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Piecewise Fuzzy C-Means Clustering and Deep Convolutional Neural Network for automatic brain tumour classification using MRI images

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Abstract
Magnetic Resonance Imaging (MRI) provides lots of information about human soft tissue, which is employed in radiology for the diagnosis of brain tumour. Accuracy and early detection are the major concerns in tumour diagnosis. This paper develops an automatic brain tumour classification method using MRI images based on the Piecewise Fuzzy C-Means Clustering (pifCM) and Deep Convolutional Neural Network (Deep CNN). Initially, the contriteness of the input MRI image is enhanced through pre-processing the image using the piecewise fuzzy c-means clustering method. The next step is feature extraction in which the texture features and statistical features are extracted using Local directional pattern (LDP), wavelet transform, principal component analysis (PCA), entropy, and mean. Finally, the tumors are classified using Exponential cuckoo-based deep convolutional Neural Network (Exponential cuckoo-based DCNN) classifier. The simulation of the proposed method of tumor classification is done using BRATS and SIMBRATS database and the performance obtained by the proposed is compared with several state-of-art techniques. The simulated results show higher accuracy of 0.8711 and minimal Mean Square Error (MSE) of 0.0197when compared with the existing methods.

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1. Introduction

The most critical organ in the human body is human brain, which consists of billions of cells. The uncontrolled division of cell may lead to the Formation of abnormal cell growth in brain, known as brain tumour. However, the abnormal cells in the body influence the normal activity of human brain and it make the healthy cells to destroy. Brain tumours are classified into two types, as benign or low-grade and

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malignant tumours or high-grade tumor. The non-progressive tumours, such as benign tumours are less-aggressive, grow slowly and do notextendany other parts in the body. Malignant tumours are the progressive tumours, which grows rapidly and spread anywhere in the body [4].The normal brain image consists of various tissues, like WM, CSF, and GM. The information from the brain tissues are obtained from the imaging techniques like CT, MRI, PET and the multimodal imaging methods like MRI/PET and MRI/CT.In MRI brain images, the segmentation is used for separating the tumour cells from the normal tissues. The manual segmentation of the tumour produces inaccurate results and huge processing time, thus automatic segmentation are gaining importance. Still, the unpredictable shape of the brain tumour makes the segmentation more challenging [5].

The brain tumour classification methods, such as, random trees [13], Deep Neural Networks [14], Deep Convolutional Neural Network [15] and rough set theory [16] are used for the automatic tumour classification. The clustering schemes were not effective, and hence Exponential cuckoo-based DCNN classifier is proposed. The classification of MRI images for the brain tumour detection consists of various steps and they are as follows: Initially, pre-processing is done in the input MRI images to increase the contrast of image. The second step is segmentation of the MRI images based on fuzzy-based clustering. The next step is feature extraction, in which the texture features and statistical features are extracted using Local directional pattern (LDP), wavelet transform, principal component analysis (PCA), entropy, and mean. Finally, the brain tumour classification is performed in the classification module using Exponential cuckoo-based deep convolutional Neural Network (Exponential cuckoo-based DCNN) classifier. The Exponential cuckoo-based DCNN classifier is trained by the information collected from the features thus, detecting the training class.

The organization of the paper is as follows: section 1 elaborates the background of brain tumour classification, Section 2 discussed some of the existing approaches of brain tumour classification. Section 3 describes the proposed model and section 4 illustrates the results and discussion of the proposed approach and finally, Section 5 concludes the paper.

