAR)*

The False Acceptance Rate (FAR) is the measure of the probability that the PKC classification system will incorrectly accept the untruthful results and it is calculated as follows,

$$FAR = \frac{\text{The number of false acceptances}}{\text{The number of identification items}} \quad (2)$$

The graphical representation of FAR with respect to number of image classes are shown in Fig 8.

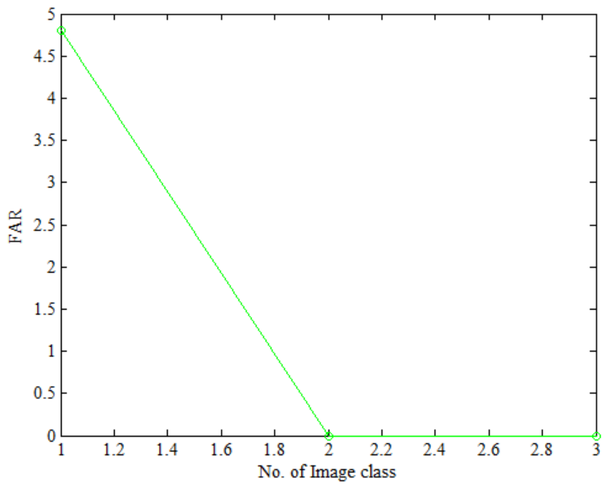

Figure 8. False Acceptance Rate (FAR)

D. *Genuine Acceptance Rate (GAR)*

GAR is defined as the (1-FRR) that is shown in Fig 9, and it is evaluated as follows:

$$GAR = 1 - \frac{\text{The number of false rejections}}{\text{The number of identification items}} \quad (3)$$

The graphical representation of GAR with respect to number of image classes are shown in Fig 9.

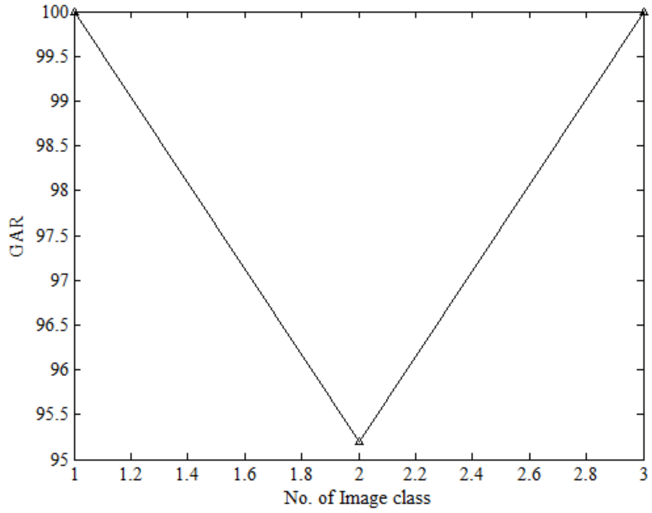

Figure 9. Genuine Acceptance Rate (GAR)

E. *Sensitivity, Specificity, and Accuracy*

Fig 10 shows the sensitivity and specificity rate of proposed PKC classification technique. Sensitivity is defined as the proportion of true positives that are correctly identified by PKC classifier, which is expressed in terms of percentage. Moreover, it is the probability of getting a positive test result in subjects. The specificity is the number of true negative results divided by the sum of the numbers of true negative plus false positive results. The sensitivity is calculated by using,

$$Sensitivity = \frac{TP}{(TP+FN)} = \frac{\text{Number of true positive assessments}}{\text{Number of all positive assessments}} \quad (6)$$

$$Specificity = \frac{TN}{(TN+FP)} = \frac{\text{Number of true negative assessment}}{\text{Number of all negative assessment}} \quad (7)$$

Where, TP - True Positive, TN – True Negative, FP – False Positive, FN – False Negative. In this analysis, the sensitivity rate is increased by 95.19%, and 97.59% is the increase in specificity rate. From this analysis, it is observed that 95.19% is the increase in the level of accuracy by using the PKC classification. The accuracy analysis graph is shown in Fig 10. The results of the MRI brain image processing returns a result with an accuracy commensurate with the sub-pixel resolution, whose reproducibility can be deducted from the frequency of occurrences. Sensitivity and specificity can determine the accuracy of PKC classifier with the presence of prevalence. The accuracy level is calculated by using,

$$Accuracy = \frac{(TN+TP)}{(TN+TP+FN+FP)}$$
$$= \frac{Number\ of\ true\ correct\ assessment}{Number\ of\ all\ assessment} \quad (8)$$

