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# Tumor Categorization Model (TCM) Using Soft Computing Techniques for Providing Efficient Medical Support in Brain Tumor Treatments

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Brain cancer identification and segmentation is a prolonged and difficult task in Medical Image Processing, which is most significant for providing appropriate treatment and increase patient's life span. With the advancements available in medical fields, soft computing techniques are incorporated to accurate detection and classification of brain tumors. Besides brain cancer detection, it is vital to categorize tumor stage based on their features. For that concern, this paper develops a Tumor Categorization Model (TCM) that includes image processing and soft computing techniques. Here, pre-processing is carried out using modified Gabor filter and segmentation process is performed with OTSU thresholding. Following segmentation, region growing is processed based on the pixel intensities of input MRI brain images. Further, Discrete Wavelet Transform is enforced for extorting image features as well as gray-level co-occurence matrix features are also derived for appropriate classifications. Finally, the input MRI images are classified using Boosting Support Vector Machine (BSVM) with the benchmark dataset called DICOM and BraTS dataset. The experimental results demonstrate accurate brain tumor detection and categorization by the efficient incorporation of image processing and soft computing methodologies, provides efficient clinical support in providing treatments.

**Keywords:** Tumor Categorization Model (TCM), MRI Brain Images, Discrete Wavelet Transform (DWT), Segmentation, Boosting Support Vector Machine (BSVM).

## 1. INTRODUCTION

In current scenario of medical sciences and digital health care systems, several clinical services are provided to provide better treatment for patients and to make appropriate decisions on clinical practices. Among several medical services provided by e-health systems, automated tumor detection mechanisms are very much significant. There are several kinds of clinical data processing that includes inputs from CT scan, MRI, X-ray and so on [1]. MRI-Magnetic Resonance Imaging of the Human Brain is one of the techniques used to diagnose brain cancer, which is one of the most severe and life-threatening disorders. Moreover, the MRI scan denotes the elements of cerebrum of brain effectively in addition to the point to point image specifications. The MRI images portray the brain tissues structure, functions and metabolism in non-invasive manner [2]. Based on the statements of Central Brain Tumor Registry of the United States (CBTRUS), brain cancer is uppermost death causing diseases than other kind of cancers [3]. For avoiding that, earlier detection of brain tumor is more significant and methodologies are to be determined accordingly.

In this paper, soft computing models are incorporated for the analytical computation and reasoning capabilities. Some of the majorly used soft computing techniques are Evolutionary algorithm, support vector machine, fuzzy based methods, neural networks, and so on. The general work process for clinical data processing in cancer diagnosis is presented in Figure 1 that incorporates image processing and soft computing techniques.

Based on the classification results provided by the defined technique, the treatment decisions can be taken by the health practitioners. Specifically, for tumors, the patients are advised to undergo radiation, chemotherapy or surgery based on the grade of the detected tumor. This appropriate or effective decision making enhances the survival rates of patients; even the earlier tumor diagnosis can reduce the patient sufferings in considerable manner [4]. Hence, the research related to brain tumors with image processing has gained significance in the department of medical sciences. With such a goal in mind, this study presents the Tumor Categorization Model (TCM), a model for classifying

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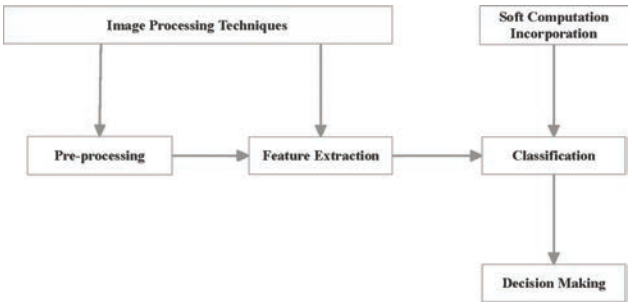


**Fig. 1.** Medical data processing for disease diagnosis.

cancer images according to their stages. Some of problems found in brain tumor diagnosis are listed below:

- As the size of the cancer tissues increases, it may completely damage the brain and other parts of the body too.
- The lesser number of training images would lead to reduced classification performance. Thus the required accuracy level can't be reached.

Here, the modality utilized for brain tumor detection is MRI images, since, it contains better image resolution. The acquired brain images are given for noise removal to the modified Gobar filter and OTSU thresholding is used for segmentation. For extracting significant features for appropriate classification, DWT and gray level occurrence matrix is employed and features are selected using Lion Optimization. Further, classification process is done through Boosting Support Vector Machine (BSVM).

