Research Article

Brain Tumor Detection & Classification Using FRFCM Segmentation and PSO Based Extreme Machine Learning and it's Implementation Through Embedded System

Tadesse Hailu Ayane[a],Satyasis Mishra[b],Davinder Singh Rathee[c], Harish Kalla[d]

[a]Dept. of ECE, SoEEC, Signal and Image Processing SIG, Adama Science and Technology University, Adama, Ethiopia

Article History: Received: 10 January 2021; Revised: 12 February 2021; Accepted: 27 March 2021; Published online: 4 June 2021

Abstract: This research work proposes a novel Fast and robust Fuzzy C Means base (FRFCM) segmentation technique for detection of brain tumor from MR (Magnetic Resonance) image that can inform the radiologist and doctor about the details of brain tumor. This segmentation technique has been employed for rician noise removal and sharpening of the image with morphological reconstruction. The MR (Magnetic Resonance) Images features have been extracted through a popular Gray Level Co-occurrence Matrix (GLCM) and Discrete wavelet transform feature extraction technique. The extracted features are applied to the, proposed PSO(Particle Swarm Optimization) based extreme learning machine(ELM) for classification of the type of malignant and benign brain tumors for visual localization. Further the classification results will be compared with the existing support vector machine and relevance vector machine model. In this research work, the weights of the proposed novel multi class extreme learning machine classifier model has been updated by the PSO algorithm to increase the performance of the classifiers. To show the uniqueness of the research, further the research work proposes for implementation of detection and classification through embedded system platform which may be the product outcome of the research work. It will help the medical staff particularly for the radiologist and doctor to understand the seriousness of the tumor. Further the embedded system platform has been used to show the classification, segmentation and features through GUI (Graphical User Interface).

Keywords:

1. Introduction

The death rate grows universally due the brain tumors according to the the "American Brain Tumor Association (ABTA)" Feb 24, 2020[1], As per to the reports of World Health Organization (WHO), it is assessed that 9.6 million people died worldwide from brain tumours in 2019 [2]. Detection of solid tumors, whether it is benign or malignant, is often difficult in brain MR images. Identifying the exact size and coverage of tumors is also challenging in brain MRI because the original medical image has the problem like noise, low contrast, and bad resolution and so on. So, it takes minutes to get MR images of a subject and more time to view the images generated on a screen and carry out visual assessment. Visual assessment of the MR images is subjective, often time consuming and hardly repetitive which might give rise to inaccurate diagnosis. There is no mechanism that detects tumors and classifies the tumors as malignant or benign in MR. This could be avoided if there exist a tool that could be used for accurate detection of abnormalities in the brain automatically by clever analysis of the MR images non-invasively. This calls for the development of methodology which could be used for effective analysis of the MR images that could robustly detect and classify brain tumors.

The increasing incidence of brain tumors increases the number of images that need to be reviewed by oncologists/radiologists. The manual detection becomes difficult for doctors which motivates us to propose automatic detection and classification model and segmentation technique for brain tumor. Segmentation techniques proposed by researchers such as "FCM based genetic algorithm" [3,4], , Berkele Wavelet wavelet transform image segmentation[5,6], "hidden markov random field models" [7] etc but fails for automatic brain tumor segmentation. To get rid of this problem, spatial information(FCM_S) segmentation[9], with spatial term[10], enhanced FCM algorithm (EnFCM) [11] by using gray levels segmentations proposed for noise removal. To reduce noise further "FGFCM (Fast generalized FCM algorithm)" proposed in [12] with a similarity measure factor. The "fuzzy local information c-means clustering algorithm (FLICM)", utilized a fuzzy factor [13]. To increase the performance of FLICM , kernel metric with local information for noise reduction[14],FCM with local information and kernel metric (KWFLICM), Adaptive "FCM algorithm based on noise detection (NDFCM)"[15] proposed To improve the performance, "a fast and robust FCM (FRFCM)", which is based on morphological reconstruction has been employed. FRFCM[16] to improve segmentation accuracy. In this research work, PSO[8] algorithm is proposed to optimize the weights of multiclass ELM model. With the modification in PSO algorithm, the performance of the ELM classifier also increases.

1.1 Contribution of the Research Work

1.1.1 Objective

The objective of the research work is to detect brain tumor tissues from MR (Magnetic Resonance) images using proposed FRFCM (Fast and Robust Fuzzy C Means algorithm) segmentation technique and classification through novel extreme learning machine model.

1.1.2 Specific Objectives

- Developing a novel FRFCM (Fast and Robust Fuzzy C Means algorithm) segmentation technique to remove noise and detect tumor from MR Images.
- Classification of the normal and abnormal brain tumor tissues using proposed PSO based Extreme learning machine model.
- GUI for automatic visualization of detection and classification through Using Raspberry Pi3.

The rest of the paper is divided as follows, section-2 presents materials and methods of the proposed research which includes the FRFCM segmentation and proposed PSO based ELM model, section -3 presents the segmentation and classification results, section -4 presents discussion the research work and section 5 presents conclusion and reference.

2. Materials and Methods

2.1 Methodology

The research steps such as (i) The magnetic resonance images has been first collected and segmented by the novel FRFCM algorithm and the features are calculated from the images utilizing "GLCM (Gray Level Co-occurrence Matrix)" technique. Further (ii) the extracted features has given as input to the proposed PSO based Extreme Learning Model(ELM) for the classification. In the third stage (iii) the weights are updated utilizing PSO(Particle Swarm Optimization) algorithm to update the weights of the extreme learning machine model. In the 4^{th} stage (iv) The classification comparison results from the proposed extreme learning model, support vector machine and relevance vector machine model will be presented.

