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TUMOR CLASSIFICATION USING ENHANCED HYBRID CLASSIFICATION METHODS AND SEGMENTATION OF MR BRAIN IMAGES

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ABSTRACT

The inherently varying nature of tumor shapes and image intensities make brain tumor detection very intricate. Since several available methods and tumor detection are far from being resolved. Initially, an optimization-based classification a new hybrid model was proposed to describe an individual use of clonal selection and particle swarm optimization (PSO) to verify a specified MR brain image as either normal or abnormal. The methodology involves two major stages. In the first stage, used sparse principal component analysis (SPCA) to reduce feature space, and selected the important features. The second phase two hybrid optimization-based negative selection models were developed to investigate the integration of clonal selection technique with PSO from the perspective of classification and detection to optimize the parameters C and σ. Fivefold cross-validation was utilized to avoid overfitting and to ensure a robust classification. Although clonal negative selection classification algorithm (CNSCA), has the best performance. The proposed method achieved 99.10% classification accuracy. The admirable features of the outcomes submit that the suggested methods may institute a basis for reliable MRI brain tumor diagnosis and treatments. A comparison with other techniques showed the competitiveness of the proposed methods.

Keyword: magnetic resonance imaging, feature selection, particle swarm optimization, clonal selection, hybrid classification.

1. INTRODUCTION

This research rationalizes the urgent necessity of systematic research to distinguishing and segmenting the brain tumor in Magnetic Resonance Images (MRI). Brain tumor being the most prevalent of brain illnesses affects and devastates health of many persons [1]. Despite many dedicated research efforts to overcome brain tumor related problems, higher survival rate of brain tumor patients is far from being achieved. Lately, approaches involving the information of medicine and computing learning are adopted for well understanding of the illness and to discover more operational systems for cure. MRI and "Computed Tomography" CT, scans of human brain are the most prevalent experiments used to detect the presence and recognize the place of brain tumor for chose appropriate treatment [2]-[3]. It also depends on whether or not the tumor is exerting compression on vital portions of the brain [4], [5]. Actually, the treatment options are critically decided by the factors such as the extent to which the tumor has prevalence to the other sections of the brain, the possible side cases on the patient [6].

In this regard, Computer Aided Diagnostics (CAD) remarkably improved the detection accuracy. The CAD system not only renders an alternative opinion to support the image interpretation of the radiologist but also reduces the image reading time significantly. Brain segmentation for anomaly find in MRI images is the most arduous work due to complex problems ingrained to the quality of the image [7], [8], [9]. Thus, the choice of various segmentation procedures is necessary to distinguish the cancerous tissue from the surrounding normal tissues. For these many methods have been searched, containing approaches based edge [10] [11], techniques depend on region [12], approaches depend on thresholding [13], Markov random field systems [14] and hybrid approaches [15] [16] [17].

In current years there has been an increasing interest in the differential evolution algorithm (DE), is new optimization method to solve numerical optimization difficulties. The method has positively been utilized to several sorts of problems as it has strength, and good convergence attributes [18].

Wavelet transform is an effective method for extracted features from MRI samples, because they allow test of images at different stages of resolution. However, this method requires big storage and is computational cost. In order to decrease and choice the feature vector dimensions and increase the discriminative power, the sparse principal component analysis SPCA has been applied. SPCA is interesting since it effectively decreases information and chooses the important data and therefore decreases the computational cost of test new data [19].

A particle swarm optimization (PSO) is utilized in this study to improve efficient and robust procedures to solve a selective set of difficult. In general, difficult with the PSO and with the other optimization systems is that they may obtain trapped in local optimum parts.

The key objective of the research is to suggest a computationally efficient segmentation technique, which is for finding and segmentation of brain tumor. The organization of the study is as follows: in division 2 Hybrid Classification Methods is studied. A description of suggested segmentation systems is presented in section 3. Division 4, illustrates the getting experimental outcomes and division 5 concludes this study.

