Tumor Detection From Brain MRI Using Modified Sea Lion Optimization Based Kernel Extreme Learning Algorithm

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Abstract

Major cause for high mortality in human being is brain tumor. Improper and delayed treatment leads to the development of malignant tumor which is untreatable. This realize us the necessity of tumor detection at earlier stage. For such early detection, initially the skull removal process is carried out in input MRI using Brain Surface Extraction (BSE) technique. The lesion enhancement process over the skull removed image is performed using Weiner filter. It is performed to attain better segmentation result. Next, the tumor region is segmented from the non-tumor part using region growing segmentation approach. Features are required to recognize whether the segmented tumor is benign or malignant. Therefore, SGLDM and LESH based feature extraction approaches are used in this method. The dimensionality of extracted features is reduced using feature selection process. Finally with that selected features the tumor classification is achieved using the MSLO based KELM approach. The effectiveness of proposed KELM-MSLO approach is determined using the benchmark datasets such as BRATS 2013 Leader board, BRATS 2014, 2015, and 2018. Finally, some performance metrics are evaluated to analyze the effective performance of presented technique on detection of tumor at former stage.

Keywords:*Brain Tumor, Segmentation, Kernel Extreme Learning Machine (KELM), Skull Removal, Region-Growing Technique.*

I. Introduction

Brain tumor is nothing it is a group of irregular cells found inside the brain. There are two different classes of tumor they are benign tumor and malignant tumor [1]. It is the major cause for death in this universe [2]. Identification and classification of medical infections are gaining huge attention in computer vision field, because nowadays it is extensively used in various medical imaging applications [3]. Advancement in information technology has revolutionized this medical imaging field by introducing machine learning and image processing for detection of disease symptoms using segmentation and classification process. Therefore, an accurate categorization and diagnosis are planned by doctors over the lesions or tumor regions [4].

Image segmentation and classification techniques attain a huge importance in various applications as they analyze, understand, extract features and interpret the medical images. These techniques are found functional in various brain imaging applications few examples such as tumor location and its volume estimation, tissue classification, surgical planning, matching, blood cell delineation, etc. The abnormalities encountered in brain in terms of size, location, or shape is resection and examines using Magnetic Resonance Imaging (MRI) scan and Computed Tomography (CT) [5]. MRI is identified as the most reliable one, as it does not produce any radiations that are found harmful to human body [6]. The occurrence of tumor in human brain is clearly examined using MRI technique. Therefore, this work highly intends to differentiate the malignant and benign tumor on the basis of textures, various features and intensities [7].

The structure of brain is found complex because the entire tissues in the brain are interconnected with each other which increase the complexity of brain tumor diagnosis process [8]. It not only improves the diagnosis complexity moreover it also improves the challenge of segmentation and classification process due to its varied shape, location, and appearance. [9]. Even though, both the segmentation and classification techniques are having similar importance, but the segmentation approach has received a high interest and popularity in treatment monitoring and surgical planning. The main intention of this segmentation process is to delineate various tumor structures like necrosis, edema, and active tumorous core. However, the experts consume enormous time to manually contour the tumor structures [10]. With the available segmentation techniques, they are classified as region based [11], and edge based segmentation technique [12]. For the past few decades, the deep learning approaches are gaining high interest in classification process. The classification results of this learning approach are found better than the conventional image processing techniques. Different literatures are now developing to illustrate the effectiveness of deep learning in classification process than the conventional techniques [13].

The contribution is as follows: Initially, the skull in brain MRI is removed using BSE approach and the tumor region from that skull removed image is segmented using region growing approach. Next, the features from that segmented portion are extracted using LESH and SGLDM approach. Then, the features that reduce the error of classification process is selected using BGOA. Finally, the optimal features selected using optimization technique is provided to KELM classifier to distinguish the benign and malignant tumor for better treatment. To enhance the effectiveness of KELM classifier a modified SLO algorithm(MSLO) is hybrid along with the KELM classifier which reduces the error value by selecting the optimal weight parameter.

Paper is organized as follows: Some existing techniques related to brain tumor classification and segmentation is reviewed in section 2. Next, the clear details about the techniques used for tumor classification in this proposed architecture are provided in section 3. After that, the results that are obtained with this proposed classification approach is discussed in section 4. Finally, the entire classification process is concluded in section 5.

II. Related Work

Tumor in brain increase the death rate, however early detection of such tumor may increase the lifetime of each patients. To achieve that early detection, the fusion process was introduced in [14] which combine the texture and structural information. For such fusion process, the Daubechies wavelet kernel hybrid with DWT (Discrete Wavelet Transform) was used. Next the noise in MRI was removed using partial differential diffusion filter (PDDF). After that the tumor was segmented tumor using a global thresholding approach. Finally, the CNN (Convolutional Neural Network) was introduced for differentiating the non-tumor and tumor regions. Tumor in brain was analyzed by Amin et al, in [15] using statistical and machine learning approach. For such analysis, primarily the input image was pre-processed with wiener filter which eliminates the noise. Next, the PF (potential field) clustering was applied to cluster the subsets pixels of tumor regions. The tumor regions were then separated from non-tumor parts using mathematical morphology and global thresholding operations. The features required for classification was extracted using Gabor Wavelet Transform (GWT), and Local Binary Pattern (LBP) techniques. SVM along with quadratic kernel function was used at last phase for tumor classification.

In [16], the super-resolution and CNN was combined along with fuzzy C means (SR-FCM-CNN) for tumor detection. The tumor region was segmented from MRI by SR-FCM approach. Next the features from that segmented portions were extracted using CNN (SqueezeNet architecture). Finally, the extreme learning machine (ELM) was introduced for classification process. The SqueezeNet architecture in CNN extracts the features with less parameters. An unsupervised fuzzy was used for segmentation process in [17]. Before that, a triangular fuzzy based median filtering was introduced for image enhancement. Two different feature extraction techniques were used in this method they are similar texture (ST), and Gabor feature. With these extracted features, the classification of brain tumor was achieved by ELM classifier.

An optimal threshold value was determined in [18] using an adaptive PSO (particle Swarm Optimization). With this PSO, an OTSU approach was combined which maximize the PSO performance. Before threshold value detection the image quality was improved by denoising using an anisotropic diffusion filtering approach. Finally, the extracted features were provided to CNN for tumor classification. However, an artificial NN (ANN) was used in [19] to achieve tumor classification. To attain a better performance this approach use GA (genetic algorithm) for feature selection. In this method, an optimization approach was used for segmentation which segment the tumor portion with less complexity.