2. Literature Review

In this section, the review of various existing techniques is presented, which stood as a motivation for developing a new method for tumor classification. A. Ortiz, *et al.* [1] developed abrain image segmentation method for defining the entropy gradients and self-organizing map. The clustering was based on the SOM measure, which generated map between input and the clustered output. Although, this method had improved segmentation performance, it had acquisition noise.N. M. Portela,*et al.* [2] modeled a semi- supervised clustering model to segment the tumour regions. In this method, the manual interpretation was very less and it didn't required label information. The GMM technique was used in clustering and along with it, the Bayesian classifier dealt with classification. The drawback was that this method was sensitive to initial parameters. AS Dhas, *et al.*, [3] designed a brain tumour classification method based on the neural network and Wavelet Transform . In this method, the segmentation was carried out by fuzzy c-means clustering such that the features were extracted using symlet and coiflet wavelet transforms and the feature classification of the magnetic resonance images (MRI) was based on Levenberg-Marquardt algorithm. This method had high accuracy, but had low computation and processing time. Heba Mohsen *et al.*,[4]modelled a deep neural network classifier for classifying the brain tumors. Here, the discrete wavelet transform (DWT) along with the Deep Neural Network (DNN) was used to classify the brain images. This method required less hardware specifications and had higher accuracy, but it took more time for processing large images.

Challenges

The major challenges faced by the existing methods of brain tum or segmentation and classification are listed below:

- The contrast among the boundaries as well as the neighbouring healthy tissue has a great influence in predicting the tumour appearance. The contrast should be strong enough to differentiate the tumour [6].
- For clinical acceptance, the interpretability and the transparency in the automatic segmentation is a very important challenge [5].
- The other challenges in MRI-based tumour classification are the artifacts. The most common artifacts are intensity in homogeneity and Partial volume effects, and these artifacts should be removed to improve the resolution of the segmented image such that well anatomical structure is not degraded in the image [5].
- The anatomical deviations due to variety in size, location, and shape of brain tumour are one of the important challenges in the classification. The edema and the other parts are significant in segmentation as the brain tumour influences other parts of the brain [5].

Proposed method of automatic brain tumour classification using Exponential cuckoo-based Deep Convolutional neural networks

The proposed Exponential cuckoo-based Deep CNN is used to perform the automatic brain tumour classification. Initially, pre-processing is done in the

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input MRI images to enhance the contrast of brain image. After pre-processing, the image is passed to the segmentation module, where the segmentation process is carried out using fuzzy-based clustering. The next step to be performed is extracting the features from the segmented image, in which the texture features and statistical features are extracted using Local directional pattern (LDP), wavelet transform, principal component analysis (PCA), entropy, and mean. Finally, the features extracted from the image are classified using Exponential cuckoo-based DCNN classifier. The Exponential cuckoo-based DCNN classifier is trained by the information collected from the features thus, detecting the training class. Figure 1 shows the block diagram

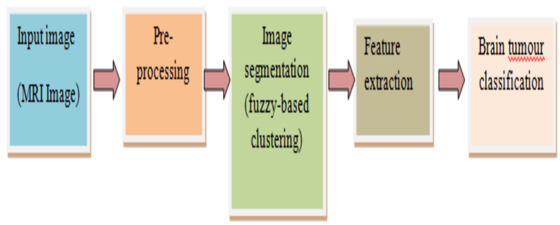

Figure 1: Block diagram of Exponential cuckoo-based deep convolutional neural networks

Pre-processing

Initially, the image is collected from the database and is subjected to the pre-processing module. The database of the brain image consists of MRI images H_1 with four different modalities, which makes the diagnosis easier. The image H_1 is pre-processed by involving two steps. In the first step, thres holding is done based on OTSU binarization and in the second step, the RGB value of the image is converted to Lab. Finally, the pre-processed image is presented for the segmentation module.