2. HYBRID CLASSIFICATION METHODS

Feature extraction is the preliminary stage in which highly informative measures are produced as representative features for brain tumor. The main stage of Magnetic Resonance Images (MRI) recognition in brain is brain tumor patterns classification. In this stage, the machine learns to the tumors to differentiate between brain tumor patterns in order to make rational decisions on the classes of the patterns [20]. In this regard, soft computing is the most promising approaches among many techniques of machine learning. The soft computing strives to achieve robust and practical solutions at reasonable cost by tolerating uncertainty, imprecision and approximation to be fragment of the computational model [21]. Artificial immune system (AIS) developed in the 1990s as a flourishing field of soft computing [22]. The AIS can exhibit robust and powerful capabilities in information processing to solve complex problems. From the perspective of computational, it has important characteristics such as maintenance, diversity, learning, and memory. Moreover, the AIS show fast convergence speed with ability to avoid the immaturity and degeneration of the searching [23]. To date, research primarily has focused on three main components within AIS which include the theories of negative selection, clonal selection and immune network [24]. The negative selection algorithm (NSA) is more appropriate for application in anomaly and fault finding compared to other AIS theories [23]. It has been proven to be an efficient algorithm for solving such difficulties. The NSA was firstly proposed for the real- time detection of computer virus [25]. Nevertheless, the random search of the traditional NSA cannot be guaranteed to generate detectors in the most efficient way. That is to say, distribution of the detectors is unbalanced in the problem space. Most of these methods use optimization techniques, i.e., (PSO), genetic algorithm (GA), and clonal selection algorithms (CSAs), to guide the search in NSA and generate detectors with optimal distribution. The optimization techniques can be employed for classification by representing each class with a centroid (class center). The goal is to optimize the positions of all centroids to build nearest centroid classifier (NCC). It is clear that CSAs and PSO can be effectively faced such problem. Many algorithms were proposed in the literature to fulfill this basic process involved in clonal selection theory of NIS. Most of them have been applied to optimization problems. The clonal selection idea leads from a computational perspective through a process of selection, cloning, and mutation to systems that iteratively develop candidate solutions to a given problem [24]. The PSO is a global optimization algorithm, simple in model, easy to achieve, robust to computationally efficient [28].
This research has studied the abilities of negative selection and clonal selection particle swarm optimization (PSO) to produce different reliable and efficient methods of the brain tumor-based recognition which has not yet been explored. Obviously, some algorithms are proposed in this research based on AIS and PSO for recognizing from brain tumor: clonal selection classification algorithm (CSCA), particle swarm classification algorithm (PSCA), clonal negative selection classification algorithm (CNSCA), swarm negative selection classification algorithm (SNSCA), clonal negative selection detection algorithm (CNSDA).

To propose these classification methods based on clonal selection and PSO for building nearest centroid classifier for tumor brain lead to further improve the efficiency of the hybrid methods proposed by configuring the hybridization on the basis of detection and estimated the achievement of the different proposed methods in diagnosing the brain tumor using MIR.

3. PROPOSED WORK

This research falls under an approach of artificial intelligence and pattern recognition. The major objective of this research is to investigate the capabilities of SPCA and PSO in classifying brain tumor to recognize the image intensities for purposes of brain tumor diagnosis. Also lead to develop hybrid negative selection classification methods using the techniques of clonal selection and PSO for recognition brain tumor. Thus, the keys stages that must be followed involves: data pre-processing, feature extraction, designed classification model, and evaluate the performance of the system. Even though the research deals with every stage, it focuses primarily on classification/detection process due to its important, whereas the pre-processing and feature extraction are considered to be necessary aspect to improve the correct classification rate. The techniques of SPCA and PSO have been used in this study to develop classification methods for brain tumor recognition as shown of the operational framework in Figure-1.

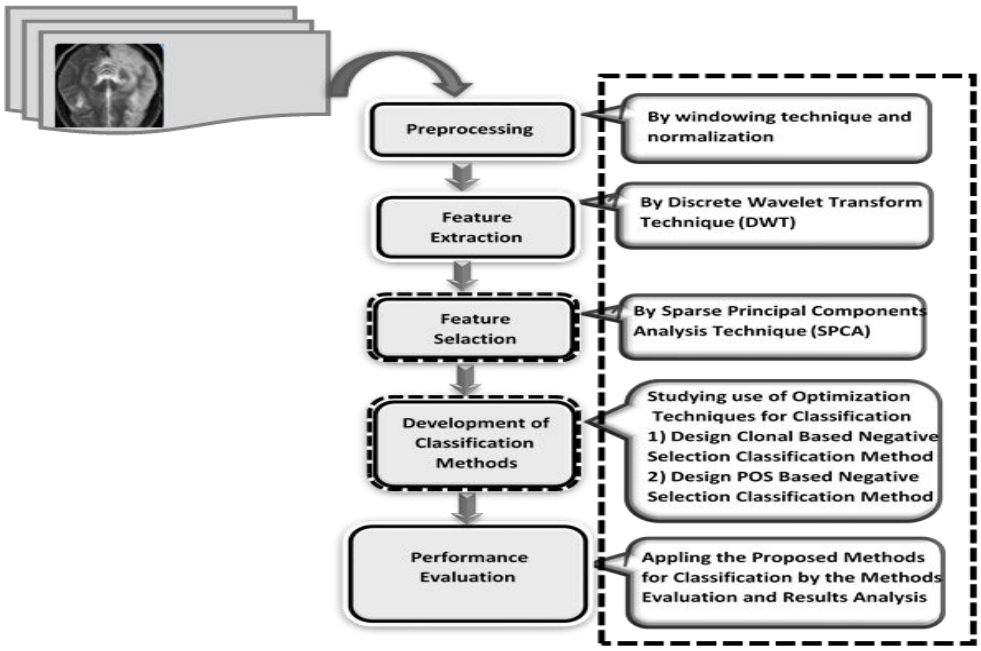

Figure-1. Operational framework of the research.

