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Brain Tumor Detection and Segmentation Using Nobel Approach of Soft Computing

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Abstract- These days one of the major concerns for human life is the disease of cancer. The growth of cancer patients is increasing day by day. There are many reasons behind the cause. There are two different kinds of brain tumors which are benign type and malignant type. Benign tumor feature is that it increase in size very slowly and do not spread to neighboring tissues while malignant tumors increase is size very fast and possibly spread to other nearby organs. For treatment of brain tumors different methods are used like radiotherapy, chemotherapy and many more. Treatment of brain tumor is dependent on accurate detection, type, age, location, size and experience of physician. In the present proposed work an intelligent system is designed with the use of soft computing techniques to automatically detect brain tumor present in the human brain. The proposed technique will filter the input image and then segments the image. After this process different features are extracted to find whether the tumor is present or not in this image. The proposed technique will be compared with other well known technique to find the worthiness of proposed brain tumor detection technique.

Keywords- Brain tumor, segmentation, soft computing, magnetic resonance imaging, accuracy, image processing.

I. INTRODUCTION

Medical image processing is one of the core areas of digital image processing. Medical images are of various typed from dicom to tiff and many more. Brain tumor is an undesirable growing of a network of fibre in brain. Long effect of brain tumor can slow down the proper functioning of brain. Usually magnetic resonance imaging technique is used to grab pictures of brain tumor. So there is need of an effective technique of segregating MR brain digital images into either normal or abnormal which were altered due to tumor.

Image segmentation involves manually or automatically partitioning the image into a set of relatively homogeneous regions with similar properties, each of which can be tagged with a single label. In order to search for the lesions perfectly usually the surgeons use the various segmentation techniques.

When we use manual tumor image segmentation then tumors are searched in various regions of the image on all the slices and this make it quite costly as well as time consuming process. [4] Soft computing techniques are a group of methodologies that is meant to handle real life problems by using analytical and reasoning capacity. These tools are emerging as a promising help in different areas of science and technology like image processing, pattern recognition, in data clustering, in medical diagnosis etc. and many more. Some of the well known soft computing techniques are neural networks and fuzzy logic, support vector machines, evolutionary algorithms. In the present research a new segmentation techniques is proposed to find location of brain tumor in MR digital images.

II. LITERATURE SURVEY

A. S. Methil et al. [1] in 2021 proposed a brain tumor detection method which was relied on the deep learning and on the digital image processing methods. Author first performed some preprocessing methods of digital image processing like histogram equalization and opening. After this step authors used a convolutional neural network model for training purposes.

Author used various digital images which were different in shape, size, and texture as well as in location of tumor. Total number of images in the dataset was around 4000 which had more than 3200 tumor images and other was non tumor digital images. Author got 99 percent accuracy in the training phase and got near by 100 percent accuracy in testing the model on the dataset.

G. Raut et al. [2] in 2020 used deep learning method for detection as well as segmentation of brain tumor in the magnetic resonance digital images. Author created convolutional neural network model for prediction of brain tumor in the sample digital images. Author trained the model on the dataset to predict images as normal or had tumor.

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Further author used autoencoders which helped in removing the unwanted details from the images. Author used well known K-means method for image segmentation. Author used Kaggle dataset which had around 250 images. Author was able to get 95 percent accuracy from the proposed technique.

G. Hemanth et al. [3] in 2019 proposed a brain tumor detection approach using machine learning approach. Author used a convolutional neural network. Author divided the complete process in different stages like pre-processing, bilateral filtering, pixel relied segmentation, feature extraction, classification with the help of CNN approach, identification of tumor.

Author compared the proposed method with the well known techniques support vector machine, conditional random field and genetic algorithm. Author technique was able to beat the other techniques in terms of efficiency and in accuracy.

B. Devkota et al. [4] in 2018 proposed a computer aided detection approach to diagnose brain tumor in its early stage. Author used the well known Mathematical Morphological Reconstruction (MMR) method for it. First of all digital images were pre-processed to remove unwanted noise and other irrelevant materials. Then author segmented to search for the regions of interest with probable tumor.

Features reduction was done with the help of well known method principal component analysis. Classification was performed with the help of Support Experimental results showed that the segmented images had a good accuracy.

