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Detection and Classification of Brain Tumor in MRI Images using EPCMA+ML-ELM

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Abstract: **Substantial clinical statistics along with analytical features can be extracted from brain tumor images. The identified quantitative measures of exact tumor regions aid physicians and radiologists in effective treatment. Magnetic Resonance Imaging (MRI) images of the brain are considered. Handling these images is challenging mainly owing to variance in addition to complexity in detecting tumors. In this paper, images are segmented using Enhanced Possibilistic C-Means Algorithm (EPCMA) and classified using Multi-Layered Extreme Learning Machine (ML-ELM). System performance is observed based on classification accuracy, sensitivity and specificity.**

Index Terms: **Brain Tumor, Possibilistic C-Means Algorithm, Extreme Learning Machine, MRI,**

I. Introduction

Early identification of brain tumors would aid the Physicians to treat them in their initial stage. Tumors can be identified using Magnetic Resonance Imaging (MRI) scan, biopsy, nerve tests, etc., Though physicians get a clear picture of tumors from brain MRI, quantified details are also essential. Brain tumor classification involves the following steps: image pre-processing, feature extraction, training and testing [1 - 3].

In medical imaging, there are chances for images to be noisy, leading to image misclassification and degradation of classifier's performance [4]. Hence, images are pre-processed by filtering to enhance image quality. Feature extraction deals with quantitative measurement of images, wherein image data is converted to statistical numeric values [5, 6]. The features include contrast, homogeneity, correlation, energy, entropy etc.,

The classifiers analyze extracted features and perform classification [7]. There are various learning classifiers like Artificial Neural Network (ANN), Probabilistic Neural Network (PNN), Extreme Learning Machine (ELM), Hidden Markov Model (HMM) and Support Vector Machine (SVM) [8, 9]. Each classifier has its own merits and demerits.

Initially, images are preprocessed to eliminate noise and enhance image quality by using Median Filter (MF). Once the quality of image is enhanced, it is segmented [10]. Image segmentation deals with splitting an image into homogeneous, distinct and significant clusters based on properties including color, texture, gray level, depth, reflectivity etc., In this work, images are segmented and classified using EPCMA+ML-ELM. The network is trained using ELM.

II. Related Work

Bahadure et al (2017) [11] have focused on enhancing performance and reducing the complexity involved in image segmentation. Berkeley Wavelet Transformation (BWT) is used for segmenting brain tumor images. To enhance accuracy of Support Vector Machine (SVM)-based classifiers, appropriate features are extracted from every segment. Performance is analyzed in terms of accuracy, specificity, Dice Similarity Index (DSI) co-efficient and sensitivity. The proposed scheme offers improved overlap between automatically and manually extracted tumor regions.

Amin et al (2018) [12] have used three convolutional, three ReLU along with one softmax layer. MR image is split into numerous patches and center pixel value of each patch is given to DNN which assigns labels based on these pixels and performs segmentation. Experiments are performed using several datasets. Results are assessed based on Accuracy, Jaccard Similarity Index (JSI), specificity, sensitivity, DSI Coefficient, precision, False Positive Rate (FPR) and True PR (TPR).

Amin et al (2020) [13] have proposed an automated scheme to facilitate easy differentiation of cancerous as well as non-cancerous brain MRI. Diverse techniques are applied for segmenting candidate lesions. Feature set is selected for each applicant lesion based on shape, intensity as well as texture. SVM involving diverse cross validations on features is applied to determine precision for varying datasets including Harvard, RIDER as well as Local. The performance of the proposed scheme is analyzed in terms of accuracy, Area Under Curve (AUC), sensitivity and specificity. It involves less processing time in contrast to present approaches.

Gull & Akbar (2021) [14] have focused on extracting vital features and identifying diverse segmentation and classification schemes which can be used for multimodal MRIs for identifying brain tumors. Several ML and DL-based classification methods are applied on tumor MRI images of different datasets.

Rammurthy & Mahesh (2022) [15] have used Whale Harris Hawks Optimization (WHHO) for identifying brain tumors from MRI images. Cellular Automata (CA) and Rough Set (RS) theory are used for segmentation. Further, features are extracted from segments that comprise of tumor size, mean, variance, Kurtosis and Local Optical Oriented Pattern (LOOP). Further, Deep Convolutional Neural Network (DeepCNN) is used, where WHHO is involved in training. A hybrid system is designed which includes Whale Optimization Algorithm (WOA) as well as Harris Hawks Optimization (HHO) algorithm. The performance of the propounded scheme is analyzed in terms of accuracy, specificity and sensitivity.