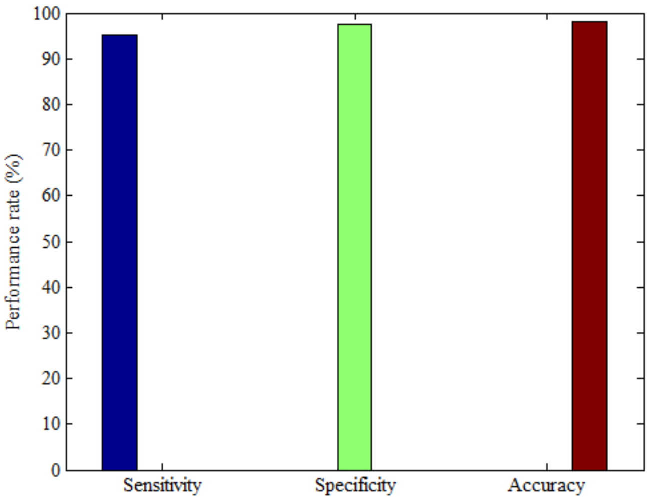

Figure 10. Sensitivity, specificity and accuracy of the PKC classification

F. Jaccard, Dice and Kappa Coefficients

The Jaccard is defined as the similarity measure that is the intersection divided by the union of the objects. It is the union overlap that finds the intersection between two similarities labeled regions r in I1 and I2 over the union. It is calculated as follows,

$$J_s = \frac{|I_{r1} \cap I_{r2}|}{|I_{r1} \cup I_{r2}|} \quad (9)$$

Where, the Jaccard coefficient Js ranges between 0 and 1, if it is 1, the two objects are identical that is the sets are equivalent; otherwise, the objects are completely different that is the sets have no common regions. Similarly, the Dice is also a similarity measure that finds the similarity between two images I1 and I2, which is calculated as follows,

$$D_s = \frac{2.|I_{r1} \cap I_{r2}|}{|I_{r1}|+|I_{r2}|} \quad (10)$$

Dice is a mean overlap that finds the intersection between two similarity labeled regions r in I1 and I2 over the average volume of these two regions. The kappa coefficient measures the difference between the observed agreements of two maps. Moreover, high kappa coefficients provide high classification rate. It is calculated as follows:

$$Kappa\ Coefficient = \frac{(n*sum\ A_{ii})-sum\ (A_{i+}*A_{+i})}{n^2-sum\ (A_{i+}*A_{+i})} \quad (11)$$

Where, the sum represents the sum across all rows in the matrix, Ai+indicates the marginal row total A+i indicates the marginal column total and n defines the number of observation. The Jaccard, Dice, and Kappa coefficients are shown in Fig 11.

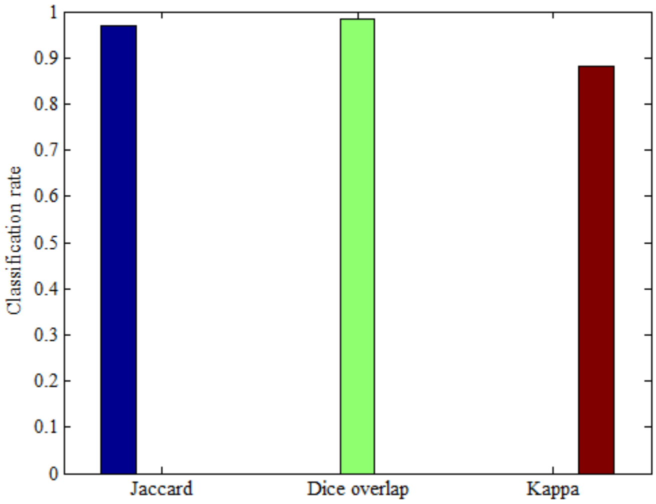

Figure 11. Jaccard, dice and kappa coefficients

G. Precision and Recall

Precision and recall are the basic measures that are mainly used to evaluate the performance of the classification technique. Precision is defined as a measure of accuracy provided by a specific class has been predicted. It is calculated as follows,

$$Precision = \frac{TP}{(TP+FP)} \quad (10)$$

Recall measures the prediction model's ability that is mainly used to select the instance of a certain class from a dataset. It is also termed as a sensitivity, which is calculated as follows,

$$Recall = \frac{TP}{(TP+FN)} \quad (11)$$

The graphical representation of precision and recall for the proposed classification system is shown in Fig 12.

