Original Article

Brain Tumor Segmentation & Classification using Optimized k-means (SFLA) and Ensemble Learning

Priyanka Kaushik[1], Rajeev Ratan[2]
[1] Electronics & Communication, (Ph.D. scholar), MVN University, (Palwal), Haryana, India
[2] Electronics & Communication, Professor, MVN University, (Palwal), Haryana, India
prianca.kaushik@gmail.com[1], rajeev.arora@mvn.edu.in[2]
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Abstract

Brain tumor is a common disease that can occur at any age in humans. Early-stage brain tumor segmentation and classification from low-contrast MRI images is always difficult. In this paper, a new hybrid optimized k-means algorithm based on the shuffled frog leap algorithm (SFLA) followed by thresholding and morphological with ensemble learning is developed. The proposed work is divided into two segments. After pre-processing of low-contrast MRI images the brain tumor area is calculated from the segmented MRI image then the most efficient features are also extracted using discrete wavelet transformation (DWT) techniques. In the second segment, these extracted features are fed as input parameters into a trained brain tumor classifier using an ensemble learning approach. The ensemble-leaning approach model is trained by a feature dataset collected from an online source. The KNN, decision tree, gradient boosting, random forest, and ANN classifiers are used to classify the type of tumor (benign or malignant) from the low contrast brain tumor MRI image. The proposed framework is more efficient and has an accuracy (average of all models accuracy) of 98.07 percent, sensitivity of 98.21 percent, and specificity of 97.25 percent in predicting the type of brain tumor.

Keywords: Brain tumor, Optimized k-means, Feature extraction, Ensemble-leaning (SVM, KNN, Random-forest, Decision tree, Gradient boosting, ANN).

