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METHODOLOGIES AND APPLICATION

ICM-BTD: improved classification model for brain tumor diagnosis using discrete wavelet transform-based feature extraction and SVM classifier

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Abstract
In medical image processing, the detection, classification and segmentation of the tumor region from MRI scans accurately are very complicated, significant and time-consuming process. When there is a scenario occurs to handle with large amount of images for tumor diagnosis, there is need of an efficient and adaptive classification model to handle with the anomalous structures of human brains. The MRI brain images show the typical internal brain structure and hence help scholars and medical practitioners in accurate disease diagnosis. With that note, this paper develops a model called improved classification model for brain tumor diagnosis for appropriate classification of tumor images from input MRI images. Initially, filtering techniques are applied for preprocessing the acquired scan images and feature extraction is done with gray-level co-occurrence matrix and discrete wavelet transform equations, which produces more precise results. And, classification is done with the technique called support vector machine, in which the binary classifications are effectively done. The proposed model is evaluated under simulation, and the obtained results outperform the results of traditional brain tumor detection process based on precision, recall and processing time.

Keywords Brain tumor diagnosis · MRI brain images · Discrete wavelet transform · Support vector machine · Classification · Segmentation

1 Introduction

Digital image processing with medical datasets is the area in which the clinical images are processing using computing models for appropriate disease diagnosis. A typical digital image is made with fixed amount of image elements called pixels, having specific intensity rates and positions. Moreover, in the domain of medical image diagnosis, the disease detection and proliferation about the internal model of the human body, magnetic resonance imaging (MRI) is utilized. When compared to CT images, the details on tissue differences provided by MRI images are more appropriate (Mustaqeem et al. 2012; Akram and Usman 2011; Shen et al. 2003). Hence, MRI images are widely used in many researches based on brain disease detection (Salman and Bahrani 2010; Ananda and Thomas 2012; Dubey et al. 2011).

The typical medical image processing includes functions such as preprocessing, segmentation, feature extraction, classification and diagnosis of diseases. Figure 1 presents the diagrammatic representation of the basic operations

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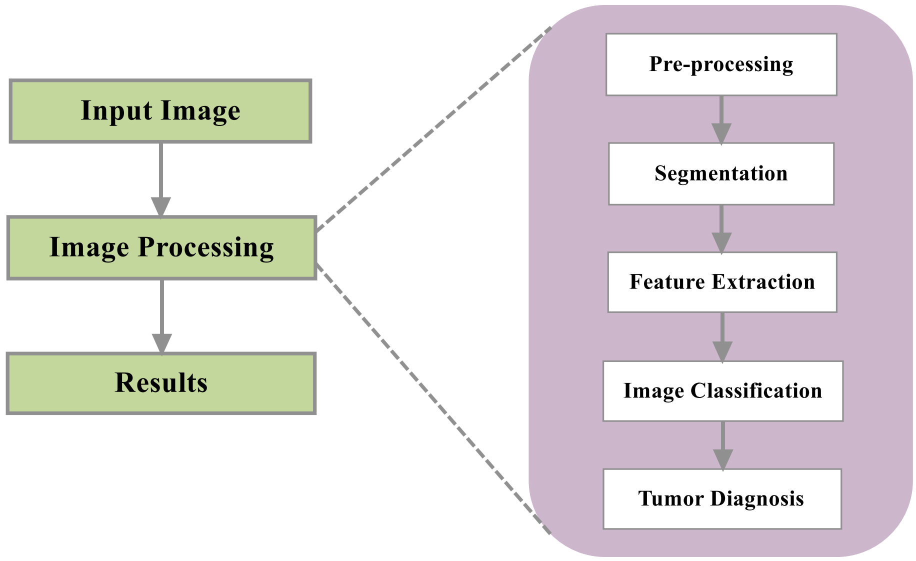
Fig. 1 Basic steps involved in image processing–tumor diagnosis



involved in medical image processing. Between the image acquisition and reporting results, those operations are to be effectively done with various computations.

In clinical practices, it is a complicated and time-consuming process to detect tumor from MRI brain images through manual detection process by doctors and radiologists; hence, there is need of an automated system for appropriate detection. Nevertheless, there may also produce some variations in results as well in analyzing the images manually (Telrandhe et al. 2015). Consequently, in the present decade, image processing is found as an effective technique for cancer diagnosis with reduced time and risk factors (Cha et al. 2006). Moreover, in general, brain tumor is defined as the anomalous growth of tumor cells in brain. It can be classified under benign and malignant stages, which can also be termed as primary and secondary stages of tumors, respectively. In that, malignant tumor is the most aggressive and dangerous (Kalaiselvi and Somasundaram 2011), in which the active tumor cells have non-uniform structures that can extend to all brain parts. According to WHO health standards, the tumor is categorized into four types: ranging from GRADE I to GRADE IV. Any kind of people at any age can be affected, and the effect of disease on every person may vary. But, in the intricate structure of brain, the appropriate detection process is very complicated.