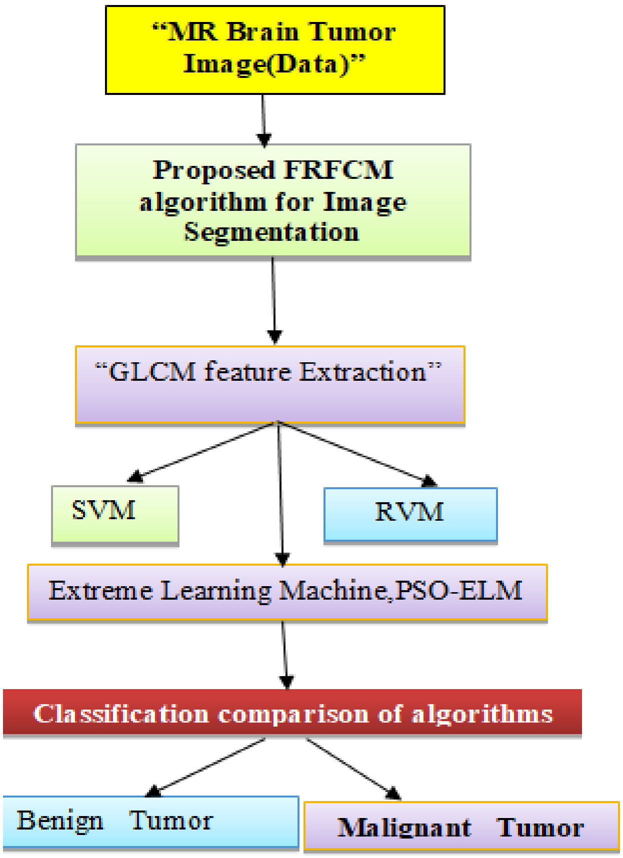

Fig.1 Research work flow diagram

2.2 Implementation:

The research flow diagram indicates the step by step accomplishment of the research work. Further the block diagram shows the flow of algorithm application for "detection and classification" of brain tumor.

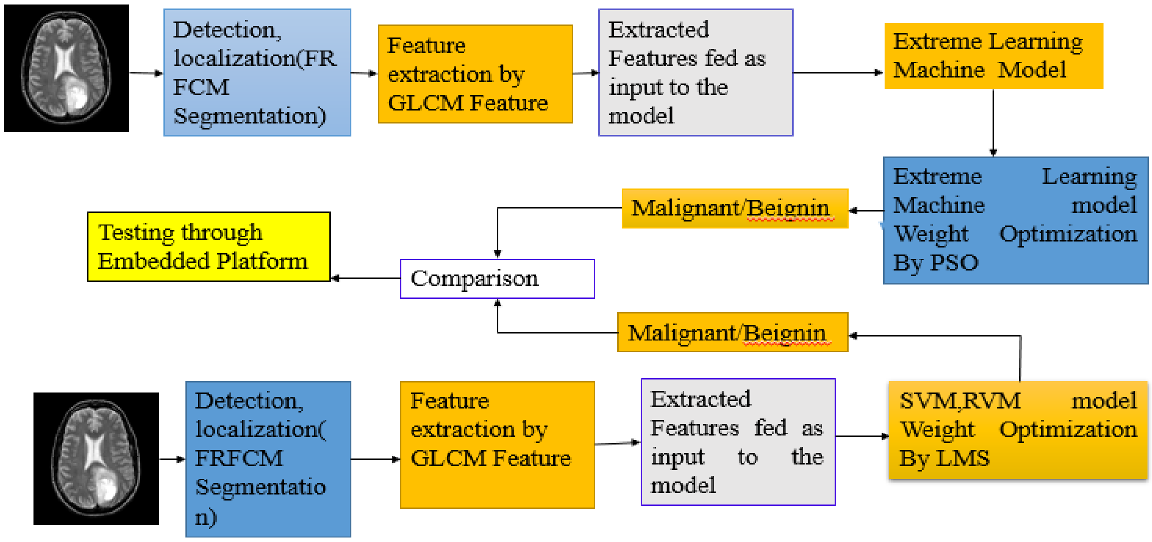

Fig.2 Block Diagram Representation of Implementation

2.3 Data Collection

The dataset collected from "Harvard Medical School website (http://med. harvard.edu/AANLIB/)" [22]and sample of the dataset is given in **Fig. 3**

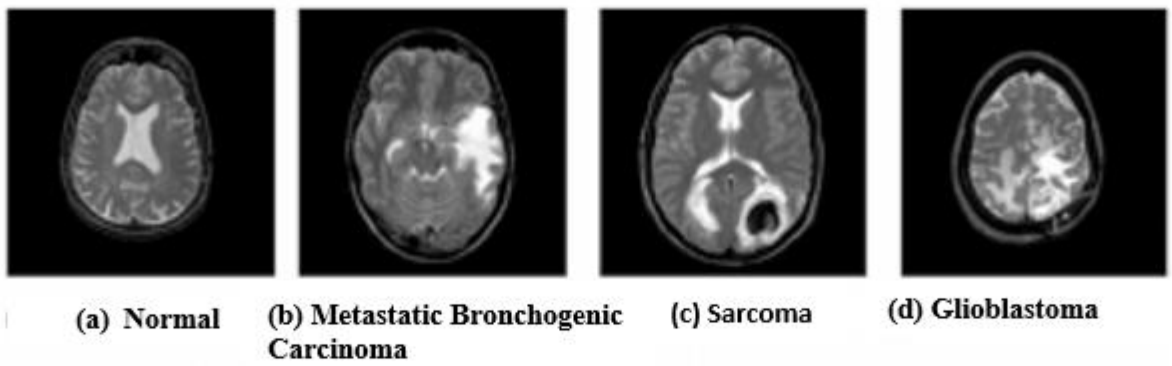

Fig.3 Diseased tumor in comparison to Normal

The real time data has been collected from the various renowned hospital of Ethiopia such as Adama general hospital and medical college, Adama,. The data has been collected from the above hospitals to analyze real time tumor tissue occurrence from the magnetic resonance image. The above hospitals have provided 5000 different types of magnetic resonance scan images for patients. The type of data to be collected involves

(i) The magnetic resonance image of the patients.
(ii) The detailed information of the patients during the growth of tumor.
(iii) The stages of tumor related to dimension.
(iv) The patient's body part condition such as eye vision, headache etc. during the starting and slow growing of tumor tissues.

The method of data collection involves as

(i) We have consulted two doctors and one radiologist from each hospital as a group and take information about the patients.
(ii) Doctors provided information about the quality of image and type of diagnosis they are considered for patients.
(iii) Doctors discussed method of their treatment of the tumor tissues and identification of tumor tissues from images.

To test the model with the real data collected, we have collected nearly 5000 images from the web www.diacom.com /"Harvard medical school architecture and Alzheimer's disease Neuroimaging" Initiative (ADNI) public database (http://adni.loni.usc.edu/), BRAT data set.

