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An Efficient Brain Tumor Classification And Detection Using Evolutionary Approach For Healthcare System

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Abstract: The growth of irregular cells within the brain region with the prearrangement of tissues is characterized as a Brain Tumor that leads death to people. Comparing to other categories of cancers, a brain tumor is the most deadly disease that has to be detected and treated in the previous stage. Due to cells' complex formation, the tumor detection process is complicated with simple image processing methodologies. Moreover, for providing proper and efficient treatment to the patients, an exact cancer segmentation and classification technique must process the input of brain images as Magnetic Resonance Imaging (MRI) scans. Based on that, this paper develops a novel approach called Soft Computing based Brain Tumor Detection and Classification (SC-BTDC) with the obtained MRI. In the present scenario of tumor detection from image processing, soft computing techniques play a significant role. Hence, it is adopted in this work. The method contains phases such as pre-processing, Fuzzy c-Means clustering-based segmentation, feature extraction, and image classification. The median pre-processing filter and edge detection methods are incorporated for noise removal and clearly define the image in the stage of the median pre-processing filter. Further, FCM based clustering is performed for the image segmentation process, following, factors of Gray Level Co-Occurrence Matrix (GLCM) found feature extraction is established. The final phase includes the classification process using the soft computing technique called Artificial Neural Network (ANN) classification. The proposed system acquires a higher accuracy rate and is compared with various existing algorithms for proving the efficiency and minimum loss of the proposed algorithm.

Keywords: Soft Computing, Brain Tumor Detection, Segmentation, Classification, FCM, GLCM, and ANN.

1. INTRODUCTION

In the current medical sciences and clinical research developments, many models have been developed for earlier tumor detection for saving a patient’s life. Perhaps, detecting tumor from MRI scans is a very time consuming and complicated process. It takes several times for segmenting the tumor cells from brain tissues [1]. Consequently, image processing techniques have been incorporated for the tumor detection process in recent times, which provides the results faster [2]. Moreover, a brain tumor can be categorized into primary and secondary, further denoted as benign and malignant. Malignant tumors are dangerous that can spread to other parts of the body. So, when the cancer is detected at the benign or initial

stages, it can be easily treated by clinical practitioners [3].
There different kinds of brain tumor diagnosis methodologies are developed in the recent decade. In general, the automatic tumor segmentation issues are complicated, and new inventions are still required to solve problems. Moreover, the processing functions include typical operations such as image pre-processing, tissue segmentation, feature extraction, and image classifications. Figure 1 displays the pictorial representation of the essential procedures involved in cancer image detection and classification. In the middle of the operation between image acquisition and result production, those operations above must be effectively processed with several calculations.

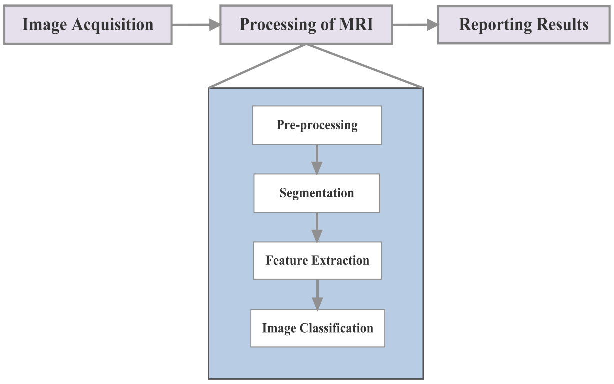


Figure 1: General Functions Involved in Tumor Diagnosis Process

An automated and efficient model is required for handling the complexities and time consumption in tumor image diagnosis from MRI scans [4]. It is observed from several types of research that soft computing techniques are effectively incorporated for processing. Here, the classification of images is performed with an efficient, gentle computing technique called Artificial Neural Networks. According to the report generated after processing the input MRI, related treatments or therapies are provided by the doctors to the concerned patients. The detection process is mainly developed for earlier detection of brain tumors. Thereby the recovery process of the patient can be made more accessible.