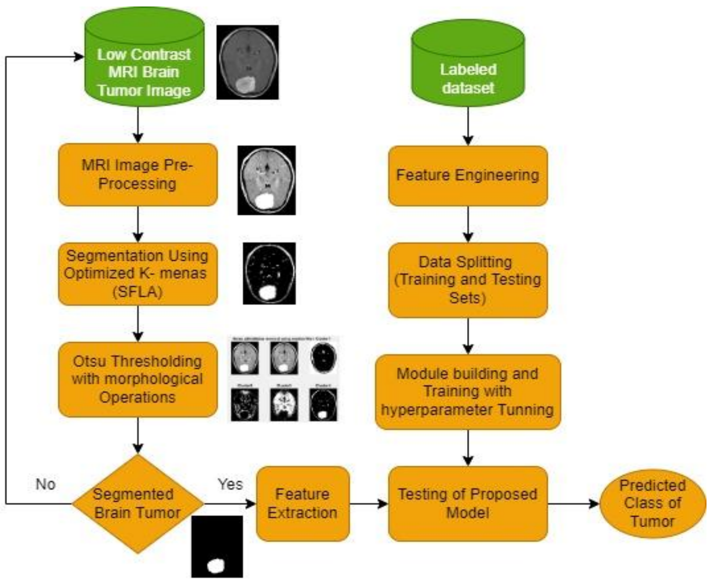
INTRODUCTION

Brain tumor, a dangerous life-threatening problem is mainly connected to our stress levels and exposure to unwanted fluids. A brain tumor occurs when abnormal cells form within the brain varies in size. it can be as small as an ant and as big as a worm. We usually come through two types of tumors: - cancerous and non-cancerous (primary)[1]. If we talk about the behavioural changes, we can seek during the brain tumor is: - inappropriate social behaviour, temper tantrums, laughing at things that merit no laughter clearly in short, our brain stops responding to us the way we want it to. It can cause depression and anxiety, it can also lead to unemployment, unstable relationships, and lack of control. Mutations and deletions of tumor suppressor genes such as p53 are thought to be the cause of some brain tumors. There is a myth that says that cell phone radiation causes brain tumors, it's not true and also proved by the biological section of science. A brain tumor can be treated in many ways: Surgery (objective of removing as many tumor cells as possible but there is a risk of brain tumor coming back), Radiotherapy (the most commonly used, the tumor is irradiated with a beta, x-rays or gamma rays) and Chemotherapy (it just prevents some drugs from reaching the cancerous cells). The survival rate in primary tumors depends on the type of tumor, age, functional status of a patient, and how the patient's family is treating him/her. Ladgham et al [2] developed an efficient and optimal brain tumor detection system using a modified shuffled frog leap algorithm (MSFLA), which recognizes the exact size and location with an improved convergence rate. Yang et al [3] suggested a hybrid model for the type of gene selection using SFLA and a genetic algorithm (GA). The accuracy rate of the proposed model for gene classification is about 92.45%. Aswathy et al [4] developed a fully automatic brain tumor segmentation and classification model using a genetic algorithm with a support vector machine (SVM) classifier. The accuracy scores of the proposed model are quite good. There are a lot of available techniques for medical image analysis but this field is always challenging. In this proposed work an optimized k-means (SFLA) with an ensemble–learning approach has been developed.

PROPOSED MODEL FOR BRAIN TUMOR SEGMENTATION AND CLASSIFICATION

In this research, a hybrid brain tumor segmentation and classification model is developed from low-contrast brain tumor MRI images. The suggested model has six stages to segment as well as classify the tumor. These six stages are low contrast MRI brain tumor image acquisition and preprocessing segmentation with an optimized k-means algorithm, morphological & thresholding operation, brain tumor extraction and feature extraction, and classify the tumor using different types of classifier [5]. A 70:30 ratio concept is used to train and test the proposed model respectively. The flow chart of the proposed brain tumor segmentation and classifier is shown in figure 1.

Figure 1: Proposed model for brain tumor segmentation and classification



The operation of the proposed model is divided into two groups. In the first phase after preprocessing and segmentation of brain tumor, the most important features like, mean, variance, correlation, entropy, etc. are extracted. In the second phase, a brain tumor classifier is developed using an ensemble-learning concept.

DATASET COLLECTION AND PRE-PROCESSING

The 500 low contrast brain tumor MRI images belonging to two classes; benign (250) and malignant (250) are collected from the online resource "UCI machine learning repository". 30 T1-weighted brain tumor (benign and malignant) are collected from a hospital for model evaluation. The collected low-contrast images are first preprocessed using an open cv library and noise-removing filters, therefore the model is less complex and efficiently classifies the brain tumor with optimal computational time. A sample of collected low contrast brain tumor MRI images and preprocessed brain tumor MRI images are shown in figure 2 and figure 3.

Figure 2: Sample of a collected low contrast brain tumor MRI image dataset

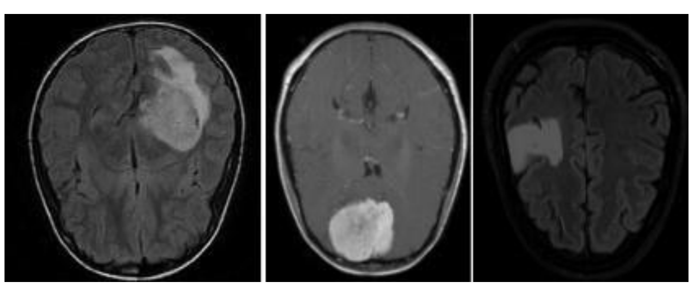
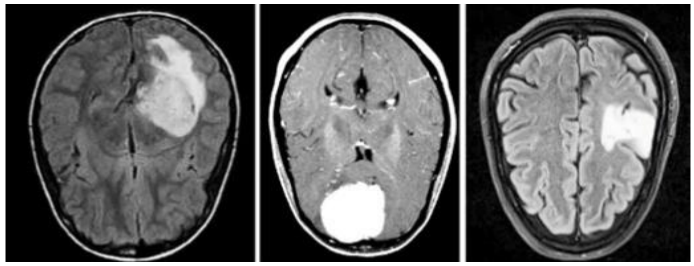


Figure 3: Sample of a preprocessed low contrast brain tumor MRI image



OPTIMIZED K- MEANS ALGORITHM

The proposed optimized k-means approach with threshold and morphological operation for brain tumor segmentation is a combination of k-means and shuffled frog leap algorithm (SFLA). The k-means clustering approach is a hard clustering and requires maximum time for the convergence of image pixels into a particular cluster [6].