2.4Feature extraction

Different statistical features are extracted and presented in Table-1 for different sample images.

Table 1 Normalized feature extraction

Features	**Feature Values**
Correlation	0.1123
DM	0.1593
Coarseness	0.3516
Skewness	**0.4282**
Kurtosis	**0.9614**
Energy	**0.2677**

2.5 Support Vector Machine

The expansion of ANN followed a heuristic path, with the applications and extensive experimentation preceding theory and suffers from multiple local minima while the solution to an SVM[17-19] is global and unique. Consider a soft margin SVM for linearly non separable classes.

For binary classification in SVM the input vector x_i for linearly separated data defines a space of labeled data point called input space and the target vector is given by $y_i = \pm 1$, where i=1,2,………m is the input pairs or number of samples.

In a arbitrary dimensional space a decision function separating hyperplane can be written as $w.x + w_0$, where w_0 =bias, which translates the hyperplane away from the origin and w is the weight. Thus we will consider a decision function of the form

$$f(x) = \mathrm{sgn}(w.x + w_0) \tag{1}$$

If $w.x + w_0 \rightarrow +ve \qquad f(x) = +1$

And $w.x + w_0 \rightarrow -ve \qquad f(x) = -1$ (2)

The SVM predictions is given by

$$y_i(x,w) = f_{svm}(x,w) = \sum_{i=1}^{N} w_i K(x, x_i) + w_0 \tag{3}$$

$$y(x,w) = \Phi(x) w \tag{4}$$

And $w = [w_0, w_1, w_2, ...w_N]^T$

Therefore the RBF kernel is given by

$$K(x_i, x_j) = e^{-\|x_i - x_j\|^2 / 2\sigma^2}$$

Where $K(x, x_i)$ is a RBF kernel function which satisfy the “Mercer Condition”.

The decision function is given by

$$“\ f(x) = \mathrm{sgn}\left(\sum_{i=1}^{N} \alpha_i y_i K(x_i, x_j) + w_0\right)” \tag{5}$$

2.6 RVM (Relevance Vector Machines)

In RVM the kernel function need not satisfy ‘Mercer Condition’ for arithmetic’s validity and does not depend on Structural Risk Minimization Principle and VC dimension. RVM attains good accuracy comparing to the SVM. To overcome the disadvantages, we illustrate our approach with a particular algorithm, a model which is identical to the `support vector machine’ (SVM). The RVM produces a much sparser approximation than the SVM.

2.7 Proposed fast and robust FCM (FRFCM) segmentation technique

After data collection the segmentation of the images will be done by proposed FRFCM (Fast and Robust Fuzzy C Means algorithm to detect the brain tumor tissues and removal of the rician noise. From literature survey, some preliminary segmentation technique have been applied with brain tumor web data, but all the algorithm fails to provide required noise removal from the image and detection of tumor. To improve the drawback that of the FCM related algorithms presented above such as FLICM, FGFCM, NDFCM, etc which is sensitive to noise, we are proposing a Fast and Robust FCM (FRFCM) algorithm by incorporating local spatial information to FCM algorithm to get better precision result.

The “objective function of the fuzzy c means algorithm with local information” [22] is given by

$$J_s = \sum_{v=1}^{N}\sum_{k=1}^{c} u_{kv}^{m}\left\|x_v - v_k\right\|^2 + \sum_{v=1}^{N}\sum_{k=1}^{c} G_{kv} \tag{6}$$

Where the fuzzy factor is given by

$$G_{kv} = \sum_{\substack{r\in N_v \\ v\neq r}} \frac{1}{d_{vr}+1}\left(1-u_{kr}\right)^m \left\|x_r - v_k\right\|^2 \tag{7}$$

The fuzzy partition matrix is given by

$$u_{kv} = \frac{1}{\sum_{j=1}^{c}\left(\dfrac{\left\|x_v - v_k\right\|^2 + G_{kv}}{\left\|x_v - v_j\right\|^2 + G_{jv}}\right)^{\frac{1}{m-1}}} \tag{8}$$

And $$v_k = \frac{\sum_{k=1}^{N} u_{kv}^{m} x_v}{\sum_{v=1}^{N} u_{kv}} \tag{9}$$

Further, considering the “morphological reconstruction” ,the reconstruction of the image is considered as ξ_p , which is given by

$$\xi_p = R_e^C(f) \tag{10}$$

Where R_e^C represents the morphological closing reconstruction.

$$R_e^C(f) = R^{\chi}_{R_f^{\beta}(\chi(f))}\left(\beta\left(R_f^{\beta}(\chi(f))\right)\right) \tag{11}$$

Where “ χ is the erosion operation, β is the dilation operation, c is the closing operation and f ” represents original image. Now, with morphological closing reconstruction the objective function is modified as

$$J_s = \sum_{k=1}^{c}\sum_{p=1}^{q}\left[u_{kp}^{m}\left\|\left(\xi_p - v_k\right)\right\|^2\right] + \sum_{k=1}^{c}\sum_{p=1}^{q} G_{kp} \tag{12}$$

2.8 Proposed PSO based ELM model

The motivations of introducing local liner model as ELM provide a frugal interpolation in high dimension spaces when modeling samples are sparse. Recently, Bayesian methods are exploited [21, 22] to learn the output weights of ELM to gain higher generalization.

Given a set of N training dataset $D = (x_i, d_i), i = 1$ to N with each x_i is a vector and d_i is the expectation output. The output function of ELM with L hidden neurons is represented by

$$y = \sum_{k=0}^{L} \beta_k h_k(w_k; x) \tag{13}$$

where $h(w;x) = [1, h_1(w_1;x), \ldots\ldots, h_L(w_L;x)]$ is the hidden feature with input $x = [x_1 \ldots. x_N]$ and β is the weight vector. $h_k(\cdot)$ is the activation function of hidden layer. Equation (13) can be written as

$$\mathrm{H}\beta = y \tag{14}$$

Where H is the $\mathrm{N} \times (L+1)$ hidden layer feature-mapping matrix, whose elements are as follows:

$$\mathrm{H} = \begin{bmatrix} 1 & h_1(w_1;x_1) & \cdots & h_L(w_N;x_1) \\ \vdots & \vdots & \vdots & \vdots \\ 1 & h_1(w_1;x_N) & \cdots & h_L(w_N;x_N) \end{bmatrix} \tag{15}$$