In [20], a Residual network was introduced for tumor classification. Because accurate tumor type identification may reduce the death rate due to brain tumor. It use a benchmark dataset to test its performance. This dataset contains 3064 images with such dataset this approach attains higher accuracy than other existing approaches. Further, the author in [21] uses CNN for accurately recognizing the 3 grades of tumors (Meningioma, Pituitary, and Glioma) but this CNN based method is found not suitable for huge dataset as it consumes huge time while processing. This CNN contains max-pooling, flattening, and convolutional layers.

Basically the tumor segmentation from brain MRI was carried out in three different ways they are Manual, semi-automated, and fully automated techniques but still these approaches show some demerits. To avoid such defects an effective approach was introduced in [22]. Before segmentation, the image needs to pre-process for removing noise and to enhance image contrast. It utilizes the deep learning based technique for tumor segmentation from MRI. Similarly segmenting the interested regions from the MRI was carried out in [23] which mainly concentrate in reducing the error and data discrepancies during segmentation. This approach utilizes canny edge detection approach for pre-processing the brain MRI. From the pre-processed image the features were extracted and the tumors are classified using CNN. Finally, an Adam optimizer was hybrid along with CNN to enhance CNN's performance.

III. Proposed Methodology

A large number of techniques are developed for tumor detection from brain MRI but none attained an effective result therefore in this proposed approach we analyzed some effective image processing approaches for tumor detection. However analyzing the brain tumor using image processing is difficult task. It includes several steps to attain an accurate result. The steps that are used in proposed method for tumor detection is shown in figure 1. The first step used in this tumor detection process is skull removal. Next the lesion enhancement using Weiner filter is achieved to obtain better segmentation result. The features present at the segmented region are extracted using SGLDM, and LESH approach. Next, an optimization based feature selection process is introduced to minimize the dimension of extracted features. Finally, with this selected features the tumor classification is achieved using KELM classifier. The accuracy rate of KELM is improved by hybriding the MSLO algorithm.

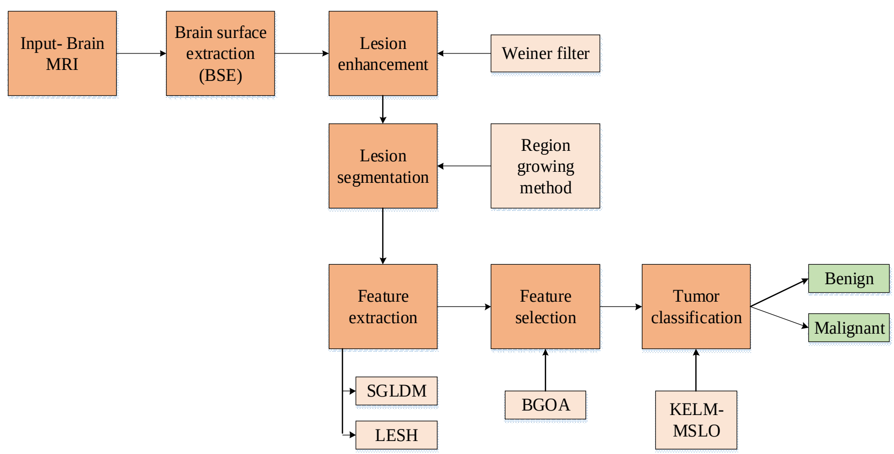
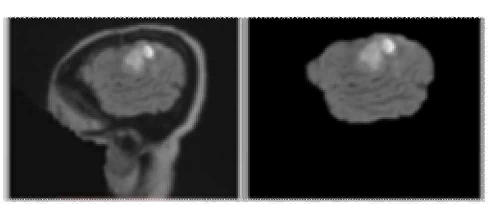


Figure 1: Workflow of proposed KELM-MSLO approach

A. Skull Removal using BSE

At the time of image acquisition, the skull, eyes, and background are present in MRI, which does not have any useful information [19]. Therefore, eliminating the non-brain region from MRI maximize the accuracy rate and reduce the processing time. The Skull removal process is performed using BSE method and its output is shown in figure 2 [19].



a) b)

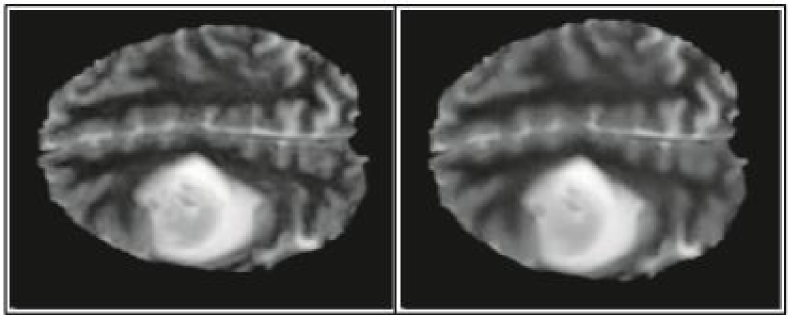
Figure 2: BSE (a) Input image, (b) Skull removed image

B. Lesion Enhancement

Few artifacts like uneven brightness (e.g., skull and eyes) and extra tissues are found in MR slices which reduce the overall accuracy. Most challenging issue in medical images is noise, therefore noise reduction is essential in pre-processing. Number of techniques are developed for noise reduction but none of them attains better performance. Further, this noise reduction approaches destroy the useful information during noise reduction. To avoid such issue an efficient filtering approach is used in this architecture for noise removal which is named as Weiner filter [15]. It process along with different wavelet bands for de-noising the image, $I(a,b)$ obtained from BSE. This filtering is applied for enhancing the lesion region to achieve better segmentation result. Weiner filter minimize the MSE and it is defined in equation (1).

$$H(a,b)=\frac{G^{*}(a,b)Spec_{I}(a,b)}{|G(a,b)|^{2}\,Spec_{I}(a,b)+Spec_{noise}(a,b)} \quad (1)$$

Where, the input spectrum of both the additive noise and input slices are represented as $Spec_{noise}(a,b)$ and $Spec_I(a,b)$. $G(a,b)$ represents the low pass filter (LPF), and the filter conjugate is represented as G^*. The image that obtained after performing lesion enhancement is shown in figure 3 [15].



(a) (b)

Figure 3: Lesion enhancement a) Input image, b) Weiner output

C. Segmentation

The tumor from the lesion enhanced image is segmented using region-growing approach. The segmentation of the image relies on the division of the picture into areas. By considering the proportional characteristics as foundation this segmentation process is implemented. The major consideration of this segmentation process is extraction of imperative components. Due to this, the data can be effectively seen. However in medical imaging field, the segmentation plays a major role in MRI for accurate tumor detection.