3.1 Preprocessing

The raw input image MRI is submitted to a set of pre-processing stages so that the image develops transformed to be suitable for the further processing. The pre-processing phase has a great significance to remove the noise from the image which contains many redundant information it. In this study, for removing noise, including two steps of data pre-processing: windowing and normalization are performed to prepare the MR brain images dataset. The windowing is needed for the process of feature extraction, whereas the other is achieved on feature vectors and it is important for classification approaches.

3.2 Feature extraction

Discrete Wavelet Transform (DWT) is been successful in the brain tumor finding due to its capability to extracts transient attributes and localizes them in both time and frequency domain exactly [27]-[28]. DWT characterizes the windowing technique with adjustable size. Thus, it preserves both time and frequency data of the signal. Another benefit of WT is that it adopts “scale” instead of traditional “frequency,” namely, it introduces the time- scale view is a various way to view information, but it is a more natural method. DWT was utilized to brain tumors at various t frequency bands and statistics over the set of the wavelet coefficients were computed to present the feature vector for hybrid classifier. According to [29], utilized WT to analyze the signals, the stages are selected such that those divisions of the signal that correlate well with the frequencies necessary for the signal classification are retained in the wavelet coefficients. The procedure of preprocessing and feature extraction to prepare the brain images for the classification methods in this study can be can be summarized as described in Figure 2. by the following steps:

a) The entire image from the MR brain images dataset are divided at the given sampling rate into segments of approximately 1.475 second using a distinct window composed of samples.

b) The MR brain images segments are analyzed forth levels into the detail wavelet coefficients: D1, D2, D3, D4 and one final approximation wavelet coefficients: A4. The sampling rate of the signal at each wavelet coefficients is 87, 45, 23, 12 and 12 Hz, respectively.

c) Different statistical features are calculated to represent the time-frequency distribution of MR brain image consist of Maximum (Max), Minimum (Min), Mean, and "Standard deviation (SD)" of the wavelet coefficients in each sub-band.

d) Finally, the extracted attributes are normalized within the range"0, 1". Then, the scaled MR brain image can be fed to the proposed methods for training and testing.

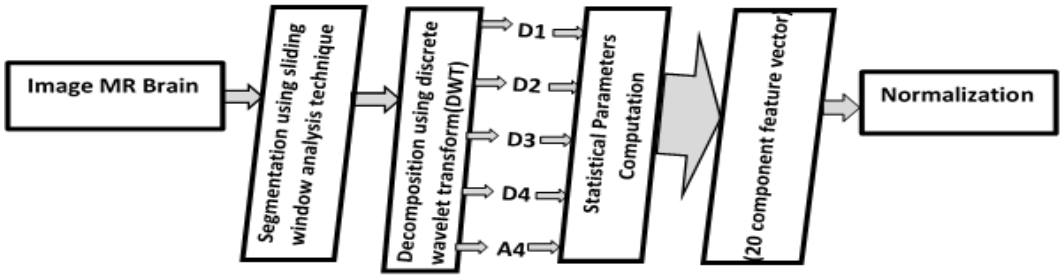

Figure-2. Preprocessing and feature extraction steps.

3.3 Feature selection

the redundant features cause an increase storage memory and make classification more difficult and complexity. It is required to reduce the number of features and selected robust features [30]-[31]. SPCA is an efficient means to decrease of a large number of interrelated data while retaining most of the differences. It is realized by transforming the high measurement to a low measurement of features according to their importance. This technique has three effects: it orthogonalizes the components of the input vectors, so that it uncorrelated with each other, it orders the causing orthogonal components, so that those with the largest difference come first, and it data those components contributing the least to the difference in the data set. The normalization is a standard procedure. Details about SPCA could be seen in [19]. Let DWT features (variables) F = (F1, F2... Fp) represent a p-dimensional random vector with a multivariate normal distribution. It is possible that some features correlate with one another. For instance, if the variables F1 and F2 are highly correlated, such that the correlation index between F1 and F2 approaches 0.9, then either F1 or F2 could be eliminated from the analysis as its role 1 is duplicated by the other. By doing this, the basis of the original features is altered to a more efficient set by using linear combinations. In the general p-dimensional case, this leads to a candidate set of new features which represent in next Eq. 1:

$$B_{SPCA1}=\left(\left|\propto_j^T {X_{DWT}}^T X_{DWT}\right|\frac{\lambda_{1,j}}{2}\right)+Sign\left(\propto_j^T {X_{DWT}}^T X_{DWT}\right), \text{ j=1,...,k} \quad (1)$$

where number of features, λ is penalty by directly imposing a constraint on PCA and $\lambda_{1,j} = 0$ call SPCA criterion. $B = (\beta_0, \beta_1, \beta_2,., \beta_k)^T$ where its regression coefficients represent the optimal minimizing, the covariance matrix ${X_{DWT}}^T X_{DWT}$, and ${X_{DWT}}^T X_{DWT}$ are represent DWT features, which represent the sparse loading of feature matrix.

3.4 Development of classification methods

In this phase, (negative selection and clonal selection) and PSO techniques are employed to develop optimization-based classification (OBC) model as shown in Figure-3, optimization based negative selection classification (OBNSC) model and optimization based negative selection detection (OBNSD) model. The models abstracted into many individual and hybrid methods for classification brain tumor. In each model, different optimization techniques are applied, clonal election and PSO. With this choice, the suitability of the optimization technique for the model can be studied. We used Optimization based Negative Selection Classification (OBNSC) model: hybrid classification methods the OBNSC Model is developed in this study as a hybrid negative selection model based on clonal selection or PSO for brain tumor recognition. The model qualifies the negative selection algorithm (NSA) to be able for dealing with the classification problem. Each optimization technique has its own mechanism to evolve its individuals towards an optimal solution. Accordingly, the optimization process takes place to update the nearest centroid classifier (NCC). NCC centroids positions of each individual until the best solution is found. In this work, the BCA (a clonal selection algorithm) and PSO techniques are employed for classifying brain tumor. As result, two classification algorithms are abstracted form OBC model, clonal selection classification algorithm (CSCA) and PSO technique respectively. They are explained in next two sections.

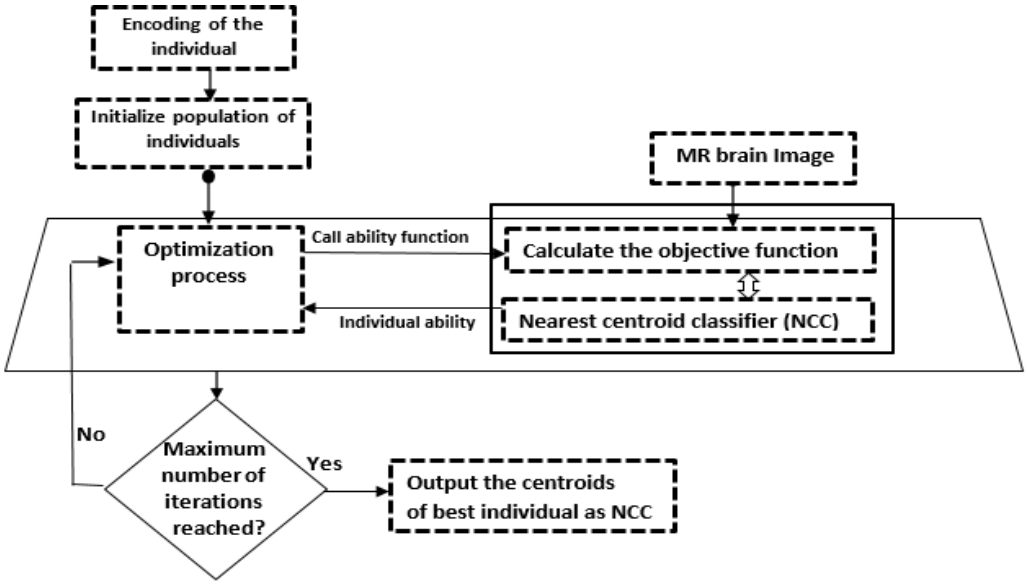

Figure-3. Proposed optimization based classification (OBC) model.

3.4.1 Particle swarm optimization technique (PSO)

The PSO technique was initially suggested by Kennedy and Eberhart [26] in 1995, The technique belongs to the broad class of stochastic optimization technique that may be utilized to detected optimal solutions to numerical and qualitative difficulties. PSO utilizes a population (swarm) of persons (particles) to probe promising areas of the search region. Depending on the topology, in the local different, each particle can be assigned to a neighborhood consisting of a predefined number of particles [32]. To obtain a well searching design between global exploration and local exploitation, scientists recommended reducing w over time from a maximal value wmax to a minimal value wmin linearly [33]. As shown in Eq. 2:

$$w = w_{max} - \frac{w_{max} - w_{max}}{t_{max}} * t \quad (2)$$

where, W is the inertia weight, t_{max} is the maximum iteration allowed and t is the current iteration number.