## 2. RELATED STUDIES

The Ref. [5], Local Binary Patterns based image processing has been carried out for extracting the local features of the input images. Moreover, the original spectral and gabor features were extracted using two fusion techniques such as decision and feature level fusion techniques. In Ref. [6], a comparative evaluation has been carried out between the Cascade Architecture and Feed Forward Neural Networks based classifications. And, Principal Component Analysis (PCA) based feature extraction was incorporated. The dataset images were obtained from the Olivetti Research Lab database dataset for training and testing for the classification evaluations.

A hybrid model has been defined in Ref. [7] that used Fuzzy C-Means clustering and SVM for brain cancer diagnosis as well as classification. Moreover, image enhancement methods have been used to enhance the image features for appropriate results. Before applying classification model, feature extraction has been performed with the Grey level run length matrix. Further, an ensemble based classification technique has been presented in Ref. [8] to improve the accuracy of classification in brain cancer detection and classification.

Unsupervised learning models were used in Ref. [9] such as FCM for tumor image classification, specifically spatial FCM was used in the process. Active contour modelling was also been used for determining the cancer tissue border in precise manner [10]. The authors of Ref. [11] presented the tumor detection model with minimal processing time using the morphological functions. Additionally, it is to be stated that the computational cost of detection process is based on the storage and processing time [12].

Therefore, feature reduction process was presented in Ref. [13] for reducing the number of features that are chosen for classification process. Furthermore, in the work [14], the local features of MRI images such localization, frequency, was observed with the Gabor wavelet factors.

In some other papers, the feature extraction have been processed with GLCM, grey level run length matrix and first order statistical features [15]. In Ref. [16], combined classification model with BPNN in addition to SVM are employed to determine accurate MRI image categorization. In general, the NN based classification takes longer processing time, since it requires to process with training and testing process. The limitation can be effectively handled and overcome using support vector machine [16].

Automated brain tumor detection has been presented in Ref. [17], which used K-means clustering and morphological function based feature selection. Further, the authors of Ref. [18] used rapid Fourier transform for feature extortion of MRI images, to reduce the number of extracted features, minimal redundancy and maximal relevance model. The brain image contains both normal and abnormal cells that are to be segmented with effective models [19]. For accurate tumor image segmentation, the authors of Ref. [20] used the combination of FCM and seed growing methods. Wavelet transform related feature extortion to detect breast cancer was described in Ref. [21].

In the work [22], the outcomes of PCA and kernel functions were given to the SVM classification to detect the tumor appropriately [28]. And, in Ref. [23], Artificial Neural Network (ANN) based classification was used for MRI brain image classification. In a different manner, localized fuzzy clustering has been used for extracting the spatial data of images in Ref. [24]. Moreover, Jaccard Similarity measurement is employed to segment brain image depending on white, gray parts and cerebrospinal fluids.

Based on the image intensities, active contour based segmentation has been applied in Ref. [25] that support exact tumor diagnosis with enhanced image features using Gaussian Mixture method. Further, in the work [26], a hybrid model that combined PCA and ANN has been used for MRI brain tumor classifications. By analysing the works presented in this survey, a new idea is framed for implementing an efficient model for brain tumor diagnosis and classification that provides better accuracy than other models.

## 3. WORK PROCESS OF TUMOR CATEGORIZATION MODEL WITH EFFICIENT IMAGE PROCESSING AND SOFT COMPUTING METHODS

The proposed Tumor Categorization Model (TCM) acquires MRI brain images as input and processed with image processing and soft computing techniques for producing appropriate classification results. Further, the classified tumor images are categorized into specific stages for supporting medical practitioners for treatment decision making. The functions involved in the proposed mode are diagrammatically presented in Figure 2.

### 3.1. Image Acquisition

Here, Magnetic Resonance Imaging of Brain samples are given as the input for the proposed model. However, MRI inputs contain some noise that may cause incorrect classifications. Hence,