Due to the increasing needs of medical or clinical support systems for tumor diagnosis, many kinds of research focus on that domain, especially in brain tumor detection and classification. With that note, this work's main objective is to develop a soft computing technique-based brain tumor diagnosis model called SC-BTDC, in which pre-processing of MRI images are done using a median filter. Following, the segmentation process is carried out using FCM, and feature extraction is performed with GLCM. And, the classification of MRI is done with ANN. The reported results are considered majorly for providing appropriate and efficient treatment process to the patients in real-time medical services. The remaining part of the paper is organized as follows: Section 2 describes the existing models for brain tumor detection and other parts of the body. Section 3 narrates the working procedure of the proposed Soft Computing based Brain Tumor Detection and Classification (SC-BTDC). Section 4 contains the results and comparative evaluations of the proposed model. Finally, Section 5 presents the conclusion of the work with some enhancement way of the present work.

2. RELATED WORKS

In [5], segmentation based brain tumor detection technique has been presented, and the accuracy of the model was determined by comparing with other existing models. In the model, the internal structure has been analyzed by considering the significant factors of tumor detection. An improved tumor approximation of brain cells was presented based on the segmentation process and two-dimensional and three-dimensional visualization for treatment planning and tumor evaluation [6]. The shape approximation of a tumor cell has been effectively designed for treatment patterns.

The work provided by the authors of [7] used the FCM technique to separate the tumor region of interest from the complete brain image. Moreover, the model avoided estimating the members of the FCM group by proper data selection and pixel setting, which are also involved in performing appropriate segmentation of cancer mass. The performance evaluations were carried out based on the significant parameters such as accuracy, precision, sensitivity, and specificity. Further, in work [8], anisotropic filtering has been used for pre-processing the input image, and SVM based classification technique was used for producing different classification results. With the use of anisotropic filtering, the noise has been effectively removed from the MRI input. After performing morphological operations, the affected part of the brain with the appropriate location have been identified correctly. Moreover, the classifications have been made with the pixel intensities obtained from the filtered MRI inputs for accurate tumor detection.

In [9], a hybrid model has been defined in which segmentation was done with the OTSU threshold-based method, and feature extraction was performed with morphological operations. The segmented outcome and the original MRI were compared and evaluated to measure the appropriate detection of the tumor region. K-Nearest Neighbor based brain tumor detection has been presented in [10]. The classifier distance has been evaluated using the Manhattan factor. Local Binary Pattern (LBP) based feature extraction has been used in [11] for effectively deriving edges and spots. Moreover, in that work, Gabor features and spectral features were extracted using two levels of fusion techniques. The obtained multiple features were concatenated to produce accurate classification results. In [12], the authors have discussed two distinctive frameworks, such as Cascade NN architecture (CASNN) and Feed Forward NN (FFNN).

Further, feature extraction has been performed using Principal Component Analysis (PCA) to minimize computational complexities. The work used the Olivetti Research Lab (ORL) database dataset for evaluations. The training and testing have been carried out using neural network techniques.

In work [13], a hybrid classification technique has been used to classify tumor images that include Support Vector Machine (SVM) and Fuzzy logic techniques. The work also incorporated image enhancement methodologies such as stretching the middle range of pictures and contrast improvement. Skull modeling was performed with morphological functions. An ensemble-based classification model has been developed in [14]. The comparisons have been established with 11 individual classifiers, and 36 datasets have been used for analysis. Pruned Associative model for cancer detection from obtained clinical images was obtained in [15]. The authors have used CT brain images for testing. And, for earlier identification of brain tumors Perceptron based Neural Network Model (PNN) has been described in [16]. The abnormality of input images has been effectively detected using the Region Severance Technique.

Statistical Association Rule Mining methodology has been used in [17] for proper tumor image detection. Moreover, Co-efficient based weight computations were used for tumor detection. Effective comparative evaluations were done in [18] by deriving the results of

Close+, Association Rule Mining, and Apriori algorithm based classifications in medical image detection. Association rule mining was used in [19] for evaluating kidney images for detecting the diseases in that. Further, the discretization based feature extraction technique has been applied in that diagnosis model for reducing the complications in mining the evaluated images.

Further, in the works of [20] and [21], association techniques and classification models used for disease diagnosis from medical images have been effectively described. In [22], backpropagation neural networks were used for kidney disease diagnosis. The processing time is not effectively determined and considered by analyzing the existing models in the medical image processed in tumor diagnosis. This paper focuses on developing a model with minima classification errors and processing time for enhancing the precision results on time for assisting the medical practitioners in disease diagnosis.

3. PROPOSED MODEL

For reducing the death rate of cancer patients, the proposed model utilized soft computing techniques for detecting the brain tumor in earlier stages. Moreover, brain tumor detection is carried out using ANN classification from the segmentation of MRI scan images. As in the general tumor detection process, the proposed Soft Computing-based Brain Tumor Detection and Classification (SC-BTDC) contains four phases, namely, MRI image pre-processing, segmentation, feature extraction, and classification.