Segmentation using fuzzy-based clustering approach

After pre-processing the image, the resultedpre-processed MRI image is segmented using the fuzzy-based clustering approach. The fuzzy-based clustering scheme segments the image into three cluster groups, such as Normal, Edema, and core. The multi-membership data is formulated to better understand the data objects and the centroids. The dataset for the membership is assumed as, $Z=\{z_1,...,z_n\}$, which is derived from the set of Bootstrap Probability (BP) with,

$$z_m=\left(\mu_m^{(1)},...,\mu_m^{(k)},...,\mu_m^{u}\right) \tag{1}$$

where, z_m is the m^{th} data object in the set of data objects ,that aligns with the membership degree of to all the clusters of BP and z_m is a $\left(\sum_{k=1}^{u} L_k\right)$ dimensional vector with $\|z_m\|_1=u\forall m$ .The piecewise clustering for fuzzy clustering is given as,

$$b_l=\left\{b_l^{(1)},...,b_l^{k},...,b_l^{u}\right\} \tag{2}$$

where, $b=\{b_1,...,b_l\}$, b_l represents the dimensional vector with u pieces. b_l^k is the l^{th} centroid of Z in k^{th} piece, whereas b_l is the piecewise centroid for Z . The fuzzy c-means clustering on the multi-membership data and the piecewise centroid [17], and the distance from z_m to b_l is given as,

$$c(z_m,b_l)=\sum_{k=1}^{u} f(\mu_m^{(k)},b_l^{(k)})\forall m,l \tag{3}$$

Thus, the optimal clustersor segments are acquired from the piFCM clustering mechanism, which are subjected to the feature extraction step in order to render effective classification accuracy.

Feature extraction from the segments

The features are extracted from the segmented image, which helps in further classification of the tumour**.** The texture features, such as LDP, wavelet transform, PCA, and the statistical features such as entropy, mean are extracted from the segments.

Local directional pattern (LDP)

From the segmented image, the LDP features are extracted, which is duly based on the intensity variation of the pixels. The LDP feature is expressed as,

$$LDP(x_d,v_d)=\sum_{m=0}^{7} u(p_m-p_b)2^m \tag{4}$$

where, p_m represents the kirchoff mask applied to the image for the extraction purpose. p_b is the highest kirchoff activation function.

Wavelet transform: The segments are subjected to the wavelet transform, which identifies the four bands of the segment and its entropy information. The wavelet features are given by,

$$V=\{s_{10},s_{11},s_{12},s_{13}\} \tag{5}$$

where, s_{10}, s_{11}, s_{12} and s_{13} are the four bands of the segment.

Principal Component Analysis (PCA): PCA is the next feature that is extracted from the segmented image. The classification results are improved by

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applying PCA as it reduces the feature dimension. The five features produced by the PCA is represented as,

$$PCA = PCA(I_f) = \{s_5, s_6, s_7, s_8, s_9\} \tag{6}$$

Entropy: Entropy is the next feature extracted from the segmented image, as it helps in identifying high information content. The entropy measure is calculated by countering the information provided by the edge and corner pixels.

3.3.5 Mean: The mean feature is the mean value of the tumour- related and the nontumor related pixels within the segmented image. Finally, asum of 14 features are extracted from the segment, and they are represented as,

$$S = \{s_1^{tr}, s_2^{ntr}, s_3^{tr}, s_4^{ntr}, PCA, V, LDP\} \tag{7}$$

The feature vector, S is formed by concatenating the features, which has the size of $[1 \times 14]$. Then, the classification is done by feeding the extracted features as the input to the classifier. Thus, the feature vector forms the input to Deep CNN, which effectively performs the accurate brain tumour classification.

Brain tumour classification using optimization-based Deep Convolutional neural network

Deep CNN contains three different layers, such as pooling (POOL) layer, convolutional (conv) layer, and a Fully Connected (FC) layer as depicted in figure 2. However, the patch of neurons from each layer is interconnected with the neurons associated in the next layer. The Deep CNN layers carry out specific functions, such as feature maps development process in the conv layers, feature map sub-sampling process in the POOL layers and classification process at the FC layer. The classification accuracy is improved by increasing the number of conv layers.