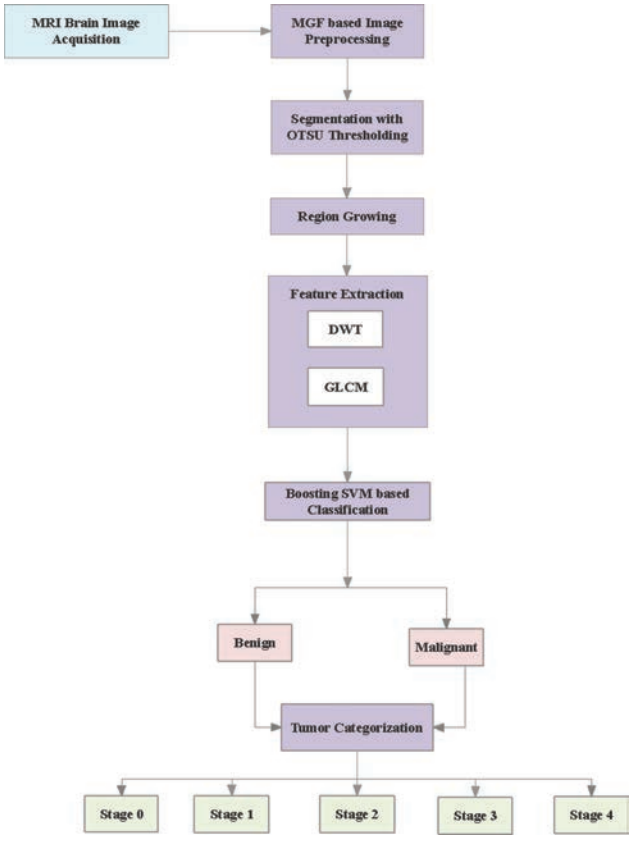


**Fig. 2.** Functions involved in proposed model.

input samples are processed and segmented for obtaining accurate brain tumor detection.

### 3.2. Pre-Processing with Modified Gabor Filter

The input brain samples are pre-processed here with Modified Gabor Filter, which is different from the gabor filter operations with minimal time consumption for processing. Moreover, the operations involved in the modified gabor filter based image processing are given as follows:

- Initially, the spatial aspect ratio are not considered, thereby, distortion of samples are reduced effectively.
- Instead, the spatial aspect ratio is taken directly at the kernel size.
- This reduces the noise level effectively and helps to obtain clear MRI samples for further processing.

Moreover, the mathematical computations involved in the Modified Gabor Filter Processing are described below:

$$f(x,y;\alpha,\theta,\gamma,\delta) = \exp\left[-\frac{1}{2}\left(\frac{x_1^2+y_1^2}{\alpha^2}\right)\cos\cos\left(2\pi\left(\frac{x_1}{\delta}\right)+\gamma\right) + \sin\left(2\pi\left(\frac{y_1}{\delta}\right)+\gamma\right)\right] \quad (1)$$

Where $x_1 = 2(x\cos(\theta)+y\sin(\theta)/(n-1)$ and $y_1 = 2(-x\cos(\theta)+y\sin(\theta))/(n-1)$, '$n$' stands the kernel size, finally, the obtained image after the application of the filter as mentioned,

$$M(x,y) = I(x,y) * f(x,y;\alpha,\theta,\gamma,\delta) \quad (2)$$

### 3.3. OTSU Thresholding Based Image Segmentation

In this section, the image samples are converted into binary image, in which the pixels are given as 0 and 1, represents two discrete states of images. Specifically, '1' represents the data in white color, whereas, '0' denotes the black color of images. For effective evaluation of cancer nodules in the image, the digital image is divided into several segments for exact identification. Here, segmentation is performed with OTSU thresholding model. Moreover, discrete states are considered here as the threshold rates, and, the pixel that are not in the range of the threshold states are removed. The binary image conversion provides number of benefits such as minimal storage usage, fast velocity dispensation and easier processing, since it requires only two states to be considered for computations. This kind of segmentation also helps in exact detection of Region of Interest (ROI) and that are to be given for tumor diagnosis process. After segmentation, Region Growing process is established and explained in the following section.

### 3.4. Region Growing

This is the process of combining pixels into some larger regions based on certain rules. For growing regions, 'seed' points are to be selected that are having similar properties for grouping. A set of points are considered as input in sample, objects are noted for segmentation. Area develops via considering the neighbour points of the defined region in iterative manner. Moreover, the pixel similarity is measured based on the pixel strength as well as mean determination of region. Neighbouring pixels that are having minimal difference are combined to frame the region, which are further to be given for feature extraction.

### 3.5. Feature Extortion

Feature extortion is the procedure that derives quantitative data from the segmented region like texture, shapes, color, and contrast. At this time, two kinds of feature extractions are performed through Discrete Wavelet Transform (DWT) as well as GLCM.

#### *3.5.1. Wavelet Coefficient Extraction*

This section defines the wavelet coefficient extraction process from MRI brain images using Discrete Wavelet Transforms. The wavelet points the frequency data of signal function that is significant for result evaluations. Moreover, the two dimensional wavelet transform is employed that produces four bands based on the two state of wavelet separation of ROI, such as,

- Low-Low
- Low-High
- High-Low
- High-High

First two states are used to denote the images with low frequency and the other two states are used to represent the higher frequency rate of images, respectively. Here, images with low states are used with (Low-Low) state of given sample and the image is further divided into second state. For better analysis of features of tumor cells, the samples are separated as spatial data that are obtained by minor sub-bands, further, the advanced frequency components are compared with the previous bands. The

variant frequency elements and each element was analyzed with scalar matching and it is mathematically given as,

$$\begin{aligned} \mathrm{DWT}f(I) &= \{d_{x,y} = \sum f(I) H * i(I-2xy) d_{x,y} \\ &= \sum f(I) L * i(I-2xy) \end{aligned} \tag{3}$$

Where, the wavelet coefficients '$d_{x,y}$' denotes the element factor in image function $f(I)$, 'H' and '$L$' denotes the high and low states of image frequencies, respectively. And, $x$ and $y$ are the wavelet scalar factors.