In this developed improved classification model for brain tumor diagnosis, gray-level co-occurrence matrix (GLCM) and discrete wavelet transform (DWT) are used for segmentation of cancerous tissues in the obtained brain image. Moreover, classification is performed with SVM classification technique. Based on the reported results, suitable surgeries or therapies will be suggested by the medical practitioners. That is, when the tumor detection is made at earlier stage, the curing process of patients can be simpler and their life span can also be increased.

In recent days, several tumor detection methodologies are developed. Among all, the automated system for brain tumor diagnosis is very exigent, which is still on the focus of myriad researchers. With that concern, the major motive of the proposed model is to build an automated system for brain tumor diagnosis appropriately from the MRI scans. After preprocessing of MRI images, segmentation is carried out for identifying the affected regions with image processing techniques. Typically, segmentation can be described as the process of segregating the images according to their textures, colors, contrasts and other features. Following that, feature extraction is performed based on DWT and GLCM. Based on that, classification is executed using the support vector machine-based classification.

The results are reported to the concern medical person for further treatment process to the patient, in real-time clinical practice applications.

The remainder of the paper is framed as follows: Sect. 2 narrates about the various available models for tumor diagnosis in brain and also from other body parts. Section 3 describes the working process of the proposed improved classification model for brain tumor diagnosis (ICM-BTD). Section 4 provides the results and comparative analysis on the accurate detection of proposed model, and comparative analysis also presented in that section. Finally, conclusion is presented in Sect. 5 along with some paths for further enhancement of the proposed model.

2 Related works

In Wang et al. (2007), brain tumor detection has been performed with both magnetic resonance imaging (MRI) and magnetic resonance spectroscopy (MRS). In addition to feature extraction, feature selection has also been performed using concentric circle model for selecting significant features to be used in classification. The work could be further enhanced with more consideration on spatial data about the tumor. In order to classify the brain tumor in appropriate categories based on the shapes and textures presented in MRI inputs, pattern-based classification model has been discussed in Zacharaki et al. (2009). In the model, feature extraction has been done with pixel intensities and shapes of the MRI scans. SVM classification technique has been used for classification.

In Rajendran and Madheswaran (2009), a pruned associative model for tumor diagnosis from medical images is given. The authors have used computerized tomography brain images. Statistical association rule mining-based algorithm has been used for tumor diagnosis in Li et al. (2010). In the model, weight coefficient was calculated for each feature, based on that scrupulous classification has been done. For earlier brain tumor diagnosis, in Flusser (2005), perceptron-based neural networks (PNNs) have been developed. Moreover, region severance algorithm has been used for abnormality detection from brain images. Further, the authors of El Far et al. (2011) provided a comparative analysis between models such as, Close+, Apriori algorithm and association rule mining for deriving attributes for appropriate medical image detection.

In Dhanalakshmi and Rajamani (2010), the association rule mining has been used for kidney disease diagnosis. In order to reduce the complications in efficient mining, discretization-based feature selection model has been applied. In Ion and Udristoiu (2011), semantic association rule mining has been used to derive features from visual images that were in low-level attributes. Further, a combined model of association and classification rule mining has been explained in Shekhawat and Dhande (2011a, b) for effective classification of input images based on disease presence. Backpropagation neural networks have been used for training, and classifying data was presented in Jose et al. (2012) for diagnosing kidney images.

Brain image segmentation using *K*-means clustering model based on tumor diagnosis was given in Joseph et al. (2014). Morphological filtering has been used for tumor detection from MRI brain images. Moreover, support vector machine (SVM)-based tumor classification was described in Alfonse and Salem (2016) and Kavitha et al. (2019). In that work, fast Fourier transform was used for feature extraction, and for feature dimensional reduction, minimal redundancy with maximal relevance method has been used. The input MRI images were divided into two sections as region with normal cells and region with abnormal or cancer cells (Coatrieux et al. 2013). Another work given in Zanaty (2012) described about the hybrid model that integrated FCM, seed growing and Jaccard similarity coefficient computation for evaluating the tumor image with cancer cells and to segment that appropriately.

The authors of Yao et al. (2009) derived a model based on wavelet transformation and SVM for brain tumor diagnosis and classification. Further, in Kumar and Vijayakumar (2015), principal component analysis (PCA) has been used for accurate cancer detection and artificial neural network-based training and testing model has been used for classification. Fuzzy-based clustering for medical image processing was given in Cui et al. (2013) and Kavitha et al. (2020). Moreover, the authors used Jaccard similarity indexing model for segmentation based on the variation on white, gray and cerebrospinal fluid. Active contour method was utilized in Chaddad (2015) for solving the issues based on image intensities. Gaussian mixture model was applied for brain tumor diagnosis from MRI input images using PCA (Sachdeva et al. 2013; Sabitha et al. 2016). In a different manner, the work presented in Bouattane et al. (2019), brain tumor segmentation model has been proposed with respect to the temperature changes on the pathological area. The works presented in Varuna Shree and Kumar (2018) and Kutlu and Avcı (2019) used discrete wavelet transform-based feature extraction for tumor diagnosis in brain and liver. By analyzing the literature survey, it can be observed that the accuracy in disease diagnosis can be increased with low computational overhead and complexities.