3.4.2 Clonal selection classification algorithm (CSCA)

The CSCA has been proposed to test the performance of the clonal selection for tumor recognition in brain. Based on tumor in brain. Algorithm 1. illuminates the phases of the suggested CSCA technique. In this research, the B-cell algorithm (BCA) which is a clonal selection algorithm has been used to present the CSCA. The mutation process in the clonal selection called affinity maturation in which the mutation proportion of an antibody is inversely related to its tumor: the smaller tumor, the higher mutation, and vice versa. [34] tested different clonal selection-inspired algorithms with seven mutation operators. The BCA outperformed all other algorithms using the mutation operator defined in Eq. 4. Each value $y_{c.d}(k)$ (See Eq. 3 and 4) in a clone y(k) is mutated as follows [35](de Castro and Timmis, 2002a):

$$x(n)=\{x_1(n).\, x_2(n) \ldots\ldots x_c(n).\ldots x_C(n)\} \quad (3)$$

$$x_c\,(n)=\{x_{c.1}(n).\, x_{c.2}(n) \ldots\ldots x_{c.d}(n).\ldots x_{C.D}(n)\} \quad (4)$$

where N (0,1) is a Gaussian random variable of zero mean and standard deviation σ = 1, β is a weight factor to control the decay of the inverse exponential function, and x(n) is the parent of the clone y(k). The value of correct classification rate (CCR) should be varied within the interval [0, 1]. A mutation is rejected if the mutated clone exceeds its domain range.

$$CCR\,(\mathrm{x}(n).Z_{Tr}) = \frac{\sum_{m=1}^{M_{Tr}} Assess(x(n).Z_m}{M_{Tr}} \quad (5)$$

$$y_{c.d}(k) = y_{c.d}(k) + \alpha N(0.1) \quad (6)$$

$$\alpha = (1/\beta)\exp(-\mathrm{CCR}(\mathrm{X}(\mathbf{n}).\mathrm{Z_{Tr}})) \quad (7)$$

The CSCA trains a set of antibodies to build a good NCC for brain tumor. Subsequently, a training set of the data is considered as inputs for the ability function (Equation. 5) to calculate the CCR of each antibody. Based on the classification evaluation, clones of these antibodies are mutated using (Equation. 6). The process is continued for improving the quality of the NCC classifiers represented in the antibodies, it is used for evaluating the proposed method.

Algorithm 1. Proposed clonal selection classification algorithm (CSCA)

Input: Take a portion ZTr with length MTr patterns from the MR Brain Images dataset as training set.

2. Training: Construct antibody by C class centroids as in Eq. 3.

3. Creating: Randomly Creates a population of N antibodies generated of ALCs, composed two subsets the memory cells (M) and the remaining (R) cells where C= M U R.

4. Optimization process: For each antibody x(n):

4.1 Affinity evaluation: Calculate the affinity between zp and each of the ALCs in C:

Calculate its efficiency value by Eq. 5, as CCR (x(n), ZTr).

4.2 Clonal selection and expansion: Generate K clones for the antibody x(n) and place Them in clonal pool y.

4.3 Metadynamics: Randomly select one clone from the pool y and randomize its values.

4.4 Affinity maturation: Mutate all the clones in y with a rate inversely proportional to the affinity of their parent using Eq. 6.

4.5 Clonal selection and replacement: Choose the best mutated clone to be kept as the memory ALC, m of zp in M if it has a higher affinity than old one. with replace nl lowest affinity ALCs in R with randomly generated ones, the clone replaces the original antibody x(n).

4.6 Affinity evaluation: For each clone y(k), calculate its ability value by Eq. 5, as CCR (y(k), ZTr).

5. Loop: Repeat step 4 until a certain termination criterion is met.

6. Output: Give the centroids of the antibody with the highest fitness in the population x as the NCC.

4. PERFORMANCE EVALUATION

The suggested system involves of pre-processing, Image Enhancement, Segmentation and the last stage represent classification technique. The MRI database that have been utilized in project. This database includes 101 MRI images, containing 87 images with brain tumor and the other 14 images without tumor. The MRI brain database is split into two collections: training database and testing database. In this, the 65 images are used for the training and the 36 images are used for testing. Comparative analysis is based on execution time and accuracy of proposed CSCA algorithm. Some of the outcomes of using the projected techniques are displayed in Figure-4. The first row represents original MRI samples; the second row represents feature extraction; the third row presents feature selection; the fourth row is the results of a classification.

