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An Automatic Segmentation of Brain Tumor from MRI Scans through Wavelet Transformations

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***Abstract*—**Fully automatic brain tumor detection is one of the critical tasks in medical image processing. The proposed study discusses the tumor segmentation process by means of wavelet transformation and clustering technique. Initially, MRI brain images are preprocessed by various wavelet transformations to sharpen the images and enhance the tumor region. This helps to quicken the clustering technique since tumor region appears good in sharpened CSF region. Finally, a wavelet decomposition method is applied in CSF region and extracts the tumor portion. This proposed method analyzes the performance of various wavelet types such as Haar, Daubechies **(**db1, db2, db3, db4 and db5), Coiflet, Morlet and Symlet in MRI scans. Experiments with the proposed method were done on 5 volume datasets collected from the popular brain tumor pools are BRATS2012 and whole brain atlas. The quantitative measures of results were compared using the metrics false alarm (FA) and missed alarm (MA). The results demonstrate that the proposed method obtaining better performance in the terms of both quantity and visual appearance.

***Index Terms*—**Clustering, K-means, Segmentation, Tumor, Wavelet.

I. Introduction

Image segmentation is a vital method for most medical image analysis tasks. In the field of medicine, good segmentations will help clinicians as they provide vital information for 2-D visualization, surgical planning and early disease recognition. The diagnosis of human being has been improved significantly with the arrival of medical imaging techniques such as Computed Tomography (CT), Positron Emission Tomography (PET), and Magnetic Resonance Imaging (MRI) [1]. Medical imaging provides a reliable source of information of the human body to the clinician in fields like reparative surgery, radiotherapy treatment planning, stereotactic neurosurgery etc. Radiologists use these images for the visualization of the internal structure of the body. In general, MRI creates pictures that can show differences between healthy and unhealthy tissues and safe scanning modality [2].

Brain tumors are abnormal and uncontrolled proliferations of cells. Some originate in the brain itself, in which case they are termed as primary. Others spread to this location from somewhere else in the body through metastasis and it is termed as secondary. Primary brain tumors do not spread to other body sites, and can be malignant or benign. Secondary brain tumors are always malignant. Both types are potentially disabling and life threatening. Because the space inside the skull is limited, their growth increases intracranial pressure, and may cause edema, reduced blood flow, and displacement, with consequent degeneration of healthy tissue that controls vital functions [3].

This proposed method introduces High-Pass-Sharpening (HSP) process using wavelet transformation. Initially the images are decomposed into four different sections (LL, LH, HL and HH) by wavelet transformations. These four sections are carefully processed by HSP process and produce the sharpen version of the input image. The sharpened image has high contrast among the normal and abnormal regions of the image. This quickens the k-means clustering technique since tumor region appears good in sharpened image region. Finally the wavelet decomposition method is applied in clustered region. This proposed method gives satisfied results for extracting the tumor region in MRI brain images.

The proposed method organized as follows. The section II describes the literature survey. The methods used for this work are explained in section III, and the proposed method is explained in section IV. The results and discussion are given in section V and conclusion is given in section VI.

II. Related Works

Nowadays, many approaches have been developed to brain tumor detection and quantification. Somasundaram and Kalaiselvi proposed an automatic method to analyze the MRI head scans and detect abnormality in brain due to tumors [4]. This method consists of three stages: brain extraction algorithm, transformation and fuzzy symmetric analyzing. This method used two measures: false alarm (FA) and missed alarm (MA) to quantify the performance of the method. This method is purely based on intensity and is applicable to MR images with single mass effect present within MRI brain tumor images.

Ali et al., proposed the tumor detection method used wavelet transformation and K-means algorithm [5]. The wavelet transformation is not sufficient to produce a good result for the brain tumor detection. K-means clustering method gives the good results from different classes in MRI images. The statistical feature, entropy is used for the normal and abnormal part of the brain for different types of images. Kole and Halder proposed a very simple method for the tumor cells detection from MRI brain images based on intensity and symmetry based features for both tumor and healthy tissue [6]. Ada boost technique can be used for selecting the discriminative features to classify the normal and abnormal tissue.

John proposed an efficient method of classifying MR brain images into normal, benign and malignant tumor [7]. The proposed method follows three steps, wavelet decomposition, textural feature extraction and classification. Discrete Wavelet Transform used to texture statistics obtained from five level of decomposition using Daubechies (db4) wavelet. The gray level co-occurrence matrix and texture statistics are fed into a probabilistic neural network for further classification and tumor detection. Ahmed et al., proposed a hybrid technique for brain tumor detection by Discrete Wavelet Transform (DWT) using DAUB-4 Wavelet, Principle Component Analysis (PCA) and Support Vector Machine (SVM) [8]. DAUB-4 wavelet used for better contrast and gives support to easily handling signals of an image. This proposed approach used wavelet for contrast enhancement of the input images only.