Mahmud et al (2023) [16] have suggested CNN-based architecture for efficient detection of brain tumors from MRI

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images. It details diverse models including ResNet-50, VGG16 as well as Inception V3 and performs a comparison between proposed framework and existing models. The performance is analyzed based on diverse metrics including accuracy, recall, loss and AUC. It is seen that the proposed scheme performs better in contrast to standard schemes. The proposed model aids in prompt identification of different kinds of brain tumors.

III. Proposed Model

The proposed scheme focuses on segmentation, feature extraction, training and classification. Tumors are segmented using Enhanced Possibilistic C Means Algorithm (EPCMA) and classified using Multi-Layered Extreme Learning Machine (ML-ELM). Deep Learning (DL) classifier is also propounded in the work.

Segmentation

In the segmentation module, MRI images are pre-processed as well as segmented to eliminate noise using EPCMA. Noise is removed using Median Filtering (MF) and features are extracted from each segment depending on shape, intensity and texture. Once features are extracted, prominent features are chosen by using RP for classification.

Feature Extraction

Most predominant features are chosen. Dimensionality of the dataset has a greater impact on accuracy. It is essential to consider aspects which lessen the system complexity.

Training

ELM-based classifiers are trained based on features of training data.

Classification

In this phase, features obtained from segmented images are sent to trained ELM classifiers to identify whether a region is affected or not.

Enhanced Possibilistic C-Means Algorithm (EPCMA)

Clustering focusses on partitioning a given set of data into significant sub-classes called clusters. It involves grouping of objects based on features, and grouping them based on similarities existing among them. The objects in a group are 'similar' to each other within a cluster, but are 'dissimilar' when compared to objects of other clusters.

In EPCMA, every cluster is independent of another. The objective function of cluster 'i' is expressed as,

$$J(\beta_i, U_i, X) = \sum_{j=1}^{n}(U_{ij})^m\, d^2(x_j, \beta_i) + \eta_i \sum_{j=1}^{n} (1 - U_{ij})^m \quad (1)$$

where,
j - Cluster
m - Fuzzifier
β_i - Prototype related to 'i'
U - Membership associated with cluster 'i'
η_i - Scale parameter

The parameter 'η_i' can be determined from distance statistics of dataset 'X' which is initialized to '1'. Membership update in Possibilistic C-Means (PCM) is given by,

$$U_{ij} = \frac{1}{1+\left(\frac{d^2(x_j,\beta_i)}{\eta_i}\right)^{\frac{1}{m-1}}} \quad (2)$$

By solving for '$d^2(x_j, \beta_i)$' in terms of 'U_{ij}',

$$d^2(x_j, \beta_i) = \eta_i \left(\frac{1-U_{ij}}{U_{ij}}\right)^{\frac{1}{m-1}} \quad (3)$$

From the objective function in Eq. (1), '$d^2(x_j, \beta_i)$' can be eliminated using Eq. (3).

$$J_i(\beta_i, U_i, X) = \eta_i \sum_{j=1}^{n}(1 - U_{ij})^{m-1} \quad (4)$$

For a given value of 'η_i', minimizing '$J_i(\beta_i, U_i, X)$' is equivalent to maximizing '$J_I(\beta_i, U_i, X)$'.

$$J_I(\beta_i, U_i, X) = \eta_i \sum_{j=1}^{n}(1 - (1 - U_{ij})^{m-1} = \eta_i \sum_{j=1}^{n}(\acute{U}_{ij}) \quad (5)$$

Where

$$\acute{U}_{ij} = [1 - (1 - U_{ij})]^{m-1} \quad (6)$$

$\acute{U}_{ij}$- Modified membership

Further, for m = 2, Eq. (5) reduces to

$$J_I(\beta_i, U_i, X) = \eta_i \sum_{j=1}^{n} U_{ij} \quad (7)$$

From Eq. (5) and Eq. (6), for a particular value of 'η_i', every C-sub objective function is improved by selecting suitable prototype locations. It is necessary to ensure that total modified membership is improved. Prototype should be positioned in a dense area as membership is a monotonically declining function that is based on distance.

For C-dense regions in feature space, each prototype converges to a dense region if proper initialization is done.

Even if 'η_i's are equal or all sub-objective functions are identical, each has 'C' unique minima conforming to C-dense regions. The right choice of fuzzifier value (m) is around 1.5.

