IMPROVED FUZZY C-MEANS USING ADAPTIVE THRESHOLD FILTERING FOR BRAIN TUMOUR DETECTION

[1]Tajinder Kaur, [2]Er.Meenakshi Sharma
[1]M.Tech Student, [2]Assistant Professor
[1]Department of Computer Science Engineering,
[1]Rayat group of Institutions, Railmajra, Punjab, INDIA.

***Abstract*:** The brain tumour extraction is the key area in the image processing paradigm, and particularly used to determine the location of the brain tumour in the brain scan images. The brain imagery includes the CT imaging, MRI imaging, X-Ray, etc, which are used as the target imagery to detect the tumour region in that scan imagery. The morphological textural analysis is performed primarily to localize the tumour regions in the target image, where different types of geodesic or morphological methods have been applied in the various research models. In this paper, the geodesic algorithms are used to determine the patterns in the image matrices, which are processed on the basis of geodesic pattern or textural analytics of image matrix. The proposed method uses fuzzy c-means (FCM) and discrete wavelet transform (DWT) to evaluate the images in different stages, particularly when the textural, residual textural, object based analysis, etc is performed, it is intended to return the more balanced and accurate results. In this paper, a more balanced and dynamic FCM method is developed, which uses the multiple factors to localize the tumour region in the target image, which is generally controlled by the 2-level decomposition of the image matrix using discrete wavelet transformation. The proposed model has learnt to outperform the existing models on the basis of accuracy based parameters.

***Index Terms*: Tumor detection , 3D blob detection, supervised classification, fuzzy-c Means .**

I. INTRODUCTION

We cannot underrate the importance of the medical profession in today's life because there seems to be a continuous advancement in the complexity and severity of many diagnosed medical disease. In this project, we will study microstructure data set of the brain tumour. Microstructure analysis is the study of the material to classify the materials using basic properties. In future, this project can be used for classification of various diseases in the medical field or to classify various elements (metals) based on their features. This work tries to develop a framework for the quantification of the brain tumour's structure, based on the concepts of fuzzy c-means (FCM) along with discrete wavelet transform (DWT) and support vector machine (SVM).

A brain tumour engages space inside the skull and can tamper with normal brain activity. It can accelerate pressure in the brain, shift the brain or drive it against the skull and harm nerves and healthy brain tissue. Brain tumours are an abnormal collection of masses within the brain. When most of the normal cells get aged or spoiled, they die, and new cells take their place. But Sometimes, this process goes wrong and new cells form even when it is not required, and aged or spoiled cells don't die as they should. These extra cells create a mass of tissue called the tumour. A Brain tumour is made up of cells that show unstrained growth inside the brain. For the detection of the tumour region, the computer vision based algorithms can be applied on the target images. The Appearance-based objectrecognition is a much easier approach. It's because the program utilizes a much less database that identifies general shapes and shades in order to match the object with a model. The algorithms measure the spectral frequency of the object's reflection to

find color since every color corresponds to a distinct frequency. Since this model correctly recognizes an object according to their shape and color, this is also able to cope with many variations due to the image formation process.

The impact of the medical imaging in healthcare is uniformly increasing. Diseases are identified beforehand and treatments become more effective. When its use is extended beyond the field of diagnostics, entering the fields of prevention and therapy, it can significantly add to reducing costs in healthcare across the world. Medical imaging indicates various distinct technologies that are used to see the human body in order to detect, observe, or treat medical conditions. Each type of method gives us different information about the area of the body being analyzed or operated, related to possible disease, injury, or the effectiveness of the medical procedure. We have different imaging technologies to identify the disease, the most commonly used are : MRI (Magnetic Resonance Imaging) and CT (Computed tomography) scanned images.

