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Fusion of Contourlet Transform and Zernike Moments using Content based Image Retrieval for MRI Brain Tumor Images

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Abstract

Background: Content based Image Retrieval (CBIR) is employed to search and retrieve the expected image from the database. Magnetic Resonance Imaging (MRI) technique plays a crucial role in diagnosing many diseases in human brain. **Methods:** In this paper, we proposed a texture fusion technique for T1 and T2 weighted MRI scans. Our proposed technique has three parts. First, texture and shape features are extracted from a brain tumor images. Next, the feature selection techniques like Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) are used to combine the texture and shape features. Finally, the popular supervised learning machine techniques like Deep Neural Network (DNN) and Extreme Learning Machine (ELM) are used to classify the brain tumor based on the selected features. **Findings:** The results of proposed MRI brain tumor diagnosis method are robust, efficient, effective, reduces the retrieval time and improves the retrieval accuracy significantly. Best overall classification accuracy results were obtained using the given DiCom Images. **Application:** The proposed MRI image based brain tumor retrieval would efficiently deal with a medical decision system based on the CT+ZM fusion method provides more accurate results, so this method can yield better result of brain tumor diagnosis in advance where this method using in medical fields.

Keywords: CBIR, Contourlet Transform, DNN, ELM, GA, PSO, Zernike Moments

1. Introduction

In recent years, the digital image collection has been rapidly increasing the size of the image. Every day, the gigabytes of pictures generate in military and civilian equipment. A huge, information is out there. By using, this obtainable information is effective, efficient strategies for storage, browsing, indexing and retrieval. The first is primarily text based, whereas the second depends on the visual properties of the information. The size of image database is extremely higher than the two problems render manual annotation ineffective. The first problem is the amount of labor involved in image annotation. The second problem is that the more essential results from the issue of capturing the rich content of images using a few keywords, the difficulty is compounded by the subjectivity of human perception[1].

1.1 Brain Tumor

MRI is the most commonly utilized technique for monitoring and evaluating the brain tumors. The three orientations of the human brain are axial (neck to the head), sagittal (ear to ear) and coronal (front to back). Proton Density (PD), Longitudinal relaxation time (T1) and transverse relaxation time (T2) are the three types of images produced by MRI[2].

1.2 Problem of Medical Images

An innovative utilization of the misdiagnosis factor for differential diagnosis using service oriented architecture technique. To overcome the problems for automated diagnosis of multiple diseases. It is more accurate and faster identification[3]. An efficacy of several different image features such as intensity, fractal texture and shape for

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segmentation of posterior-Fossa (PF) tumor for pediatric patients. To discriminate tumor regions of normal tissue in multimodal brain MRI. It is robust, effective and improved PF tumor segmentation[4]. The shape retrieval based on manifold learning by fusion of dissimilarity measures. The Centroid, farthest in contour based, squared and Zernike in the region based are used in the fusion of four shape identification methods. It is improved in retrieval performance[5]. The texture and shape feature extraction method such as Gabor and Zernike moments. The major issue of the texture and shape feature is size invariant[6]. The extraction of the shape features like Zernike momentswith four distance metrics for extreme learning machine with hamming distance the retrieval performance of brain image gives the higher result[7].

2. Materials and Methods

The computational analysis is implemented on Intel i5 processor and 2.90 GHz computer with 4 GB RAM. The support analysis software used is Matlab 2013. In order to evaluate the performance of our algorithms and methodology, the experiments results were conducted in MRI Brain tumor data set.

The major problem in feature extraction of content based image retrieval with the brain tumor of finding a robust texture descriptor image. In this paper, fusion of texture and shape feature extraction problem is solved. The fusion proposed fusion method has taken five stages. The first stage of the method is preprocessing is utilized to enhance and contrast of the brain tumor image. Second stage, texture and shape features are extracted in brain tumor images. The fusion method like Contourlet Transform and Zernike Moments are utilized. The third stage, feature selection is utilized to reduce the irrelevant images in the brain tumor image using Genetic Algorithm and Particle Swarm Optimization. The fourth stage, Deep Neural Network and Extreme Learning Machine are the classifier utilized for brain tumor images. The Final stage, image retrieval is used to find the similarity matching of the brain tumor image. The Deep Neural Network and Extreme Learning Machine are the two classifiers used to find the best suited techniques for this fusion method. Figure 1 shows that detailed process flow of the proposed method.