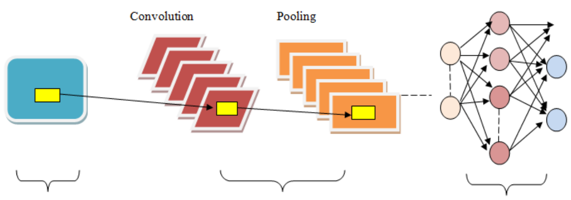


Figure 2: Architecture of Deep CNN

Convolutional layers*:*The convolution filters in the layers receive the feature maps and the filters that are connected with the receptive fields provide an interlinkedbetween the neurons of the previous layer and the successive layers using the set of trainable weights. The input of the deep CNN is considered as, B and the output obtained from the conv layer is given as,

$$\left(B_x^y\right)_{p,q} = \left(U_x^y\right)_{p,q} + \sum_{e=1}^{e_1^{b-1}} \sum_{\gamma=-e_1^y}^{e_1^y} \sum_{u=-e_2^y}^{e_2^y} \left(\alpha_{x,b}^y\right)_{u,\gamma} * \left(B_b^{y-1}\right)_{p+\gamma, f+u} \tag{8}$$

where, $*$ is the convolutional operator, $\left(B_x^y\right)_{p,q}$ is the output of the y^{th} conv layer that is centered around (p,q). However, the output of the previous $(y-1)^{th}$ layer is fed as the input to the y^{th} conv layer. Let the weights and bias of the y^{th} conv layers be, $\alpha_{x,b}^y$ and U_x^y. Consider there are w conv layers, $(1 \le g \le w)$ and e, α and u are the notations that indicates the feature maps, which acts as the conv filter output.. The output of the y^{th} ReLU layer specifies the activation function of the previous $(y-1)^{th}$ layer. An element-wise activation function is utilized by theReLU layer and it is expressed as,

$$A_x^y = Afn\left(A_x^{y-1}\right) \tag{9}$$

POOL layers: The fixed operations are performed in this layer and there is no bias and weights, as the POOL layer is the non-parametric layer.

Fully connected layers: The input given to the FC layer is the output of POOL layer. The signals are converted into the single signal at the end of the network. The output computed from the FC layer is represented as,

$$R_x^y = \eta\left(A_x^y\right) \text{with}$$

$$A_x^y = \sum_{e=1}^{e_1^{b-1}} \sum_{\gamma=-e_1^y}^{e_1^y} \sum_{u=-e_2^y}^{e_2^y} \left(\alpha_{x,b}^y\right)_{u,\gamma} * \left(B_b^{y-1}\right)_{p+\gamma, f+u} \tag{10}$$

Deep CNN classifier is trained using exponential cuckoo algorithm in order to generate the optimal solution.

*Training of the classifier:*The exponential cuckoo search algorithm has similar behaviour as cuckoo search algorithm [10] and the update process is modified based on EWMA concept [11].The optimization selects the optimal weights and bias based on the fitness function,which is evaluated by minimum square distance and it is given by,

$$Fitness = \sum_{s=1}^{n} {}_{l\in(1,2,\ldots,b)} clu_l(s) \tag{11}$$

where, s is the feature data, and $clu_l(s)$ represents l^{th} cluster formed with s^{th} feature data. The algorithm of the exponential cuckoo search algorithm is presented below:

1. Initially, the position of the host nest is randomly initialized. Let R be the number of host nests in the solution space and it is expressed as,

$$F = [F_1, F_2, ..., F_R] \tag{12}$$

2. *Position update:* The final position of the host nest is updated based on Exponential cuckoo search algorithm, which is given by,

$$F_{t+1} = \frac{L_{t+1} - (1-\eta)L_t}{\eta} + dB_t \tag{13}$$

3. Until the maximum iteration, the best possible centroids are retrieved for classification usingthe exponential cuckoo search algorithm. The minimization fitness function is derived by calculating the best centroid. The optimal cluster centroids are selected at the end of the iteration and provided to deep CNN for further classification.

3. Results and Discussion

The simulation of the proposed approach is done using BRATS and SIMBRATS databases in MATLAB and the results are analyzed with the state-of-art techniques in terms of the performance metrics, like MSE, and accuracy.

