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Brain Tumor Classification by EGSO Based RBFNN Classifier

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Abstract- Tumor classifier is modelled employing a proposed Enhanced Group Search Optimizer based Radial Basis Function Neural Network model is applied in this research contribution to acquire the ideal instances from the developed VOI instance an as well EGSO is utilized to optimize the weight values of the Radial Basis Function Network classifier by limiting the mean square mistake. The anticipated EGSO based RBFNN classifier brings better characterization precision and accomplished insignificant error with quicker process. The simulation results computed prove the effectiveness of the RBFNN classifier to be better in comparison with the other proposed classifiers in this thesis and that available in the literature. The proposed pattern evaluation technique presents an automatic cancer categorization procedure thru the ultimate facets which fantastic characterizes MRI brain image is benign and malignant cancers. The planned method may perhaps stretch to categorize exceptional classes of tumor (eg. Meningioma, glioma etc.,) and depth of malignancy.

Keywords: EGSO, GSO, k-NN, PSVM, RBFNN, SVM.

I. INTRODUCTION

This paper, a tumor classifier is modeled employing a proposed EGSO Based RBFNN model. As presented in previous chapters, it is observed that the employed SVM and PSVM classifier has been employed for performing effective brain tumor classification but had the limitations of local minima occurrence and longer computational time respectively. It is highly important for performing brain tumor classification through increased classification accuracy and reduced error rate. This chapter attempts to avoid local minima problem, stagnation and results in faster convergence employing the proposed EGSO Based RBFNN classifier to classify the cancerous and non-cancerous tissues. EGSO is employed in this research contribution to acquire the best feature groups since the produced VOI structures then as well EGSO is used to optimize RBFN classifier weight values by decreasing the mean square error. In the previous chapters, SVM and PSVM classifiers are employed wherein both of these employ kernel functions and it always involve high computational burden in locating the decision boundary line in these cases. Hence, in this chapter RBFNN is employed wherein non-linear activation function, Gaussian function is employed for computing the outputs of the neuronal layers and subsequently their weights and bias are optimized using

The proposed EGSO technique. simulated outcomes demonstrate the viability of the innovative EGSO based RBFNN method over the existing classifiers from the literature and as well the other classifiers proposed in this thesis.

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II. BACKGROUNDS ON APPLICABILITY OF PROPOSED TECHNIQUES

The considered RBFNN classifier is employed in this research chapter with proposed Enhanced GSO for performing brain tumor classification and thereby the applicability of RBFNN classifiers and Group Search Optimizer in various thrust research areas are as discussed in the following paragraphs.

In [1] author investigated a very simple radial basis function neural network (RBFNN) for image classification. when the number of training samples is very large a parallel processing method is used to reduce computing time in matrix inversion. The proposed method is used for hyper spectral remote sensing image classification. In [2] a new learning way for RBFNNs. A upgraded midpoint modification procedure for RBFNNs and a new width assessment algorithm were suggested to maximize the performance of the Optimum Steepest Decent (OSD) algorithms. In [3] the author examined artificial neural network efficiency in the detection of medical images utilizing Bezier curves such an extractor function. A strong 96 percent classification rate were obtained using the RBF when wavelet-based extraction of the Daubechies (db4) functionality has been used. As discussed by author [4] RNFNN has been introduced for scripted Indian language character recognition over eight positional attributes of differential features.In [5] the author proposed Automatic classification using NN and SVM classifiers. Decisions indicate which vector machine clustering algorithm aid to quadratic kernel mechanism works better than kernel mechanism RBF and NN classifier plays better than twenty-five secret nodes of fifty secret nodes. In [6], the author proposed a RBFNN for the taking out of images in the similar parts and dissimilar ones. In [7] the inventor proposed a RFRBFN method. The proposed procedure changed fuzzy RBF calculation by consolidating spatial data and a flattening constraint into its goal effort. In [8] the author proposed PBL and McRBF. The exhibition of PBL-McRBF has been contrasted and a quadratic bit bolster vector machine.

In [9] a sexual orientation order technique utilizing a M-estimator based RBF neural system was proposed. The FERET catalogue is utilized to assess the technique in the examination. Sandoval et al 2014 proposed a procedure to achieve a harvest sorting chore over satellite imageries built on the GLCM and RBFNN.

Based on the above presented applicability of the considered GSO and RBFNN approaches, this thesis proposes a new Enhanced GSO based RBFNN classifier to carry out the brain tumor classification of three – dimensional MRI bran images.