Proposed model detected the cancer with 92 percent accuracy which was higher and classifier had accuracy of 86.6%. Author showed that the proposed solution could be utilized to diagnose brain tumor in patients.

III. METHODOLOGY AND PROPOSED ALGORITHM

In this section research methodology and the proposed algorithm steps are discussed.

1. Methodology:
The following strategy will be followed to get the desired results.

- **Step 1:** Study and analyze different existing tumor detection and segmentation algorithms
- **Step 2:** Use of Discrete Wavelet Transform (DWT) and Discrete Cosine Transform (DCT), Support Vector Machine (SVM) for feature extraction.
- **Step 3:** Study the classification of various tumors
- **Step 4:** Reliable and accurate segmentation of brain tumors were achieved.

2. Proposed Algorithm:

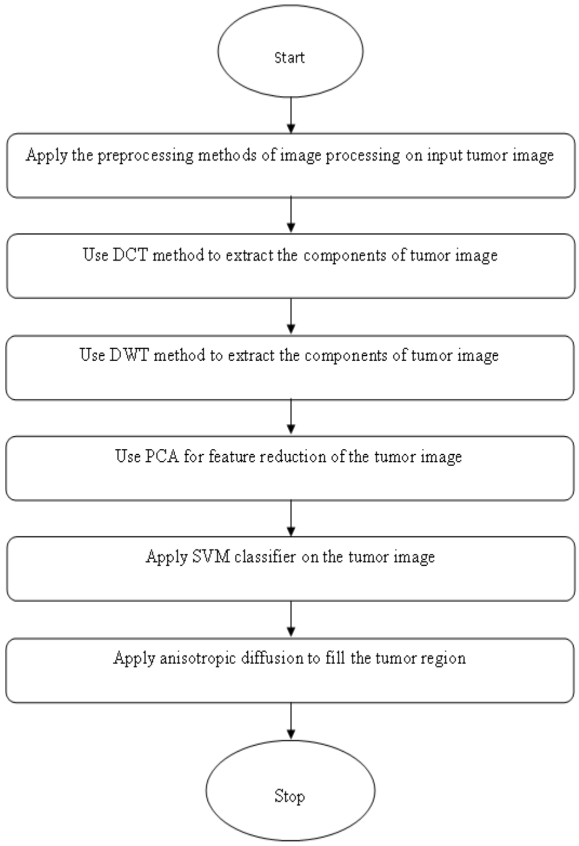


Fig 1. Proposed Algorithm.

IV. OBJECTIVE PARAMETERS

Seven different objective parameters are used for the performance measurement of the proposed algorithm.

1. Peak Signal to Noise Ratio (PSNR):

$$\text{PSNR} = 10\log_{10}\frac{255^2}{MSE}$$

The value of Peak Signal to Noise Ratio should be high that signifies that the data available in the output image is more while the unwanted information which is also known as noise is very less.

2. Mean Square Error (MSE):

$$\text{MSE} = \frac{1}{MN}\sum_{j=1}^{M}\sum_{k=1}^{N}\left(x_{j,k} - x'_{j,k}\right)^2$$

Where, M and N are rows and columns, respectively of the image. $x_{j,k}$ is input digital image and $x'_{j,k}$ is the corresponding output digital image.

The MSE should be very low which signifies that the pixel value of the input as well as output digital image should be as fine as possible.

3. Correlation:
The cost of each and every pixel in a correlated digital image is a parameter which of how close the output digital image matches with the input digital image at that point.

4. Entropy:

$$\textbf{Entropy} = -\sum_{s=1}^{256} h(s) \times \log_2 h(s)$$

Where, *h(s)* is the normalized histogram of the output digtial image. This parameter is utilized to explore the content strength present in the digital image.