D. Region-Growing Technique

It is an ordinary segmentation approach which implicates the selected preliminary seed points. This type of segmentation performs division by looking over the neighbouring pixels of preliminary seed points. Finally it decides whether the pixel national needs to be included within the locale or not. The tumor boundary and its growth rate is determined by region growing approach [24]. It evaluates the neighbouring pixel from the smaller region to larger region. That pixel inside the same collection of properties is used to allocate pixels to develop area phase. On intensity basis the shape of each region develop. The brain MRI contains enormous connected seed points and this region growing process initiate its process from seed points. This process continues automatically by integrating the seeds to the region. It continues till the seed points are not available for integration within the region.

The Euclidean distance between the seeds is established for an increasing eight-related seed neighbors (r, s).

$$f = \|d(p,q) - d(r,s)\| \qquad (2)$$

With this region growing approach, the interested regions are segmented from MRI. Finally, from the segmented image the tumor is effectively determined.

E. Feature Extraction

After segmentation, perform feature extraction from MRI. In this method two popular approaches are used they are SGLDM, and LESH which maximize the classification accuracy. The performance of feature extraction depends on the surface, structure, and shape of tumor in MRI.

SGLDM (Spatial Grey Level Dependency Matrix): For this type of feature extraction the co-occurrence matrix is evaluated. It is modified form of GLCM (Gray-Level Co-Occurrence Matrix) approach which efficiently extracts the features from the segmented image. Using this SGDLM [25], the 2nd order statistical features are extricated. Based on the pixel pairs sharing, the statistical data present in MRI is extricated using co-occurrence matrix. The pixel pairs from the MRI is evaluated using distance 'd' and angle 'θ' parameter. The obtained co-occurrence matrix is executed in four different directions (horizontal, vertical, and two diagonal) having distance d. Four different angle values are 0°, 45°, 90° and 135°. With this approach six features are obtained from MRI they are mean, contrast, energy, homogeneity, entropy, and variance. The equations of these six different features are shown in below table 1.

Table 1. GLCM features

Features	Equation
Contrast	$contrast = \sum_i \sum_j (i-j)^2 f(i,j)$
Mean	$mean = \sum_i \sum_j f(i,j)$
Variance	$variance = \sum_i \sum_j (1-mean)^2 f(i,j)$
Energy	$energy = \sum_i \sum_j f(i-j)^2$
Entropy	$entropy = \sum_i \sum_j f(i,j) \log(f(i,j))$
Homogeneity	$homogeneity = \sum_{i,j} \frac{1}{1+(i-j)^2} f(i,j)$

LESH: For the image of interest, LESH (Local Energy based Shape Histogram) [26] feature extraction approach is primarily used which depends upon the idea of calculating the local energy pattern histogram. Using phase congruency scheme, the local energies are calculated with different orientations. Local energy is computed as follow

$$E = \frac{\sum_n W(x)\left[A_n(x)\left(\cos\left(\varphi_n(x) - \phi(x)\right) - \left|\sin\left(\varphi_n(x) - \phi(x)\right)\right|\right) - T\right]}{\sum_n A_n(x) + \varepsilon} \quad (3)$$

Where, T is a factor for noise cancellation, W represents the sine of phase deviation and factor. The local histogram h is expressed as below:

$$h_{r,b} = \sum W_r \times E \times \delta_{LB} \quad (4)$$

Where, δ_{LB} represents the Kronecker's delta, local energy is computed by E and W_r is represented as Gaussian weighting function of region r, orientation label map is represented by L and current bin is represented as b. Gaussian weighting function of region r is given as follow.

$$W_r = \frac{1}{2\pi\sigma} e^{\left[(x-r_{x0})^2 + (y-r_{y0})^2\right] / \sigma^2} \quad (5)$$

With the above two approaches (SGLDM and LESH), the feature extraction from MRI is accomplished. These extracted features are then provided to feature selection process.

F. Feature Selection

Feature Selection is commonly referred as an optimization issue and solved using Swarm Intelligence based techniques. It helps to reduce the amount of data particularly in case of high dimensional datasets. In addition, not all features are utilized as classifier inputs. The inapt features are regarded to result worst accuracy for the classifier while increasing the computational time.

Binary Grasshopper Optimization Algorithm (BGOA)

BGOA [27] is the SI technique utilized to choose appropriate features which enhances classification accuracy. In this work, for classification purpose BGOA is employed that selects optimal feature subset.

The objective function used for this optimization is given as,

$$f(x^{(i)}) = \max\left(\frac{f_S}{f_T}\right) \tag{6}$$

Where, f_S = selected features, f_T = total features

Binary values [0, 1] signify the search space. Based on its current position, each solution is updated also best grasshopper position is named as target. In this work, sigmoid function is utilized as transfer function to perform the squash of continuous results in several dimensions. So that the grasshoppers are forced to move in the binary search space.
Transfer function is given as,

$$T(x^{(i)}) = \frac{1}{1+e^{-x}} \tag{7}$$

The outputs are to be limited by using the threshold to get the binary value as output. The stochastic threshold is applied as,

$$\tau = \begin{cases} 0, & if\ r < T(x^{(i)}) \\ 1, & if\ r \geq T(x^{(i)}) \end{cases} \tag{8}$$

Where, τ=represents the threshold condition and r = random value.

Based on the outcome of the threshold condition, the decision is taken whether the feature is selected or not. If the output is one means the feature gets selected. Also, feature is not selected when the outcome is zero. For optimized feature selection, the function used to evaluate the fitness is given in equation (9),

$$F = \psi f(x) \tag{9}$$

Where, ψ is the constant and $f(x)$ represents the objective function.

G. Kernel Extreme Learning Machine based Tumor Classification

Establishing classification technique by means of ML approach is the last procedure in sentiment classification. Here, ELM based Classifier is suggested in the classification of Sentiments. ELM is an advanced learning method recommended for SLFNs. ELM is not appropriate in certain situations due to the random selection of biases as well as weights among input in addition to hidden layer. Thus, KELM is proposed to overcome this limitation. The idea of weight initiation among input as well as hidden layer is removed in KELM [28]. Conversely, classifier performance is extremely dependent on dual important aspects, specifically, (γ) kernel and (C) control factor. SLFN is conveyed as follows:

$$f_{ELM}(x_1) = h(x_1)\beta = H\beta \tag{10}$$

Where, x_1 = sample, $f_{ELM}(x_1)$ = NN output, H or $h(x_1)$ = feature mapping matrix of hidden layer, β = weight among hidden, output layer. The value of β can be considered as follows,

$$\beta = H^T\left(\frac{I}{C} + HH^T\right)^{-1} T \tag{11}$$

Where,I = unit matrix, T= target vector of training sample, C= cost factor

Substitute eqn. (9) in (8). The output of ELM is expressed as,

$$f_{ELM}(x_1) = h(x_1)\beta = h(x_1)H^T\left(\frac{I}{C} + HH^T\right)^{-1} T$$

(12)

As the feature mapping $h(x_1)$ value is unknown, a kernel matrix for ELM is defined as,

$$\Omega_{ELM} = HH^T \tag{13}$$

$$\Omega_{ELMs,t} = h(x_s)h(x_t) = K(x_s, x_t) \tag{14}$$

Substitute eqn. (11), (12) in eqn. (10). The final outcome of ELM can be rewritten as follows:

$$f(x_1) = \begin{bmatrix} K(x, x_1) \\ \cdot \\ \cdot \\ K(x, x_N) \end{bmatrix}^T \left(\frac{I}{C} + \Omega_{ELM}\right)^{-1} T \tag{15}$$

The kernel function in KELM is expressed as,

$$K(m,n) = \exp\left(-\gamma \|m-n\|^2\right) \tag{16}$$

Where, γ = kernel factor. Subsequently, the outcome of KELM is influenced by the choice of two factors namely, kernel factor (γ) in addition to Cost factor (c). Also, the factors need to be optimized efficiently.