II. LITERATURE REVIEW

VeeraraghavanSundararaghavanet. al. [8] utilized a multi-class support vector machine classification 14 method in conjunction with principal component analysis to build a dynamic and evolving microstructure library that can be used to 15

efficiently describe single-phase polyhedral microstructures. Lower-orderd descriptors are initially used to associate the material 16 microstructure to classes of microstructures stored in a digital material library.**Stephen et. al. [9]** presented a novel microstructure quantification framework that facilitates the visualization of complex microstructure relationships, both within a material class and across multiple material classes. This framework, based on the stochastic process representation of microstructure, serves as a natural environment for developing relational statistical analyses, for establishing quantitative microstructure descriptors.**HongyiXuet. al. [10]**proposed a new machine learning-based method for identifying the key microstructure descriptors from vast candidates as potential microstructural design variables. With a large number of candidate microstructure descriptors collected from literature covering a wide range of microstructural material systems, a four-step machine learning-based method is developed to eliminate redundant microstructure descriptors via image analyses, to identify key microstructure descriptors based on structure–property data.**Brian et. al. [11]** proposed SVM for classification of microstructure data. The support vector machine (SVM) was trained to classify microstructures into one of seven groups with greater than 80% accuracy over 5-fold cross validation. In addition, the bag of visual features was implemented as the basis for a visual search engine that determines the best matches for a query image in a database of microstructures.**Xioaoet. al. [12]** proposed SVM method in this work. The Support Vector Machine (SVM) method is used to solve the inverse problem of parameters extraction.Yu, Chen-Ping et. al. [13] has worked on 3D blob based brain tumour detection and segmentation in MR images. The authors have presented a fully automatic, unsupervised algorithm that can detect single and multiple tumours from 3 to 28,079 mm3 in volume.Tarabalka, Yuliyaet. al. [14] has proposed Spatio-Temporal Video Segmentation With Shape Growth or Shrinkage Constraint. The authors have proposed a new method for joint segmentation of monotonously growing or shrinking shapes in a time sequence of noisy images.

I. EXPERIMENTAL DESIGN

The brain tumour detection using computer vision technique will be developed using a combination of various digital image processing techniques. The whole system will run in a series of steps mentioned in proposed design and i.e. Image acquisition, Feature Extraction and Recognition, Feature Positioning, and Harvesting. For the feature recognition and feature extraction, a blend of image segmentation using an effective plus novel image segmentation algorithm along with shape recognition algorithm can be used. The proposed automatic harvester will recognize the brain tumour in 2-D and 3-D vision. In 3-D space, the computer vision method will realize the depth of the object, whereas, in 2-D space, computer vision method will get the location of the brain tumour in the flat ground image of the MRI scanning with the particular positioning algorithm for the different color planes has been utilized.

The following algorithm explains the brain tumour detection model in the both 2-D and 3-D analysis models. The algorithm flow has been explained with detail in the following section:

Algorithm 1: Proposed brain tumour detection algorithm

Assumptions:

1.) All images are MRI images

2.) All images are clicked from a certain distance.

3.) All images are minimum medium or high resolution images.

Algorithm Flow:

1.) Image Acquisition

Load Image (filename) → I

2.) Shape Analysis

Shape (I) → shape Pos[][]

3.) Extract Shapes

Extract (I, shape Pos[][]) → I_O

4.) Color Analysis

Color (I_O, $C_{template}$) → detect Pos[][]

5.) Extract Objects

Extract (I_O, detect Pos[][]) → I_C

6.) Second level template based shape and color analysis

Extract (I_C, $C_{TEMPLATE}$, $S_{TEMPLATE}$) → I_{CS}

7.) Remove the unlike objects from the computer vision frame

RemoveUnlike (I_{CS}) → I_{RO}

8.) Calculate 2-D position

Distance (I_{RO}, 2d) →posArray[][]

9.) Calculate 3-D position

Distance (I, posArray[][]) →pos Array[][][]

10.) Return the marked regions in the 2-D and 3-D outfits

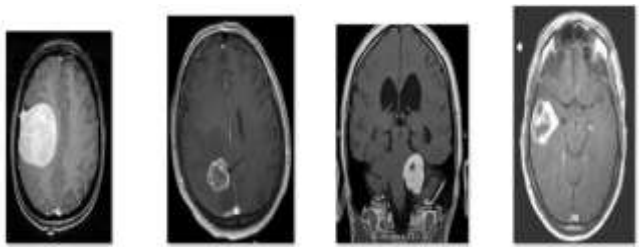
The proposed model utilizes the in-depth 3-D blob analysis with the SVM classification over the results obtained from the different color planes for the accuracy object localization and positioning for the tumour detection in the given MRI images. The proposed model finds the tumour regions in the input image by using the 3-D object localization model. The proposed model has been designed with the 2-D and 3-D analysis models for the tumour region classification based vector classification using the support vector machine (SVM) based classification between the testing and training data pre-saved for the tumour classification. The proposed model utilizes the vectorized feature vectors to evaluate the type of the detected tumour in the given image data. The probabilistic classification model is utilized under the proposed model in order to analyze the type of the brain tumour in the proposed model design. The algorithm design has been explained in the following algorithm:

Algorithm 2: Brain tumour classification using FFBNN algorithm

1. Load the testing image
2. Get the size of testing image
3. If original image depth is 2-D
    1. Convert the image to grayscale
    b. Apply 3-D blob analysis over the testing image for brain tumour detection
    c. Obtain the 2-D tumour regions from the target image
    d. Load the testing image
4. Else if image is 3-D
    a. Get the size of testing image
        1. Extract the input image in the color planes of red, green and blue
        2. Apply 3-D blob analysis over each of the plane in the testing image for brain tumour detection
        3. Obtain the tumour regions from the target image for the particular region
    b. Combine the brain tumour areas in all of the planes
    c. Return the tumour region after combining all of the results
5. Acquire the training data, which denotes the samples associated with the BENIGN and MALIGNANT tumours
6. Apply the SVM model between the training and testing data
7. Compute the probability of the matching and finalize the detection type
8. Return the decision logic containing the type of the tumour

II. RESULT ANLAYSIS

The simulation scenario is based upon the detection of Benign and Malignant tumour in the brain scans, where total of 11 Benign tumour samples and 12 Malignant tumour samples for the testing of the proposed model. Also, the classification model has been designed to analyze the target tumour regions, which based upon the supervised classification models. Some of the tumour image examples are shown in the following figure:



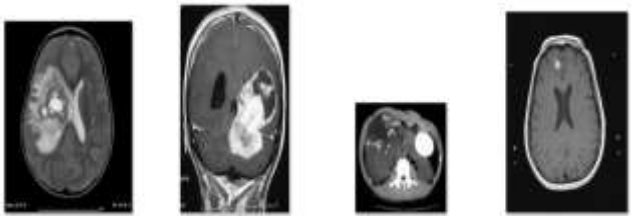


Figure 1: The benign and malignance brain tumour CT scan image examples used for the tumour detection model evaluation

The result analysis of the proposed model is based upon various parameters and visual presentation. The performance parameters of accuracy, time and other statistical methods are used to determine the overall performance of this tumour detection model. Some of the results the produced by the proposed model are observed and presented in this section.

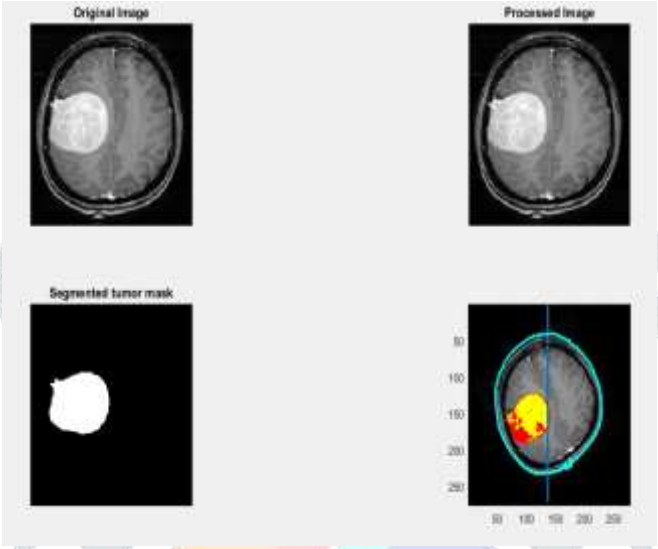


Figure 2: Detection of ordinary BENIGN tumour

The above image (Figure 2) shows the detection of a large benign tumour, which are generally detected well by almost all of the tumour detection methods. The tumour region is detected with perfection, and complete tumour region is accurately marked. The different colours in tumour representation mask (i.e. red and yellow colours) shows the confidence interval of the target pixel, where red is highly confident decision, which is followed by the yellow coloured pixel mask.