2.1 Preprocessing

The preprocessing step is used to perform contrast enhancement of a brain tumor image. The visual appearance of a brain tumor image is to enhance and adjust the lightness or darkness of an image.

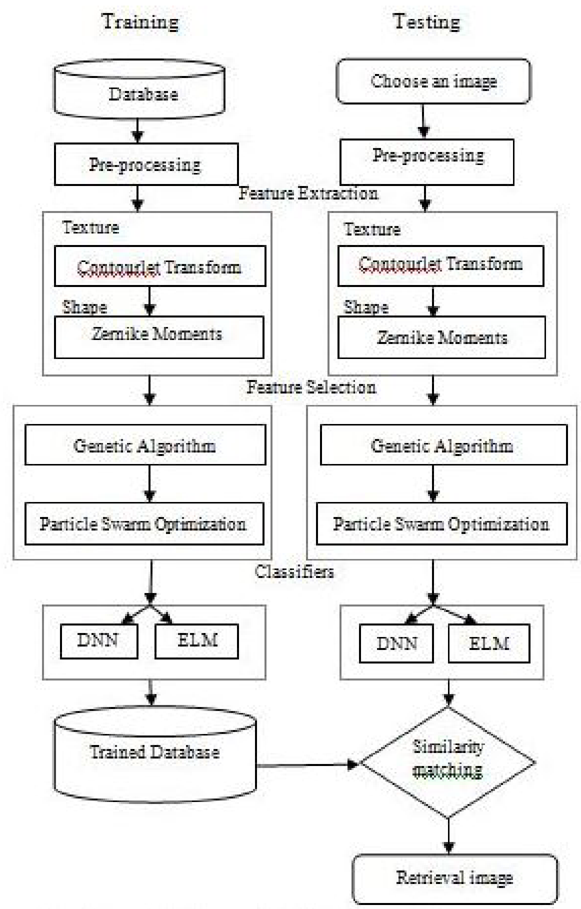

Figure 1. Flowchart of proposed CT+ZM method.

2.2 Feature Extraction

Feature extraction is a large amount of data are to be processed and redundant, so it can be transformed into a set of features.

2.3 Texture Feature

Texture refers to the spatial or statistical repetition in pel intensity and orientation. Texture analysis is a vital issue utilized in a range of image and video applications as well as image segmentation, image retrieval, object recognition, contour detection, scene classification and video indexing. Texture features are visual pattern comprises of contrast, uniformity, coarseness, and density. Multiscale transform-based methods encompass the Dennis Gabor transform, the wavelet transform, the ridgelet transform and the contourlet transform[8].

2.4 Contourlet Transform

Contourlet Transform may be variations of directional multiresolution image representation, illustration and created from a smooth region's partition by smooth boundaries. There are four frequency compounds like LL (Low Low), LH (Low High), HL (High Low) and HH (High High). It has two levels are laplacian pyramid and directional filter bank. First, laplacian pyramid produces low pass output (LL) and a band pass output (LH, HL, HH). Then the band pass output is sent into a directional filter bank and it produces the contourlet coefficient. Finally, the low pass output is again passed through the Laplacian pyramid to provide more coefficients. The method is repeated till the fine details of the image are retrieved[9].

2.5 Shape Feature

Shape is an important role to identify the human recognition and perception. To identify the object, shape feature provides a powerful clue for human perception and segment the image into regions or objects. The major issues in content based image retrieval for finding robust shape descriptor image. In the medical field, shape is used to describe the similarity of medical scans.

2.6 Zernike Moments

Zernike Moments, a kind of moment function, are the mapping of an image onto a set of complex Zernike polynomials. Zernike polynomials are orthogonal to every alternative; Zernike Moments will represent the properties of an image with no redundancy or overlap of data between the moments. Due to these characteristics, Zernike Moments are used as feature sets in content-based image retrieval[10,11].