3 Work process of the proposed improved classification model for brain tumor diagnosis (ICM-BTD)

The major motive of this work is to perceive the tumor from MRI brain images to help the clinical practitioners to treat patients in better way. The proposed IMC-BTD comprised the following steps in the process of effective tumor diagnosis.

1. Data preprocessing
2. Skull masking
3. KMC-based segmentation
4. Feature extraction
   - Using DWT
   - Using GLCM
5. SVM-based classification.

3.1 Preprocessing

This process is very significant to enhance the standard of input images and provided appropriate results that aids in disease diagnosis in medical image processing. It also aids in enhancing features of input images that includes increasing the rate of signal to noise in visual effect of the input samples. The pixel intensity of each input MRI image is clearly defined for enhancing the result accuracy. Moreover, preprocessing process includes unnecessary noise removal, smoothing inner regions and edge framing.

3.2 Skull masking

Skull detection is the next process that is performed in the proposed model for properly detecting the exact boundaries of elements. For appropriate tumor diagnosis, the non-brain tissues are to be separated from brain tissues, and the operation is termed as skull masking. Moreover, the information about the edges is used to determine the region of interest (ROI), which defines the image and contains the tumor cells. For this, centroid is computed and a central lane is marked in the skull center, which can segregate the skull into two halves. One half is considered as the test image, and other is taken for reference. For contouring the cancer presented region boundary, the axial view of each MRI image is considered, in which it can be stated that the tumor cells can be presented in any axis symmetry that may be left or right. The histogram intensities of both sides are different, and the intensities outside the boundary of the cancer tissue are alike. In this work, it is to be considered that the tumor tissues are presented at any one part among the two separations.

3.3 KMC-based segmentation

For segmentation, *K*-means clustering technique is used here, in which the similar tissues are grouped together. It mainly aids in the determination of structure of abnormal cells. Moreover, in KMC, the cells are grouped based on the extracted features, which frames, *K* number of groups, based on the number of features extracted. Here, the clustering operation is accomplished with the computation of minimal Euclidean distance between the data and the centroid. Figure 2 shows the process of KMC-based segmentation of MRI images in tumor diagnosis.

As in Fig. 2, the input MRI brain image is separated into '*K*' number of groups; following, centroids are determined for each clusters and the distance between each pixel of brain image and centroids is evaluated. Then, segmentation process is carried out till the last existing pixel in that image is completed.

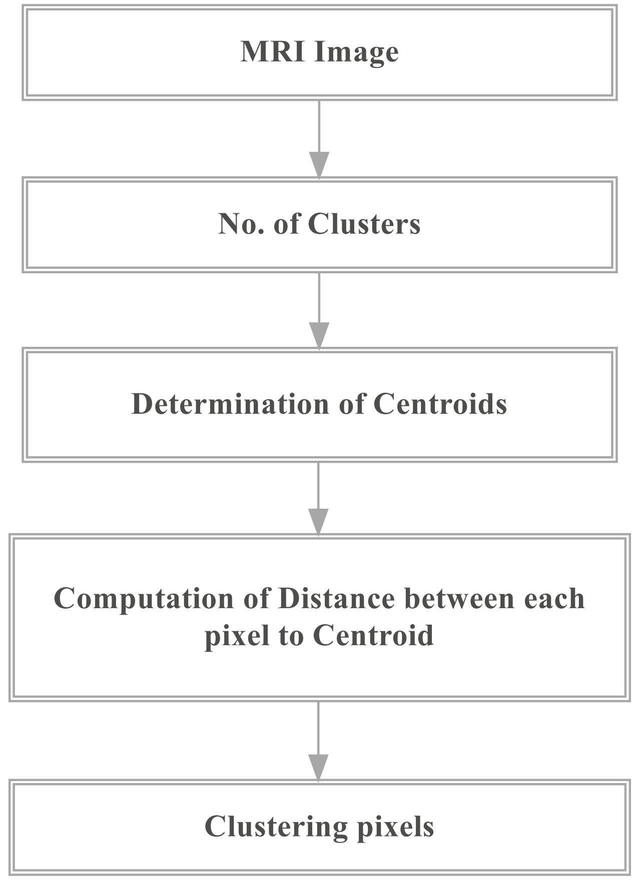


Fig. 2 KMC-based segmentation

3.4 Feature extraction

The main features of MRI scan images such as color, pixel intensity, texture and shapes are considered for feature extraction. Here, two methods of feature extraction are accomplished, which are explained as follows.