And $h_L(w_N;x_N) = [w_1x_1 + w_1x_1 \ldots\ldots. w_N x_N] e^{\left(\frac{-\left\|(x_N - v_i)\right\|^2}{2\sigma_n{}^2}\right)}$

Where σ_n^2 is controlling parameter, v_j is the center of the hidden node. Equation (15) is a linear system, which is solved by

$$\beta = \mathrm{H}^{\dagger} d, \qquad \mathrm{H}^{\dagger} = \left(\mathrm{H}^T\mathrm{H}\right)^{-1}\mathrm{H}^T \tag{16}$$

Where $\mathrm{H}^{\dagger}$ is the "Moore–Penrose generalized inverse" of matrix H

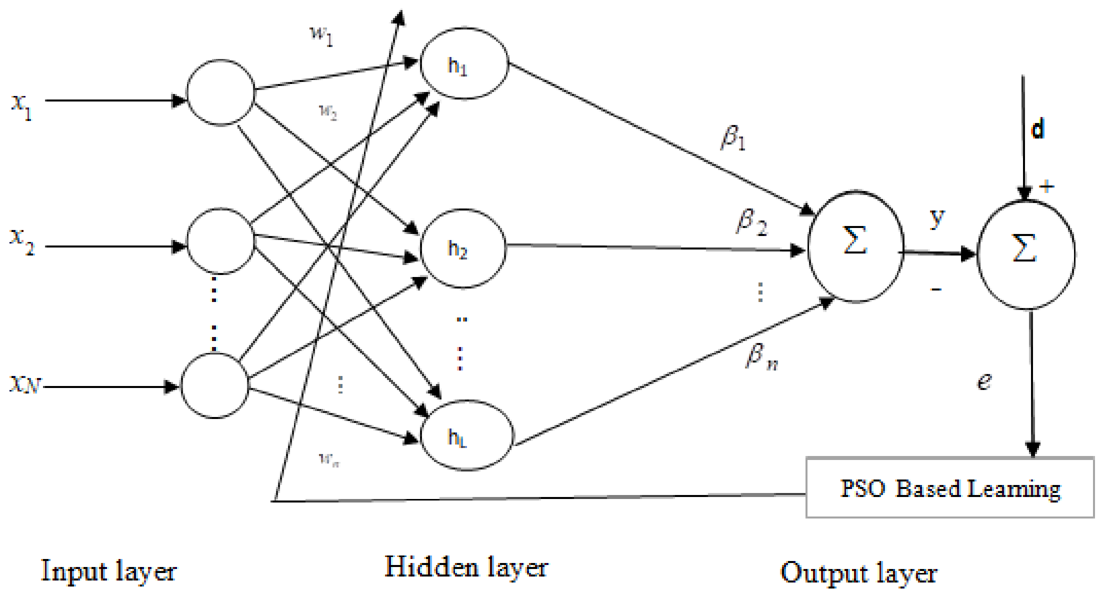

Fig. 4 PSO Based ELM Model

And $d = \begin{bmatrix} d_1 \\ d_2 \\ \vdots \\ d_n \end{bmatrix}$, $\beta = \begin{bmatrix} \beta_1 \\ \beta_1 \\ \vdots \\ \beta_n \end{bmatrix}$

2.8.3 Weight optimization by PSO

Particle swarm optimization (PSO) [23] has been applied to virtually every area in optimization, computational perspicacity, and design/scheduling applications.

Let" x_i and v_i be the position vector and velocity" for particle i[th], respectively. The new velocity vector is determined by the following formula

$$v_i^{n+1} = v_i^n + \alpha \in_1 \left[g^* - x_i^n\right] + \gamma \in_2 \left[x_i^* - x_i^n\right] \tag{17}$$

Where" $\in_1$ and $\in_2$ are two random vectors, between 0 and 1". In standard PSO algorithm, and the most noticeable improvement is probably to use an inertia function $\theta(n)$ so that v_i^n is replaced by $\theta(n)\ v_i^n$

$$v_i^{n+1} = \theta v_i^n + \alpha \in_1 \left[g^* - x_i^n\right] + \gamma \in_2 \left[x_i^* - x_i^n\right] \tag{18}$$

Where θ ∈ (0,1) .

Further the weights are mentioned as $W = \left[w_{i0} + w_{i1}x_1 + \ldots\ldots\ldots. w_{iN}x_N\right]$ and the weigthts are mapped and updated using

$$W_i^{n+1} = (1-\gamma)W_i^n + \gamma g^* + \alpha \in_n \tag{19}$$

Traditionally, in order to train ELM, to minimizing the cost function, the MSE is given by

$$MSE = \sum_{j=1}^{N}\left(\sum_{i=1}^{N} d_j - \beta_i h(w_i \cdot x_j)\right)^2 \tag{20}$$

When " H is unknown gradient-based learning algorithms" are generally used to search the minimum of $\|H\beta - d\|$.

2.8.4Pseudo code: PSO Algorithm implementation for weight optimization of ELM Model

Pseudo code: **PSO Algorithm implementation for weight optimization of ELM Model.**

1. Initializing weights of the model with random position and velocity vectors.

2. Evaluate fitness function

3.The Population size =50

4.The control parameter α = 0.85n, γ =0.75

5. Initialize the position velocity equation and map with the weights

6.Initialize the weights as W_i^n

7.%starting of loop

update(W_i^n) as

$$W_i^{n+1} = (1-\gamma)W_i^n + \gamma g^* + \alpha \in_n$$

End

update W_i^{n+1} to obtain minimum weight values

end of for loop
8.Stopping criteria: Continue till optimization gets minimum error values
9. If not converges, repeat until nearly zero error satisfied.