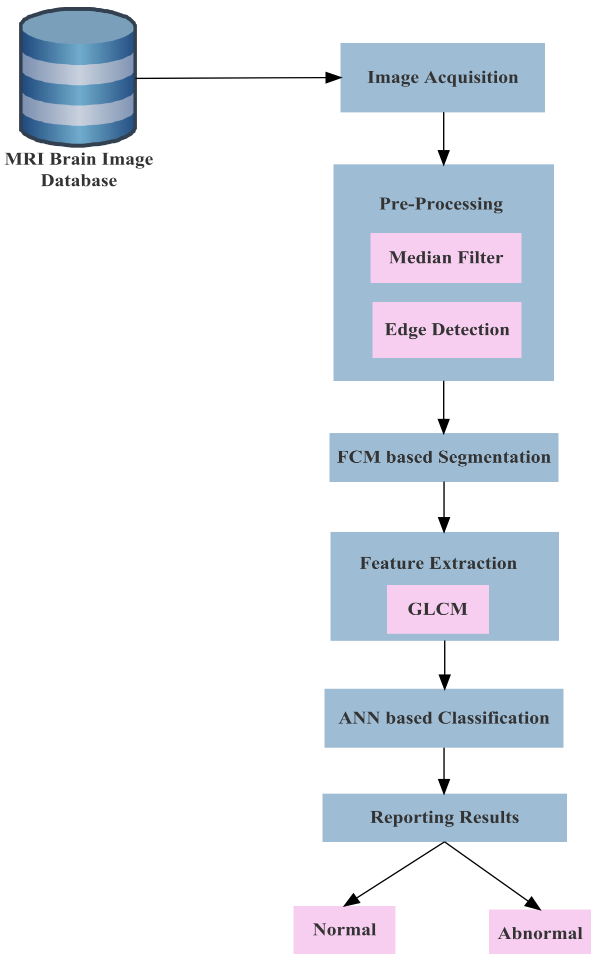


Figure 2: Work Process of Soft Computing based Brain Tumor Detection and Classification (SC-BTDC)

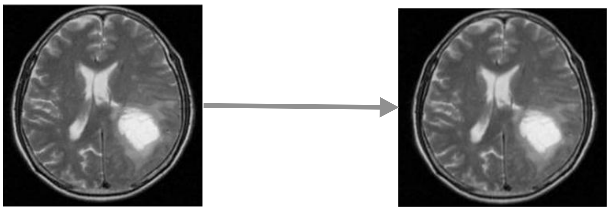
The initial pre-processing phase is carried out using a median filter and edge detection to reduce the noise in from the obtained image and clearly define the vision for further process. Following, the images used for segmentation, which is done with Fuzzy C-means Clustering, and the feature extraction process, are performed to select appropriate features through which the brain tumor is detected precisely, which is done with GLCM incorporation. After completing all, the filtered images are given to Artificial Neural Networks for classification that performs training and testing effectively. The work process of the proposed model is presented in Figure 2.

Pre-Processing:

The human brain images are complex and composite in structure, which makes the processing complicated. It is required to remove the unwanted noises from the obtained MRI image. Here, the pre-processing phase is carried out using the median filter and edge detection.

A. Median Filter:

Noise elimination from the input MRI images performed with the Median filter uses a non-linear filtering process. This kind of filter is used to remove salt and pepper noise, specifically based on the average pixel rates. The following Figure 3 presents an MRI brain image results after applying a median filter into that.

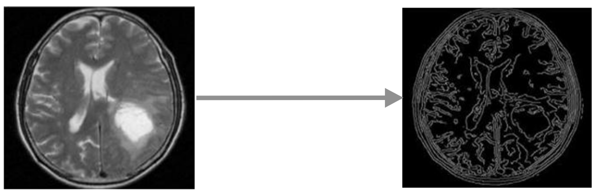


(a) (b)

Figure 3: Process of Applying Median Filter in MRI Brain Image, (a) Image With Noise and (b) Image After Noise Removal

B. Using Edge Detection:

Edge detection is used here to detect and identify the pointed discontinuities in the MRI scan. Here, the Canny Edge Detection technique is used for appropriate localization of edge points. And, the identified edge points using the edge detection model is presented in Figure 4.