The algorithm is a variation of the possibilistic method. In case fuzzifier 'm' is eliminated, an alternate formulation is obtained as follows:

For instance,

$$J_I(\beta_i, U_i, X) = \sum_{j=1}^{n}(U_{ij}) d^2(x_j, \beta_i) + \eta_i \sum_{j=1}^{n}(U_{ij}.log\, U_{ij} - U_{ij}) \quad (8)$$

'U_{ij}' is updated as shown below.

$$U_{ij} = exp\ exp\left\{-\frac{d^2(x_j,\beta_i)}{\eta_i}\right\} \quad (9)$$

Prototype update equations are unchanged. Exponential function rapidly deteriorates for high values of '$d^2(x_j, \beta_i)$'. This seems to be suitable when clusters are close to one another.

It is seen that, similar to '$(1 - U_{ij})^m$', '$U_{ij}.log\, U_{ij} - U_{ij}$' is a monotonically declining function in range [0,1]. If Mahalanobis distance is used for '$d^2(x_j, \beta_i)$', then 'η_i' can also be eliminated (set η_i = 1).

Multi-Layer Extreme Layer Machine (ML-ELM)

In the proposed methodology, tumor images are classified using ML-ELM [17]. Auto Encoders (AE) are used as building blocks in every layer for learning. Activation

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functions may be linear or non-linear. ELM-AE reproduces input signals. Input is mapped to ELM feature space of L-dimensions and output is given by,

$$f_l = \sum b_i \quad (10)$$

$$\underline{h}_i(x) = \underline{h}(x).b \quad (11)$$

Output weight matrix amid hidden and output nodes is computed as shown below.

$$b = [b_1, \ldots . b_L]^T \quad (12)$$

For input 'x', output of hidden node is represented as,

$$\underline{h}(x) = [g_1(x), \ldots ., g_L(x)] \quad (13)$$

Where,

$g_i(x)$ - Output of hidden node 'i'

For 'n' training samples $\{(x_i, t_i)\}_{i=1}$, ELM is proficient in solving the learning problem.

$$\underline{h}b = T \quad (14)$$

Target labels are given by,

$$T = [t_1, \ldots, t_N]^T \quad (15)$$

$$\underline{h} = [\underline{h}^T(x_1), \ldots ., \underline{h}^T(x_N)]^T \quad (16)$$

Output weights (b) are computed as shown below.

$$b = \underline{h} \dagger T \quad (17)$$

Where,

$\underline{h}\dagger$ - Moore-Penrose inverse of '$\underline{h}$'

Regularization is done to increase performance of ELM.

$$B = \left(\frac{I}{C} + \underline{h}^T\underline{h}\right)^{-1} \underline{h}^T.\underline{h} \quad (18)$$

Weights as well as biases are orthogonally selected so as to increase the performance of ELM-AE [18]. In ELM-AE, input may be projected to varying or similar dimension space as in Johnson- Lindenstrauss lemma.

$$\underline{h} = g(a.x + m) \quad (19)$$

Where,

$$a^T.a = I \quad (20)$$

$$m^T m = 1 \quad (21)$$

Orthogonal random weights are given by,

$$a = [a_1, \ldots . a_L] \quad (22)$$

Orthogonal random biases amid input as well as hidden nodes are given by,

$$m = [m_1, \ldots . m_L] \quad (23)$$

For sparse as well as compressed ELM-AE illustrations, output weight 'B' is computed as:

$$B = \left(\frac{I}{C}.H^T H\right)^{-1} H^T X \quad (24)$$

Hidden layer outputs are given by,

$$h = [h_1, \ldots, h_N] \quad (25)$$

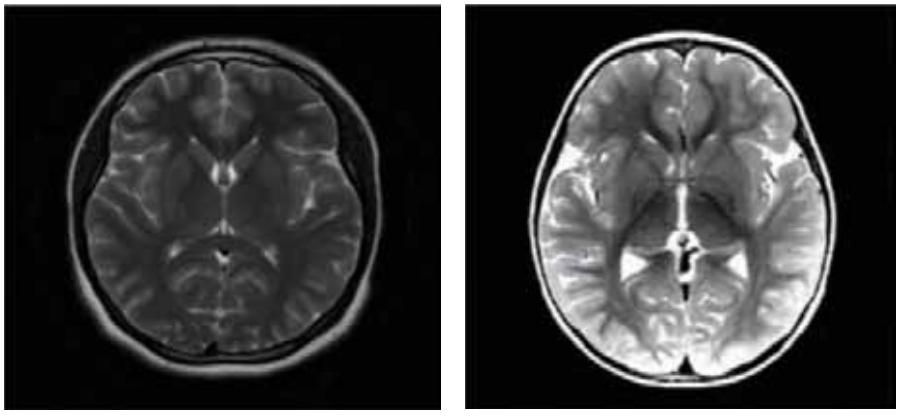
IV. RESULTS AND DISCUSSION

MRI images from the Kaggle dataset are taken. The proposed technique for identifying brain tumors is applied and performance is analyzed. The proposed scheme offers improved accuracy, sensitivity as well as specificity in contrast to other methods for real-time as well as benchmark datasets.

Experimental setup and assessment metrics

The proposed scheme is implemented using MATLAB. True and False Positive (TP & FP), and True and False Negative (TN & FN) are determined depending on which sensitivity, accuracy and specificity are calculated.

Figure 1 shows some sample input MRI images. Figure 2 shows the images after applying EPCMA+ML-ELM.



(a) (b)

Figure 1: Input MRI Images

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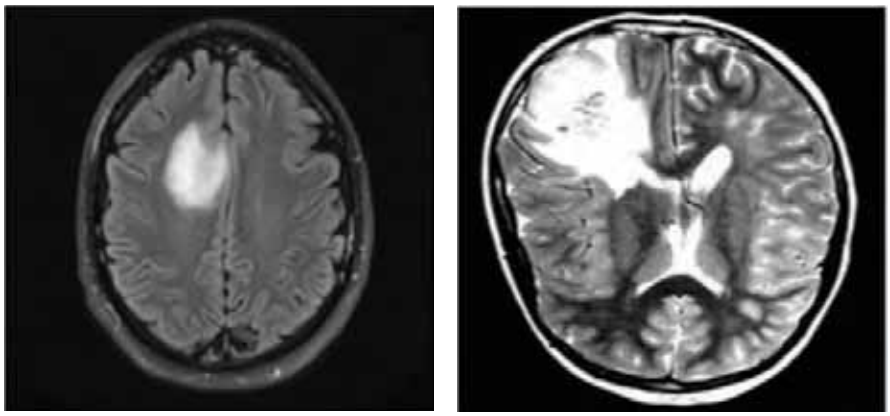

(a) (b)

Figure 2: MRI Image after implementing EPCMA+ML-ELM

Sensitivity is the ratio of TPs which are properly determined using diagnostic tests. It shows the efficiency of a test in identifying a disease.

$$Sensitivity = \frac{TP}{TP + FN} \quad (26)$$

Specificity is a ratio of TNs suitably identified by a test. It shows how an efficient test detects normal conditions.

$$Specificity = \frac{TN}{TN + FP} \quad (27)$$

Accuracy shows the amount of true outcomes, either TP or TN. It denotes the veracity level of a test.

$$\text{Accuracy} = \frac{\text{TN} + \text{TP}}{\text{TN} + \text{TP} + \text{FN} + \text{FP}} * 100 \quad (28)$$

Performance analysis

The performance of propounded scheme is analyzed in terms of sensitivity, specificity as well as accuracy for varying number of hidden neurons in the range of 50 to 200 in step of 25.

Figure 3 shows sensitivity. EPCMA+ML-ELM offers 13% and 5% better sensitivity when compared to ELM and ML-ELM respectively.