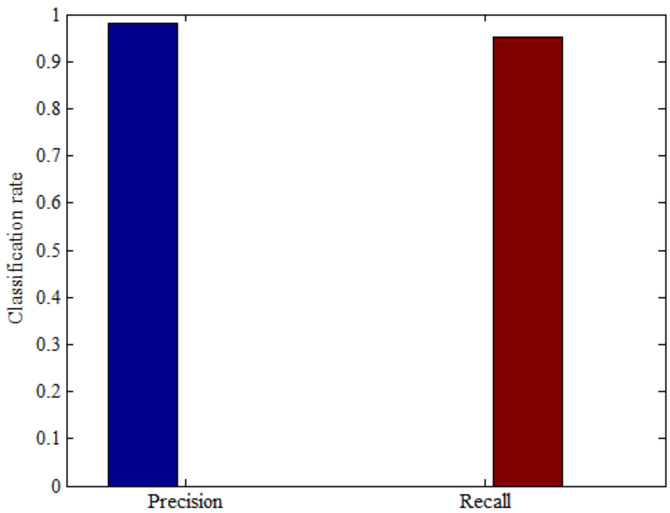

Figure 12. Precision and recall measures

H. Evaluation Results

The performance of Firefly optimization depending on the optimally selected features and the firefly light intensity is shown in Table 1. The performance is evaluated using accuracy, where the accuracy level is increased by increasing the intensity. Here, the total number of features taken are 256. The obtained results for each and every performance metrics is illustrated in Table 2.

Table 1. Optimization performance

α	*Optimal Selected features*	*Accuracy*
0.2	212	89.53 %
0.4	197	91.26 %
0.6	182	94.53 %
0.8	167	96.12 %
1	154	98.65 %

Table 2. Performance evaluation for the overall brain tumor classification system

Metrics	*Values*
True Positive (TP)	218
True Negative (TN)	447
False Positive (FP)	11
False Negative (FN)	11
Sensitivity (%)	95.1965
Specificity (%)	97.5983
Precision (%)	95.20
Recall (%)	95.20
Jaccard Coefficient (%)	96.80
Dice Overlap (%)	98.37
Kappa Coefficient (%)	88.11
Accuracy (%)	95.19

I. Comparative Analysis

In this work, some of the existing clustering techniques [23] are compared with the proposed NCA technique for proving the better performance of the proposed system. The existing works compared in this work are, K-means, Mutual Information (MI), Markov Random Field (MRF), Weighted Probabilistic Neural Network (WPNN), Information Theoretic Discriminative Segmentation (ITDS) and Supervised ITDS. The clustering results are evaluated and compared with CSF, WM, GM and time (s) for both IBSR and BrainWeb datasets, which is shown in Table 3.

Table 3. Comparative analysis between existing and proposed classification techniques

Methods	*IBSR*				*BrainWeb*			
	CSF	GM	WM	Time (s)	CSF	GM	WM	Time (s)
K means	0.51	0.75	0.78	8	0.86	0.84	0.82	12
MI	0.52	0.79	0.8	19	0.87	0.86	0.85	23
MRF	0.53	0.76	0.87	521	0.89	0.9	0.91	636
ITDS	0.6	0.81	0.86	26	0.92	0.92	0.93	32
WPNN	0.63	0.83	0.87	92	0.93	0.93	0.91	151
SITDS	0.67	0.86	0.89	29	0.94	0.95	0.94	35
NCA	0.71	0.89	0.92	4	0.97	0.98	0.97	7

The comparison between the existing and proposed techniques based on the dice similarity coefficients is shown in Table 4.

Table 4. Dice Similarity coefficients

Methods	*IBSR*	*BrainWeb*
SITDS	0.78	0.94
WPNN	0.73	0.9
NAC	0.87	0.97

Moreover, the comparison between existing dictionary learning [24] and proposed segmentation techniques is analyzed using of CSF, GM, and WM and the results are shown in Table 5. From this comparative analysis, it can be clearly seen that best results are yielded by the proposed technique than others.

Table 5. Average dice coefficients

Method	*3% Noise*			*5% Noise*		
	CSF	*GM*	*WM*	*CSF*	*GM*	*WM*
Dictionary Learning	0.9454	0.9472	0.9598	0.932	0.9319	0.9472
NAC	0.9847	0.9757	0.9648	0.9775	0.9345	0.9857

CONCLUSION AND FUTURE WORK

This work proposed a new detection and classification system based on Pointing Kernel Classifier (PKC) for the brain tumor. The major contribution of this work is to classify the given MRI brain image as normal or abnormal (benign, malignant and metastatic). For this purpose, various image processing techniques are utilized in this work. At first, the given MRI image is preprocessed by using the DAF technique, where the speckle noise and other unwanted noises get eliminated. Then, it will be segmented by using the NAC clustering technique. After that, the features of the segmented MRI are extracted by using DBA technique. Then, the best features are selected from the extracted features with the help of Firefly optimization technique. Finally, the proposed PKC technique is employed to classify both the normal and abnormal brain images. For proving the better performance of the proposed technique, some of the existing techniques are compared using sensitivity, specificity, accuracy, FAR, FRR, GAR, ROC, precision, recall, Jaccard, Dice and Kappa coefficients. From this analysis, it is observed that the proposed technique provides the better results than the other methods.

In future, the proposed MRI brain segmentation and classification model can be enhanced by the fusion of multiple brain slices.

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