2.6.1 Zernike Moments Algorithm

- Calculate the radial polynomial.
- Compute the Zernike basis function from the radial polynomials.
- Compute the Zernike Moments by projecting the image on to the basic functions.

$$A_{nm} = \frac{n+1}{\pi}\sum_x \sum_y f(x,y)V^*_{nm}(x,y),\ x^2 + y^2 \leq 1 \qquad (1)$$

Where f(x,y) is a class of polynomials, n is an order, m is a repetition, $V^*_{nm}(x,y)$ is a complex conjugate of $V_{nm}(x,y)$. A_{nm} A_{nm} denotes Zernike Moments.

3. Feature Selection

Feature selection is an image reduction is used for image mining and knowledge discovery. It removes the irrelevant and redundant features and quality of the image recognition system is to be improved for enhancing the performance of learning systems.

3.1 Genetic Algorithm

Genetic Algorithm (GA) is a search technique that is employed to optimize general combinational problems and that they use operator like selection, crossover and mutation. GA is one of the most popular evolutionary algorithms based on survival of the fitness. GA is employed to solve difficult optimization problems. The solution of GA is called individuals and the groups of individuals is called populations[12–14]. The brief description of a genetic algorithm is shown in Figure 2.

There are three main operators in GA.

- A selection which equates to the survival of the fitness.
- Cross over which represents mating between individuals.
- Mutations introduce random modifications.

3.1.1 Steps of Genetic Algorithm

Step 1: Initial population is formed indiscriminately, which may be done by setting a gene to random values.

Step 2: The fitness function of every chromosome is calculated.

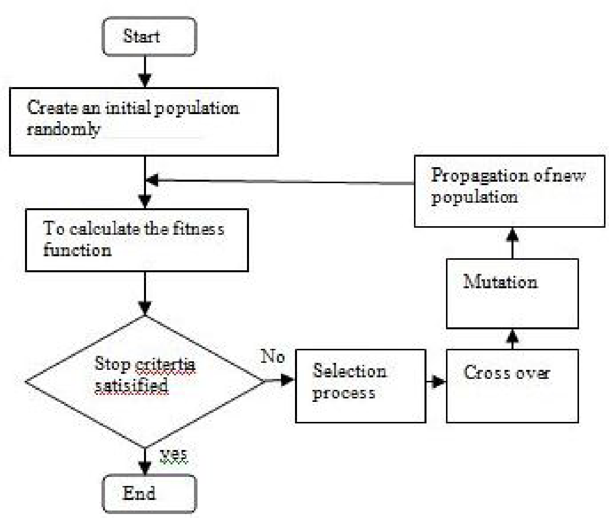

Figure 2. Flowchart of Genetic Algorithm.

Step 3: Chromosome selection method, fittest members of the current population are selected for reproducing the new solutions.
Step 4: In crossover operation, the two chromosomes are selected to exchange genes by some purpose.
Step 5: In mutation operation, randomly a gene is selected and its value is changed.
Step 6: Finally, if the fitness is low, then terminate the method otherwise go to Step 1 repeat the process.

3.2 Particle Swarm Optimization

Particle Swarm Optimization (PSO) is that the swarming or collaborating behavior of biological populations of the recent heuristic search method. PSO is an optimization technique that provides an evolutionary based search. It is used to solve the optimization problems. The term PSO refers to best solutions to numerical and qualitative issues. The most important objective of this method is to extract features from the brain tissue[15,16]. The process flow of Particle Swarm Optimization is briefly shown in Figure 3.

The PSO algorithm consists of three steps

- Generating particles, positions and velocities.
- Velocity update.
- Position update.

3.2.1 *Steps of Particle Swarm Optimization*

Step 1: Initial population of n particles with random position x_i and velocity v_i.