5. Precision:

$$Precision = \frac{True \quad Positive}{True \quad Positive + False \quad Positive}$$

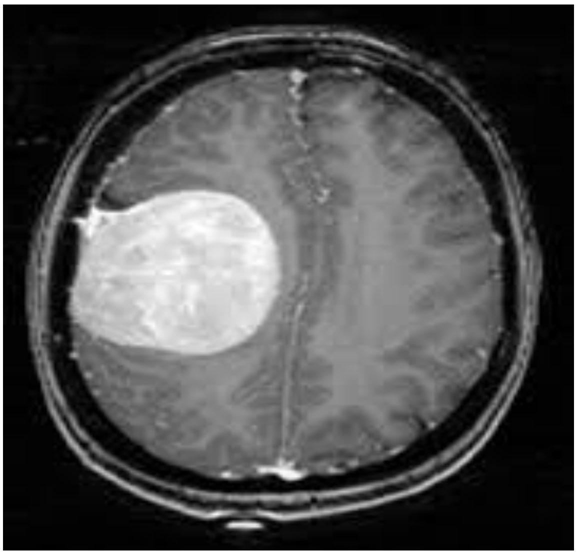
6. Recall:

$$Recall = \frac{True \quad Positive}{True \quad Positive + False \quad Negative}$$

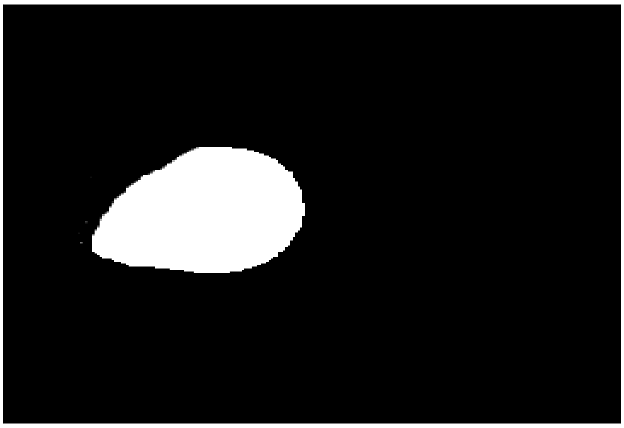
7. F1 Score:

$$F1 \quad Measure = 2 \quad X \quad \frac{precision \ X \ recall}{Precision + recall}$$

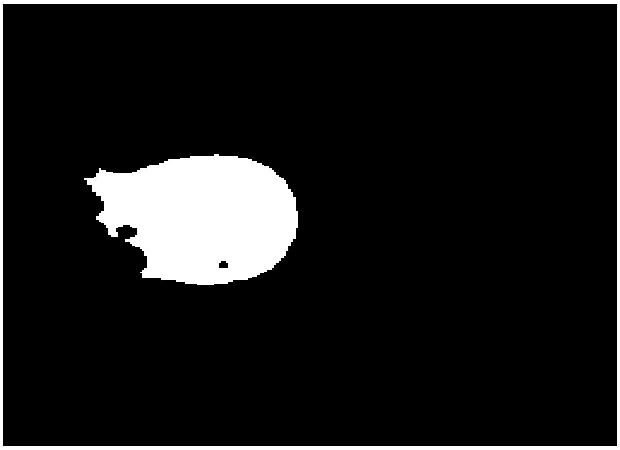
V. RESULTS



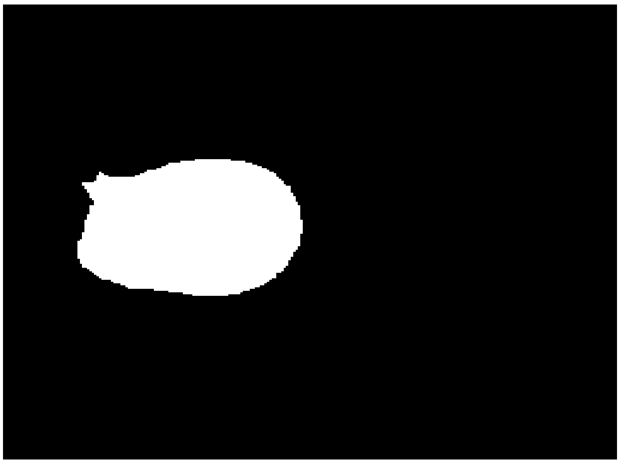
(a) Original.



(b) Filtered by DWT.



(c) Filtered by DCT.