(a) (b)

Figure 4: (a) Input Image and (b) After Edge Detection

3.2 FCM in Image Segmentation:

Segmentation is a significant process in the tumor detection process that segregates the input image into several regions overlapping each other. It is used to define the object boundaries effectively and the segmented parts are combined to get the full image. The segmentation process is processed based on image intensities that mainly concentrate on the similarity and discontinuity factors of images. There are several available techniques for image segmentation, amongst which; fuzzy c-means clustering model is used. Here, the FCM method is used for enhancing the precision in image segmentation with an appropriate definition of the object function. Further, the local and non-local based object segmentation is processed by the effective definition of the objective function.

The image of the MRI scan is divided into several pixels, which are given as $P = \{p_1, p_2, \dots p_n\}$. And, based on the member rate of each pixel, it as belonging to one or more clusters. Several iterations are carried out for reducing the objective function with the member set 'F' called fuzzy membership and 'U' is considered to be the cluster center.

$$Objective\ Function\ (A) = \sum_{i=1}^{n} \sum_{j=i}^{U} F_{ij}^{m} (p_i - U_j)^2 \qquad (1)$$

Where, 'F_{ij}^{m}' denotes the pixel member table, 'm' fuzzy parameter of the cluster and $(p_i - U_j)$ is the Euclidean Distance between the pixel member and the cluster center. It is evaluated that point closer to 'U' has the highest rate of membership than the other points towards the boundaries. In FCM, the cluster centers are initially assigned and rate for each cluster. Then, the center points are moved to the exact point by increasing the number of iterations based on the data set. The data presented in the image and the fuzzy parameter is defined by the pixel member. Further, the pixel member F_{ij} and cluster center 'U' are updated based on the defined objective function, which is given as follows,

$$F_{ij} = \frac{1}{\sum_{k-1}^{U} \left(\frac{\|p_i - U_j\|}{\|p_i - U_k\|}\right)^{\frac{2}{m-1}}} \qquad (2)$$

The derivation process will end, when the value reaches $maxi_{ij}\left\{\left|F_{ij}^{(k+1)} - F_{ij}^{k}\right|\right\} < \alpha$, where, '$\alpha$' is the ending factor that lies between 0 and 1. Moreover, the cluster center vector is calculated as,

$$U_j = \frac{\sum_{i-1}^{n} U_{ij}^{m} p_i}{\sum_{i-1}^{n} U_{ij}^{m}} \qquad (3)$$

The steps in FCM based segmentation is described below,

1. Initialization with Cluster center U=[u_{ij}] matrix, U(0).
2. At kth step, the cluster center is calculated as given in (3).
3. The iterations can be terminated at the point it reaches, $maxi_{ij}\left\{\left|F_{ij}^{(k+1)} - F_{ij}^{k}\right|\right\} < \alpha$, else, go to step 2.

3.3 Gray-Level Co-Occurrence Matrix-based Feature Extraction:

Extracting proper features from the images is a significant process for defining effective classification patterns for précised result categorizations. In this work, the feature extraction process is computed with GLCM, which is an effective arithmetic process that uses the spatial pixel similarities for computations. Based on the pixel intensities of the input images, the spatial similarities between two pixels can be defined as the relationship between the pixel of interest and the adjacent pixel in horizontal positions. For each pixel element (a,b) in defining GLCM, is considered by the number of occurrences of the pixel with 'a' presented in the described spatial similarity to another pixel with the value 'b' in the obtained MRI. Moreover, the process is very much helpful in pointing the exact tumor location and its present stage to providing proper treatment assistance.

In this model, the main features considered for evaluation are Shape, color, image intensity, texture, Contrast, Homogeneity, Correlation, and Energy.

i. Shape:

As a general definition, shape denotes the geometrical features of an object or its clear edges concerning their composition, color, and image texture.

ii. Color and Image Intensity:

Here, color is also considered as an important feature, which can be noted by the image coordinates, and the strength of color is denoted as intensity.

iii. Texture:

The visual quality of the image is noted as texture, which is also derived here.

iv. Contrast:

Contrast is evaluated by analyzing the separation of lighter and the darker area in the image as,

$$contrast = \sum_{ab=0}^{n-1} p_{ab}(a-b)^2 \qquad (4)$$

v. Homogeneity:

It denotes the closeness of element or object distribution on to the matrix diagonals, which points to the homogeneous quality.