3.4.1 Discrete wavelet transformation-based feature extraction

In this process, as the name represents, distinct frequency sets are used at different levels to process the input images. From the process, wavelet coefficients are derived from the input images. The frequency data of signals are confined by the computed wavelet coefficients which are significant factors for categorization of tumors. By applying the DWT model, four sub-bands are framed based on the ROI as follows:

i. Low–low (L–L)
ii. Low–high (L–H)
iii. High–high (H–H)
iv. High–low (H–L)

Moreover, the disintegration of an MRI image provides an approximation that denotes the levels of wavelet frequencies in each image. The approximations rates for lower levels are given as: $L–L_1$, $L–L_2$, whereas the higher levels are denoted as: $L–H_1$, $H–L_1$, $H–H_1$, $H–H_2$, respectively. Those representations are used to represent the horizontal and vertical directions of pixels, based on the wavelet levels. Here, the low-level image determinations are used to represent the approximation over real data and the high-level approximation is obtained by the decomposition of previous representations and image data. This process is iterated till an appropriate level of pixel resolution is obtained.

In this DWT-based feature extraction, the obtained images are divided into spatial frequency elements that are derived from lower and the higher sub-bands of wavelets. For efficiently describing the image features, both levels of sub-bands were utilized. The variant frequency components based on its resolution with respect to the frequency scale are given as:

$$F_{\mathrm{DWT}}(s) = \begin{cases} \mathrm{EA}_{i,j} = \sum f(s)h(s) * i(s - 2ij) \\ \mathrm{EA}_{i,j} = \sum f(s)l(s) * i(s - 2ij). \end{cases} \tag{1}$$

From the above equation, the coefficients '$\mathrm{EA}_{i,j}$' denote the element attribute in wavelet transformation function '$F_{\mathrm{DWT}}(s)$' for signal 's.' The elements represent the approximation rates based on the high level and low level of functional determinations, '$h(s)$' and '$l(s)$,' respectively. Further, the factors, 'i' and 'j' denote the wavelet measure and translation parameter of images.

3.4.2 Gray-level co-occurrence matrix-based feature extraction

Analyzing the texture of input brain images creates a greater impact on classifying the normal and abnormal brain images easily. This also provides way for effective machine learning in disease diagnosis. Moreover, it enhances the precision rate of appropriate feature extraction for earlier recognition of brain tumor. Initially, in the first part of computation, the first-order-based analytical texture evaluation based on the feature data from the image intensities has been derived and grayscale frequencies at an auxiliary image positions are evaluated. The correlation coefficient or co-occurrence is not considered in the process. In the second part, the second-order-based textural computation is carried out in accordance with the gray-level occurrence at random distance and pixel intensities.

In this work, gray-level co-occurrence matrix (GLCM) is incorporated, in which (x, y)th component is the frequency of occurrence of function 'x' happening with 'y.' It is a distance function D = 1; at horizontal phase, angle will be at 0°, positive diagonal at angle 45°, negative angle at angle 90° (at vertical phase) and negative angle at angle 135°. It is also determined that the frequency of occurrence of the pixel intensity 'x' happens in accordance with another pixel 'y' at certain distance function D and direction. Moreover, in this model, the features such as energy, contrast, correlation, entropy, homogeneity and variance are acquired from the low-level and high-level sub-bands. The computation process of the considered features is given as follows:

i. *Energy (EY)* Energy is considered here as the quantity of reoccurring pixel pairs. It is the derivation of similarity of pixels in an MRI scan, and the equation is given as:

$$\mathrm{EY} = \sqrt{\sum_{x=0}^{i-1}\sum_{y=0}^{j-1} f^2(x, y)}. \tag{2}$$

ii. *Contrast (CT)* Contrast is determined by the pixel intensities along with the adjacent pixels of an image, and the derivation is given as:

$$\mathrm{CT} = \sum_{x=0}^{i-1}\sum_{y=0}^{j-1} (x - y)^2 f(x, y). \tag{3}$$

iii. *Correlation (CN)* It is derived as the computation of spatial features between the image pixels

$$\mathrm{CN} = \frac{\sum_{x=0}^{i-1}\sum_{y=0}^{j-1}(x, y)f(x, y) - N_{xN_y}}{\sigma_x\sigma_y}. \tag{4}$$

iv. *Homogeneity (HM)* It is observed on the basis of local regularity in an MRI image. It is computed by the variations on textured and non-textured features, which can be stated as inverse variant moment.

$$\mathrm{HM} = \sum_{x=0}^{i-1}\sum_{y=0}^{j-1} \frac{1}{1 + (x - y)^2} f(x, y). \tag{5}$$

v. *Entropy (ET)* Entropy is computed by considering the designated noisiness of the input image based on textures. It is calculated as:

$$\mathrm{ET} = \sum_{x=0}^{i-1}\sum_{y=0}^{j-1} f(x, y)\log_2 f(x, y). \tag{6}$$

Based on the computation of the above features, peak signal-to-noise ratio (PSNR) and mean square error (MSE) are the factors which are evaluated.

vi. *Peak signal-to-noise ratio (PSNR)* It is determined by the features of reframed image from the obtained image. The formula is given as:

$$\mathrm{PSNR} = 20\log_{10}\frac{2^m - 1}{\text{Mean Square Error}}. \tag{7}$$

vii. *Mean square error* It is computed by image comparison based on the similarity scores.

$$\mathrm{MSE} = \frac{1}{X \times Y}\sum\sum\left(f(i,j) - f^G(i,j)\right)^2. \tag{8}$$

By these methods of feature extraction, the derived features are given for the SVM classification model for training and testing, for efficient tumor detection in MRI scan images of brain. The overall framework of the proposed model is presented in Fig. 3.