III. CONTRIBUTIONS TO OPTIMAL FEATURE SUB-SELECTION

In image processing applications, sub-selection process aims to gain the optimum f structures groups since the compete structures extracted to achieve the desired output. Sub-selection involves determining the greatest nominal subsets through the extracted unique component set rather than converting the given value into various sizes. Numerous computes are considered for analyzing the features from various analogies, but certain features extracted tend to perform their operations in a similar way without showing any specific operational changes. Further, attempting to improve the dimensionality of the texture features results in decrease of memory and the computational time. The importance of feature sub-selection is to identify the features that are capable of correlating and identifying the required classification model. Objective of the sub-selection process is to maximize the prediction accuracy and minimize the error computed during the generations

A. Group Search Optimiser Algorithm – Revisited

A nature inspired evolutionary optimisation algorithm developed based on the members of producers and scroungers are the group search optimizer [10]. In order to compute the solutions in a quick method, the fewer effective group followers will be eliminated. Only if there is active activity of the followers inside a group the GSO procedure can converge at a faster rate, thus in this research thesis, an enhanced GSO (EGSO) is proposed to achieve the faster convergence and to handle the said limitations. Fundamentally, there exist three categories of members in GSO algorithmic process and it includes – builders, cadgers and isolated followers. Considering the whole cluster, one creator is noted to be present and the other members belongs either to scrounger category or to the dispersed member category. Since the dispersed members in the group perform random walk in the search space, they are treated as less efficient member in the group. At the time of generation process, a member in the group will be noted for its presence at the location wherein the fitness value is the best and that member becomes the producer. The producer locates that position as the prominent position with the best fitness value and remains unchanged at that position.

The steps adopted to reach the fittest solution employing producer – scrounger mechanism stands as specified lower:

Step1: Initially, the maker begins to filter at zero degree and afterward it checks along the side by arbitrarily testing three focuses in the examining field: one point at nil degree, one point in the correct hand side hypercube and one point in the left-hand side hypercube as spoke to in conditions (i), (ii) and (iii) respectively.

$$X_z = X_p^k + r_1 l_{\max} D_p^k\left(\phi^k\right) \quad \text{(i)}$$

$$X_r = X_p^k + r_1 l_{\max} D_p^k\left(\phi^k + r_2\theta_{\max}/2\right) \quad \text{(ii)}$$

$$X_l = X_p^k + r_1 l_{\max} D_p^k\left(\phi_k - r_2\theta_{\max}/2\right) \quad \text{(iii)}$$

$\theta_{\max} \in R^1$ Agrees the maximum detection perspective and $l_{\max} \in R^1$ specifies the maximum detection distance. $r_1 \in R^1$ Being a typically dispersed arbitrary figure with mean zero and normal nonconformity one then $r_2 \in R^{n-1}$ stands a consistently dispersed arbitrary order in the range between 0 to 1.

Step2: The greatest fact through the greatest source (neutral function cost) will then be identified by the producer. On determination of the best point wherein it is noted to possess a best value than present location of it, it tends toward remain at this position else or this will move towards the present location and then change its starting point to a novel arbitrarily produced direction.

$$\phi^{k+1} = \phi^k + r_2\alpha_{max} \quad \text{(iv)}$$

where, $\alpha_{\max} \in R^1$ represents the highest rotating direction.

Step3: When the manufacturer does not invent a fine part next to a generation, then it drives its starting point return to zero point,

$$\phi^{k+a} = \phi^k \quad \text{(v)}$$

where, $a \in R^1$ is fixed one. at a particular kth rotation, ith cadger paces default to the manufacturer.

$$X_i^{k+1} = X_i^k + r_3 o\left(X_p^k - X_i^k\right) \quad \text{(vi)}$$

where, $r_3 \in R^n$ speaks to a uniform irregular succession in the scope of 0 to 1. The administrator 'o' is the Hadamard item or the Schur item, which computes the section savvy result of the two vectors. At the point when a scrounger finds a superior area than the present maker and different scroungers, at that point it gets exchanged as maker in the cutting edge [20].