K-Means Clustering

The basic steps of the k-means clustering approach are listed below.

Step 1: Low contrast MRI image acquisition and define the no. of clusters using the elbow method.

Step 2: Randomly select the center of each cluster (using average method).

Step 3: Calculate the euclidian distance between each pixel with the center value of each cluster.

Step 4: The selected pixel moves to a cluster with minimum euclidian distance.

Step 5: Calculate the new center of the cluster in which the selected pixel is moved.

Step 6: Repeat step 3, 4, and 5 till all image pixels belong to a particular cluster.

SHUFFLED FROG LEAP ALGORITHM (SFLA)

The frog leap algorithm (FLA) is an efficient and optimized technique that improves the convergence rate so that computational time is reduced [7]. The FLA gives more optimized results for complex problems with a large amount of population. The total population is based on two parameters; memeplexes and the number of frogs in each memeplex. This approach is based on local and global searches. The basic steps of shuffled FLA are given below.

Step 1: Initialize the parameters; p (population), m (memeplexes), n (no. of frogs), and no. of shuffling iteration.

Step 2: Evaluate the total population for initialized m and n.

Step 3: Evaluate the fitness of each result.

Step 4: Analyse and sort the frogs as per the performance.

Step 5: Divide the sorted frogs into memeplex.

Step 6: Shuffle the memeplex and repeat the above step still all pixels belong to this

The proposed optimized k-means algorithm for brain tumor segmentation is more efficient in terms of pixels convergence rate and detects the region of interest (ROI) from low contrast brain tumor MRI images in minimal computational time.

THRESHOLDING AND MORPHOLOGICAL OPERATIONS

Thresholding is a binarization process in which any image is converted into binary or black and white according to a threshold value. The pixels below are predefined threshold level belong to 'o' or black and above or equal to belongs to '1' or white pixels [8]. But how to select the threshold value is a big task, so optimal thresholding (otsu) is a better choice. The otsu thresholding is based on the variation of grayscale value in an image histogram [9]. To achieve the optimal threshold value for binarization or separation in between the foreground and background of an image, the maximum of difference in grayscale values of the two clusters (V_b) or of minimum difference within the grayscale values of clusters (V_w) are considered and shown in equations no. 1 & 2.

$$V_w = w_{1*}v_1 + w_{2*}v_2$$

$$V_w = \frac{w_1 * \sum_{p_i \in c_1}(p_i - \mu_1)^2}{N * w_1} + \frac{w_2 * \sum_{p_i \in c_2}(p_i - \mu_2)^2}{N * w_2}$$

$$V_w = \frac{\sum_{p_i \in c_1}(p_i)^2}{N} - w_1 * {\mu_1}^2 + \frac{\sum_{p_i \in c_2}(p_i)^2}{N} - w_2 * {\mu_2}^2 \qquad (1)$$

$$V_b = w_{1*}(\mu_1 - \mu_t)^2 + w_{2*}(\mu_2 - \mu_t)^2$$

$$V_b = w_{1*}\, w_2(\mu_1 - \mu_2)^2 \qquad (2)$$

Where,

w_1 & w_1=probability of two class c_1 & c_2 at t

v_1 & v_2 = total variance of an element in class c_1 & c_2

N = total number of image pixel

μ_1 & μ_2 = total mean of an element in class c_1 & c_2

μ_t = total mean at threshold t

The morphological operators are used to add the pixels or remove the pixels from the image boundary. There are four types of morphological operations; dilation, erosion, opening, and closing. The dilation-operated image becomes more visible because it adds the pixels at the boundary so that small holes are considered but in erosion, boundary pixels have removed so that most important information is lost. In this work, first opening (erosion then dilation), then erosion morphological operations are used.