3.5 SVM-based classification of brain images

In this proposed ICM-BTD, the supervised learning technique called support vector machine is used for classification. SVM-based classification provides accurate classification results by analyzing and processing the large dataset of MRI images. Moreover, the classification is performed by the formation of decision planes, by which the dissimilar class elements are being separated by hyperplane. Specifically, linear support vector machine-based classification technique is used here for detection of tumor presence from the input brain images. Moreover, Gaussian radial basis function (RBF) is used here to perform the binary classification. In this, it is considered that the training elements can be linearly divisible. The function is given as:

$$F(p) = ATp + q(1) \tag{9}$$

where 'p' is the training sample; for each sample, the function obtains $F(p) \geq 0$, in a case, if $p = +1$, and $f(p_i) < 0$, when $q_i = -1$. From Eq. (9), 'q' denotes the invariant factor and 'A' is the unit vector. Based on the provided training dataset, many hyperplanes can be framed that enhance the dividing margin between the classifications of normal and abnormal images. Further, the derived support vectors are presented at the boundary line of the hyperplane between classifications.

4 Results and comparative analysis

4.1 Dataset description

The evaluation of the proposed model is executed in MATLAB tool, using the benchmark dataset called DICOM dataset, which contains MRI brain image samples (http://www.dicom.com) that are built by radiologists on practice with several modalities of images. Here, for result analysis, 750 samples are taken into account from 30 images of the obtained dataset content. There are some challenges in processing the dataset images like low contrast, intensity and so on. It is also to be stated that the dataset images are effectively partitioned for training and testing functions. For providing evidence for the proposed model, the obtained results are compared with the existing models such as PNN- and FCM-based cancer detection.

4.2 Result evaluations

In the proposed work, the feature extraction is performed based on DWT and GLCM. Based on the sub-band rates obtained from L–L and H–L derivations of wavelet transformation, the images are divided into different levels. Following, based on GLCM, the analytical features such as, energy, contrast, correlation, homogeneity and entropy are derived. These features are given for SVM classifier for tumor image classification from obtained sample of MRI images. Based on the DWT-based image decompositions, for analyzing, brain image (BR) = $\{BR_1, \ldots BR_5\}$ is considered here with different sub-bands of DWT. As mentioned earlier, the extracted features are fed for classification. Moreover, Tables 1 and 2 contain the analytical features computed from GLCM with different levels of sub-bands for both the training and testing phases.

Further, the values calculated for MSE, PSNR, area of tumor tissue and area of BR in pixel are presented in Table 3. The brain images presented in Fig. 4 depict the BR considered for the assessment of the proposed model that are acquired from DICOM dataset. In the proposed model, after preprocessing, the important operation performed is skull masking. Figure 5 contains the image output, after performing skull masking, for appropriate disease diagnosis from brain images. Following, the feature extraction is performed with DWT and GLCM. According to that, the classification process of normal and abnormal brain images is performed. The performance is evaluated by the values obtained by the calculation of PSNR and MSE.

Figure 6 presents the enhanced brain image after the process of feature extraction. From the obtained results given in Table 3, it indicates that the minimal MSE and maximal PSNR value denotes better value of signal-to-noise ratio in the processed input. For evaluating the performance of a classification model and comparative analysis between models, accuracy-related factors such as specificity, sensitivity, precision and accuracy and