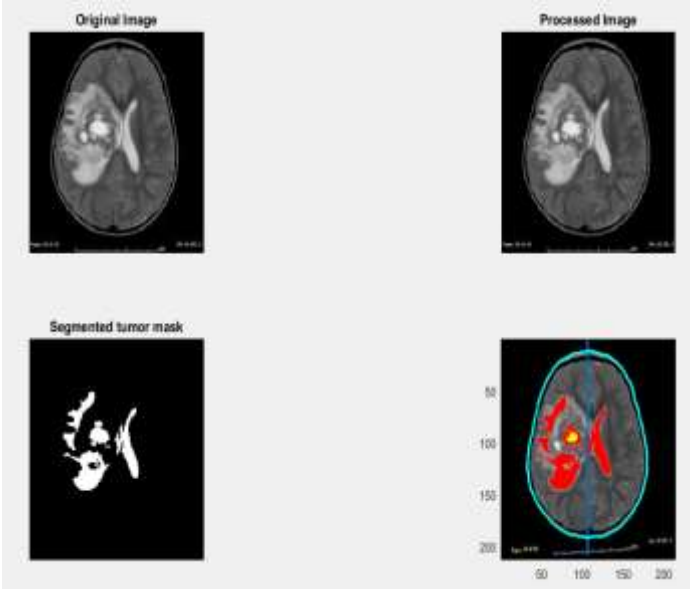


Figure 3: Detection of the MALINGNANT tumour

The figure 3 shows the results obtained for the testing of malignant tumours, which the tumour region is perfectly detected, and mostly marked as the high accuracy pixel detection and marked with red coloured mask. The proposed model is able detect the complex shape of the tumour with perfection, which is the result of multi-layered fuzzy c-means based evaluation for the

detection of the tumour regions. The following image shows the detection of medium sized malignant tumour, which is evident from the high confidence of region detection. The proposed model is capable of detecting all the regions of the tumour region.

The time based analysis has been performed over the proposed model, which is considered the critical factor for the image processing applications. In the time based analysis, per image time is recorded for both Benign and Malignant tumour images for the tumour detection and classification. The following tables (Table 5.1 & 5.2) are showing the detection time and classification time for both types of tumour detection and classification.

Table 1: Benign and Malignant based time analysis for detection and classification time

Image Index	Benign Detection Time	Benign Classification Time	Malignant Detection Time	Malignant Classification Time
1	0.062446293	0.029724712	0.060250423	0.029804952
2	0.051697869	0.031829611	0.052963514	0.029596887
3	0.052920129	0.031928045	0.054454018	0.030966099
4	0.067797179	0.036567502	0.05437891	0.029802619
5	0.05477078	0.02969812	0.054551519	0.029877727
6	0.05261503	0.029642139	0.054859883	0.028840672
7	0.05181403	0.029138773	0.054387307	0.029824079
8	0.051698335	0.02907906	0.054583708	0.030681993
9	0.058320465	0.031226879	0.057245156	0.031014616
10	0.053884874	0.029221812	0.053019962	0.029438274
11	0.054561782	0.03118256	0.05172446	0.029418214
AVERAGE	0.055684251	0.030839928	0.054529399	0.029861983

In table 1, the detection time and classification time for the Benign tumour is enlisted, where the average detection time is observed at 0.056 seconds, which is very quick time for the image analysis. This is followed by the 0.031 seconds for classification, which is again a very small time for the purpose of classification and shows the effectiveness of the proposed model. In table 1, the detection time and classification time for the Malignant tumour is observed, where the mean time for detection of tumour is recorded at 0.055 seconds, which is very quick time for the image analysis, and slightly faster than Benign tumour detection time. This is followed by the 0.030 seconds for classification, which is again a very small time for the purpose of classification and shows the effectiveness of the proposed model.

The tumour regions are detected using the pattern and texture based improved fuzzy c-means (FCM) method and its infusion with discrete wavelet transformation (DWT) for the detection. The features shown in the tables below, describes the different aspects of the tumour region, which is detected using the proposed methodology. The following definitions explain each of the term individually:

Mean: The mean value of the tumour region is computed over all of the pixel values of the tumour containing pixels, which is generalized by the averaging equation in the terms of mean value.

Standard Deviation: The standard deviation shows the distribution of the pixels containing the tumour region, which is elaborated in the form of its spread over a 2-D plane, and in accordance with their magnitude and pointed density.

Entropy: The entropy value computes the uniqueness of the pixels in the target region, which is generally given by the number of similar pixels over total pixels. The entropy values are considered higher, if recorded with value greater than 1. In case, the entropy value is greater than 2 or 3, it shows higher order of uniqueness. The uniqueness may be caused by slightly different values also, because entropy value considers exactly similar pixels.