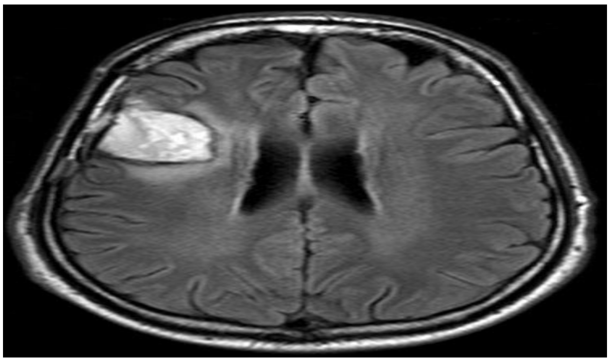
(d) Filtered by Proposed Technique.
Fig 2. (a, b, c, d): Original and processed filtered images of MRI Tumor 1.

Fig 4.1 (a) is the original input image. Fig 4.1 (b) is the image received after applying Discrete Wavelet Technique (DWT) on the original image. Fig 4.1 (c) is the image obtained by applying Discrete Cosine Transform (DCT) on the original image. Fig 4.1 (d) is the image obtained by applying proposed tumor detection technique on the original tumor image.

Table 1. Objective parametric values of above images of tumor 1

	DWT	DCT	Proposed
RMSE	.4152	.4027	.3581
PSNR	.38	.44	.48
Correlation	.092	.2248	.2427
Entropy	1.2	2.1	2.4

Outcomes of above Table 4.1 revealed that value of objective parameter root mean square error for the proposed method is less in comparison to DWT and DCT methods. While values of peak signal to noise ratio, correlation, and entropy have maximum in case of the proposed method in contrast to DWT and DCT methods.



(a) Original.

(b) Filtered by DWT.

(c) Filtered by DCT.

(d) Filtered by Proposed Technique.

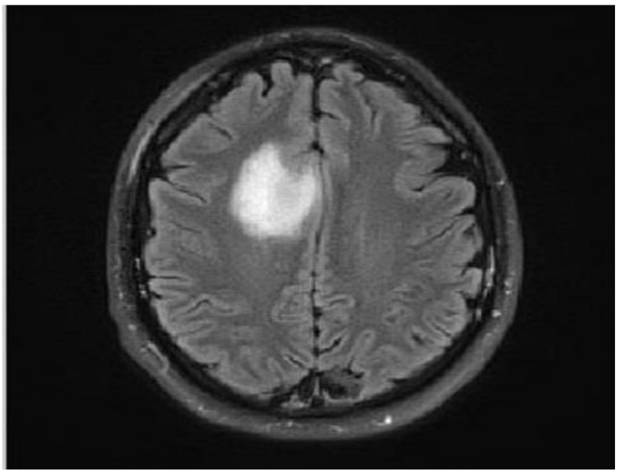
Fig 3. (a, b, c, d): Original and processed filtered images of MRI Tumor 2.

Fig 4.2 (a) is the original input image. Fig 4.2 (b) is the image received after applying Discrete Wavelet Technique (DWT). Fig 4.2 (c) is the image obtained by applying Discrete Cosine Transform (DCT) and Fig 4.2 (d) is image obtained by applying proposed tumor detection technique.

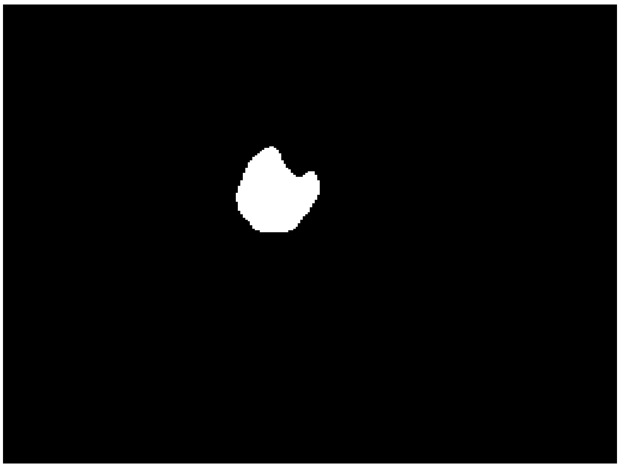
Table 2. Objective parametric values of above images of tumor 2.