#### 3.5.2. GLCM Based Feature Extraction

For enhancing the accuracy rate of classification results, the feature extraction is carried out using Gray-Level Co-occurence Matrix. Based on the spatial information and relations between pixels, the statistical features of images are derived in this section. Moreover, it is determined with two dimensional histogram that has ($x$, $y$) element is the frequency of incidence of '$x$' amid '$y$.'

Here, the gray scales are termed as $x$ and $y$, with distance function $D=1$ and computes the regularity of incidence with pixel strength $x$ that occurs regarding $y$. Further, the textural features such as correlation, image contrast, energy, entropy and homogeneity are determined depending on lower as well as higher sub bands of wavelet computations. Calculations for textural feature determinations are presented below:

(i) Image Contrast (IC):

The difference between the pixel intensities of particular image is given as,

$$\mathrm{IC} = \sum_{p=0}^{m-1} \sum_{q=0}^{n-1} (p-q)^2 f(p,q) \tag{4}$$

Where, $p$ and $q$ defines the pixel intensities of the given MRI image.

(ii) Correlation:

Correlation (CRR) can be defined as the measurement of dependencies between the spatial data of pixels in the image, which is mathematically presented as,

$$\mathrm{CRR} = \frac{\sum_{p=0}^{m-1} \sum_{q=0}^{n-1} (p,q) f(p,q) - M_{pM_q}}{\sigma_p \sigma_q} \tag{5}$$

Where, $\sigma_p$ and $\sigma_q$ are the variances of $p$ and $q$.

(iii) Energy (EY):

Determination of affinity in any image is given as Energy computations, which can be further defined as the measurable amount of recurring pixel pairs. The computation is presented as,

$$\mathrm{EY} = \sqrt{\sum_{p=0}^{m-1} \sum_{q=0}^{n-1} f^2(p,q)} \tag{6}$$

(v) Entropy (EPY):

The designated intrusion of textural image is calculated as the entropy of the image, which is expressed as,

$$\mathrm{EPY} = \sum_{p=0}^{m-1} \sum_{q=0}^{n-1} f(p,q) \log_2 f(p,q) \tag{7}$$

(v) Homogeneity (HY):

Local uniformity of MRI sample is termed as homogeneity computation that can differentiate textural and non-textural image properties.

$$\mathrm{HY} = \sum_{p=0}^{m-1} \sum_{q=0}^{n-1} \frac{1}{1+(p-q)^2} f(p,q) \tag{8}$$

The extorted features are finally provided to the Boosting SVM for classifications of MRI inputs under benign and malignant categories.

### 3.6. BSVM Based Classification

The soft computing technique incorporated here for classification is Boosting Support Vector Machine based classifications, denotes the operations of SVM is infused with the boosting mechanism for accurate classification of MRI images. Moreover, the signification features are extracted with the DWT and DLCM in the previous section, which are utilized for classification performance. The BSVM mechanism performs effectively when handling with large data and high dimensional medical data. Primary benefit of using BSVM classification method is that model decreases the computational complexities and processing time in efficient manner. The hypothesis of the incorporated classification technique is expressed based on the boosting technique, as hyperplanein feature space. Here, the coefficients are selected in such as manner to reduce the error rate on training data.

#### 3.6.1. Size and Stage Description of Tumors for Classification

After processing the images with BSVM, the samples are evaluated for tumor size and cancer stages based on the following descriptions.

- Stage 0: the size of tumor is detected as very small and it can be named as Edema and categorized under Stage 0.
- Stage 1: when the diagnosed tumor size is $\leq$0.5 mm, then it is categorized under benign stage
- Stage 2: when the detected tumor size is ranges between (1 and 4 mm), it can be classified under stage 2 and denoted as Necrosis. This kind of tumour contains several abnormal cells.
- Stage 3: the size of tumor is ranges between 5 to 10 mm, then it comes under Stage 3 and may contains several dead and dividing tissues. And, that can be termed as Anaplastic Astrocytoma or Ependyoma clinically.
- Stage 4: When the tumor size $\geq$10 mm, then it is considered as the stage 4 and stated as Glioblastoma. This stage of tumors is to be critically treated.