Smoothness: The smoothness is the parameter to define the average similarity between the pixels from one direction to another direction, which shows the presence of the image gradient. The higher smoothness shows the highly effective regions in the images.

Table 2: Benign based statistical analysis

Image Index	Mean	Standard Deviation	Entropy	Smoothness
1	0.00341	0.08974987	2.99489	0.92696676
2	0.00311	0.08976082	3.17345	0.92045693

3	0.00235	0.08978391	3.26982	0.89742184
4	0.00324	0.08975615	3.57972	0.92344692
5	0.00251	0.08977964	3.31556	0.90324602
6	0.00206	0.08979090	3.51816	0.88496933
7	0.00193	0.08979394	2.66316	0.87784469
8	0.00193	0.08979377	3.65492	0.87825988
9	0.00253	0.08977899	3.07564	0.90404672
10	0.00352	0.08974558	3.15619	0.92910670
11	0.00068	0.08981209	2.74648	0.71863648

The maximum mean value of the pixels is observed at 0.00068 and 0.00352 respectively, which is considered adequately lower to define the efficiency of the target model, which is also evident from the standard deviation value of approx. 0.089 for all of the images. The entropy is consistently greater than value of 2, which makes it highly effective and dense distribution. The maximum mean value of the pixels is observed at 0.001 and 0.003 respectively, which is considered adequately lower to define the efficiency of the target model, which is also evident from the standard deviation value of approx. 0.090 for all of the malignant tumour images, however it's slightly higher than benign tumour, which is due to the multi-part and multi-scale presence of the malignant tumours.. The entropy is consistently greater than value of 2, which makes it highly effective and dense distribution.

III. COMPARATIVE ANALYSIS

The proposed model has been compared to the existing fuzzy c-means (FCM) with k-means clustering based model for the detection of the tumour region in both malignant and benign formations. The proposed model is observed higher by more than 1% for the overall detection accuracy. The proposed model based upon fuzzy c-means algorithm (FCM) combined with discrete wavelet transformation (DWT) and support vector machine (SVM) is observed with 96.50% overall accuracy in comparison with existing model's 94.60% observation.

Table 3: Comparison of proposed model with FCM & K-means based method

TECHNIQUE	**OVERALL DETECTION ACCURACY**
FCM with K-means [23]	**94.60%**
Proposed	**96.50%**

The proposed model is also compared against another tumour detection model, which is known as 3D blob detection method. The proposed model is also based upon the 3D tumour detection, hence also compared against one 3D tumour detection method. In this comparison, the proposed model is observed with higher precision, recall and overall detection accuracy, which makes it most efficient mechanism.

Table 4: Comparison of the proposed model with 3D blob detection model

PERFORMANCE EVALUATION PARAMETER	PROPOSED MODEL	3-D BILATERAL BLOB DETECTION
Precision	**95.08%**	35.79%
Recall	**96.10%**	92.55%
Detection Rate (Accuracy)	**96.50%**	51.61%

The proposed model is observed with 95.08% precision, which is significantly higher than the 35.79% of the existing model, whereas the recall value shows the slight improvement in comparison with existing model's 92.55% observation. However, the

detection rate is considerably higher than existing model (51.61%) in proposed model (96.50%), which shows the robustness of the proposed model.

IV. CONCLUSION

It can be concluded that the main purpose of this project is to develop a method to detect brain tumour which operates in the same order of work of a doctor, examining his experience and knowledge. This approach successfully extracted features of a tumour from MRI images. This method was developed using FCM and DWT. FCM was used to extract basic features of tumour and DWT-FCM is used to extract the type of tumour. This research presents a step-by-step detection of MRI brain tumour segmentation and classification.The research work further presented a unique algorithm for segmentation and classification of brain tumours. In this method, preprocessing was done extracting texture features like Contrast, Correlation, Energy, Homogeneity, Mean, Standard_Deviation, and Entropy using the PCA method. The extracted features are then given to the FFBNN classifier. Using this algorithm one could segment the brain tumours accurately from an MR brain image. This algorithm was also used to classify the tumours into benign and malignant.Finally based on the analysis it has been found that the overall accuracy of classification is above 90%.

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