	DWT	DCT	Proposed
RMSE	.32	.20	.15
PSNR	.41	.52	.58
Correlation	.20	.28	.42
Entropy	1.3	2.3	2.5

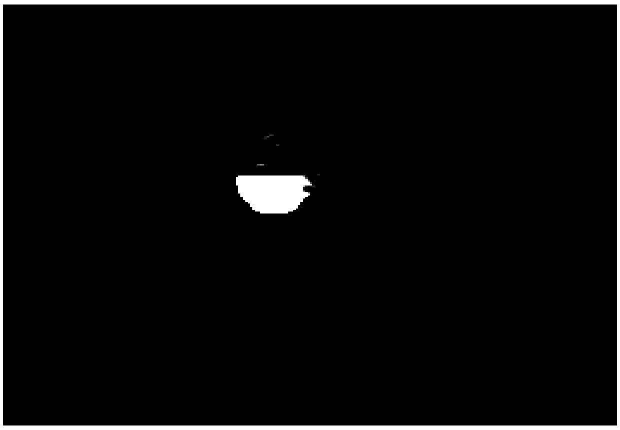
Outcomes of above Table 4.2 revealed that value of objective parameter root mean square error for the proposed method is less in comparison to DWT and DCT methods. While peak signal to noise ratio, correlation, and entropy have maximum in case of the proposed method.



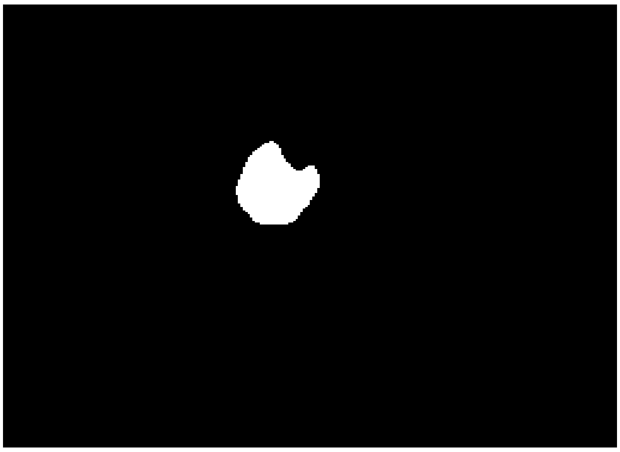
(a) Original.



b) Filtered by DWT.



(c) Filtered by DCT.



(d) Filtered by Proposed Technique.

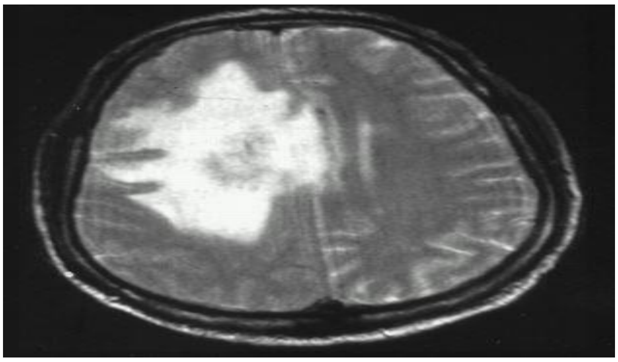
Fig 4. (a, b, c, d): Original and processed filtered images of MRI Tumor 3.

Fig 4.3 (a) is the original input image. Fig 4.3 (b) is the image received after applying Discrete Wavelet Technique (DWT) on the original image. Fig 4.3 (c) is the image obtained by applying Discrete Cosine Transform (DCT) on the original image. Fig 4.3 (d) is the image obtained by applying proposed tumor detection technique on the original tumor image.

Table 3. Objective parametric values of above images of tumor 3.