## 4. RESULTS AND DISCUSSION

For evaluations, the input MRI brain samples are obtained from the DICOM [26] and BraTS [27]. BraTS 2020 employs preoperative MRI scans from many institutions and concentrates on segmenting (Task 1) fundamentally diverse (in look, form, and histology) brain cancers, such as gliomas. In this work 80 MR brain images were utilized for evaluation. 80% of the images are used for training, while 20% are used for testing. MATLAB simulation is used to evaluate the suggested model. Also shown in Figures 3 and 4 are example images taken from aforementioned databases.

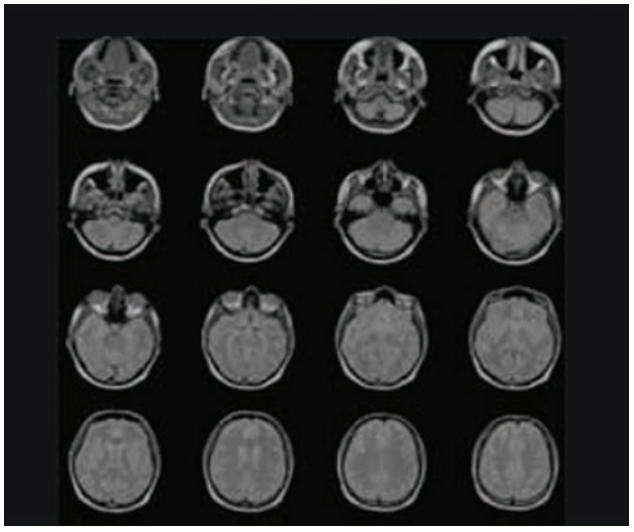

**Fig. 3.** Sample images from DICOM dataset.

From DICOM dataset, 18 images are taken for processing with the proposed TUmor Categorization Model. Among, 9 images are provided for training and left over samples are given for testing. From another benchmark database BraTS, 150 images are considered from processing, amongst, 75 have tumor images with benign state and the rest in malignant state.

The measures, such as the Peak Signal to Noise Ratio (PSNR) and Mean Square Error (MSE), are used to assess the effectiveness of the suggested model. The equations are expressed as follows,

$$\mathrm{MSE}=\frac{1}{XY}\sum_{i=1}^{X}\sum_{j=1}^{Y}(a(i,j)-b(i,j))^2 \tag{9}$$

$$\mathrm{PSNR}=10\log_{10}\frac{(2^m-1)^2}{\sqrt{\mathrm{MSE}}} \tag{10}$$

Where, $a(i,j)$ is actual sample, $b(i,j)$-the modified sample, $(i,j)$ is pixel position for $X*Y$. Further, Accuracy, Precision and Recall rates are calculated by the following expressions,

$$\begin{aligned}\text{Accuracy} = {} & (\text{True Positive}+\text{True Negative}) \\ & /(\text{True Positive}+\text{True Negative} \\ & +\text{False Positive}+\text{False Negative})\end{aligned} \tag{11}$$

$$\text{Precision}=\frac{\text{True Positive}}{\text{True Positive}+\text{False Positive}} \tag{12}$$

$$\text{Recall}=\frac{\text{True Positive}}{\text{True Positive}+\text{False Negative}} \tag{13}$$

For pre-processing, modified Gabor filter is used, which reduces the additional noise in source MRI brain image. Subsequent to the application of MGF, enhanced image in presented in Figure 5 with respect to source MRI brain image with benign cancer and Figure 6 presents the results of MGF for malignant tumor, respectively.

Further, the filter image is given for OTSU based thresholding for segmentation. The obtained result over the malignant tumor image is portrayed in Figure 7. And region growing is determined for appropriate tumor tissue definition with precise borders. Following, the significant attributes are extorted from image for appropriate classifications. Depending on those attributes the classification model is trained and tested for evaluations. The finally segmented brain tumor image is given in Figure 8, which has to be provided for measuring the size and shape of the tumor for classification.