SEGMENTED BRAIN TUMOR AREA

The basic steps for determination of the brain tumor area from the segmented MRI image are [10];

Step 1: Segmented image is a combination of black and white pixels.

$$Segmented\ image = \sum_{i=0}^{255}\sum_{j=0}^{255} I(0) + I(1) \qquad (3)$$

Step 2: The grayscale value of pixels related to a tumor is high as compared to normal, therefore calculate the total number of white pixels.

$$Total\ number\ of\ white\ pixels\ (W) = \sum_{i=0}^{255}\sum_{j=0}^{255} I(1) \qquad (4)$$

Step 3: Brain tumor area (mm^2) = [($\sqrt{W}$)^2 $*\ Area\ of\ one\ pixel$

FEATURE EXTRACTION

To classify the type of tumor, the most efficient features related to benign and malignant tumors are extracted using discrete wavelet transformation [11]. Some important features are listed below.

Mean

To analyze the image's background and foreground, the mean is calculated. It is the average of all pixels' intensity. If $G_1, G_2, \dots . G_n$ are the grayscale values of n number of pixels then the mean (μ) is calculated using equation no. 3.

$$Mean = \frac{\sum_{i=1}^{n} G_i}{n} \qquad (5)$$

Contrast

The variation in gray level co-occurrence is measured using contrast. The contrast is low for similar grayscale values of image pixels, which measure the accuracy of cluster formation of similar image pixels.

Entropy

The entropy is a texture feature of an image and it measures the randomness of pixel intensity.

Correlation

To evaluate the linear dependence of image pixels on their neighboring pixels, the correlation feature is used.

Variance

A measure of within distance between the mean and pixel intensity of the cluster is called the variance of an image. For good clustering, approach variance is low.

BRAIN TUMOR CLASSIFIER

When the tumor area and features are extracted from the low contrast brain tumor MRI image using the first phase of the proposed model, then these features as a reference are used by the classifier to classify the type of brain tumor (benign or malignant). Before testing the brain tumor classifier, the model is trained using a training dataset with some data augmentation operator and shuffling. There are many classifiers but some are explained below.

K-nearest neighbors (KNN) classifier

The K-nearest neighbors (KNN) classifier gives better results for regression as well as classification problems. it is a slow learning algorithm that requires too much time. The result of the KNN classifier is based on the majority of the nearest neighbors[12],[13]. After selecting the random number of k clusters (max. value = no. of features), the belongingness of the new pixel to clusters depends on the euclidian distance or manhattans distance as given below in equations 6 and 7. This process for pixel convergence to the k number of clusters is repeated till no pixels are left without a cluster name.

$$Euclidian\ distance = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2} \qquad (6)$$

$$Manhattan\ distance = |(x_2 - x_1) + (y_2 - y_1)| \qquad (7)$$

Where;

x_2 , x_1= horizontal coordinates of a points

y , y_1= vertical coordinates of a points

Random forest classifier

The random forest (supervised algorithm) approach is based on decision trees[14]. It is part of ensemble learning, in which one algorithm is applied multiple times or multiple algorithms is applied a single time. The final prediction of random forest is based on the voting or average of all-time predicted results. The basic steps of the random forest approach are given below.

Step 1: Select the random samples from the dataset

Step 2: construct the decision tree and predict the results for all samples.