$$Homogeneity = \sum_{ab=0}^{n-1} \frac{p_{ab}}{1+(a-b)^2} \qquad (5)$$

vi. Correlation:

The correlation coefficients are generally ranged between -1 and +1 and computed as,

$$Corr = \sum_{ab=0}^{n-1} p_{ab} \frac{(a-\mu)(b-\mu)}{\sigma^2} \qquad (6)$$

vii. Energy:

Here, Energy is defined as the sum of squared pixels rates of the defined Gray-Level Co-Occurrence Matrix, which is computed as,

$$Energy = \sum_{ab=0}^{n-1} (p_{ab})^2 \qquad (7)$$

3.4 Artificial Neural Network (ANN) based Classification:

In the proposed work, Artificial Neural Network (ANN) is used for performing the classification operation. This classification technique is incorporated here for its adaptive learning abilities, self- organization pattern, and well suitable nature of real-time implementations. The network pattern contains three layers, input layer, hidden layer, and output layer, which are given in Figure 5.

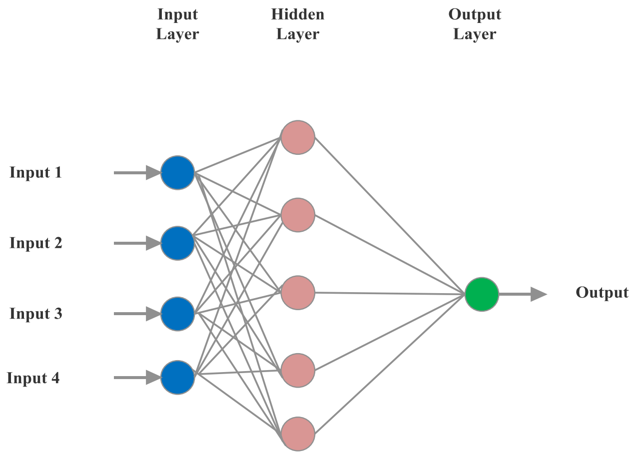


Figure 5: ANN Structure

There are two kinds of operations are performed in ANN, namely, training and testing. In training operation, the neural network is trained with the obtained features that are extracted from the previous section, and testing is performed effectively for validation of results. The parameters that are used for ANN designing are presented in the following Table 1.

Table 1: Parameters Definition for ANN

Parameters	**Initial Values**
Activation Functions	'purelin' and 'tansig'
Nodes in Hidden Layer	16
Learning Model	Levenberg-Marquadrt Backpropagation
Learning Rate	0.005
Number of Epochs	500
Mean Square Error	10^{-5}
Minimum Error	0.002
Momentum Rate	0.6
Training Time	50 seconds

The Activation function used here is 'purelin' and 'tansig' that represents the hyperbolic tangent sigmoid function and linear transfer function. And, the learning model used here is Levenberg-Marquadrt Backpropagation, which is the speed training method. The Mean Square Rate is the computation of the number of errors that occurred in the classification process. Here, the artificial neural network is trained with input MRI images that contain 5 nodes in hidden layer nodes and 1 node at the output layer. The activation functions are applied at the hidden and output layer. After retrieving features from the feature extraction process, training samples and testing samples are divided and given for testing in ANN and backpropagation method, respectively. The obtained results are evaluated using the evaluation parameters such as sensitivity, specificity, precision, and accuracy.

4. RESULTS AND COMPARISONS

The proposed model is analyzed using the MATLAB tool for implementation with the benchmark dataset known as DICOM databases containing MRI brain images [22]. Clinical

practitioners develop brain images in the database with different brain modalities. For evaluating the present model, 750 brain samples are considered for training and testing with the Artificial Neural Networks. The results are compared with the existing models to justify the proposed model's accuracy and efficiency in producing outcomes.
For providing evidence for the proposed model, the obtained results are compared with the existing models such as PNN and FCM based cancer detection. Support Vector Machine (SVM) and Perceptron found Neural Network Model (PNN). Each training and testing phase is processed with 18 brain samples divided into 9 each for training and testing, respectively. The trained representatives are provided as input to the ANN for training, and the validation is carried out with the testing samples. After performing simulations, the value computed for models without tumor is almost similar to 0, and cancer presented images to obtain about 1 and classified based on that. The sample brain images obtained from the Dicom library are shown in Figure 7. The Brain Images that are diagnosed with tumors after performing 500 iterations are given in Figure 6.