Evidently, KELM is time-consuming as well as the performance achieved by means of the selected parameters is suboptimal. For γ and C optimal selection, the combinatorial search space turn out to be exponentially large. Therefore, to proficiently discover the huge search space, numerous nature-inspired algorithms are utilized. For the purpose of automatically selecting the factors of KELM, we use MSLO algorithm to train KELM. From various metaheuristic algorithms, the behaviour of SLO was inspired.

The navigations of sea lions rely upon their age, sexual orientation and capacity they have for the entire colony [29]. The sea lions have three phases (i) using the whiskers the sea lion tracking and chasing the prey (ii) once it finds the prey the sea lion calling different individuals to joined their subgroup and surrounding the prey. And then the prey is attacked by sea lion. The fitness function used to evaluate the best optimal KELM parameter is given in equation (17),

$$f(x)=\begin{cases} x, & \min error \\ x, & \max accuracy \end{cases} \quad where\ x=\gamma, c \qquad (17)$$

Detecting and Tracking Phase: To recognize shape, position and size of features, the sea lions utilized their whiskers. This encourages sea lion to detect the existing feature and to recognize their position when the whiskers course is on the other way of water waves. The position of the features is recognized by the sea LIONS and consider different individuals that will join its subgroup to locate the ideal features.

$$\vec{Dist} = \left| 2\vec{B} \cdot \vec{P}(t) - \vec{SL}(t) \right| \qquad (18)$$

Where, the distance between the target feature is indicated by $\vec{Dist}$, the position vector of the target features and sea lion is represented as $\vec{SL}(t)$ and $\vec{P}(t)$, t is denoted as the current iteration and random vector is represented as $\vec{B}$. The sea lions move towards the target features to be nearest at the next iterations. The mathematical model of this behaviour is in below equation.

$$\vec{SL}(t+1) = \vec{P}(t) - \vec{Dist} \cdot \vec{C} \qquad (19)$$

Where, $\vec{C}$ is decreased linearly from 2 to 0 and $(t+1)$ define the next iteration.

Vocalization Phase: Since the sea lions live in both marine and terrestrial so, they are named as amphibians. When compared to the land, the sound generated by this sea lion is 4 times faster in water. When they are in hunting process, they generate different kinds of sounds to communicate with each other. The sea lion makes sounds to call other associates to encircle and hit the prey when they identify the prey. The given below expressions explain the mathematical model of this phase.

$$SP_{leader} = \left| (V_1(1+V_2))/V_2 \right| \qquad (20)$$

Here, the speed of sound of sea lion leader in water as well as air is mentioned as V_1 and V_2 as well as sea lion leader's speed of sound is denoted as SP_{leader}. The generated sound reflected in air is mentioned as $\sin\phi$ and the sound refracted at the underwater is mentioned as $\sin\theta$. Here, both ϕ and θ means the reflection angle and refraction angle.

Finding Best Parameter: Sea lions can detect the targets prey position and surround them. The hunting system is conducted by the leader (the best search agent), who finds prey and inform them concerning others. Typically target prey is measured the finest results for the current candidate.

$$\vec{SL}(t+1) = \left| \vec{P}(t) - \vec{SL}(t) \right| \cdot \cos(2\pi m) + \vec{P}(t) \qquad (21)$$

Searching for prey (Exploration phase): The sea lion swims in zigzag manner to find the target prey with their whiskers. So, C is engaged with the random values in this study. The sea lions are missing from the sea lions leader and target prey if the value of C is greater than one or less than negative one. Based on the best search agent, the sea lions update their locations in exploitation phase. In exploration stage, search agents update their location based on the randomly selected sea lion. The SLO technique determines the global optimum solution when C is greater than one. This is represented in the given below expression.

$$D = \left| 2BS_{rand}(t) - S(t) \right| \qquad (22)$$

$$S(t+1) = S_{rand}(t) - D \cdot C \qquad (23)$$

Here, random sea lion is indicated by $S_{rand}(t)$ in which it is selected from current population.

For finding the best γ and c, first we update the position by using galactic swarm optimization (GSO) algorithm. GSO position is updated in sea lion optimization to get the optimal parameters (γ and c).

$$y^{(i)} \leftarrow y^{(i)} + v^{(i)} \qquad (24)$$

Where, $y^{(i)}$ is represented as the position of GSO. $\left|\vec{P}(t) - \vec{SL}(t)\right|$ denotes the distance among the finest optimum solution (target feature) and the search agent, random number is represented by m and $\cos(2\pi m)$ is utilized to represent the features behaviour. The Pseudocode for proposed KELM-MSLO is given in table 2.

Table 2. KELM-MSLO Algorithm

```
Pseudocode for KELM-MSLO algorithm
Begin
    for i = 1, identify the agent number
    Initialize position, γ and c
      Estimate the fitness function
      Train KELM and store the test values in fitness array
End
Perform sorting on obtained fitness values, and save best solution
Initialize, total solutions (γ and c) and current best search agent
While (I < max − iter)
    for each search agent
        Estimate the speed of each solution (γ and c) using equation (20)
if S_l < 0.25, then
        if (c < 1) then
            update the current position of γ and c using equation (22)
else if (c > 1)
            Select γ and c randomly

        end if
      end if
if S_l > 0.25
        Update the current position of γ and c using equation (17)
      end if
    end for
Perform position updation for γ and c using equation (23)
Estimate the fitness function of each γ and c using equation (17)
Update the position of parameters using GSO algorithm using equation (24)
Return, best optimized γ and c.
```

The MSLO algorithm is used to optimize the KELM parameters (γ and c). With this optimized parameters the classification accuracy of KELM gets improved with reduced error rate. The reduced error rate minimize the complexity of the classification process.