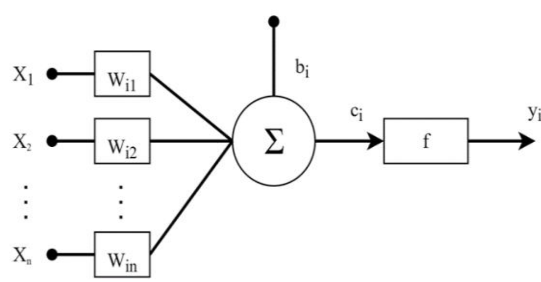
Step 3: for every sample result, voting will be performed.

Step 4: Final prediction based on the average of all votes or most of the time predicted the same result.

Artificial Neural network (ANN) classifier

The ANN (neural networks or neural nets) is an interconnected node or artificial neuron's structure with some predefined weights. The backpropagation algorithm is used to train the model [15]. These weights are updated till the model predicts the results with good accuracy. The structure of a single neuron in the ANN classifier is shown below in figure 4

Figure 4: ANN classifier structure



$$y_i = f * c_i$$

$$y_i = f * \left[\left((X_1 * W_{i1}) + \cdots + (X_n * W_{in})\right) + b_i\right] \qquad (8)$$

Where;

$X_1, X_2, \dots\dots, X_n$ = no. of input neurons (features)

$W_{i1}, W_{i2}, \dots\dots, W_{in}$ = weight assigned to each neuron

b_i = biased (constant that control the output)

c_i = intermediate output $\{(input * weight) + bias\}$

y_i = output of the neural network

EXPERIMENTAL RESULTS

The suggested brain tumor classifier for low contrast MRI images is implemented in jupyter notebook with python 3.9. The proposed model is tested using a system that has 4 GB RAM, and an 8th generation i7-2.5 GHz processor. The low contrast brain tumor MRI image segmentation using an optimized k-means algorithm is shown in figure 5

Figures 5: Brain tumor segmentation by optimized k-means algorithm

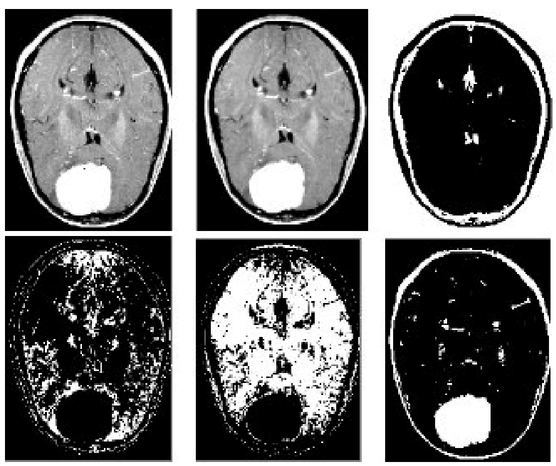


Figure 5, shows the segmented brain tumor using an optimized k-means algorithm with otsu thresholding and morphological operations. After contrast improvement and noise removal, the input brain tumor MRI image is segmented and the area of the brain tumor in the input MRI image is calculated using the tumor area calculation approach [16].

Figure 6, shows the segmented brain tumor area in terms of no. of white pixels from the input MRI image using an optimized k-means algorithm. The segmented brain tumor area of an input image is 2384 white pixels.

Figure 6: Segmented brain tumor (area=2384) by optimized k-means algorithm

After brain tumor area segmentation, the discrete wavelet transformation (DWT) approach is used to extract some most important features like; mean correlation, variance, standard deviation, contrast, entropy, kurtosis, etc. Table 1, shows the extracted most efficient features for input image number 3, from the database.

Table 1: Extracted features (image no. 3) using DWT

Feature Name	Value
Mean	5.9582
Variance	959.7120
Standard Deviation	30.9792
Entropy	0.0015
Skewness	5.6780
Kurtosis	33.4289
Contrast	151.2297
Energy	0.0320
ASM	0.0010
Homogeneity	0.2439
Dissimilarity	7.7010
Correlation	0.9642

These extracted features are fed to the brain tumor classifier to classify the type of brain tumor.