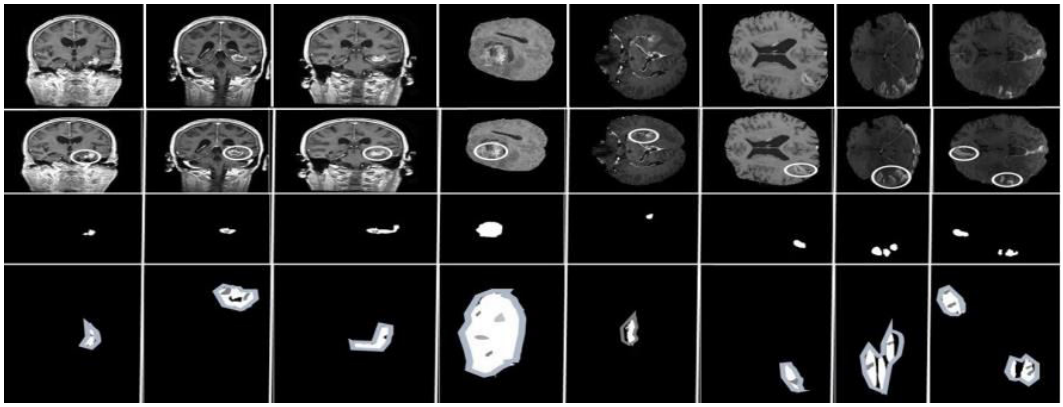

Figure-4. The first row shows the MRI images, the second row, the third row are the results of the pre-processing and selected feature, and the fourth row are the final outcomes of CSCA technique

From the results obtained CSCA algorithm represented a well quantity proportion for all the input samples. these k outcomes are utilized to evaluation achievement measures for the classification method. The common achievement measures utilized in medical diagnosis tasks are accuracy, sensitivity and specificity. Accuracy measured the capability of the classifier to obtained accurate diagnosis. The measure of the ability of the model to recognize the occurrence of a target class accurately is determined by sensitivity. Specificity is determined the measure of the ability of the method to separate the target class. The classification accuracies for the databases are computed as in Eq. 8:

$$\text{Accuracy}(Z) = \frac{\sum_{i=1}^{|z|} assess(z_i)}{|Z|} \quad (8)$$

Where: z = The patterns in testing set to be classified $z._c$ = The class of pattern z and classify (z) returns the classification of z by classification algorithm

For analysis sensitivity and specificity, the following equations can be used in Eq. 9, 10:

$$\text{Sensitivity} = \frac{TP}{TP+FN} \quad (9)$$

$$\text{Specificity} = \frac{TN}{TN+FP} \quad (10)$$

where, TP, TN, FP and FN denotes true positives, true negatives, false positives and false negatives respectively. The DWT coefficients at the fourth level (D1-D3, D4 and A4) were computed. The statistical features that have been calculated over the set of the wavelet coefficients reduced the dimensionality of the

feature vectors to 20 data points. As it is seen in Table-1, the obtained test classification accuracies were 98.15, 99.10 and 98.22%, respectively.

Table-1. The obtained classification accuracy, sensitivity and specificity by CSCA algorithm for brain MRI images classification.

Dataset from training-testing	Sensitivity	Specificity	Accuracy
40-60 Random selection	99.84	97.35	98.15
60-40 Random selection	99.94	98.30	99.10
80-20 5-fold cross	99.39	97.75	98.22
validation Average	99.94	98.30	99.10

However, the CSCA algorithm gives the highest classification accuracy, 99.28% over other methods. Then the results are compared to the existing methods. Outcome of the comparison are presented in Table-2.

Table-2. Classification accuracy of the proposed method for brain MRI images classification with classification accuracies obtained by other methods.

Author	Feature extraction techniques	Feature selection techniques	Classification techniques	Classification Accuracy in %
El-Dishan *et al* (2010)	HAAR wavelet	PCA	ANN	97
Jafari *et al* (2012)		GA	SVM	83.22
Rajalekshmi *et al* (2013)	Wrapper approach	-	MC-SVM	92.6
Mahmood *et al* (2014)	HAAR wavelet	-	FIS and FFNN	95.66
M. Madheswaran *et al* (2015)	GSDM and Tamura method	GA with Joint entropy	SVM-GRBF	98.83
V. Vijay, *et al* (2016)	-	EDPSO	ANFIS	95
Present Work (2018)	DWT technique	SPCA technique	CSCA classification technique	99.10