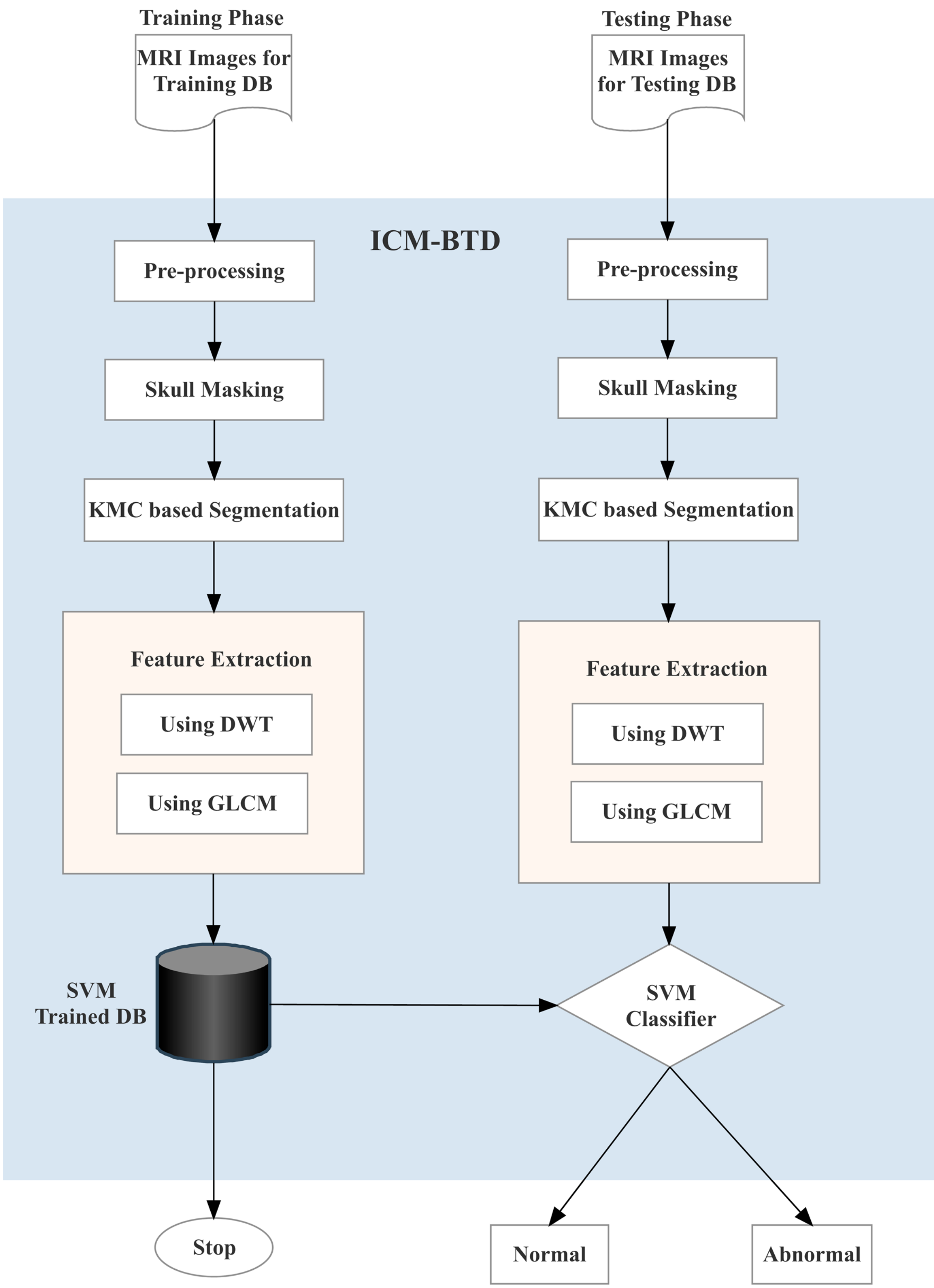


Fig. 3 Framework of the proposed model

Table 1 Values obtained for analytical features from GLCM derivation with variant sub-bands under training phase

Brain images	EY	CT	CN	HM	ET
BR_1	0.977	0.0112	0.0206	0.903	0.332
BR_2	0.992	0.0036	0.0381	0.965	0.339
BR_3	0.966	0.0168	0.0259	0.901	0.337
BR_4	0.989	0.0054	0.0027	0.766	0.272
BR_5	0.974	0.0125	0.0477	0.683	0.337

Table 2 Values obtained for analytical features from GLCM derivation with variant sub-bands under testing phase

Brain images	EY	CT	CN	HM	ET
BR_1	0.899	0.0073	0.0198	0.870	0.389
BR_2	0.954	0.0110	0.0295	0.910	0.321
BR_3	0.832	0.0120	0.0243	0.891	0.302
BR_4	0.820	0.0043	0.0034	0.745	0.253
BR_5	0.893	0.0108	0.0450	0.864	0.330

processing time are to be analyzed based on the TRUE POSITIVE, FALSE POSITIVE, TRUE NEGATIVE and FALSE NEGATIVE rates in classification results. The graph portrayed in Fig. 7 represents the comparison of accuracy rate among models for classifying brain images. It is explicit from the figure that the proposed ICM-BTD model achieves better results than compared works. The accuracy rate of brain tumor detection between the compared and the proposed model is evaluated. By the effective incorporation of KMC-based segmentation and feature extraction techniques, the proposed model achieved better rate of accuracy than others. In average, the model achieves 94.2% of accuracy in cancer image classification.

Figure 8 presents the factor-based evaluation for evaluating the performance of the proposed model. Based on the classification results with TRUE POSITIVE, FALSE POSITIVE, TRUE NEGATIVE and FALSE NEGATIVE rates, the sensitivity, specificity, precision and accuracy rates are computed and the results are presented. It is obvious from the graph that the proposed model produces better results than compared models. And, Fig. 9 compares the processing time taken for providing classification results. It is obvious from the comparative analysis; the proposed model provides accurate classification results in minimal time, which helps in earlier cancer detection and treats the patients in better ways.

5 Conclusion

This paper presents a new model called improved classification model for brain tumor diagnosis (ICM-BTD), which comprises steps such as preprocessing, skull masking, segmentation, feature extraction and classification. Preprocessing is for removing noise from obtained MRI scan images. Skull masking is performed for enhancing the obtained image by deleting the skull tissues, which are not considered for tumor detection in brain. Moreover, KMC-based segmentation is carried out for clustering similar elements that makes the detection process more efficient. The significant section of the adduced work is feature extraction using DWT and GLCM. Based on this, salient features are derived from the smoothened MRI image and given for SVM-based classification for finding the class of the processed MRI, which can be normal or abnormal. The results are evaluated based on the factors such as accuracy rate, precision and processing time, and it is to be stated that the proposed model provides better results than the compared works and evidenced the efficacy of the model. The application of the proposed model can be effective in brain tumor diagnosis in clinical practices in earlier stages.