Confusion Matrix

The confusion matrix is used to evaluate the classifier scores. Multiple models like; k-nearest neighbors, decision trees, random forest, logistic regression, and artificial neural networks are used as a part of an ensemble-learning approach. The suggested hybrid model for low contrast brain tumor MRI images is first trained using a feature dataset after selecting the most important features like; variance, kurtosis, contrast, skewness, and standard deviation collected from online sources are tested. To calculate the classifier score parameters, following mathematical equations are used as given below [17].

$$Precission = \frac{True\ Positive}{(True\ Positive + False\ Positive)} \quad (9)$$

$$Sensitivity = \frac{True\ Positive}{(True\ Positive + False\ Positive)} \quad (10)$$

$$Specificity = \frac{True\ Negative}{(True\ Negative + False\ Positive)} \quad (11)$$

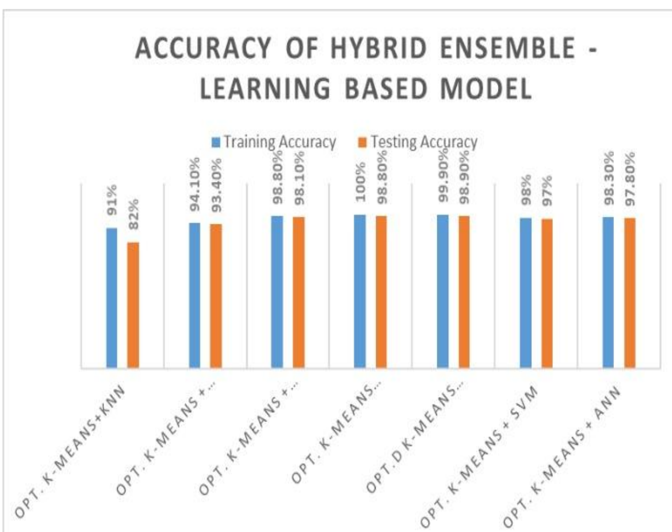
$$Accuracy = \frac{True\ Positive + True\ Negative}{(Positive + Negative)} \qquad (12)$$

The accuracy score & corresponding bar graph of the proposed model with different types of models used in the ensemble-learning approach is shown below in table 2 and figure 7. The model complexity and computational time are also reduced when a fine tuned dataset in terms of the most important feature dataset which is responsible only for the classification of brain tumors [18],[19].

Table 2: Accuracy of the proposed model with different classifiers

Hybrid Algorithm	**Training Accuracy**	**Testing Accuracy**
Optimized K-Means+ KNN	98%	97.5%
Optimized K-Means + Logistic Regression	97.1%	98.4%
Optimized K-Means + Decision Tree	98.8%	98.1%
Optimized K-Means + Random Forest	100%	98.8%
Optimized K-Means + Gradient Boosting	99.9%	98.9%
Optimized K-Means + SVM	98%	97%
Optimized K-Means + ANN	98.3%	97.8%

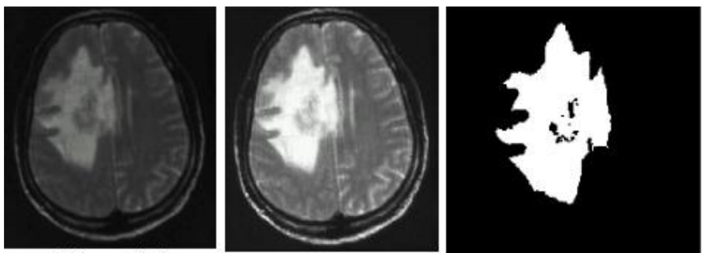
Figure 7: Bar graph of proposed model accuracy with different classifiers.