An image from BraTS dataset is processed with the Tumor Categorization Model with the operations in that for categorizing tumor stages. The results are presented in Figure 9, which acquires the input from benchmark brain tumor dataset and given for pre-processing, segmentation and region growing. The segmented image is further utilized for feature extraction with DWT

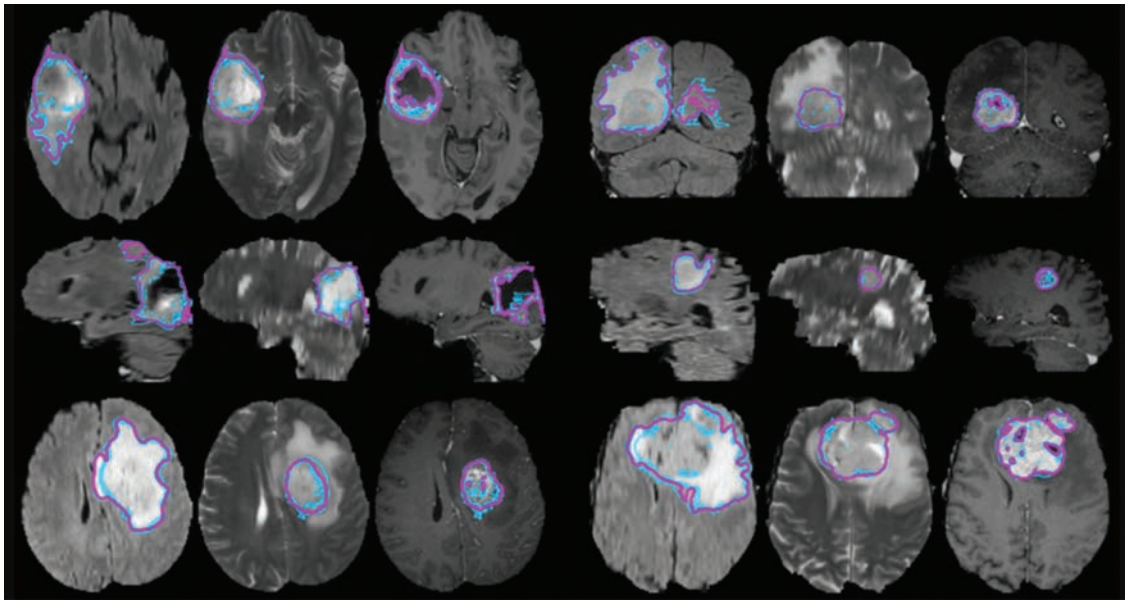

**Fig. 4.** MRI brain samples from BraTS dataset.

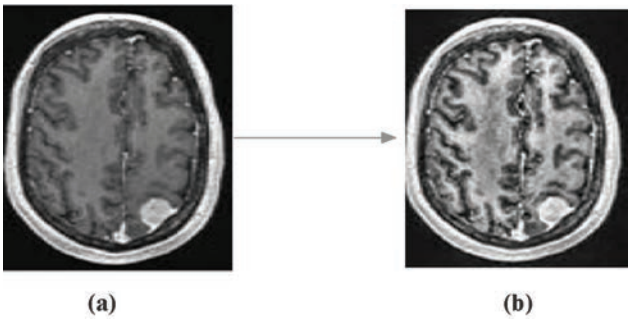


**Fig. 5.** (a) Original input (b) after the application of MGF.

and GLCM. Then, BSVM based classification is carried out for separating images under benign and malignant classes. When TCM comes into act, the size and shape of the segmented tumor image is measured. Specifically, in the given example, the size of the segmented image is measured as 5.6 mm. Based on that, the brain tumor comes under the categorization of Stage 3. Following, the appropriate treatment suggestions are provided to the medical practitioners for providing better treatments.

The suggested model's performance will be assessed in order to demonstrate its efficacy. The specificity, sensitivity, accuracy, precision, as well as recall of the findings are used to evaluate them. Additionally, comparative evaluations are made with the existing models such as SVM [9] and ANN [23]. The evaluated results based on the performance factors are portrayed in the Figure 10. The suggested framework produces a higher level of precision and accuracy than the comparative works, according to the research.

The Figure 11 displays the results of accuracy rates with respect to the compared works. Because of the effective utilization of image processing and soft computing techniques, higher