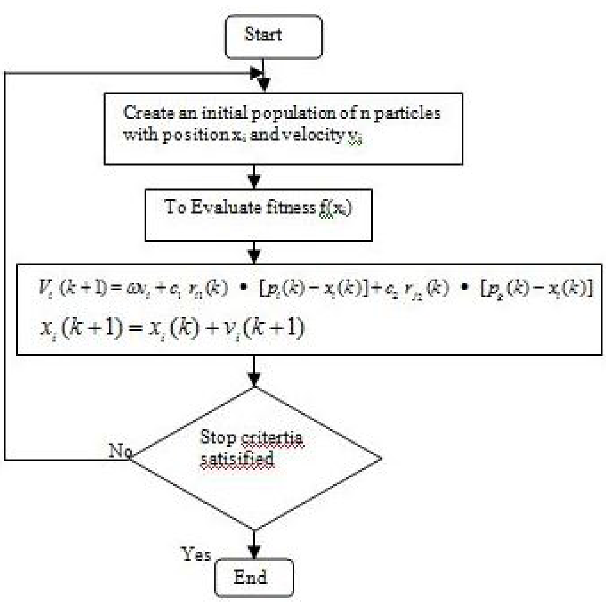

Figure 3. Flowchart of Particle Swarm Optimization.

Step 2: For every particle position evaluates fitness.
Step 3: If new position is best, then set it for the whole population.
Step 4: Determine the global best p_g
Step 5: Update the particle and velocity.

The position of individual particles updated as follows:

$$V_i(k+1) = \omega v_i + c_1 r_{i1}(k) * [p_i(k) - x_i(k)] + c_2 r_{j2}(k) * [p_g(k) - x_i(k)] \quad (2)$$

Where $x_i(k)$ is the n dimensional position vector of particle i at iteration k.

$v_i(k)$ is that the n-dimensional velocity vector of particle i at iteration k.

$p_i(k)$ is that the n-dimensional personal best of particle i found through iteration k.

ω is that the inertia weight between 0 and 1, which stimulates friction.

c_1 is that the cognitive acceleration constant.

c_2 is that the social acceleration constant.

$r_{i1}(k)$, $r_{j2}(k)$ are pseudo-random vectors with each dimension sampled from $U(0,1)$

$*$ denotes element-wise multiplication between vectors.

With the velocity calculated as follows

$$x_i(k+1) = x_i(k) + v_i(k+1) \quad (3)$$

Step 6: Finally, if probability value is low, then terminate the method otherwise go to Step 1 repeat the method.

4. Classification

Deep Neural Network (DNN) and Extreme Learning Machine (ELM) are the classification techniques utilized in the feature extraction of brain tumor retrieval.

4.1 Deep Neural Network

Deep Neural Network (DNN) may be a multilayer neural network model that has more than one layer of hidden units between its inputs and its outputs. The two necessary processes are utilized in the classification are training and testing part. In the training part, the features of training information are trained using deep learning classifier. Commonly used neural network uses back propagation algorithm. Deep Neural Network contains an input and an output layer, separated by l layers of hidden units. The input layer is totally connected to the first hidden layer, that is totally connected to the second layer and up to the output layer[17,18]. Figure 4. shows that detailed process of the supervised greedy layerwise procedure for deep neural network.

4.2 Extreme Learning Machine

Extreme Learning Machine (ELM) solves the problem of a gradient based algorithm by analytically calculating the optimal weights of the Single-Hidden Layer Feedforward Neural Networks (SLFNs). ELM as an emerging learning technique provides economical, unified solutions to generalized feed-forward networks, however, not limited to (both single- and multi-hidden-layer) neural networks, Radial Basis Function (RBF) networks, and kernel learning[19]. The architectural diagram of extreme learning machine is detailed shown in Figure 5.

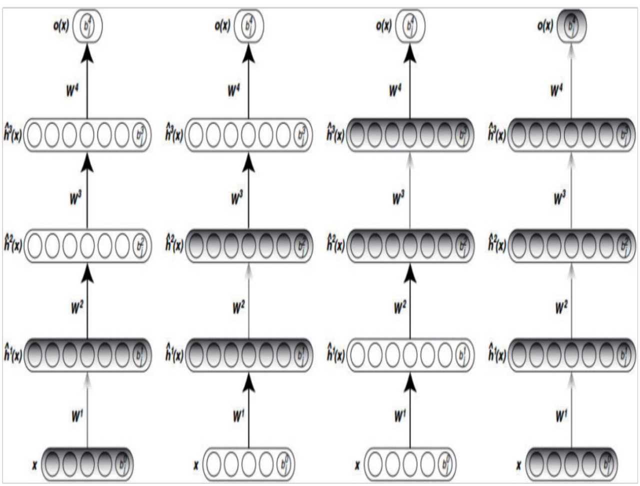

Figure 4. Supervised greedy layerwise training procedure.