Step4: The gathering individuals, who are noted to be less effective foragers than the predominant, gets scattered from the gathering. At the point when the Ith bunch part is scattered, it performs going. At the kth cycle, it produces an irregular head position ϕ_i via (iv); then the arbitrary distance is selected,

$$l_i = ar_1 l_{\max} \quad \text{(vii)}$$

and it travels to the new position,

$$X_i^{k+1} = X_i^k + l_i D_i^k\left(\phi^{k+1}\right) \quad \text{(viii)}$$

On any associate moving towards the no achievable position, it is enforced to travel back to the earlier location for guaranteeing a better result.

B. Proposed Enhanced Group Search Optimizer (EGSO) for feature sub-selection

Basically, in regular GSO the movement of members inside the search space is based on their pursuit angle, head angle and turning angle. During the generation process, it is observed that the movement of scroungers or rangers towards attaining the best position is sluggish in nature and results in premature convergence. Once a producer is identified, then it remains stand still at that particular position and the scroungers along with dispersed members moves invariantly in a random walk manner towards the solution point, without knowledge on producers in few cases. To overcome this problem, this thesis focused on eliminating the minimum angles traversed by the members of the group so that the particular path will be eliminated totally, and results in faster convergence avoiding the scroungers traversing in random different directions. The scanning field mechanism is re-modified in EGSO for all the three points eliminating the minimum angle position. Each of the three point at 0-angle, the right side of hypercube and leftward side of hypercube are given by,

$$X_{zo} = X_p^k + r_1 l_{max} D_p^k\left(\phi^k\right) - r_1 l_{min} D_p^k\left(\phi^k\right) \quad \text{(ix)}$$

$$X_{ro} = X_p^k + r_1 l_{max} D_p^k\left(\phi^k + r_2\theta_{max}/2\right) - r_1 l_{min} D_p^k\left(\phi^k + r_2\theta_{min}/2\right) \quad \text{(x)}$$

$$X_{lo} = X_p^k + r_1 l_{max} D_p^k\left(\phi_k - r_2\theta_{max}/2\right) - r_1 l_{min} D_p^k\left(\phi_k - r_2\theta_{min}/2\right) \quad \text{(xi)}$$

Where, l_{min} and θ_{min} are the minimum pursuit distance and minimum pursuit angle and, in this case, the minimum points traversed by the members of the group will be totally eliminated and henceforth the movement will not be focused in that specified direction. With respect to the movement based on the turning angle, considering the minimum turning angle does not result in any significant positional change and hence this is avoided. During the generation process the less efficient members in the group than the dominant, gets dispersed from the group. Automatically, at this point ranging operation is initiated. At this juncture, the random head angle is given by,

$$l_i = ar_1 l_{max} - ar_1 l_{min} \quad \text{(xii)}$$

And the new point will be based on this 'l_i' value and is given by,

$$X_i^{k+1} = X_i^k + l_i D_i^k\left(\phi^{k+1}\right) \quad \text{(xiii)}$$

Employing the stated mechanism, the movement of the scroungers is limited and gets focused on the solution point or the point located by the producers. The process of traversing towards the minimum point eliminates the unwanted distance traversed by the members of the group. This enhances the convergence of the basic GSO resulting in enhanced GSO algorithm. Thus, based on the minimum pursuit angle and its respective distance, the modification is carried out. Accordingly, the developed Enhanced GSO Algorithm is presented in Table I.

Table I. Enhanced GSO Algorithm

```
Start
    Randomly generate the members of the group
    Initialize the directions and head position of the
    generated associates of the group
    While the stopping condition not met, perform the
        following   for every associate in the set
            Evaluate the suitability cost
            Identify the producer based on the computed
            fitness value
Do Enhanced Producing operation:
    Carry out the producing mechanism based on
     equations (4.9) through (4.11)
     If the producer stays back in the current position,
         then employ equation (4.4)
    Do Scrounging operation:
        Arbitrarily choose 75% members from the group
         to complete Scrounging.
         Do Enhanced Limit Operation:
             Employ equations (4.12) and (4.13) for the
                remaining 25% members to carry out the
                 ranging operation.
         End
     End
  End
Stop
```

As the considered research problem in this thesis is of complex in nature, the developed enhanced GSO is employed to compute the optimal feature subsets and as well to train the RBFNN used for brain tumor classification [11-15], [17-18].

IV. PROPOSED EGSO BASED RBFNN CLASSIFIER FOR BRAIN TUMOR RECOGNITION

This paper employs RBFNN to perform the effective brain tumor classification. it is a n dimension feedforward neural network with hidden layer present between the input layer and output layer. In RBFNN modeling, for weight updating process it employs gradient descent learning rule and the output from the network layers are determined using the non-linear Gaussian stimulation method. The applicability of the Gaussian stimulation method results in obtaining the near solutions and thus increases the convergence of the neural network. This section presents the basic RBFNN classifier model and the proposed EGSO based RBFNN model to be employed for brain tumor classification [16], [19].