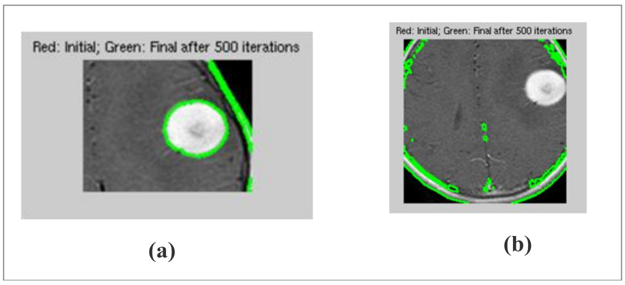


Figure 6: Brian Images Diagnosed with Tumor

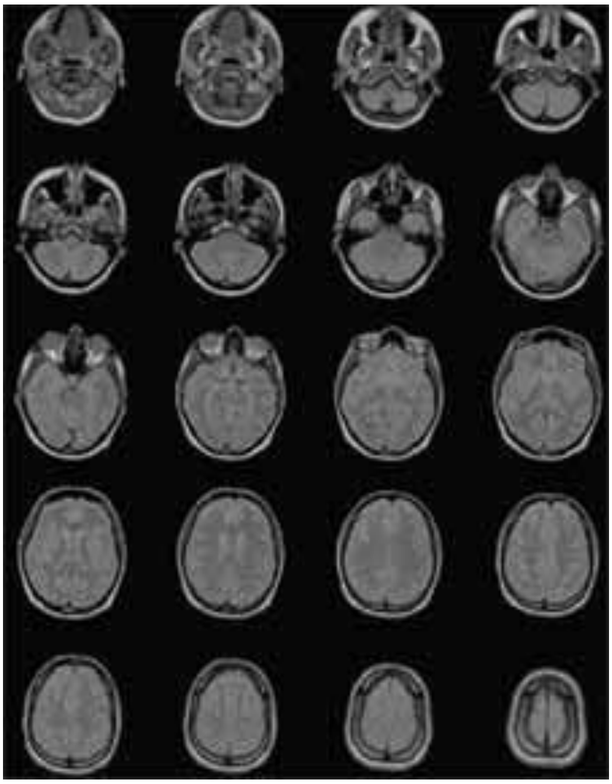


Figure 7: Sample Brain Images from DICOM Datase

4.1. Performance Measures:

The performance of the proposed model is measured using metrics such as specificity, sensitivity, and accuracy rates using true positive, true negative, false positive, and false-negative rates. Moreover,

- True Positive rate is to evaluate brain images with tumor are correctly detected as abnormal.
- True Negative is defined as the normal samples are mentioned as normal.
- A false Positive is the tumorless sample is falsely identified as containing a tumor.
- False Negative is the abnormal samples are incorrectly defined as normal.
- Here, Sensitivity, specificity, and accuracy rates are computed as,

$$Sensitivity = \frac{True\ Positive}{True\ Positive + False\ Negative} \times 100 \quad (8)$$

$$Specificity = \frac{True\ Negative}{True\ Negative + False\ Positive} \times 100 \quad (9)$$

$$Accuracy = \frac{True\ Positive + True\ Negative}{True\ Positive + True\ Negative + False\ Positive + False\ Negative} \times 100 \quad (10)$$

Based on the above factors and computations, the performances of the proposed work in classifying brain tumor images are evaluated.

4.2. Comparative Evaluations:

When applying the ANN computing for tumor image classifications, the performance is evaluated with the training, testing, and validation results. The performance graph is given in Figure 8 with the assumption of 50 iterations and the minimum mean square error is considered as 10^{-5}. At the 19th iteration, the best value is achieved with a minimal error rate of 0.0000041.

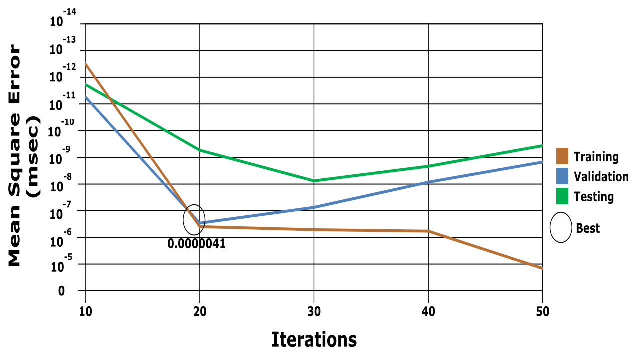


Figure 8: Performance Analysis Graph

The results obtained on accurate classification results are evaluated and portrayed in Figure 9. It is observed from the figure that the proposed SC-BTDC received a better accuracy rate than other classification techniques. The proposed soft computing based cancer detection model produces a 42% or higher accuracy rate than other classification models. The efficient incorporation of segmentation, feature extraction, and soft computing-based classification ensures maximum accuracy.