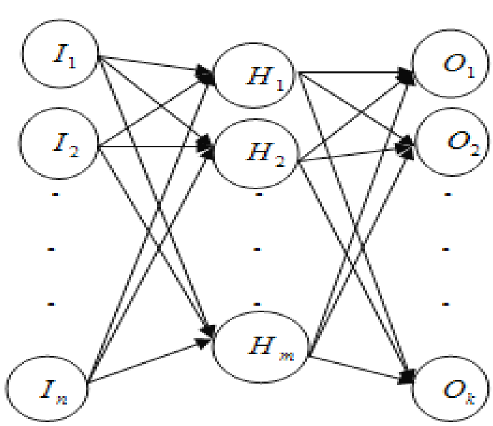

Figure 5. Extreme learning machine architecture.

4.2.1 Extreme Learning Machine Algorithm

Given a training set $\aleph = \{(x_i, t_i) | x_i \in R^n, t_i \in R^m\}$, I = 1….N activation function g(x) and hidden node number $\tilde{N}$

A set of N arbitrary distinct samples(x_i, t_i), where $x_i = [x_{i1}, x_{i2}, \dots, x_{in}]^T \in R^n$, chosen from any internal of R^n and R^m, $t_i = [t_{i1}, t_{i2}, \dots, t_{im}]^T \in R^m$.

Step 1: Randomly assign input weight w_i and bias b_i, I = 1,….,$\tilde{N}$.

Step 2: Calculate the hidden layer output matrix H.

Step 3: Calculate the output weight β.

$$\beta = H^{\tau}T \tag{4}$$

H^{τ} is that the Moore–Penrose generalized inverse matrix

Where, $\beta = [\beta_1, \dots, \beta_n]^T, T = [t_1, \dots, t_n]^T$.

5. Performance Metrics

To evaluate the performance of the proposed fusion technique, Sensitivity (S) and Specificity (Sp), Accuracy, Error rate, Jaccard similarity index (J) and F-measure metrics are developed[20].

$$Sensitivity = \frac{TP}{(TP+FN)} \text{ X } 100 \tag{5}$$

$$Specificity = \frac{TN}{(FP+TN)} \text{ X } 100 \tag{6}$$

$$Accuracy = \frac{TP+TN}{TP+FP+TN+FN} \text{ X } 100 \tag{7}$$

$$Errorrate = 100 - Accuracy \tag{8}$$

$$JaccardCoefficient = \frac{TP}{TP+FP+FN} \text{ X } 100 \tag{9}$$

$$F - measure = \frac{2TP}{2TP+FP+FN} \text{ X } 100 \tag{10}$$

Where TP- True Positive, FP- False Positive, TN- True Negative, FN- False Negative.

5.1 Dataset

The data set for experimental analysis were obtained from Aarthi scans, Tirunelveli, Tamil Nadu, India. Tests are executed on various brain MR image datasets having a tumor. A T1 and T2 weighted MRI brain tumor images are used. The proposed fusion technique is performed on brain tumor image that is sagittal and axial kind. The original input brain tumor images are shown in Figure 6. The

MRI brain tumor image database contains 1000 images. The original dataset has taken from 10 patients in Digital Imaging Communication Medicine (DICOM) images. Brain tumor images contain 5 categories and every category has 200 images. The resolution of every image is 256 x 256. The output image of the proposed method is shown in Figure 7.