A. RBFNN Classifier model

RBFNN classifier neuronal model adopts a multi-layer feed forward architecture with a single layer of hidden units as shown in Figure 1. Figure II shows the nonlinear Gaussian activation function that plays a major role in increasing the computational efficiency of the network. RBFNN classifier training process is constructed on weight initialization process, feed forward of the inputs and subsequent calculated outputs, error computational process and updating the set weights and bias of the network [34].

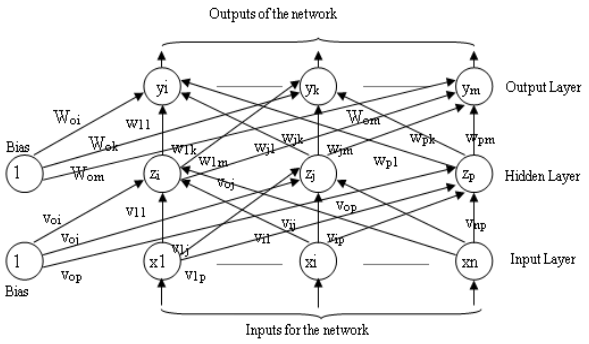


Figure I. Multi-layer Architecture of RBFNN classifier model

B. Proposed EGSO based RBFNN Classifier model

This proposed technique hybridizes the concept of EGSO for optimizing the weights in Radial Basis Function Neural Network. This enhanced GSO with RBFNN avoids the random selection of weights and enables the selection of input weights and bias for increasing the generalization ability and the situation of the lone layer feed-forward NN. The several stages of the planned technique are as follows:

Step1: Initialize the parameters of EGSO i.e, positions and head angles are set with values of input weights and hidden biases. $[W_{11},W_{12},\ldots,W_{1n},\ldots, W_{21},W_{22},\ldots,W_{2n},\ldots, W_{H1},W_{H2},\ldots,W_{Hn}, b_1,b_2,\ldots,b_H]$. These values are randomly declared within the limit of -1 to 1 on D sizes in the search space.

Step2: For every associate in the set, the particular output final masses are computed by RBFNN classifier as given in equations (xxv) and (xxvi).

Step3: Appeal Enhanced GSO which presented in Table I

Step4: The suitability function here is the Mean Square Error and is given by,

$$MSE = \frac{1}{N}\sum_{i=1}^{N} E_i^2 = \frac{1}{N}\sum_{i=1}^{N}(y_k^i - d_k^i)^2 \qquad \text{(xxvii)}$$

where, N is the quantity of exercise models, and the y_k and d_k is the error of the real outcome and desired goal output of the *k-th* outcome neuron of *i-th* sample. For avoiding extra -fits of the lone layer FNN, the suitability of every associate in the group is assumed as the (MSE) the validated group only as a substitute of the entire train set.

Step5: Search the builder of the set based on the suitability values evaluated.

Step6: Refresh the location of every member as given in equations (ix) through (xiii).

Step7: End up the state – the procedure recalls steps 2 - 6 till specified conditions are reached, with solid boundary value as determined number of repetitions. once terminated, the procedure reports the instances at which optimum masses with nominal Mean Square Error as its result.

The developed Enhanced GSO (EGSO) with RBFNN governs the finest optimum masses W and bias b so, the suitability grasps the least to attain faster convergence avoiding local minima with better generalization performance and minimal error considering the advantages of EGSO and RBFNN model. In the method of choosing the input masses, the enhanced GSO reflects not lone the MSE on justification group but as well the norm of the output weights. The proposed EGSO based RBFNN classifier combines the feature of Enhanced GSO into RBFNN to compute the optimum masses and bias to obtain minimal Mean Square Error.