In future, the work can be enhanced by incorporating with some other efficient segmentation and classification model based on the real-time applications in clinical practice. Another path for enhancement can be considered the volume analysis of the detected tumor from MRI scans of brain with some other datasets such as BioGPS and BraTS.

Table 3 Performance analysis based on MSE and PSNR

Brain images	Peak signal-to-noise ratio	Mean square error	Area of BR in pixel	Area of tumor tissue
BR_1	12.82	3.216	66,824	9774
BR_2	13.12	8.058	50,608	7323
BR_3	13.59	5.54	24,944	4664
BR_4	13.72	7.69	50,419	3678
BR_5	14.23	6.152	16,284	4397

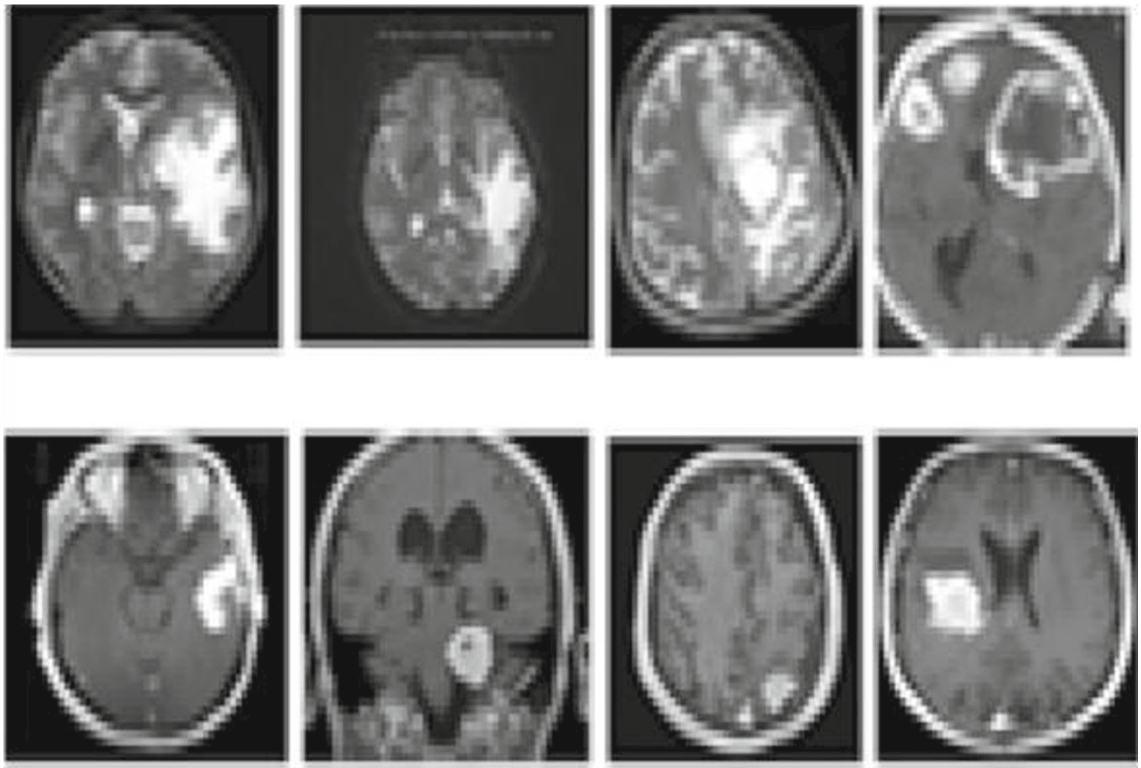


Fig. 4 Brain images obtained from dataset for evaluation

Fig. 5 Image obtained after the removal of skull tissues from a BR

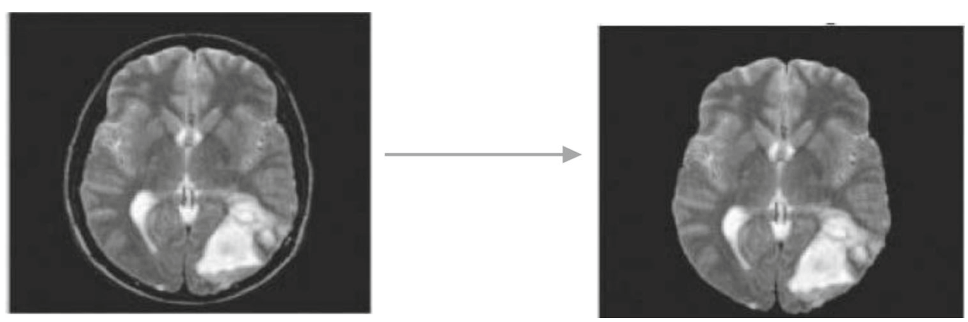