IV. Result Analysis and Discussion

The method that is discussed in this proposed work is tested using BRATS 2013 Leader board, 2014, 2015 datasets. Two different experiments are evaluated they are pixel-based segmentation and feature based classification interms of extracted features. This evaluation is carried out on Intel Core I7 3.4 processor, NIVIDIA GeForce GTX 1080 GPU with MATLAB 2019. The description of dataset is discussed in below section. Three different datasets such as 2013 Leader board, BRATS 2014, and BRATS 2015 datasets are used in this method to test its performance. 2013 Leader board dataset use 21 HGG and 4 LGG for training and testing. BRATS 2014 contains 300 images among that 200 are used for training and 100 are applied for testing. BRATS 2015 contains 384 cases, among that 220 HGG and 54 LGG cases are used for training, and 110 LGG and 274 HGG cases are used for testing. 75 LGG and 191 HGG cases are used by BRATS 2018 for training and testing.

A. Evaluation Metrics

The performance of presented approach is evaluated using accuracy, Positive Predictive Value (PPV), DSC, sensitivity (SE), False Positive Rate

(FPR), specificity (SP), JSI, and False Negative Rate (FNR),. This performance metrics are determined using 4 different parameters they are TP (True Positive), FP (False Positive), TN (True Negative), and FN (False Negative). Where, TP (a) – The image that is correctly classified, TN (b) – The image that is incorrectly classified, FP (c) – The image that is positive but it is incorrectly classified as negative and FN (d) – The image that is negative but it is incorrectly predicted as positive. The equations that are used to evaluate these metrics are given in equations (25-30),

$$Accuracy = \frac{a+b}{a+b+c+d} \quad (25)$$

$$Sensitivity = \frac{a}{a+d} \quad (26)$$

$$Specificity = \frac{b}{b+c} \quad (27)$$

$$FPR = \frac{c}{c+b} \quad (28)$$

$$FNR = \frac{d}{d+a} \quad (29)$$

$$PPV = \frac{a}{a+c} \quad (30)$$

B. Pixel based Segmentation Results

DSC (Dice Similarity Coefficient) and JSI (Jaccard Similarity Index) are evaluated for attaining the pixel based segmentation results, for that four different benchmark datasets are used. This dataset contains ground truth image and this ground truth image is compared with segmented result to determine its effectiveness. The skull removed images are provided to segmentation process, before segmentation process the quality image is enhanced by applying a Weiner filter. Finally, the output image obtained from this segmentation process is shown in figure 3.

$$DSC(A,B) = 2\frac{|A \cap B|}{|A|+|B|} \quad (31)$$

$$JSI(A,B) = \frac{|A \cap B|}{|A|+|B|-|A \cap B|} \quad (32)$$

The equation that are used to evaluate the DSC and JSI is given in equations (31, 32). Where, A= Ground truth image, B = Segmented image.

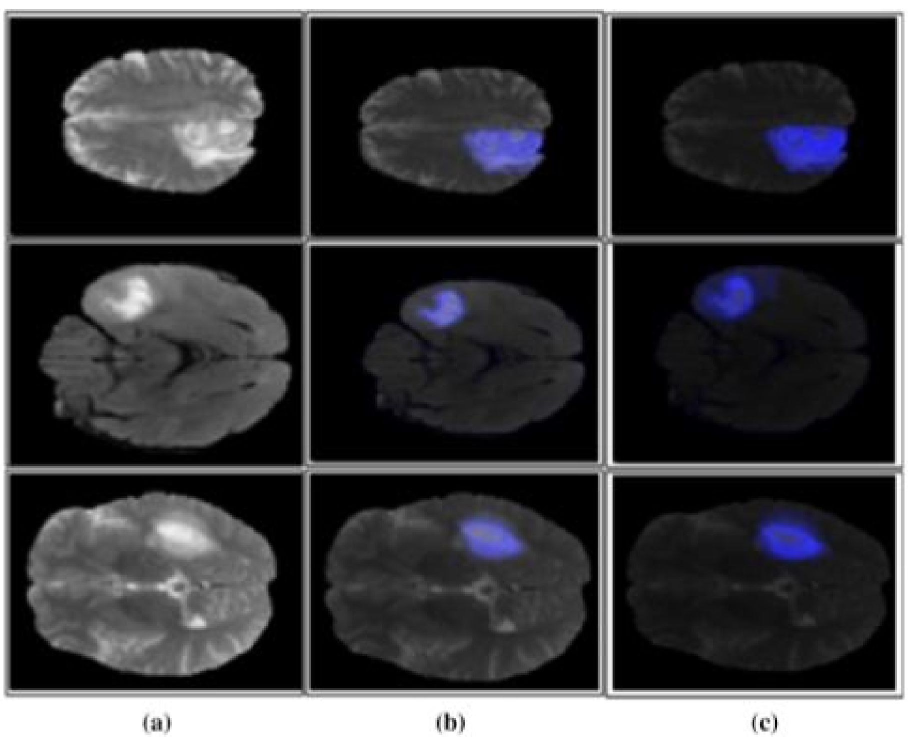


Figure 4: Segmentation of tumor portion a) Input, b) segmentation, c) Ground truth

The results obtained due to pixel based segmentation are analyzed in this section. The sample ground truth, input and output of segmentation process is shown in figure 4. The segmented tumor region in output image is shown in blue color.

Table 3. Results attained by proposed method(KELM-MSLO)

Dataset	Techniques	Complete tumor	Non-enhance tumor	Enhance tumor
2013 Leader board	RF	0.792 ± 0.1	0.652 ± 0.08	0.44 ± 0.26
	CRF-RNN	0.70	0.62	0.64
	ELM	0.93	0.97	0.95
	KELM-MSLO	0.95	0.93	0.98
BRATS 2014	CNN	0.83	0.75	0.77
	ELM	0.91	0.88	0.96
	KELM-MSLO	0.98	0.9	0.978
BRATS 2015	3D-CNN	84.9	66.7	63.4
	FCN	86	86	65
	ELM	0.97	0.86	0.95
	KELM-MSLO	0.989	0.9	0.96
BRATS 2018	ELM	0.87	0.92	0.95
	RELM-LOO	0.91	0.95	0.97
	KELM-MSLO	0.973	0.96	0.985

The result attained by proposed KELM-MSLO method for complete, enhance, and non-enhance tumor is tabulated in table 3. This value is obtained for four different datasets they are 2013 Leader board, BRATS 2014, 2015, and 2018. This challenging datasets attain better performance for this proposed KELM-MSLO approach. The existing techniques taken for comparison are random forest (RF), ELM, Fully convolutional network (FCN), CRF-RNN (Conditional Random Field-Recurrent Neural Network), Convolutional NN (CNN), and RELM-LOO (Regression ELM with leaves one out) [17].

C. Feature based Classification Result

The classification process mainly depends on the extracted features, with that extracted features high accuracy is achieved by proposed KELM-MSLO method. For analysing its performance, four different BRATS datasets are used, with that data high performance is achieved. The confusion matrix for four different datasets are shown in figure 5.