5. CONCLUSIONS

The most significant influence of this study is the propose of an enhanced hybrid classification method, integrating DWT, SPCA, PSO and (CSCA), used for identifying normal MR brains from abnormal MR brains. Optimization based classification model has been introduced for separating tumor of brain from those which are normal using MRI brain images. The features are extracted using The Discrete Wavelet Transform method and the optimized features are selected using sparse principal component analysis technique that has the ability to discriminate between the normal MR brains and abnormal MR brains. The data set is large, varied and the training and testing set do not overlap. The algorithm is comprehensive and effective within a short computation time. Two optimization techniques: clonal selection-based algorithm and particle swarm optimization (PSO) were applied to the model resulting in method: clonal selection classification algorithm (CSCA) performs well compared to other techniques. Generally, the experimental outcomes demonstrated that the projected techniques have ability to produce a reliable classification for MRI brain images. The overall accuracy of the method proposed is 99.10%. We consider that the suggested scheme can be an efficient means by facilitating the test of a patient's data and decreasing the time and effort necessary to make correct resolutions on their patients.

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REFERENCES

[1] Siegel, R. Desantis *et al.* 012. Cancer Treatment and Survivorship Statistics. CA: A Cancer Journal for Clinicians. 62(4): 220-24.

[2] Polidais. 2006. Medical Imaging in Cancer Care: Charting the Progress. US Oncology and National Electrical Manufacturers Association (NEMA). pp. 1-32.

[3] Jeena R. S., *et al.* 2013. A Comparative Analysis of MRI and CT Brain Images for Stroke Diagnosis. Emerging Research Areas and 2013 International Conference on Microelectronics. Communications and Renewable Energy (AICERA/ICMiCR), IEEE. pp. 1-5.

[4] A. Horská, *et al*. 2010. Imaging of Brain Tumors: MR Spectroscopy and Metabolic Imaging. Neuroimaging Clinics of North America. 20(3): 293-310.

[5] Tommaso S. 2012. Imaging Gliomas after Treatment. First Edit. Milan, Italia: Springer.

[6] M., Thomas, E *et al.* 2010. Brain Tumors across the Age Spectrum: Biology, Therapy, and Late Effects. Seminars in Radiation Oncology. 20(1): 58-66.

[7] D., Hutchison, *et al*. 2011. Machine Learning in Medical Imaging. Springer-Verlag Berlin Heidelberg.

[8] M. Moghaddam, *et al.* 2011. Medical Image Segmentation Using Artificial Neural Networks. Artificial Neural Networks-Methodological Advances and Biomedical Applications. pp. 121-138.

[9] K. Reddy *et al*. 2012. Confidence Guided Enhancing Brain Tumor Segmentation in Multi- Parametric MRI. IEEE, International Symposium on Biomedical Imaging (ISBI). pp. 366-369.

[10] S. He, X. Shen, *et al*. 2001. Research on MRI rain Segmentation Algorithm with the Application in Model –Based EEG/MEG. IEEE Transactions on Magnetics. 37(5): 3741-3744.

[11] G. B. Aboutanos, *et al*. 1999. Model Creation and Deformation for the Automatic Segmentation of the Brain in MR Images. IEEE Transactions on Biomedical Engineering. 46(11).1999.

[12] A. Kouhi, *et al*. 2011. A Modified FCM Algorithm for MRI Brain Image Segmentation. Machine Vision and Image Processing (MVIP), 2011(7th Iranian Digital Object Identifier: 10.1109/IranianMVIP.2011.6121551, pp. 1-5.

[13] P. Kalavathi. 2013. Brain Tissue Segmentation in MR Brain Images using Multiple Otsu's Thresholding Technique. The 8th International Conference on Computer Science & Education (ICCSE 2013) April 26-28.

[14] J. Tohka, *et al.* 2010. Brain MRI tissue classification based on local Markov random fields. Magnetic Resonance Imaging. 28(4): 557-573.

[15] M. Stella *et al.* 2009. Fully Automated Hybrid Segmentation of Brain. Handbook of Medical Imaging: Processing and Analysis Management, I. Bankman, Ed.

[16] B.S. Anami, *et al.* 2013. A combined fuzzy and level set based approach for brain MRI image segmentation. Computer Vision, Pattern Recognition, Image Processing and Graphics (NCVPRIPG), 2013 Fourth National Conference on Digital Object Identifier: 10.1109/NCVPRIPG.2013.6776216. pp. 1-4.

[17] E. Hancer, *et al*. 2013. Extraction of brain tumors from MRI images with artificial bee colony-based segmentation methodology. Electrical and Electronics Engineering (ELECO), 8th International Conference on Digital Object Identifier: 10.1109/ELECO.2013.6713896, pp. 516-520.