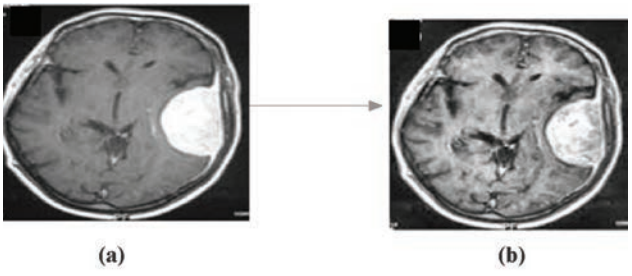


**Fig. 6.** (a) Original malignant tumor sample (b) filtered image.

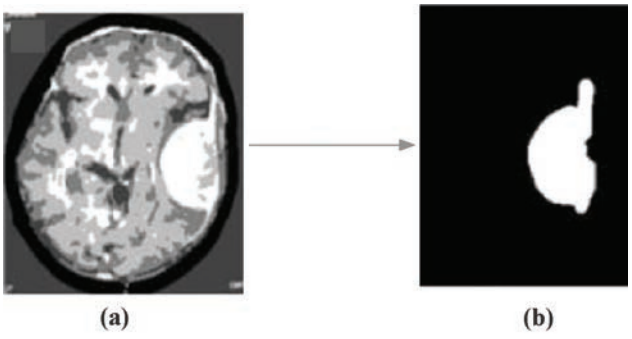


**Fig. 7.** (a) Malignant tumor image (b) image after segmentation.

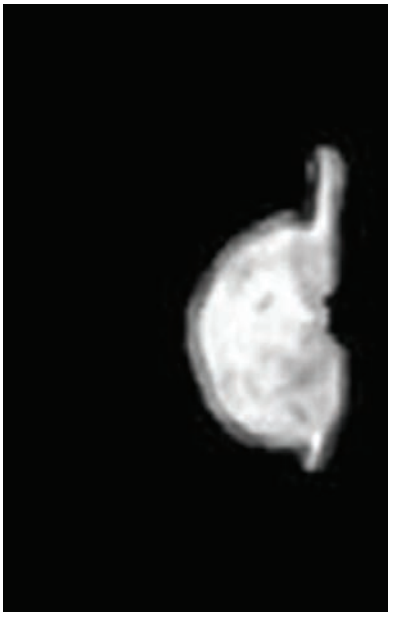

**Fig. 8.** Segmented brain tumor cells after region growing.

rate accuracy in tumor image classification and categorization is achieved in the proposed model. The proposed TCM attains 96.8% of accuracy in average with the effective accumulation of image enhancement and segmentation process.

While designing a tumor classification model, the processing time is to be significantly evaluated. Here, the BSVM classification model is used, in which the model reduced the computational complexities and processing time for training and testing

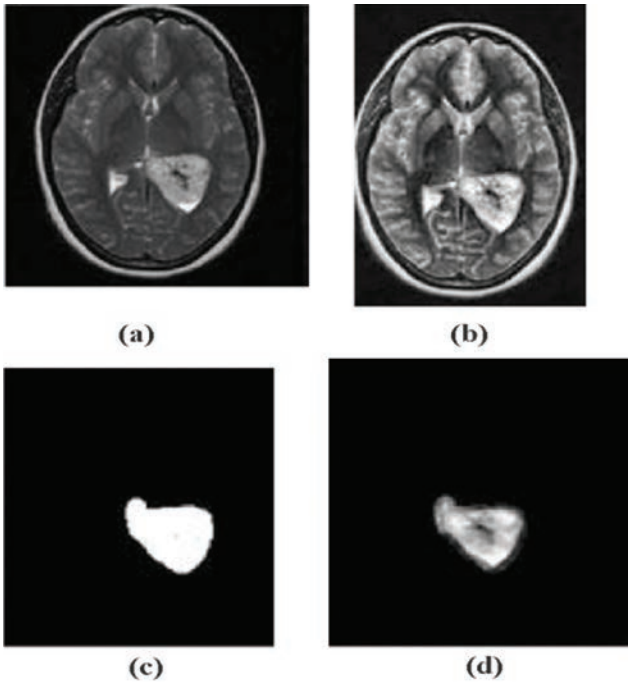


**Fig. 9.** Processing with BraTS brain image sample (a) source raw image (b) filtered image (C) segmented image (d) refined image.