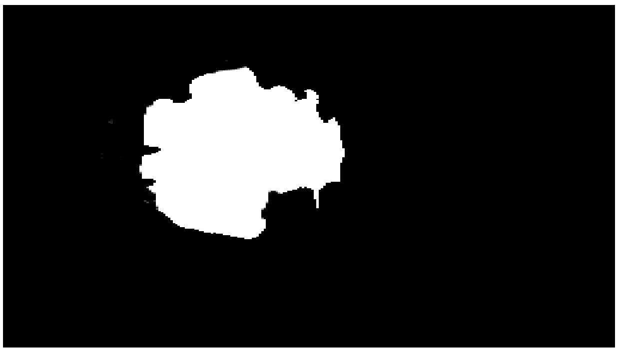
	DWT	DCT	Proposed
RMSE	.42	.30	.21
PSNR	.47	.54	.56
Correlation	.31	.34	.37
Entropy	1.5	2.7	2.9

Outcomes of above Table 4.23 revealed that value of objective parameter root mean square error for the proposed method is less in comparison to DWT and DCT methods. While values of peak signal to noise ratio, correlation, and entropy have maximum in case of the proposed method in contrast to DWT and DCT methods.



(a) Original.

(b) Filtered by DWT.



(c) Filtered by DCT.

(d) Filtered by Proposed Technique.

Fig 5. (a, b, c, d): Original and processed filtered images of MRI Tumor 4.

Fig 4.4 (a) is the original input image. Fig 4.4 (b) is the image received after applying Discrete Wavelet Technique (DWT) on the original image. Fig 4.4 (c) is the image obtained by applying Discrete Cosine Transform (DCT) on the original image. Fig 4.4 (d) is the image obtained by applying proposed tumor detection technique on the original tumor image.

Table 4. Objective parametric values of above images of tumor 4,

	DWT	DCT	Proposed
RMSE	.53	.40	.31
PSNR	.61	.64	.71
Correlation	.31	.38	.43
Entropy	1.4	2.4	2.7

Outcomes of above Table 4.4 revealed that value of objective parameter root mean square error for the proposed method is less in comparison to DWT and DCT methods. While values of peak signal to noise ratio, correlation, and entropy have maximum in case of the proposed method in contrast to DWT and DCT methods.

Table 5. Characteristics of the labeled training set and test set.

Database	Classes	Total Images	Tumor Images	Rest Images
1	2	200	160	40

Table 6. Result obtained on the test set by DWT method.

TP	FN	TN	FP	Precision	Recall	F1 Measure
135	30	8	27	0.83	0.82	0.82

Table 7. Result obtained on the test set by DCT method.

TP	FN	TN	FP	Precision	Recall	F1 Measure
130	35		30	0.81	0.79	0.80

Table 8. Result obtained on the test set by proposed method.

TP	FN	TN	FP	Precision	Recall	F1 Measure
140	25	15	20	0.88	0.85	0.86

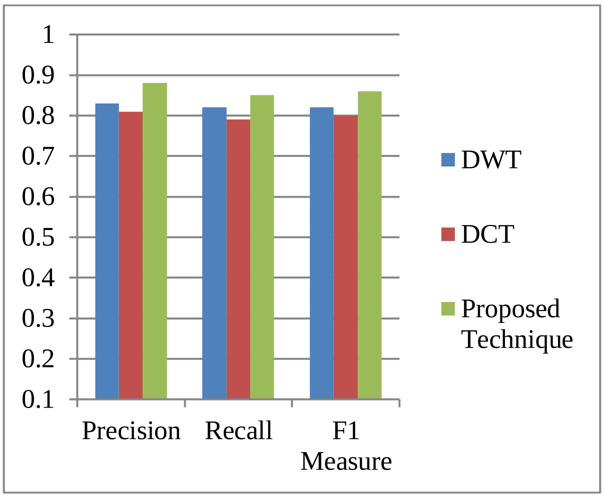


Fig 6. Graph of precision, recall and F1 score of DWT DCT and Proposed techniques.

VI. CONCLUSIONS

From the results it is cleared that the proposed technique performed better in comparison to other techniques. Value of mean square error is always less in case of proposed technique in contrast to discrete wavelet transform and discrete cosine transform techniques.

While values of peak signal to noise ratio, correlation, entropy is always higher for proposed technique in comparison to other techniques. The proposed technique has sharp edges for the tumor boundaries in comparison to other techniques.

In the future work various other known technique can also be utilized to make a detailed comparison with the proposed method. Various other objective parameters for performance evaluation can also be taken for comparison purposes and algorithm can be improved further to get the more accurate results.

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