THE PROPOSED MODEL SEGMENTATION AND CLASSIFICATION AFTER FEATURE EXTRACTION-USING DWT

The suggested hybrid low contrast brain tumor segmentation and classification have two phases. In the first phase, the low contrast brain tumor MRI image is acquired from the brain tumor MRI database then after performing preprocessing steps the tumor is segmented using an optimized k-means algorithm followed by thresholding and morphological operations after that the important features are extracted using discrete wavelet transformation (DWT). In the second phase, different types of classifiers like; KNN, decision tree, random forest, logistic regression, gradient boosting, and artificial neural networks are implemented in google cloab and trained features dataset of benign ('0') or malignant ('1') brain tumor MRI images of about 3763. The whole feature dataset is divided into training and testing sets in a ratio of 70:30 percent [20]. Figure 8 (a), (b), and (c) shows the acquired input low contrast brain tumor MRI image, preprocessed and segmented brain tumor using optimized k-means respectively.

Figure 8: (a) Low contrast, (b) preprocessed, and (c) segmented brain tumor images by optimized k-means



(a) low contrat image (b) Pre-processed image (c) Segmented brain tumor

Figure 9, shows the model predicted results according to extracted features using DWT

Figure 9: Model predicted results with labels

```
brain_tumor()

Enter the value Mean:9.8046
Enter the value of Variance:1147.0
Enter thevalue of Standard Deviation:34.259
Enter the value of Entropy :0.0035
Enter the value of Skewness:3.9785
Enter the value of Kurtosis:16.325
Enter the value of Contrast:67.358
Enter the value of Energy:0.02457
Enter the value of ASM:0.00245
Enter the value of Homogeneity:0.4586
Enterthe value of  Dissimilarity:4.78524
Enter the value of Correlation:0.99254
The expected type of Brain_Tumor 1
```

When extracted features from a segmented brain tumor are fed to the classifier the predicted output label of low contrast brain tumor MRI image is '1' which means the type of brain tumor is malignant and for a benign tumor, this value is '0'.

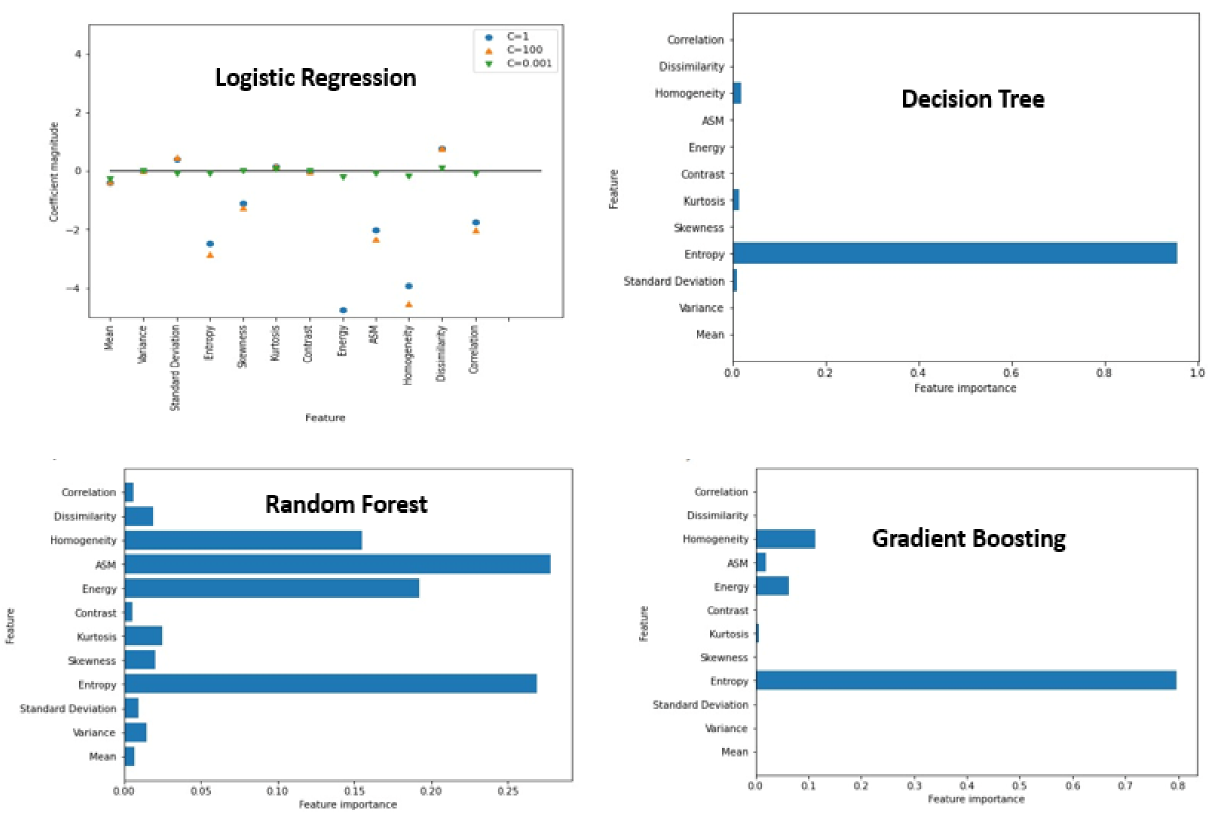
Figure 10, shows the training of an artificial neural network as a part of a hybrid model with an optimized k- means algorithm.