2.8.5 Set up for visualization of detection and classification of brain tumor using Raspberry Pi 3 B+

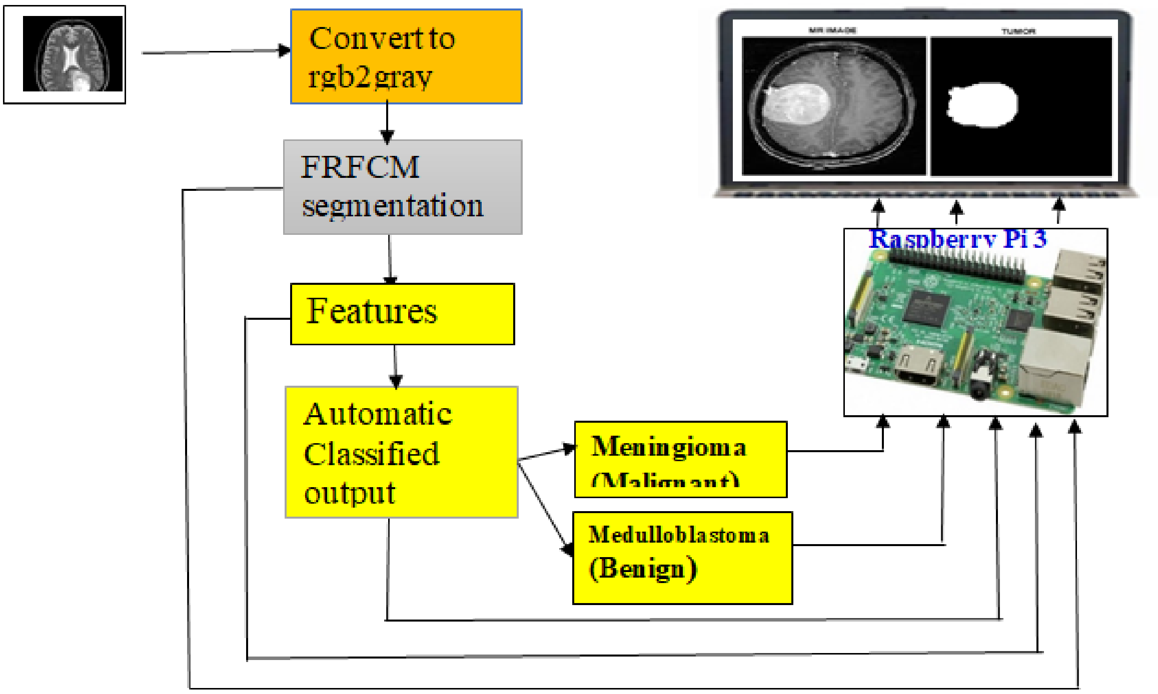

Fig.5 GUI for visualization of segmentation, Feature and classification results

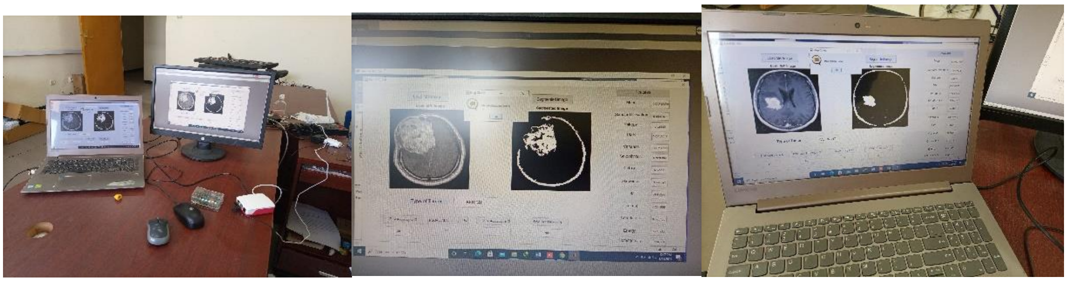

Fig.6 GUI for visualization results on system

3. Results

3.1 FCM algorithm based Image segmentation results

In this research work, image segmentation results are presented which are shown from Fig.7 to Fig.10. The experiments are carried out with the software MATLAB2018a.

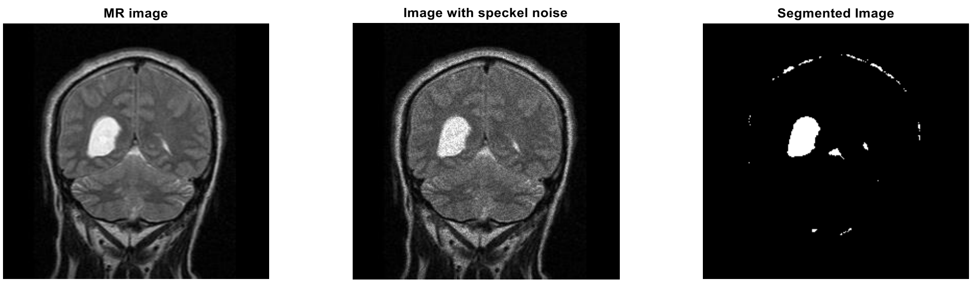

Fig. 7 Segmentation Using NDFCM Algorithm.

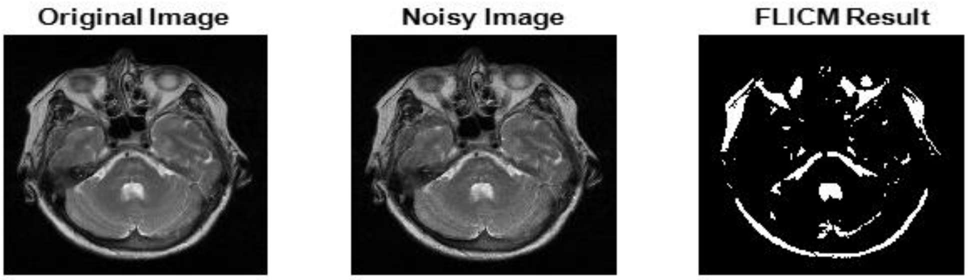

Fig.8 Segmentation Using FLICM Algorithm

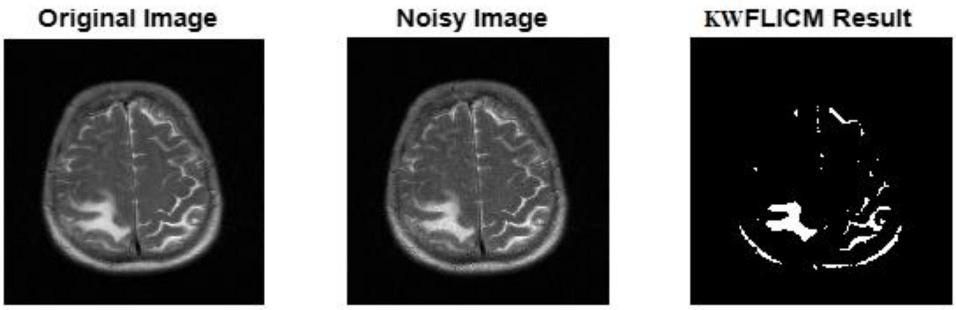

Fig. 9 Segmentation Using improved KWFLICM Algorithm.