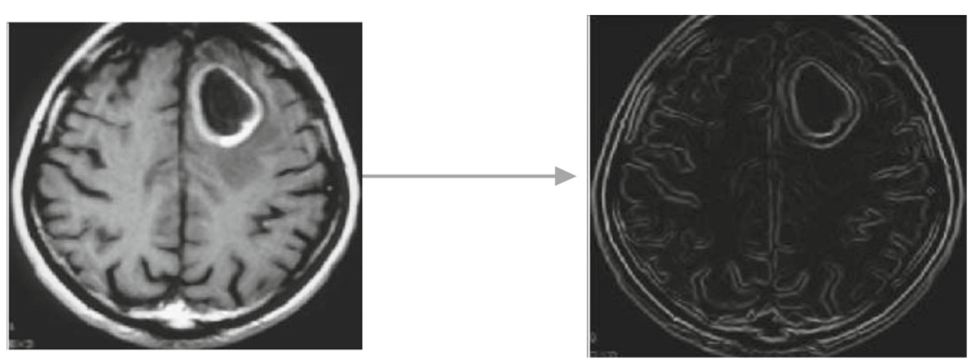


Fig. 6 Enhanced BR after feature extraction



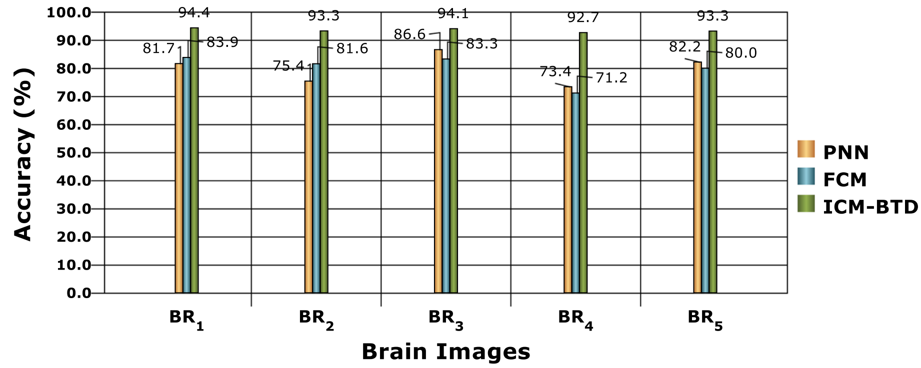


Fig. 7 Accuracy comparison among models

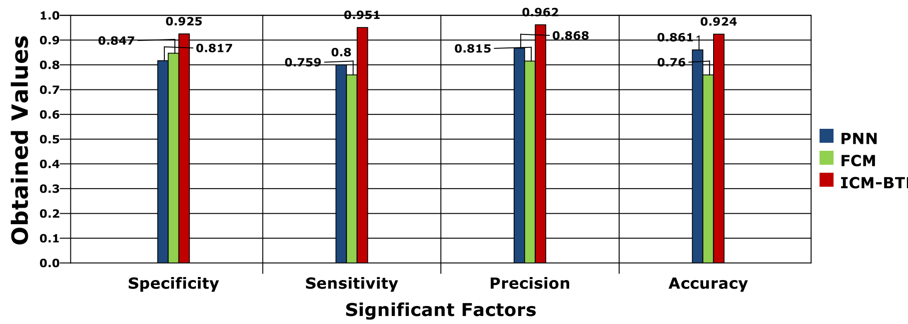


Fig. 8 Factor-based evaluation between compared models

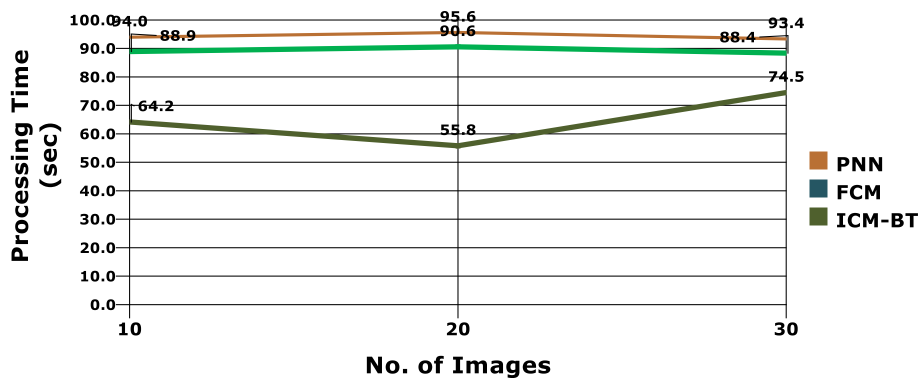


Fig. 9 Processing time comparison

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Compliance with ethical standards

Conflict of interest The authors declare that they have no conflict of interest.

Research involving human participants and/or animal This article does not contain any studies with human participants or animals performed by any of the authors.

Informed consent All referred study is highlighted in the Literature Review.

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