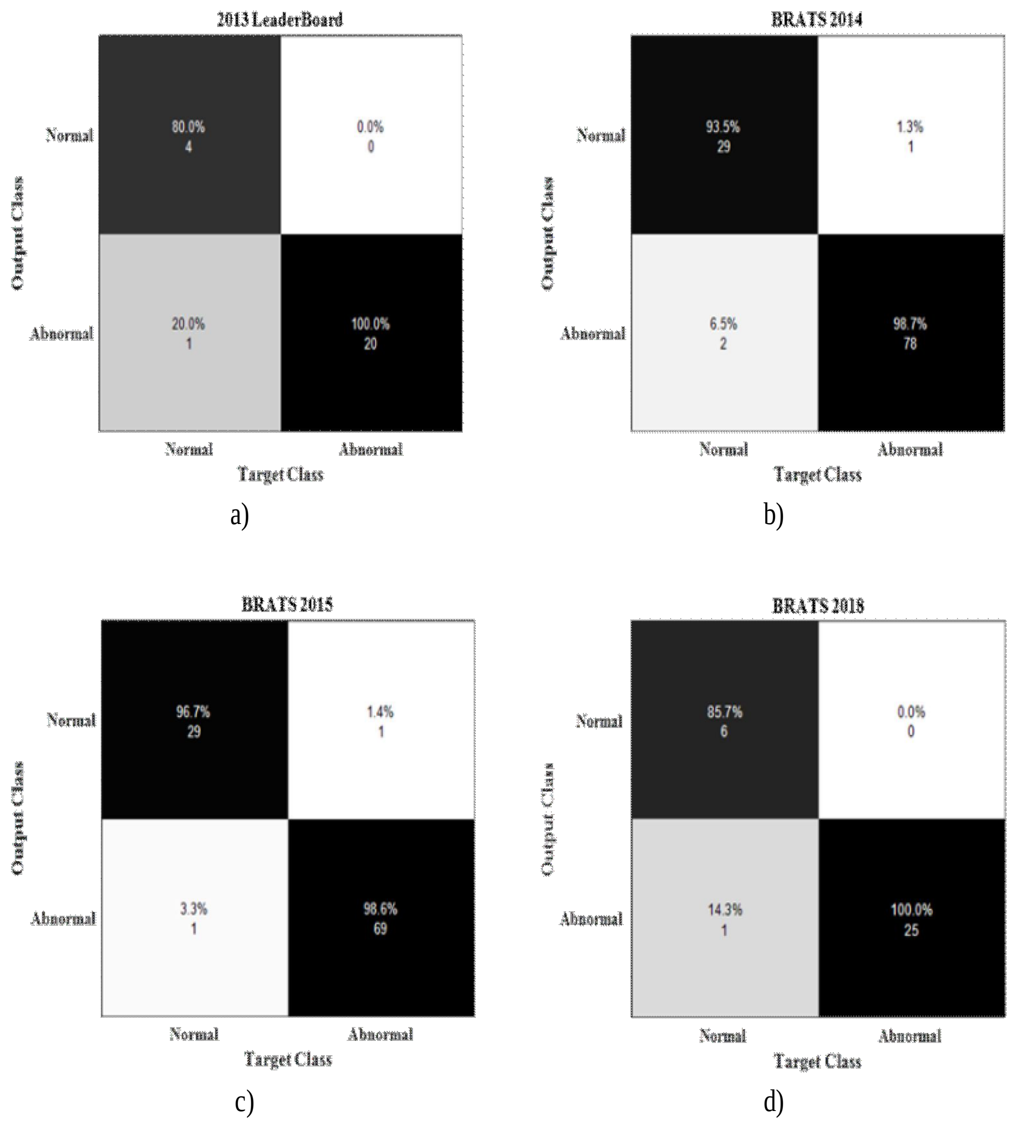


Figure 5. Confusion matrix [(a) 2013 Leader board, (b) BRATS 2014, (c) BRATS 2015, and (d) BRATS 2018]

The confusion matrix for both normal and abnormal classes are shown in figure 5. With this matrix the TP, FP, TN, and FN are evaluated. The images taken for testing and training process is discussed above. The presence of Weiner filter improves the quality of image due to this the segmentation results and classification accuracy has gets improved.