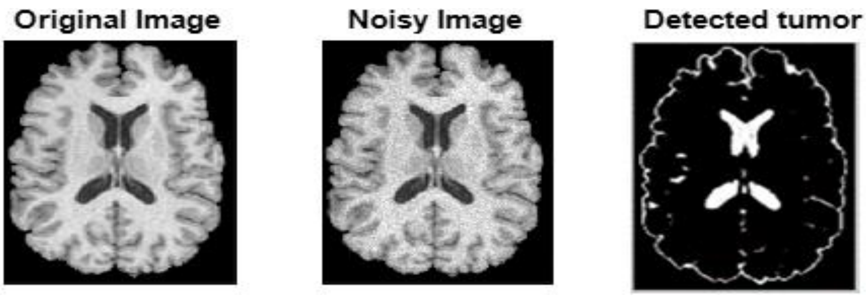

Fig. 10 Segmentation Using FRFCM Algorithm.

Table 1 Segmentation Accuracy

Algorithm	Noise level	
	Rician Noise ($\sigma_n = 10$)	Rician Noise ($\sigma_n = 20$)
“FLIFCM”	97.45	96.27
“KWFLICM”	97.92	96.31
“NDFCM”	98.81	98.21

"FRFCM"	**99.21**	**98.87**

3.2 Performance Measure of classifiers

"Sensitivity, specificity, accuracy" are the measure of classification performance [16,24].

Table 2 Performance measure of different classifiers

Classifier	Sensitivity	Specificity	Accuracy in (%)
RVM	0.96	0.87	94.60
SB-RVM	0.98	0.92	96.86
ELM	0.99	0.94	98.82
SB-ELM	0.98	1.0	**96.85**

Table 3 Performance measure of different classifiers

Classifier	Sensitivity	Specificity	Accuracy in (%)
SVM	0.98	0.94	96.26
RVM	0.96	0.87	94.60
ELM	0.99	0.94	98.82
ELM+PSO	0.99	1.0	**99.41**

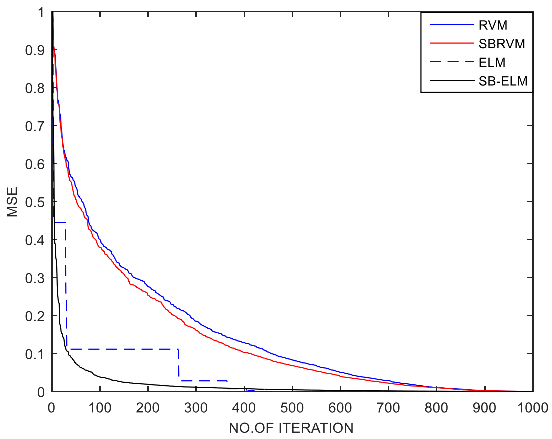

Fig .11 Mean Squared Error Convergence -1

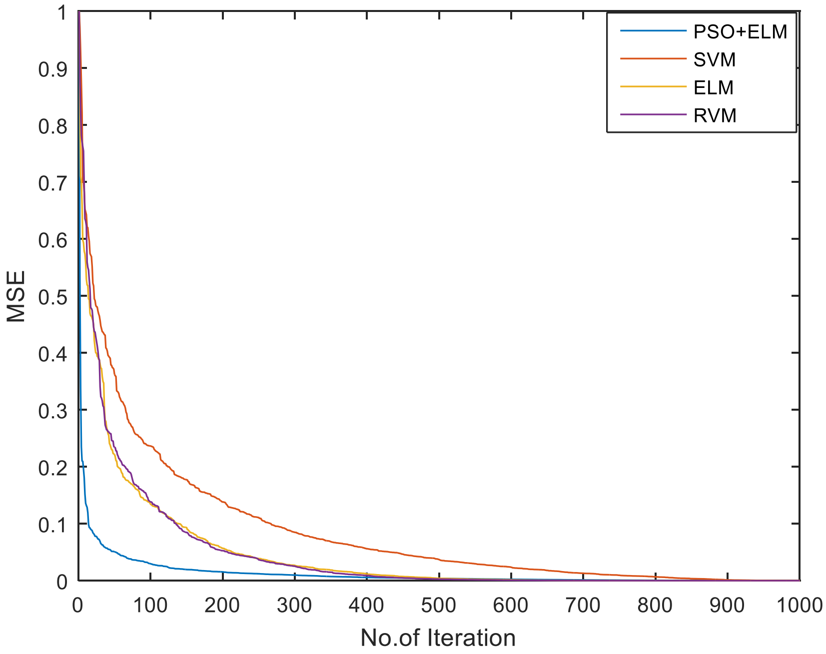

Fig .12 Mean Squared Error Convergence -2

3.3 GUI(Graphical User Interface) for automatic visualization of detection and classification through Using Raspberry Pi3.