Experimental setup

The proposed method of brain segmentation process is implemented in MATLAB tool. The implementation requires a PC configuration with Windows 10 OS, 4 GB, and Intel I3 processor, respectively. The images for the proposed method are extracted from BRATS [8] and the SIMBRATS [9] database.

Performance metrics

The performance metrics used to evaluate the performance of the proposed approachover the existing methods are accuracy and MSE.

Accuracy: The brain tumour is identified by depicting the exactness of the classifier and it is represented as,

$$Accuracy = \frac{p+q}{p+q+r+s} \tag{14}$$

where, p indicates true positive, q specifies the true negative, r denotes the false positive, and s represents the false negative achieved during tumor classification.

MSE: It refers to the deviation of the classifier from the actual ground response and it is represented as,

$$MSE = Er((\rho_i - \mu_i)^2) \tag{15}$$

where, ρ_i indicates the classifier average output response , and μ_i represents the ground response of the i^{th} image.

Comparative methods

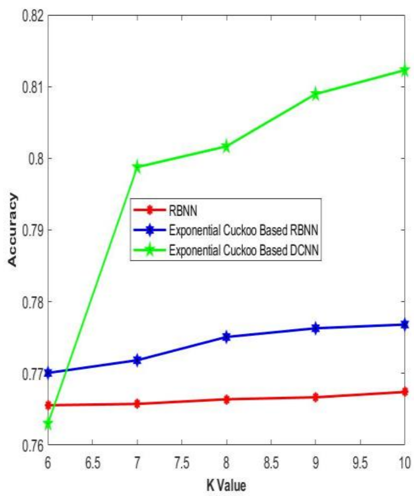
The experimentation results obtained by the proposed Exponential cuckoo based DCNN classifier is analyzed by comparing the proposed with the existing approaches such as RBNN [12],Exponential cuckoo based RBNN classifier [7].

Comparative analysis

The comparative analysis of the proposed exponential cuckoo-based DCNN is simulated using BRATS [8] and SIMBRATS [9]database and the performance metric, such as MSE and accuracy are evaluated with respect to theK-fold and training percentage.

Using BRATS database

i) Analysis using K-fold: Figure 3 portrays the performance of the comparative techniques from the BRATS database by varying K-fold. Figure 3a) represents the accuracy of the comparative techniques from the BRATS database by varying K-fold. The accuracy of the RBNN, Exponential cuckoo-based RCNN method, and the proposed Exponential cuckoo-based DCNN methods for k=10 is given as, 0.7674, 0.7768, and 0.8123, respectively. Figure 3b) depicts the MSE of the comparative methods by varying K-fold. The MSE of the methods, RBNN, Exponential cuckoo-based RCNN method, and the proposed Exponential cuckoo-based DCNN method for k=10 is given as, 0.0334, 0.0360 and 0.0269, respectively.



(a)

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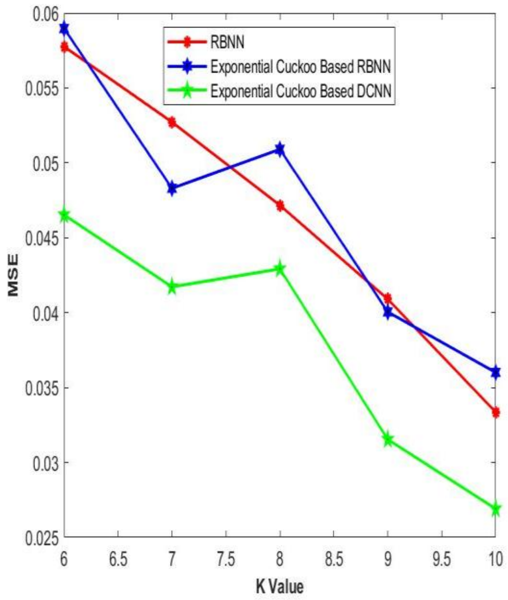
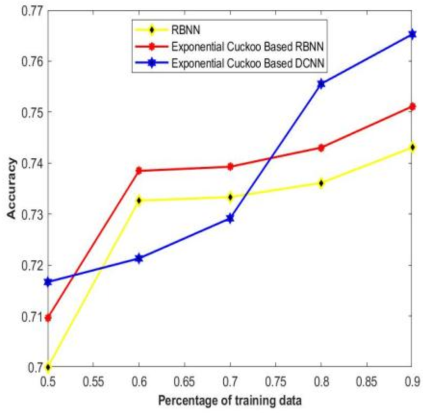