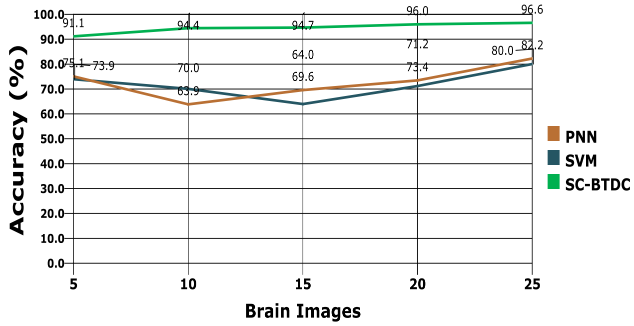


Figure 9: Accuracy Rate Comparisons

As mentioned in Section 4.1, the performance measures to the derived model are computed and the obtained results are

They are presented in Figure 10. The obtained results are compared for the existing models, such as PNN and SVM. It can be noted from the figure that the Soft computing based classification model acquired better results than the compared models. The model produces 96% of accuracy in brain tumor detection and classifications. Moreover, the model uses minimal processing time than other models, which is considered a significant factor in evaluating a classification model. In the proposed model, the median filter and edge detection methods are used for pre-processing, making the detection process faster than other methods. It is given in the following Figure 11. Here, the processing time is estimated against the number of brain images processed over seconds. The comparative evaluations results show the efficiency of the proposed model in producing accurate and précised results with minimal processing time.

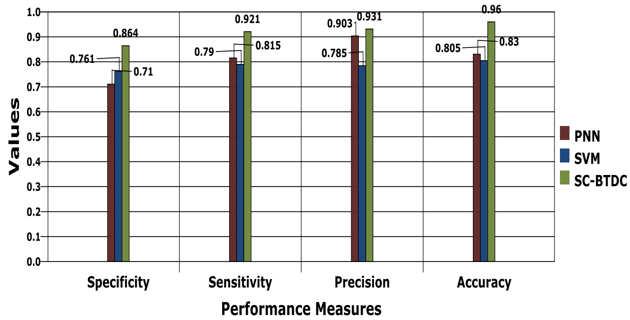


Figure 10: Evaluation of Methods with Performance Measures

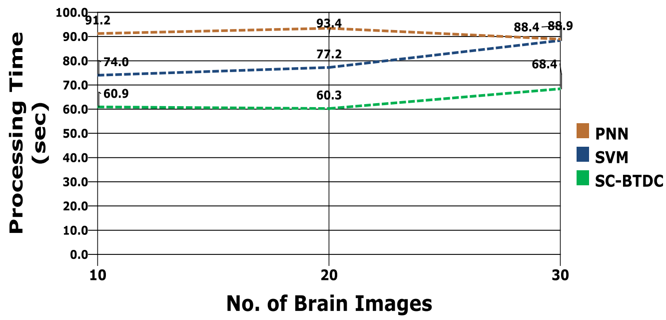


Figure 11: Processing Time Comparisons

5. CONCLUSIONS AND FUTURE ENHANCEMENT

In the present scenario of medical image processing, an efficient methodology is required for accurate tumor diagnosis. This paper presents a new model using a soft computing technique based on brain tumor detection and classification for assisting the radiologists in providing efficient treatments to the affected persons. Moreover, the median filter is used here for noise removal, and edge detection is used to accurately define the MRI brain image. For segmenting the tumor image effectively, Fuzzy c-means clustering is incorporated. Further, the feature extraction for performing efficient classification is performed with GLCM. The derived features of obtained brain images are given for ANN-based sort, which results in an appropriate type with an accuracy rate of 96.6%. The simulation results show that the proposed work produces better classification results compared to the existing models in terms of metrics such as classification accuracy, error, model efficiency, and processing time.
In the future, the work can be enhanced in such a manner to categorize the stages of the tumor for improving the decision pattern to provide treatments.

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