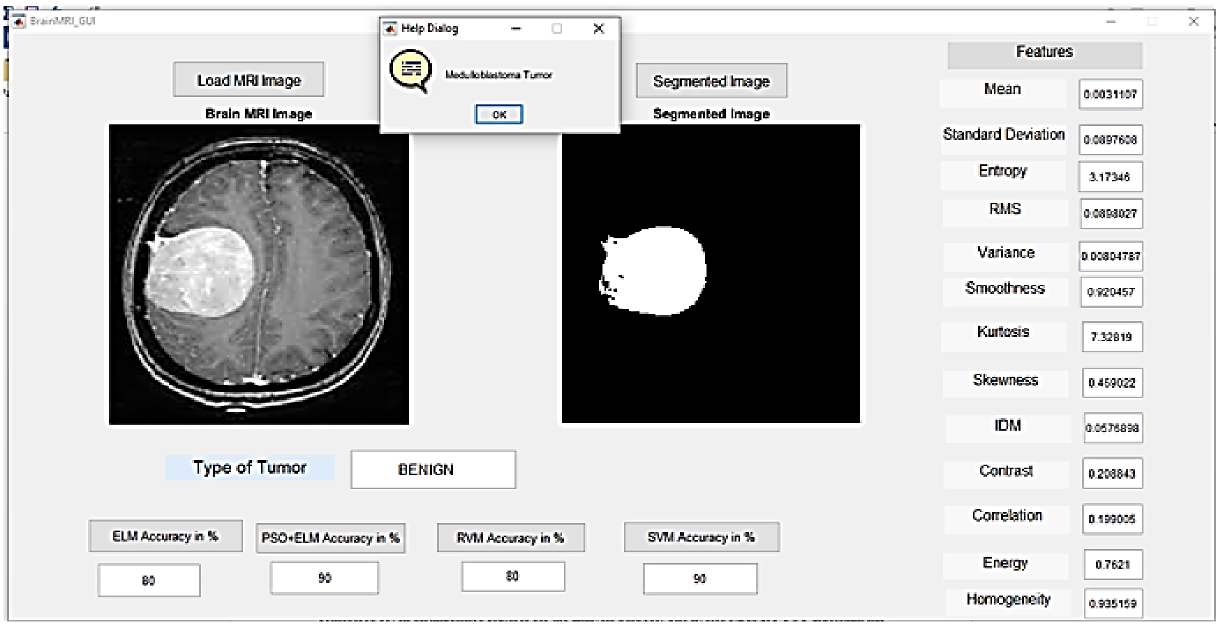

Fig. 13 Segmentation and classification result using GUI (Benign-1)

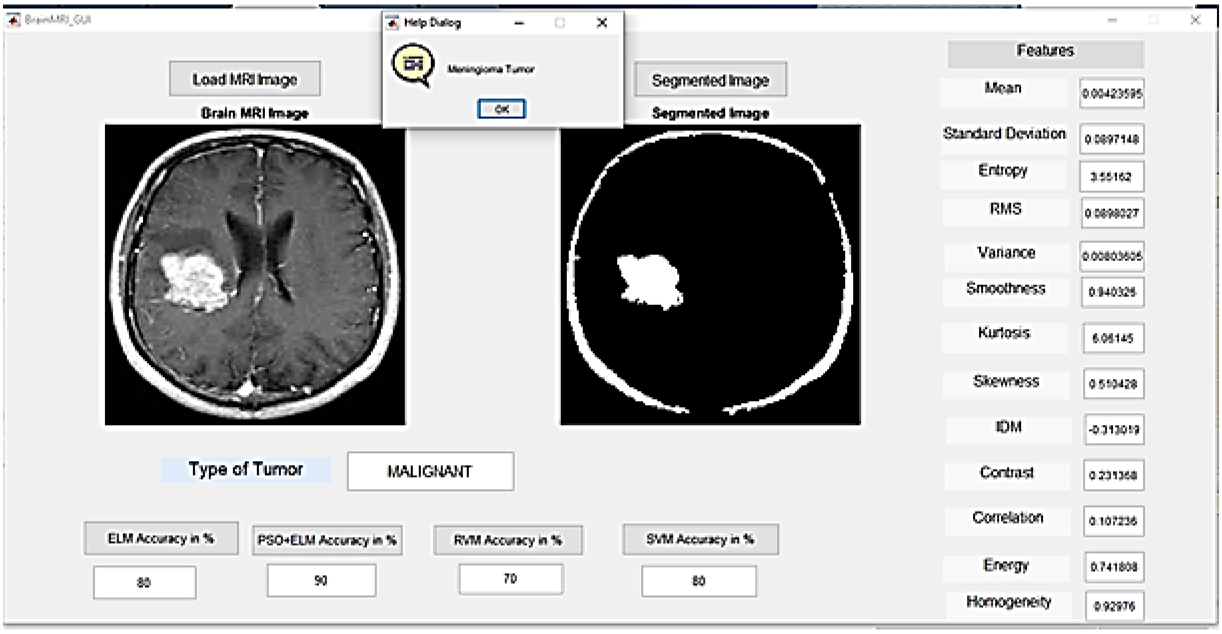

Fig. 14 Segmentation and classification result using GUI (Malignant-1)

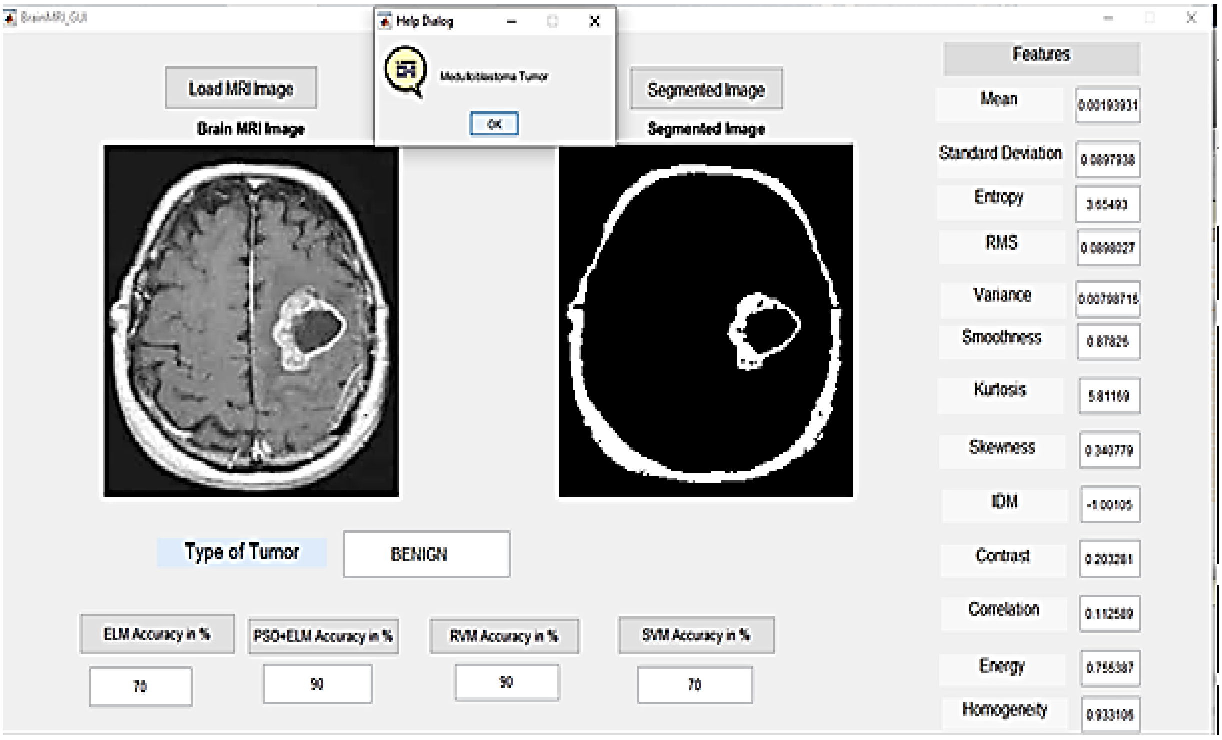

Fig. 15 Segmentation and classification result using GUI (Benign-2)