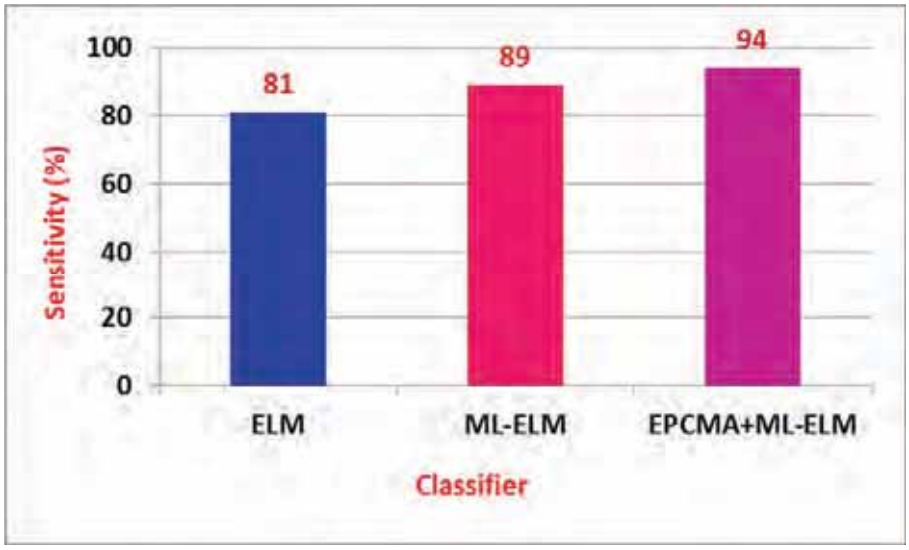

Figure 3: Sensitivity

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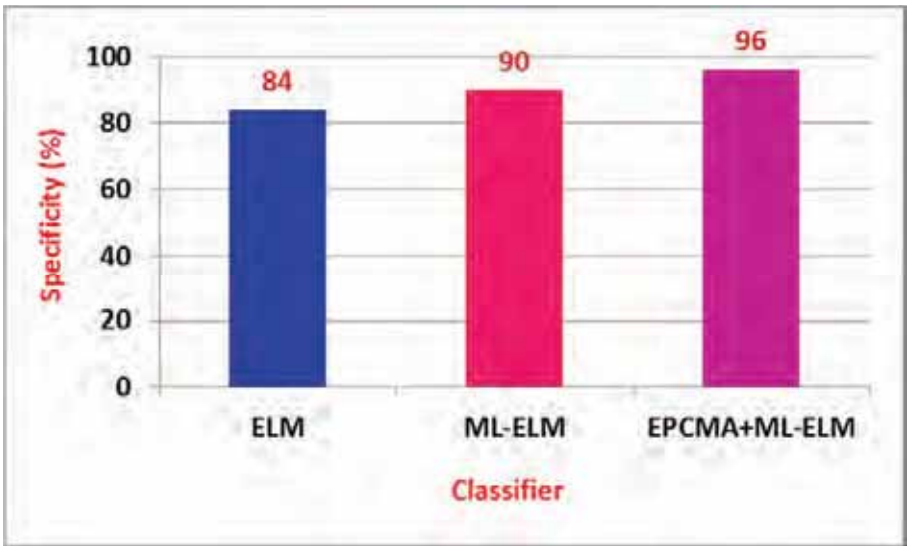

Figure 4: Specificity

Figure 4 shows the specificity. EPCMA+ML-ELM offers 12% and 6% improved specificity in contrast to ELM and ML-ELM respectively.

Figure 5 shows the classification accuracy. EPCMA+ML-ELM offers 13% and 7% better classification accuracy when compared to ELM and ML-ELM respectively.

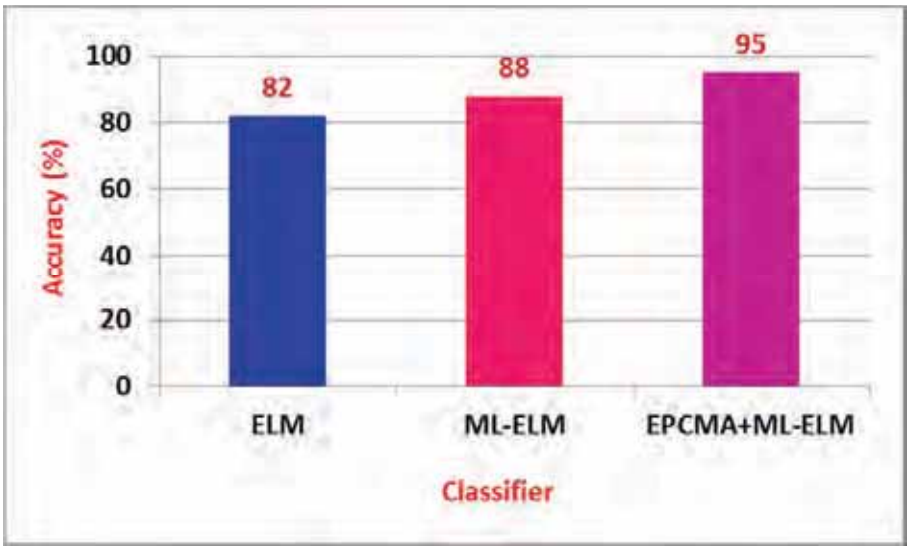

Figure 5: Classification Accuracy

Figure 6 shows the training accuracy. EPCMA+ML-ELM offers 9% and 5% better training accuracy in contrast to ELM and ML-ELM respectively.