V. RESULTS AND DISCUSSIONS

The planned Enhanced GSO based RBFNN classifier is employed in this thesis for the real time 320 brain clinical image samples. Enhanced GSO is initially employed for obtaining the optimal feature subsets of the considered real time images and is employed then to optimize the weight and bias values of RBFNN classifier. As in case of previous chapters, to apply the proposed technique, the training and testing datasets are divided for their applicability employing leave one out classification (LOOC) and here 10-fold cross validation with the 10-bin operation is used. Once the normalization process is completed, then the volumetric features are extracted and based on these features, the classification process will be initiated. VOIs will be selected with care so to avoid the signals from the near adjacent tissues. Histogram and VOI are employed in a suitable way to carry out the normalization process. The normalization process takes care to avoid the presence of sparse matrices and aims to obtain the required features. The features extracted in the initial stage for the real time datasets include the fourteen GLCM features, eleven run length matrix features and two gradient parameters for three-dimensional volume of interest. These 27 relevant features are noted from the area under curve of the receiver operating characteristics curvature then from p values of 2 last student T test. As it's already known, higher values of AUC and lower values of 'p' from student's t-test indicates the most prominent features of the considered images. Here, employing proposed enhanced GSO along with student's t-test 7 optimal feature set is obtained. Table III gives the optimal features obtained using the proposed EGSO and is noted to improve the classifier accuracy. Table II shows the what are the parameters taken for the RBFNN classifier model.

Table II. Parameters for the RBFNN classifier model

Parameters	RBFNN Classifier model
No. of input neurons	7(Optimal feature subset selected using proposed EGSO)
Learning rate	1
Activation Function	Gaussian Activation function
Momentum factor	0.3
No. of hidden neurons	7 (equal to input neurons)
No. of output neurons	1 (cancerous or non-cancerous tissue)
Maximum Iterations	500

Table III. Optimal features sub-selected from proposed EGSO approach and student's t-test for 3D VOI

Selected Optimal Features	Rank	3D VOI			
		Healthy Brain		Tumorous Brain	
		Min	Max	Min	Max
Short Run Emphasis	1	0.94	1.24	3.98	7.75
Variance	2	4.03	4.91	10.09	14.56
Energy	3	0.75	4.09	23.99	29.76
Gradient vector Parameter	4	0.43	4.91	22.03	28.16
Gray-Level Non-uniformity	5	0.24	0.46	0.57	0.87
Contrast	6	0.34	2.71	1.12	2.76
Sum Variance	7	0.25	0.56	3.05	7.80

The benign is found to have a larger spread with respect to SRE feature than the malignant. except 7 features sub selected with assistance the evaluate ability to benign and malignant cancer recognition, the model of lone like instance (SRE) for couple classes are shown in Table VI. The classification is performed employing RBFNN with optimized weights and is correlated with BPN, k-NN, SVM then PSVM classification procedures as presented in previous work.

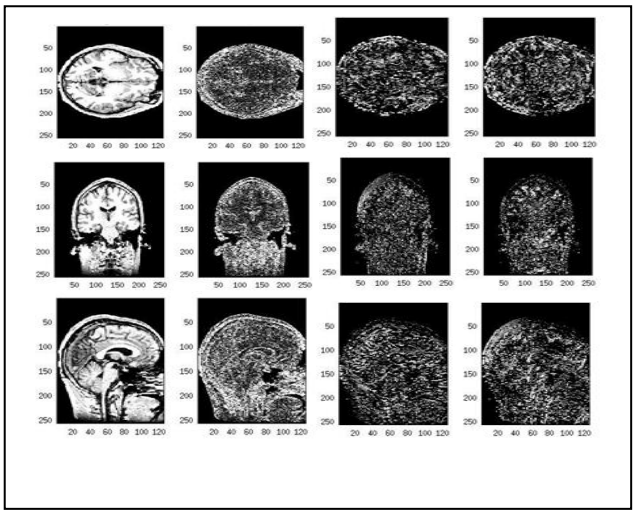
Figure II shows the features extracted and tumor segmentation for another brain image. In this manner, the tumor segmentation and classification process are carried out. Figure III presents the mockup outcomes of different classifiers then Table III presents the outcomes of the planned classifier along with the other classifiers considered for comparison. The optimal weights computed for RBFNN classifier using the proposed EGSO is presented in Table VI.

From the Table VI, observed that the proposed EGSO based RBFNN classifier employing its Gaussian function achieved minimal errors. The classifier model accuracy is based on the evaluation among the True Negatives (TN) and False Negatives (FN). Classification correctness is measured by ROC. The surface in a ROC (Az cost) gained by the planned method which obtain 0.99 used by Leave-one-Out validation in selection of 320 clinical data group. Figure III shows the model ouputs of different classifiers.