Figure 10: Training of ANN classifier

```
Epoch 1/10
301/301 [==============================] - 1s 2ms/step - loss: 0.4780 - accuracy: 0.9219
Epoch 2/10
301/301 [==============================] - 1s 2ms/step - loss: 0.1313 - accuracy: 0.9807
Epoch 3/10
301/301 [==============================] - 1s 2ms/step - loss: 0.0705 - accuracy: 0.9821
Epoch 4/10
301/301 [==============================] - 1s 2ms/step - loss: 0.0598 - accuracy: 0.9834
Epoch 5/10
301/301 [==============================] - 1s 2ms/step - loss: 0.0561 - accuracy: 0.9827
Epoch 6/10
301/301 [==============================] - 1s 2ms/step - loss: 0.0537 - accuracy: 0.9844
Epoch 7/10
301/301 [==============================] - 1s 2ms/step - loss: 0.0523 - accuracy: 0.9837
Epoch 8/10
301/301 [==============================] - 1s 2ms/step - loss: 0.0510 - accuracy: 0.9834
```

Figure 11, shows the weightage of the most important features according to different type classifiers, used to classify the type of tumor. According to figure 11, it is clear that the weightage of most features used to classify the type of brain tumor from low-contrast MRI images is varying in nature. The classification accuracy of logistic regression is good for a lower value of the learning parameter. The accuracy of gradient boosting and decision tree classifiers mainly depends on the entropy features but in the case of random forest, it highly depends upon entropy, Active shape model (ASM), energy, and homogeneity type of features.

Figure 11: The weightage of the important features for different classifiers



CONCLUSION AND FUTURE WORK

In this presented work, an optimized k-means algorithm followed by a thresholding and morphological approach is developed for low contrast brain tumor segmentation from MRI images. Some important features are extracted from a segmented brain tumor and these features are fed to a brain tumor classifier, which is based on an ensemble learning approach i.e. multiple models are used to classify the type of brain tumor at a time. The used models are logistic regression, k nearest neighbor (KNN), decision tree, random forest, gradient boosting, support vector machine (SVM), and artificial neural network (ANN). The proposed model is trained by the 70% part of the feature dataset related to the benign and malignant types of tumors. The comparative study according to training and testing accuracies of hybrid optimized k-means and ensemble learning approach-based classifier is shown in table 2. According to table 2, the performance of gradient boosting is quite good as compared to classifiers. The accuracy score of random forest is also good but its training accuracy is 100% i.e. the sign of overfitting. The accuracy scores of the proposed model is quite good but still, it requires some improvements. In the future, that will be achieved by using deep learning and transfer learning approaches.

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