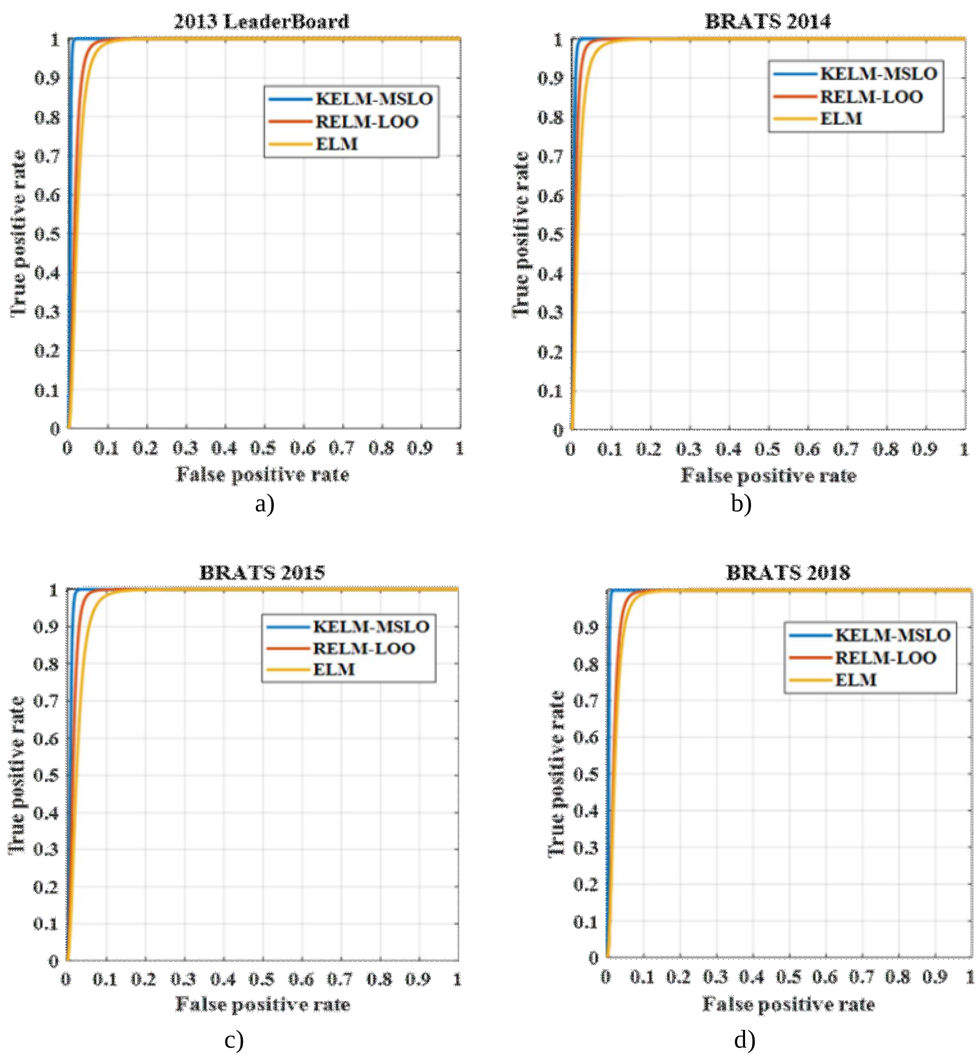


Figure 6. ROC analysis of different BRATS datasets (a) BRATS 2013 Leader board, (b) BRATS 2014, (c) BRATS 2015, and (d) BRATS 2018

The ROC analysis of proposed KELM-MSLO method using four different datasets (2013 Leader board, BRATS 2014, 2015, and 2018) is shown in figure 6. This ROC is plotted between the TPR and FPR. The equation used to evaluate TPR and FPR is shown in equation (22 & 24). The ROC analysis of proposed KELM-MSLO approach is compared with ELM and RELM-LOO techniques. While comparing with these two techniques the proposed KELM-MSLO approach depicts better ROC result. However, the BRATS 2014 and 2018 have illustrate better result for proposed KELM-MSLO approach than 2013 Leader board and BRATS 2015 datasets. The optimal weight parameter of KELM-MSLO approach required for back propagation is selected using MSLO algorithm. Due to this the performance of proposed KELM-MSLO approach is increased.

Table 4: Computational Time Comparison

Datasets	**Methods**	**Computational time**
2013 Leader board	ELM	0.05519
	RELM-LOO	0.003
	KELM-MSLO	0.0026
BRATS 2014	ELM	0.00933
	RELM-LOO	0.0017
	KELM-MSLO	0.00097
BRATS 2015	ELM	0.004
	RELM-LOO	0.00573
	KELM-MSLO	0.00351
BRATS 2018	ELM	0.003
	RELM-LOO	0.00473
	KELM-MSLO	0.0031

The computational time attained by existing and proposed KELM-MSLO approach for four different datasets 2013 Leader board, BRATS 2014, 2015, and 2018 is given in table 4. Two different methods taken for comparison are ELM, and RELM-LOO methods, both techniques attained better performance in tumor detection. Therefore these two techniques are used in this method for comparison. The computational time attained by proposed KELM-MSLO method for four different datasets are 0.0026 (2013 Leader board), 0.00097 (BRATS 2014), 0.00351 (BRATS 2015), AND 0.0031 (BRATS 2018). Among these four datasets, the KELM-MSLO classifier with BRATS 2014 dataset attains less computational time (secs) than other three datasets.

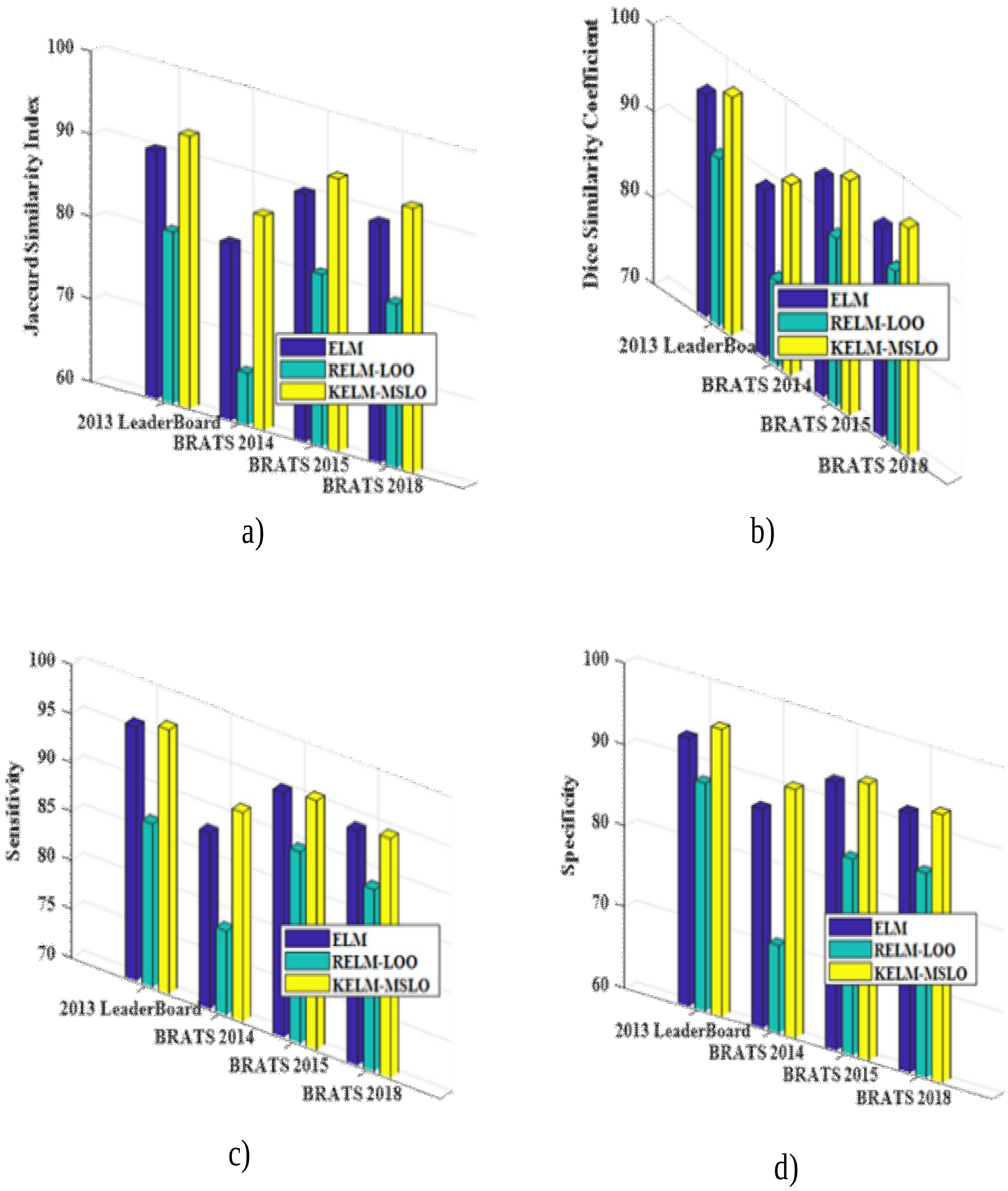


Figure 7: Performance results of proposed approach on 2013 leader board, BRATS 2014, 2015, and 2018 dataset [(a) JSI, (b) DSC, (c) Sensitivity, and (d) Specificity]