6. Results and Discussion

The proposed fusion technique is applied on a variety of images. The experiments are carried out by applying the proposed technique on some MRI axial T1 weighted images and MRI sagittal T2 weighted images. For analysis, the Sensitivity (S), Specificity (Sp), Accuracy, Error rate, Jaccard Coefficient (J) and F-measure parameters are evaluated.The test results of each DNN and ELM classifier are given here. The graph diagram shows that the performance of a DNN and ELM classifier of the proposed method is shown in Figure 8 and 9. Experiment results show that the average sensitivity for DNN – 51.48%, ELM- 51.33%, specificity for DNN- 40.19%, ELM- 47.6%, error rate for DNN-16.12%, ELM- 4%,the Jaccard coefficient for DNN- 49.72%, ELM- 50.48%, f-measure for DNN- 65.09 and ELM- 67%.

Table 1 shows that comparative analysis of existing classification accuracy with proposed classification accuracy. The total time calculation and comparing with other methods is shown in Figure 10 and 11. The results show that proposed fusion method for an average accuracy CT+ZM+DNN- 88.8% and CT+ZM+ELM- 96%. So, ELM classifier is better than DNN. The proposed fusion method CT+ZM+ELM is well suited for brain tumor retrieval.

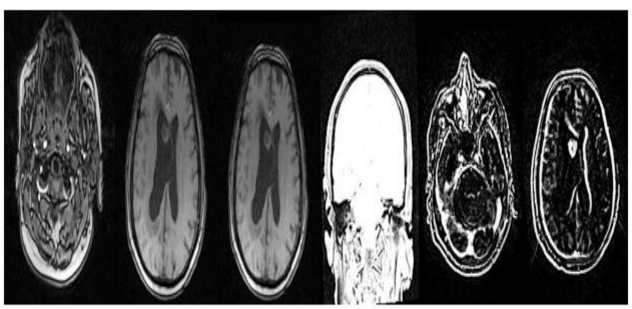

Figure 6. Input images.

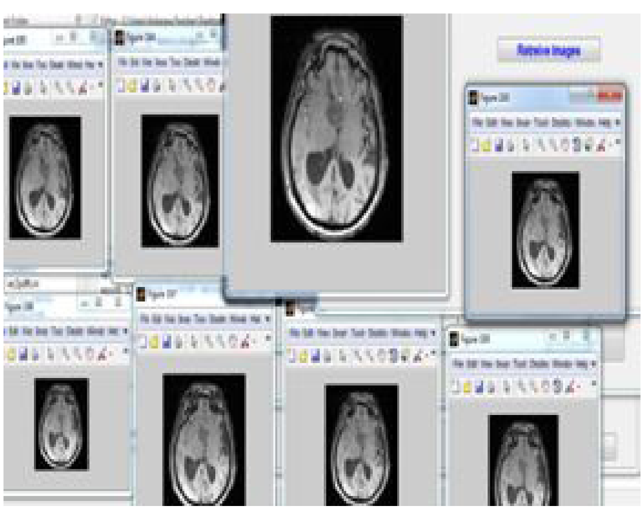

Figure 7. Retrieval of brain tumor images.

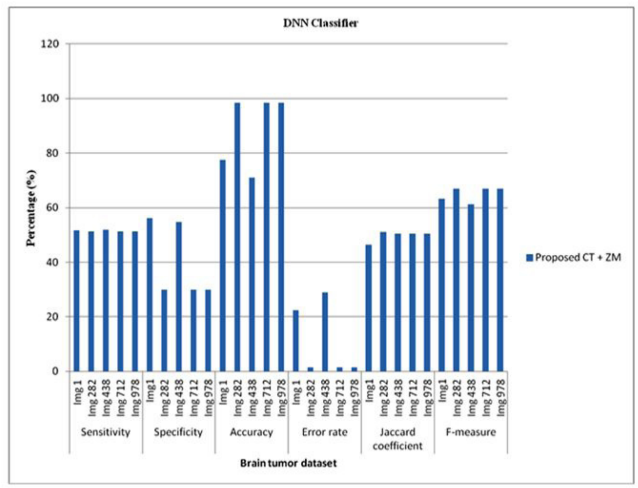

Figure 8. Retrieval of sensitivity, specificity, accuracy, error rate, jaccard coefficient and F- measure for DNN classifier in CT + ZM method.