Table IV. Composed calculation of the classifier's activity

S.no	Methods	AUC %
1	BPN	0.83
2	k-NN	0.90
3	SVM	0.96
4	PSVM	0.98
5	**RBFNN**	**0.99**

Table IV shows the activities of all classifier model with respect to AUC. The RBFNN provides highest AUC in percentage.



Original MRI Slices **Features Extracted**

Figure II. Features extracted employing the proposed model

Table V. The optimal operating points of the proposed and other existing classifiers models.

Methods	FP	TP
BPN	0.42	0.84
k-NN	0.20	0.89
SVM	0.15	0.94
PSVM	0.11	0.97
RBFNN	0.07	0.98

Table V the values inside the braces which mentions True and False positives. above specified values indicate the highest optimal values when the five classifiers are valuated with the whole clinical evaluation dataset. For examining the importance of the considered classifier models, a Wilcoxon Signed-Rank assessment a non-parametric is implemented to examine the importance among the combinations of the pattern measures. With respect to RBFNN, the result presents a statistical important variation on an importance range of 0.016, however for BPN and k-NN, in two methods the variance in AUC of the ROC are important with P = 0.793, for SVM with P = 0.05 and for PSVM with P = 0.03. Table VI presents the computed mean ouputs for the planned EGSO based RBFNN with BPN, k-NN, SVM and PSVM with esteem to the performance measures - Specificity, Sensitivity, Accuracy, ROC and Mean Square Error. It is well established from Table VII that the developed RBFNN classifier optimized using EGSO is noted to achieve minimum MSE of 0.0003 in evaluation with that of the existing classifier models. Further to this, RBFNN has resulted in highest level of accuracy proving

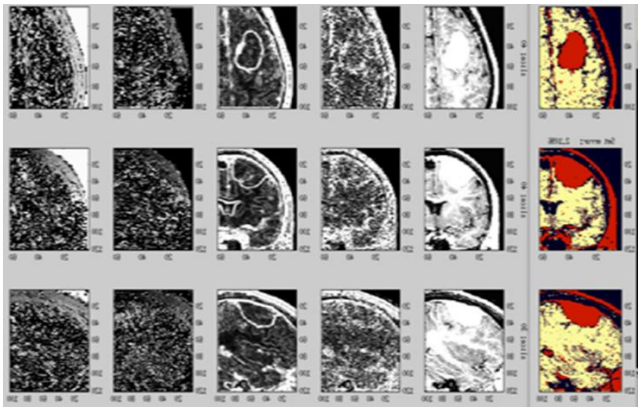


Figure III. Proposed EGSO based RBFNN model for Feature extraction and tumor segmentation in a brain image (clinical dataset)

Table VI. Performance of the Proposed EGSO based RBFNN Classifier

Methods	Efficiency at Training Stage			
	Mean	STD	RMSE	MAE
k-NN	97.34	0.75	0.125	102.33
BPN	98.34	1.01	0.128	155.45
SVM	100	0	0.004	0.231
PSVM	100	0	0.0029	0.176
EGSO RBFNN	**100**	**0**	**0.001**	**0.132**
Methods	**Efficiency at Validation Stage**			
	Mean	**STD**	**RMSE**	**MAE**
k-NN	90.12	5.6	0.183	138.33
BPN	89	5.9	0.175	177.32
SVM	98.45	4.4	0.101	0.281
PSVM	100	0	0.091	0.259
EGSO RBFNN	**100**	**0**	**0.056**	**0.037**

Table VI represents the efficiency of data set in training and testing stages. Comparability the EGSO RBFNN provides better results than the other classifiers.

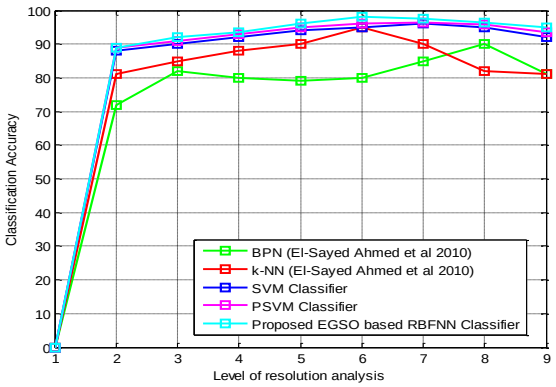


Figure IV. Accuracy of all the Classifiers

its efficiency. The best classifier is the radial basis function classifier meanwhile in this ROC is positioned in the Figure IV.