Figure 7 shows the testing accuracy. EPCMA+ML-ELM offers 13% and 6% better testing accuracy when compared to ELM and ML-ELM respectively.

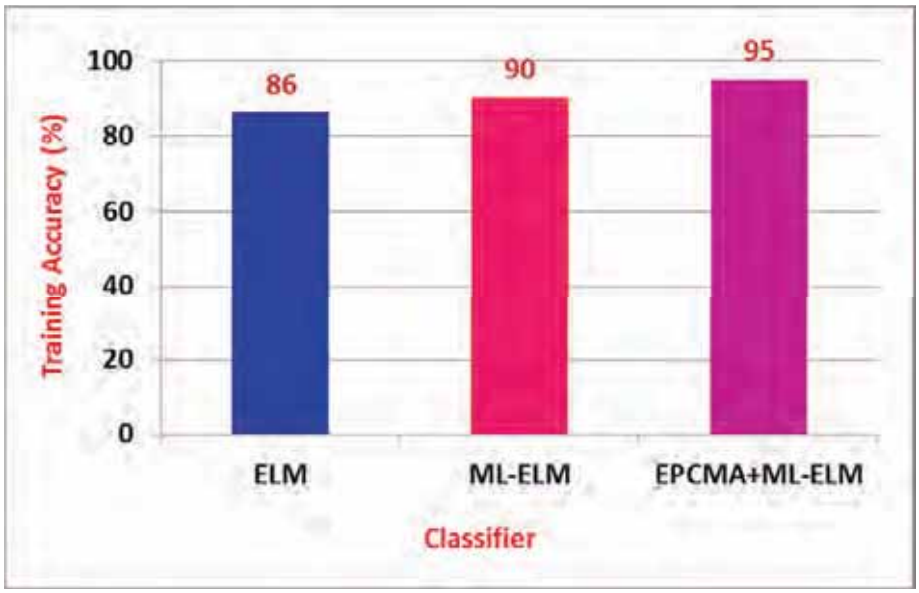

Figure 6: Training Accuracy

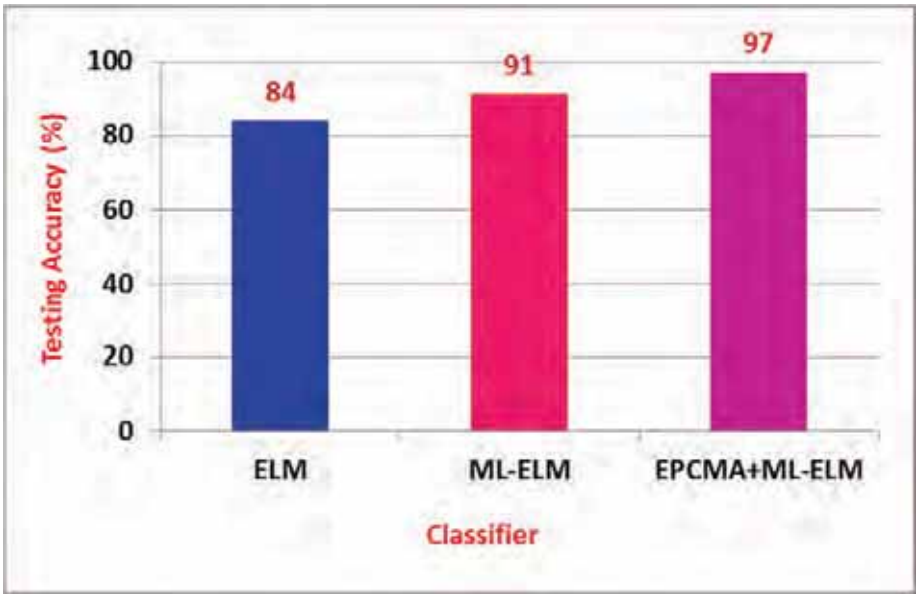

Figure 7: Testing Accuracy

V. Conclusion

In this paper, MRI images of tumors are segmented using EPFCM and classified using ML-ELM. The performance of the proposed mechanism is assessed in terms of sensitivity, specificity and classification accuracy, training as well as testing accuracies. It is seen that EPCMA+ML-ELM yields better results in contrast to DL classifiers and ELM.

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