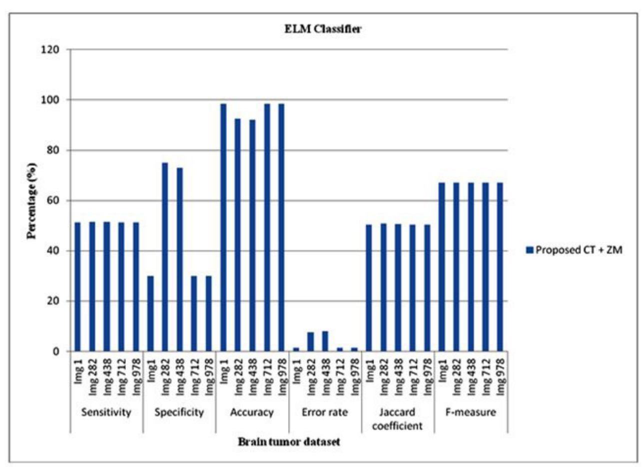

Figure 9. Retrieval of sensitivity, specificity, accuracy, error rate, jaccard coefficient and F-measure for ELM classifier in CT + ZM method.

Table 1. Classification accuracy for performing the proposed method and comparison with different methods

Sl. No.	Methods	Accuracy (%)
1	SGLDM+GA+SVM	94.44%
2	SVM+PSO	95%
3	DWT + SOM	94.72%
4	Second order + ANN	92.22%
5	FCM	86.6%
6	K-means	83.3%
7	**CT+ZM+DNN (Proposed Method)**	**88.8%**
8	**CT+ZM+ELM (Proposed Method)**	**96%**

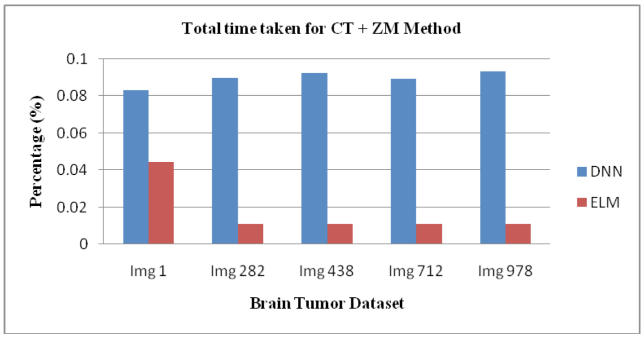

Figure 10. Retrieval of total time taken for DNN and ELM classifiers in CT + ZM method.

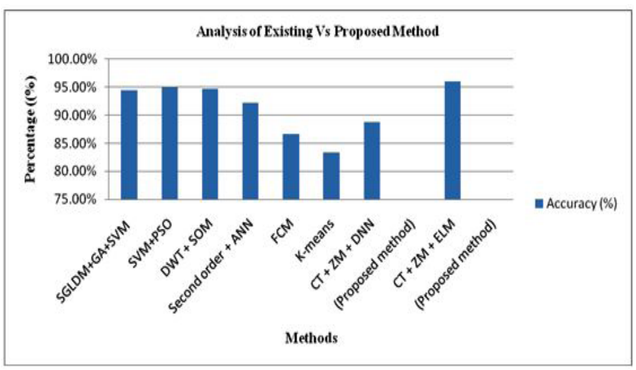

Figure 11. Analysis of proposed method and comparison with different methods.

7. Conclusion

In this paper, a proposed fusion method with combination of texture and shape feature based on genetic algorithm and particle swarm optimization is developed. The major drawback of content based image retrieval is time consuming and retrieval accuracy. In time values, the extreme learning machine classifier is better than deep neural network. The proposed fusion method of texture and shape feature could overcome the drawback of size invariant properties, time consuming and retrieval accuracy. Finally, it is concluded that the automation of content based image retrieval is utilized to detect the MRI brain tumor image. In future work, the axial and sagittal type of MRI brain tumor image is detected; still a coronal type of MRI brain tumor image is not yet finished.

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