Table VII. Mean outputs of the 3 Dimension feature removal prototype for multiple classifiers on 320 actual patient data sets

Classifiers	Spec%	Sen %	Acc %	ROC (A_z)	MSE
BPN	68.17	89.58	88.85	0.89	0.21
kNN	76.19	91.84	91.14	0.93	0.10
SVM	95.0	98.94	98.4	0.99	0.015
PSVM	97.8	99.01	99.25	1.00	0.009
Proposed EGSO based RBFNN classifier	**99.1**	**99.36**	**99.81**	**1.00**	**0.0003**

The Table VII shows the specificity, sensitivity, accuracy, ROC and then Mean Square Error of the all experimented classifiers. The EGSO based RBFNN classifier, that classifies the patients to the cancerous or non-cancerous class which is sometimes the results in any patient data being classified wrongly, foremost towards a right classification measure of 98% for the 30-sample real patient's dataset. This is shown in Figure II, where a scatter plot of the classification for the 30 patients is shown. The scatter plot for various other classifiers as shown in Figures II, III and IV and Figure V correspondingly. The rings are mentioning a patient's malignant cancer prediction, although the advantages are benign tumor prediction of the patients. The 50% stripe are fault or right classification range. The x and y axis in the figure represent the images, for every patient that is categorized by two classes, with benign on the y-axis and malignant on the x-axis.

Table VIII. Measures the accuracy of all the classifiers for feature selection and segmentation of 2D and 3D images

Texture Measures	Methods	Acc % w/o FS	Acc % with FS
2D GLCM + 2D RUN LENGTH + 2D SGLDM (El-Sayed Ahmed et al 2010)	BPN	72.45	81.20
	KNN	84.34	89.45
	SVM	89.55	91.02
	PSVM	91.37	92.00
	EGSO + RBFNN	**91.76**	**93.92**
Proposed 3D GLCM + 3D RUN LENGTH + 3D SGLDM	BPN	81.65	88.85
	KNN	89.55	91.14
	SVM	90.78	98.40
	PSVM	94.73	99.37
	EGSO with RBFNN	**95.22**	**99.71**

Table VIII shows the accuracy of existing and proposed methods of with and without Feature Selection (FS) for 2D and 3D images. The proposed EGSO approach are choosing the optimum feature subgroup aims to overcome the trap of local optimum and minimizes the computational time incurred during the training session. The remaining is achieved among the investigation and mistreatment mechanism during the search process increases the EGSO procedure as capable technique for the feature sub choosing on high measurement space. Table VIII presents the activity measures of the existing 2D methods and the planned new method along with SVM and PSVM classifier. Table VII infers the planned 3D method EGSO based RBFNN classifier attains improved measure rate with PSVM, SVM, BPN then k-NN classifiers. This model is experimented in MATLAB with necessary specifications. In this research contribution, the developed EGSO is applied for selecting sub-optimal features and the selected sub-optimal features acts as input for the RBFNN classifier. Further, EGSO is also employed to optimize the weight values of RBFNN. On carrying out the simulation process, it is noted that EGSO as a better global optimization algorithm resulted in better solutions. The experimental result shows that the EGSO resulted in better solutions for optimal feature sub-selection and RBFNN classification. Thus, the proposed EGSO – RBFNN improved the accuracy of classification methods by smaller improvements of feature subsets.

VI. CONCLUSION

An EGSO is applied in this proposition to perform the feature sub-set selection of the considered high-dimensional clinical brain image datasets. Fundamentally, VOI results in a greater number of features being extracted, but certain features are highly non-relevant and may be omitted. This is taken by the feature sub-selection process carried out employing EGSO in this paper work. The proposed EGSO extracted the relevant sub-features and the separated features are employed as RBFNN classifier model inputs. Added to this, the Enhanced GSO optimizes the weight values of the RBFNN during the training process. This new approach used faster convergence method to produce the improved accuracy for classification with minimal error rate. The stability of the proposed classifier is guaranteed since it completely avoided the local minima problem and reduced the computational time incurred. Simulation results obtained confirm the effectiveness of the proposed EGSO based RBFNN classifier over the early proposed classifiers from the literature and that proposed prior in this paper – PSVM and SVM. The presented work in this paper will aid to analyze the pathologies and increase the medical practitioners more consistent diagnosis. The proposed model results in an automatic brain cancer discernment method done the optimal features which better characterize MRI Brain is a benign and malignant cancers.

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