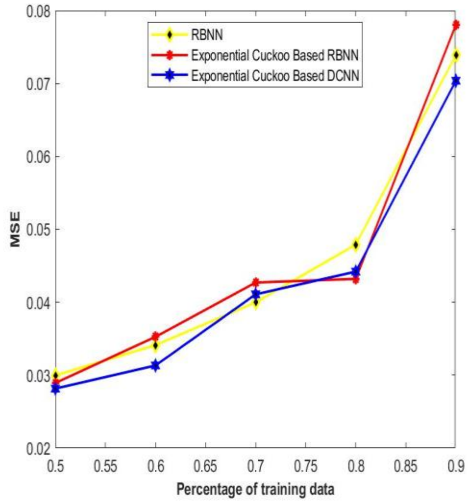
(b)

Figure 3: Comparative analysis using BRATS database with respect toK-fold based on (a) Accuracy, and (b) MSE

ii)Analysis by varying the training percentage: The performance of the comparative methods from the BRATS database by varying the training percentage is depicted in the figure 4. Figure 4a) depicts the accuracy of the comparative methods by varying the training data percentage. The accuracy of the RBNN, Exponential cuckoo-based RCNN method, and the proposed Exponential cuckoo-based DCNN method for 90% training data is given as, 0.7431, 0.7511 and 0.7653, respectively. Figure 4b) portrays the MSE of the comparative methods from the BRATS database by varying the training data percentage. The accuracy of the RBNN, Exponential cuckoo-based RCNN method and the proposed Exponential cuckoo-based DCNN method for 90% training data is given as, 0.0739, 0.0781, and 0.0704, respectively.



(a)

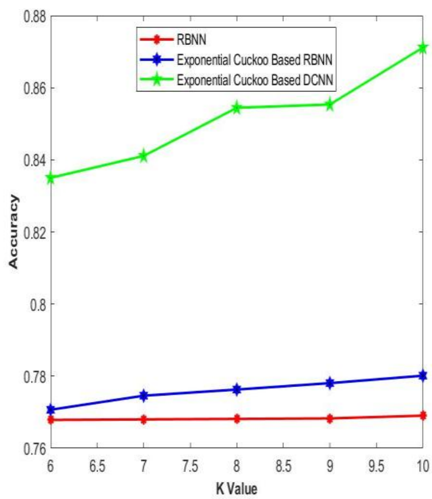


(b)

Figure 4: Comparative analysis on BRATS database by varying training percentage in terms of (a) Accuracy, and (b) MSE

Using SIMBRATS database

i) Analysis by varying K-fold: Figure 5 shows the performance of the comparative from the SIMBRATS database using K-fold. Figure 5a) shows the accuracy of the comparative methods from the SIMBRATS database by varying K-fold. The accuracy of the RBNN, Exponential cuckoo-based RCNN method and the proposed Exponential cuckoo-based DCNN method for k=10 is given as 0.7690, 0.7801 and 0.8711, respectively. Figure 5b) depicts the MSE of the methods by varying K-fold. The MSE of RBNN, Exponential cuckoo-based RCNN method, and the proposed Exponential cuckoo-based DCNN method for k=10 is given as, 0.0283, 0.0274, and 0.0197, respectively.