[18] E. Cuevas, *et al.* 2010. A novel multi-threshold segmentation approach based on differential evolution optimization. Expert Systems with Applications 37, pp. 5265-5271.

[19] A Yahya Ebrahim. Detection of breast cancer in mammograms through a new features and decision tree based, classification framework. Journal of Theoretical & Applied Information, 2017 - jatit.org.

[20] Majumdar K. 2011. Human scalp EEG processing: Various soft computing approaches. Applied Soft Computing. 11(8): 4433-4447.

[21] Goel, N., *et al*. 2013. A Review of Soft Computing Techniques for Gene Prediction. ISRN Genomics. (Article ID 191206), p. 8.

[22] X. Gao, *et al*. 2009b. Fusion of clonal selection algorithm and differential evolution method in training cascade-correlation neural network" Neurocomputing. 72(10-12): 2483-2490.

[23] I. Aydin. 2010. Chaotic-based hybrid negative selection algorithm and its applications in fault and anomaly detection. Expert Systems with Applications. 37(7): 5285-5294.

[24] S, Smith, *et al.* 2008. An immune network inspired evolutionary algorithm for the diagnosis of Parkinson's disease. Biosystems. 94(1-2): 34-46.

[25] S. Forrest, *et al*. 1994. Self-nonself discrimination in a computer. Proceedings of the 1994 IEEE Computer Society Symposium on Research in Security and Privacy. 16-18 May. Oakland, California, 202-212.

[26] Y. Shi, *et al.* A modified particle swarm optimizer. Proceedings of the IEEE World Congress on Computational Intelligence, May 4-9, IEEE Press, Anchorage, AK., USA., pp. 69-73. DOI: 10.1109/ICEC.1998.699146.

[27] A. Subasi A. 2006. Automatic detection of epileptic seizure using dynamic fuzzy neural networks. Expert Syst. Appli. 31: 320-328. DOI: 10.1016/j.eswa.2005.09.027.

[28] P Bhirud, *et al.* 2014. Performance Evaluation of Filters of Discrete Wavelet Transforms For Biometrics. International Journal of Informatics and Communication Technology. 3(2).

[29] A. Subasi. Epileptic seizure detection using dynamic wavelet network. Exp. Syst. Appli. 29: 343-355. DOI: 10.1016/j.eswa.2005.04.007.

[30] T.Hlaing. 2012. Feature Selection and Fuzzy Decision Tree for Network Intrusion Detection. International Journal of Informatics and Communication Technology. 1(2).

[31] K. Saravanan. 2009. An Efficient Detection Mechanism for Intrusion Detection Systems Using Rule Learning Method. International Journal of Computer and Electrical Engineering. 1(4).

[32] S. Ba-Karait, *et al*. 2008. Handwritten Digits Recognition using Particle Swarm Optimization. Second Asia Intern ational Conference on Modelling & Simulation, May 13- 15, IEEE Xplore Press, Kuala Lumpur, Malaysia. pp. 615-619. DIO: 10.1109/AMS.2008.141.

[33] Shi E.Y. 2001. Particle swarm optimization: Developments, applications and resources. Proceedings of the Congress on Evolutionary Computation, May 28-30, IEEE Xplore Press, Seoul, South Korea. pp. 81-86. DOI: 10. 110 9/CEC.2001.934374.

[34] K. Trojanowski, *et al*. 2009. Immune-based algorithms for dynamic optimization. Information Sciences. 179(10): 1495-1515.

[35] De Castro, *et al.* 2002. Learning and Optimization Using the Clonal Selection principle. IEEE Transactions on Evolutionary Computation, Special Issue on Artificial Immune systems (IEEE). 6(3): 239-251.

[36] A El-Dihshan, *et al*. 2010. Hybrid intelligence techniques for MRI brain image classification. ELSEVIER, Digital Signal Processing. 20: 433-441.

[37] M. Jafari, *et al*. 2012. A hybrid approach for automatic tumor detection of brain MRI using support vector machine and genetic algorithm. Global Journal of Science, Engineering and Technology. 3: 1-8.

[38] N Rajalakshmi, *et al.* 2013. Automated classification of brain MRI using color converted K-means clustering segmentation and application of different kernel functions with multi-class SVM. Proceedings of 1st annual international interdisciplinary conference.

[39] A. Fadhil Mahmood, *et al.* 2014. Automatic brain MRI slices classification using hybrid technique. Al-Rafidain Engineering. 22(3).

[40] Asmaa Shaker Ashoor. 2015. Performance analysis between distance vector algorithm (DVA) & link state algorithm (LSA) for routing network. Journal of Babylon University /Pure and Applied Sciences/No. (4)/Vol. (23).