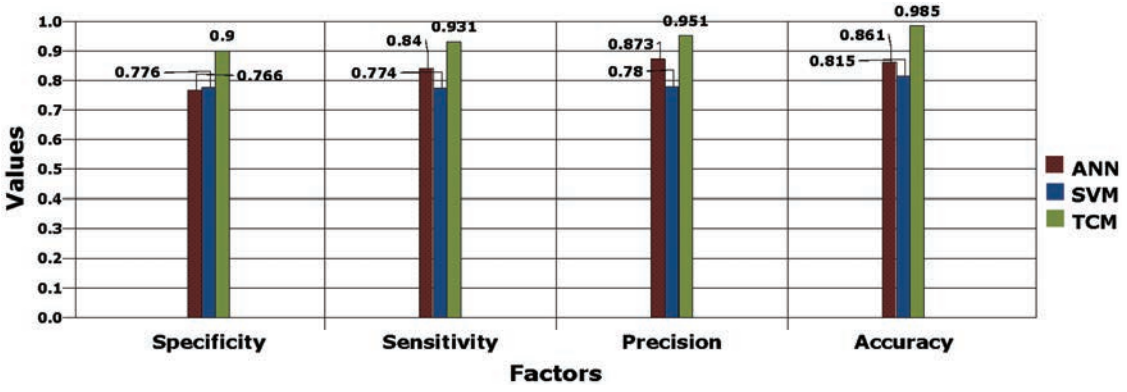


**Fig. 10.** Performance comparison based comparative evaluations.

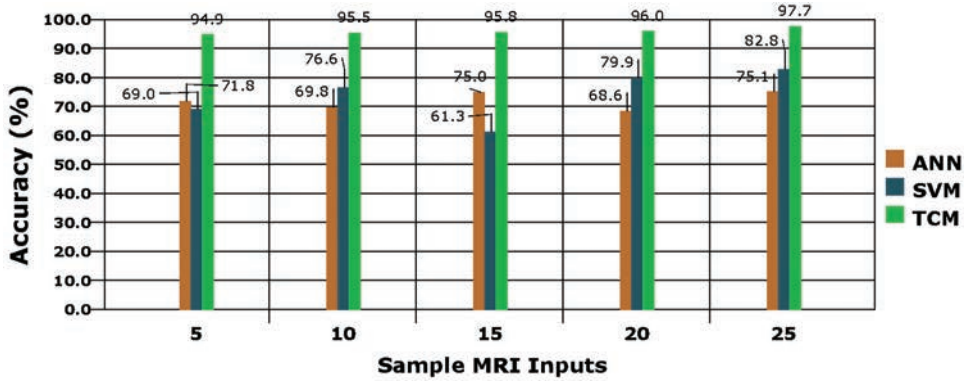


**Fig. 11.** Accuracy rate comparisons between models.

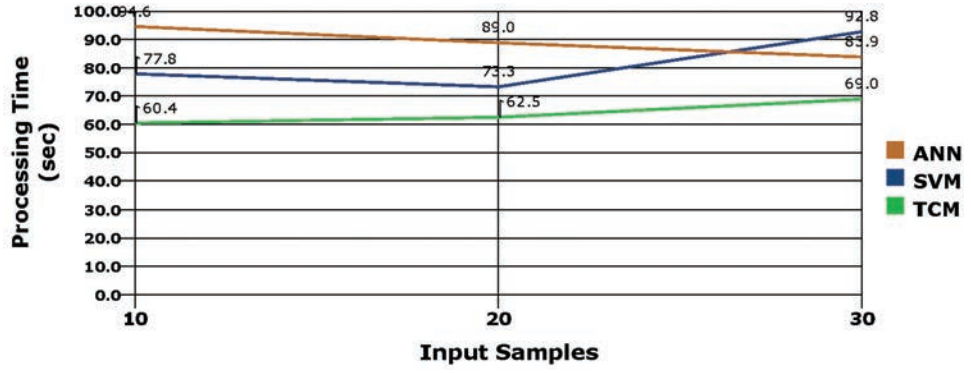


**Fig. 12.** Analysis with processing time.

brain samples in an effective manner. The evaluation results are plotted against the input samples, where the model takes more time when the number of samples to be processed is becoming higher. Comparably, the proposed model acquires minimal processing time than compared works as displayed in the Figure 12.

Here performance analyses of the proposed and existing methodologies are given based on processing time parameter. This investigation shows that the suggested TCM technique requires less processing time for brain cancer identification, whereas SVM and ANN require greater processing time.

## 5. CONCLUSION AND FUTURE WORK

In addition to the appropriate Brian Tumor Diagnosis and Classifications, the category of tumor or appropriate tumor state are also known to the medical practitioner for providing better services to save people lives. For that, a Tumor Categorization Model (TCM) with the effective incorporation of image processing and soft computing techniques is developed and evaluated in this paper. The model utilizes the Modified Gabor filter for removing additional noise. OTSU thresholding and region growing methods are used for exact segmentation of tumor tissue with appropriate marginal definitions. Further, feature extraction is carried out with two techniques called DET and GLCM

for deriving significant features for tumor image classification, which is processed with the BSVM based model. Additionally, the classified images are further given for measuring its size and shapes, to identify about the stages of tumor. Further, the model is evaluated using the images from two different benchmark datasets called DICOM and BraTS datasets and acquired solutions are contratsed with the present classification models. Based on comparisons, proposed TCM provides better rate of accuracy with lower processing time. The proposed TCM attains 96.8% of accuracy in average with the effective accumulation of image enhancement and segmentation process. In future, the work can be developed further by developing models for processing hyperspectral images with soft computing methodologies for forwarding the image processing research to the next levels in disease diagnosis.

## DECLARATIONS

### Ethical Complaints

Necessary ethical standards were maintained in this research study. All procedures were carried out in line with applicable laws and regulations.

### Funding Statement

For such a research, the author(s) did not receive any specific funding.

### Conflicts of Interest

The researchers assured that they also have no competing interests to declare in this work.

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