(a)

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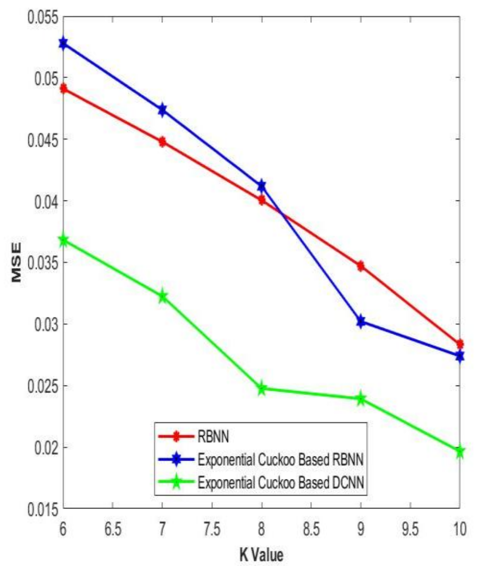
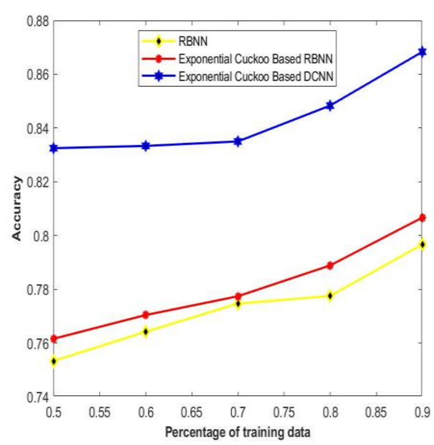


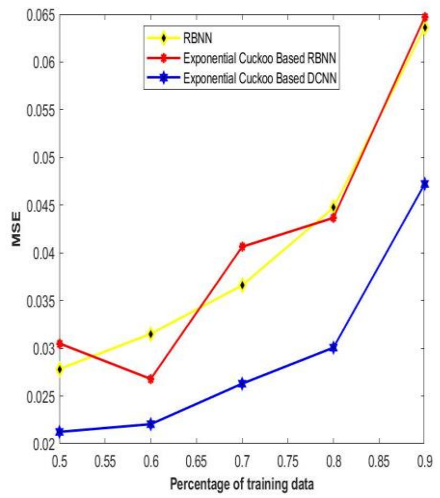
(b)

Figure 5: Comparative analysis on SIMBRATS database usingK-fold based on (a) Accuracy, and (b) MSE

ii)Analysis usingtraining percentage: The performance of the comparative methods from the SIMBRATS database using the training percentage is depicted in the figure 6. Figure 6 a) depicts the accuracy of the comparative methods by varying training data. The accuracy of the RBNN, Exponential cuckoo-based RCNN method and the proposed Exponential cuckoo-based DCNN method for 90% training data is given as 0.7967, 0.8067, and 0.8683, respectively. Figure 6 b) portrays the MSE of the comparative methods from the SIMBRATS database by varying training data. However, the accuracy of the RBNN, Exponential cuckoo-based RCNN method and the proposed Exponential cuckoo-based DCNN method for 90% training data is given as, 0.0636, 0.0647, and 0.0472, respectively.



(a)



(b)

Figure 6: Comparative analysis on SIMBRATS database using training percentage based on (a) Accuracy, and (b) MSE

4. Conclusion

The proposed method of tumour segmentation and classification is developed using a clustering framework. Initially, the images are fed to pre-processing and then, segmented using piecewise fuzzy C-Means clustering method. The piFCM clustering enable to find the effective centroid, which is required for further classification. From the segmented image, the texture features and statistical features are extracted using Local directional pattern (LDP), wavelet transform, principal component analysis (PCA), entropy, and mean for further classification. Based on the extracted features, the classification is performed using optimization-based deep convolutional neural networks. The proposed method is simulated through the images acquired from BRATS and SIMBRATS database and the performance is analyzed based on MSE and accuracy.The simulated results show high accuracy of 0.8711 and minimal MSE of 0.0197 than the existing techniques, such as RBNN, Exponential cuckoo-based RBNN classifier, Exponential cuckoo-based DCNN classifier.

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