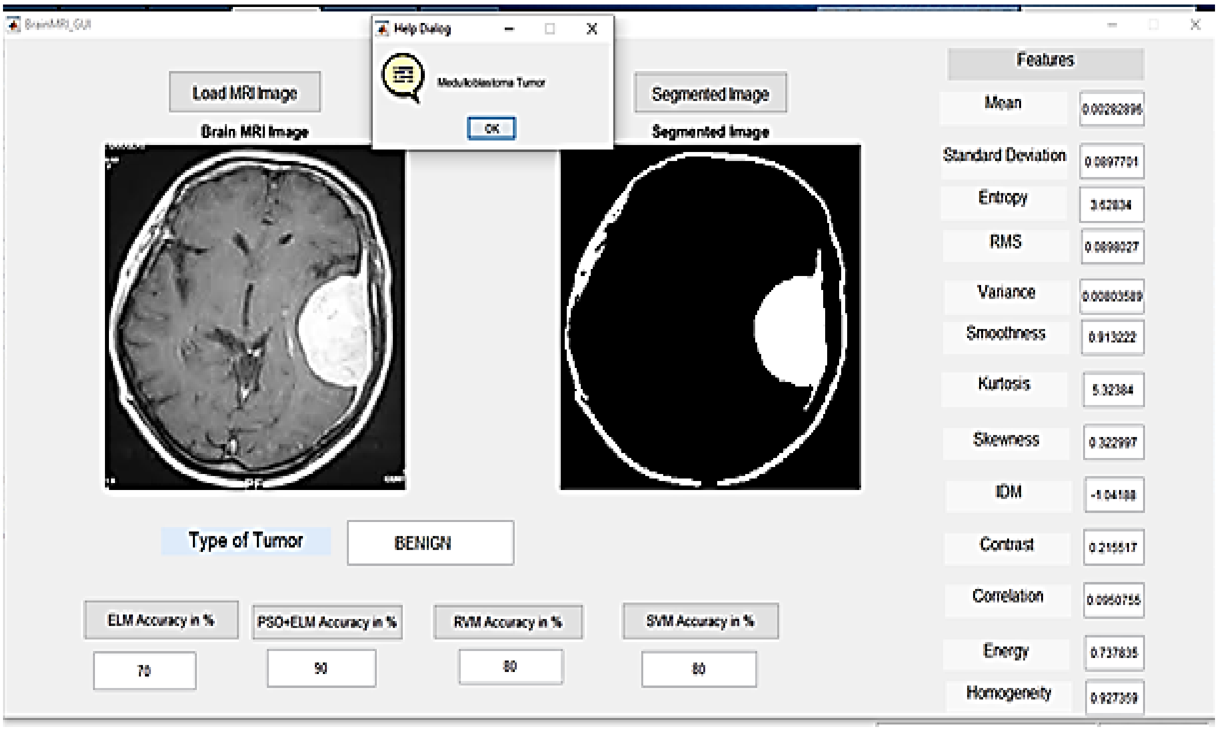

Fig.16 Segmentation and classification result using GUI(Benign-3)

4. Discussion

The segmentation accuracy achieved by FRFCM and other FCM based algorithms are presented **Table 1**. **Table 2 and Table3** shows the performance measure of all classifiers. The accuracy obtained by utilizing RVM,SB-RVM,ELM and SB-ELM are 94.60%, 96.86%, 98.82%, 96.85% respectively. The SVM, RVM, ELM, ELM+PSO accuracies are 96.26%, 94.60%, 98.82%, 99.41% respectively. The computational time of each stage of the proposed ELM+PSO method is recorded as 8.4127 sec. The computational time for SVM, RVM, ELM are calculated as 16.2564 sec, 12.4125 sec, and 10.3234 sec. The error plots are shown in **Fig.11** and **Fig.12**. The performance rate of proposed ELM+PSO classifier depends on the convergence parameters setting. It is observed from the **Fig.11** that the proposed SB-ELM model takes near about 340 iterations to converge. **Fig.12** shows that the SVM model took 790 iterations nearly, whereas the RVM and ELM model took 430 and 400 iterations for convergence. It is observed from result that the accuracy in ELM and ELM+PSO are nearly similar, but the convergence is faster in the case of ELM+PSO classifier.**Fig.13 to Fig.16** shows the GUI model outputs of segmentation along with feature values and classification accuracy for different test brain tumor images..

5. Conclusion

This research work utilizes FRFCM algorithm for segmentation to remove rician noise and smoothen the image. The real data has been collected from the reputed hospitals of Ethiopia and “Harvard medical school of architecture” for the purpose of segmentation and classification. Seven distinguished features are extracted using “GLCM feature extraction technique” and fed as input to SVM, RVM, ELM,SB-ELM and proposed PSO Based ELM for classification of the brain tumor into benign and malignant tumors from the magnetic resonance images. The PSO algorithm updates the weights of ELM model for the improvement of the performance of the model. The SVM, RVM, ELM classifiers results are compared with the proposed PSO based ELM classifier and presented. The accuracy of the classifiers SVM, RVM, ELM and PSO+ELM are presented in the Table-2 and Table-3. The proposed PSO+ELM has good potentiality in classifying the tumor which helps in diagnosing process by clinical experts. The hybrid algorithm such as WCA(water cycle algorithm) and SCA(sine and cosine algorithm) optimization algorithm can be utilized for weight updation of weights of ELM to improve further the performance of ELM in terms of classification.

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