The sensitivity, DSC, specificity, and JSI attained by proposed KELM-MSLO method for datasets 2013 Leader board, BRATS 2014, 2015, and 2018 is shown in figure 7. The effectiveness of proposed KELM-MSLO method is compared with two different approaches they are ELM, and RELM-LOO. The result attained by proposed KELM-MSLO approach is found higher than other two techniques. The accuracy attained by proposed KELM-MSLO method for datasets 2013 Leader board, BRATS 2014, 2015, and 2018 is 98%, 89%, 97%, and 97.12%. The PPV attained by proposed KELM-MSLO method for datasets 2013 Leader board, BRATS 2014, 2015, and 2018 is 96.2%, 93.7%, 96.1%, and 96.01%.

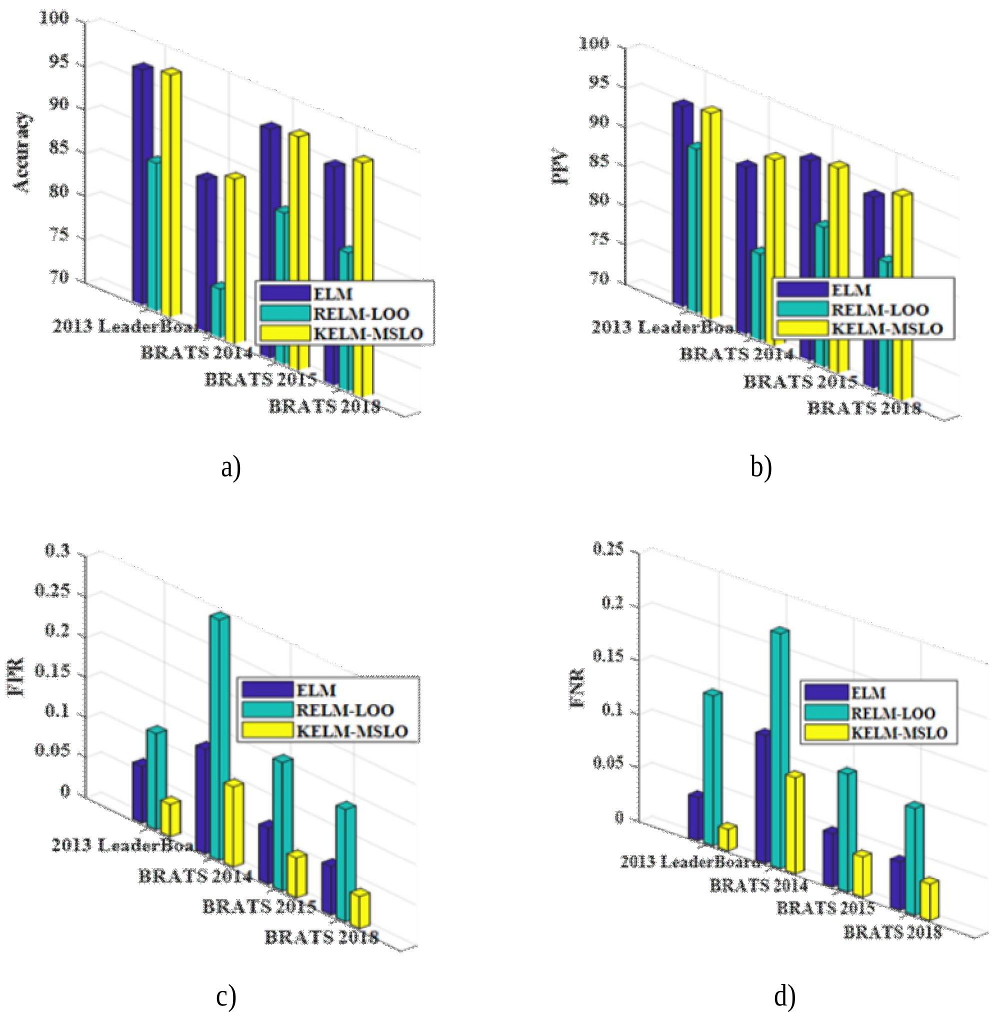


Figure 8. Performance results of proposed approach on 2013 leader board, BRATS 2014, 2015, and 2018 dataset [(a) Accuracy, (b) PPV, (c) FPR, and (d) FNR]

The accuracy, PPV, FPR, and FNR attained by proposed KELM-MSLO method for datasets 2013 Leader board, BRATS 2014, 2015, and 2018 is shown in figure 8. The comparison is performed between proposed and two existing techniques they are ELM, and RELM-LOO. The result attained by proposed KELM-MSLO approach is found higher than other two techniques. The accuracy attained by proposed KELM-MSLO method for datasets 2013 Leader board, BRATS 2014, 2015, and 2018 is 98%, 89%, 97%, and 97.12%. The PPV attained by proposed KELM-MSLO method for datasets 2013 Leader board, BRATS 2014, 2015, and 2018 is 96.2%, 93.7%, 96.1%, and 96.01%.

Tumor detection at earlier stage is essential for present life condition as it may increase the lifetime of various tumor affected patients. By taking this into consideration an efficient approach is introduced in this method for tumor detection. The presence of MSLO improves the classification rate of KELM by reducing the error rate. Further, the feature selection using BGOA reduces the computational complexity of entire detection process.

V. Conclusion

The complicated structure of brain maximize the difficulty of tumor detection process. To reduce that complication, a hybrid machine learning approach is introduced in this method. It is an efficient approach which accurately detects the tumor at earlier stage from MRI. Further a modified BGOA is introduced for feature selection which maximize the performance of classification approach. At the initial phase, the BSE approach is used which removes the skull regions which does not carry any useful information. Before introducing the region growing based segmentation, the Weiner filter is introduced for lesion enhancement. Finally with the optimal extracted SGLDM, and LESH features the benign and malignant tumors are classified using a KELM classifier. The optimal parameter required for KELM classifier is identified using MSLO algorithm which improves the classification performance of KELM classifier. To evaluate the performance of whole approach four different benchmark datasets are used they are BRATS 2013 Leader board, 2014, 2015, and 2018 dataset. Few performance metrics like accuracy, precision, FPR, sensitivity, FNR, specificity, and recall are evaluated to test the performance of KELM-MSLO (proposed) approach. The performance of KELM-MSLO is compared with RELM-LOO, and ELM techniques. The experimental outcomes illustrates that the proposed KELM-MSLO architecture gains higher classification result than other two existing techniques.

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