EL-Dahshan et al., reviewed current studies of the different segmentation, feature extraction, and classification algorithms [9]. This segmentation method consists of six stages namely, preprocessing, feed-back pulse coupled neural network (FPCNN) for segmentation, discrete wavelet transform (DWT) for feature extraction, principal component analysis (PCA) for dimensional reduction and artificial neural network (ANN) for classification. Porwik and Lisowska proposed a method for image processing based on the continuous or discrete image transforms [10]. The Haar functions are the simplest wavelets. It also presents a method of image analysis by means of the wavelets Haar spectrum. Some properties of the Haar and wavelets spectrum were investigated, to compare the wavelets and the Haar functions in two–dimensional space and the decomposition levels for both the Haar matrix based method and wavelets. Gavlasov et al., proposed a method using wavelet transform for feature extraction associated with image pixels and their classification in comparison with the watershed transform. Haar Wavelet is used for feature extraction in MRI images [11]. Anam Mustaqeem et al., proposed an efficient brain tumor detection algorithm by using watershed segmentation, thresholding and morphological operators. This method provided satisfied results in MRI brain images and thus locating the tumor in images [12].

III. METRIALS AND METHODS

A. Materials

Our proposed method used 5 volumes of the datasets from BRATS2012 [13] and Whole Brain Atlas (WBA) [14]. The different set of input medical images such as MRI considered for experimentation. The T2-weighted images in BRATS2012 database were using MR scanners from different vendors with different field strength as 1.5T and 3T, axial 2D acquisition, with 2-6mm slice thickness.

B. Discrete Wavelet Transform

In the family of transforms, Discrete Cosine Transform (DCT) is the most popular choice for image compression because of several advantages. However, DCT has performance limitations such as blocking artifacts at very low bit rates. The Discrete Fourier Transform (DFT) is a mathematical transform operation that converts digital signal form the spatial or temporal domain to the frequency domain. The signal is expressed as a set of coefficient which is factor of known sinusoidal components. The Discrete Wavelet Transformation (DWT) is similar to the DFT as both express the original signal as a combination of simpler signal called basic function [15]. Unlike DCT and DFT, which use sinusoidal waves as basic functions, wavelet transform use small waves of varying frequency and of limited extent, known as wavelets as basis [16].

In DWT, basis functions are 'small' varying frequency with limited duration. DWT has the added advantages over the DFT that it can analyze the signal at different resolution. It deals with on approximation coefficient and detail coefficient. This is similar to passing the signal through several band-pass filters. The decomposition of the signal into different frequency bands is obtained by successive low-pass and high-pass filtering of the signal and down sampling the signal after each filters. After the image to be decomposed through wavelet, it has four parts are shown in Fig.1. DWT can be executed in multilevel. The data matrix used in each level is the approximation matrix generated in the previous level. In 2D wavelet decomposition, the wavelet transforms can be applied again on the lowpass-lowpass (LL) version of the image, yielding seven sub images [17]. Hence N level decomposition in 2D cases resulting in 3N+1 different frequency bands namely, LL, LH, HL and HH as shown in Fig.1.

This proposed method analysis the performance of various wavelet types such as Haar, Daubechies (db1, db2, db3, db4, and db5), Coiflet, Morlet and Symlet in MRI scans. Initially, these wavelets are used for preprocessing the input images by separating the high details and thus sharpening process.

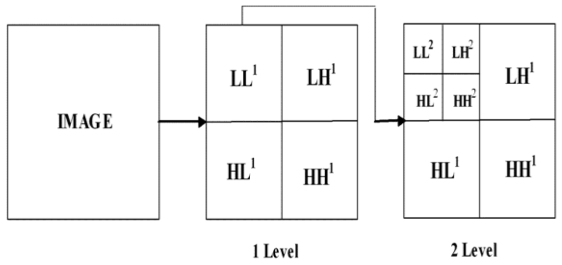

Fig.1. Structure of wavelet decomposition

C. K-means Clustering

Many approaches to image segmentation have been proposed over the years. K-means clustering is one of the simplest, and has been widely used in segmentation of grey level images. The k-means method aims to minimize the sum of squared distances between all points and the cluster centre [18].

This algorithm is composed of the following steps with a data set x_i, i=1,2,..n.

Step 1: Initialize the centroids c_j, j=1,2,..k

Step 2: Assign each data point to the group that has the closest centroid.

Step 3: When all points have been assigned, calculate the positions of the k centroids

Step 4: Repeat Steps 2 and 3 until the centroids no longer move. This produces a separation of the data points into groups from which the metric to be minimized can be calculated.

This algorithm aims at minimizing an objective function, in this case a squared error function.

The objective function is given by

$$J = \sum_{j=1}^{k} \sum_{i=1}^{n} \left\| x_i^j - c_j \right\|^2 \quad (1)$$

when $\left\| x_i^j - c_j \right\|$ is a measure of intensity distance between a data point xi and the cluster center cj. For simplicity, the Euclidean distance is used as the dissimilarity measure.

IV. PROPOSED METHOD

The proposed work consists of 3-stages, stage-I and stage-III apply wavelet transformation and stage II uses k-means clustering technique for tumor segmentation. The flowchart of this 3-stage proposed method is shown in Fig.2. In this proposed method, wavelet transformation is used as pre- and post-processing operation. In stage-I, as a preprocessing tool, various wavelet transformations are used to sharpen the brain tissue regions and its boundaries. This supports to quicken the clustering algorithm that applied in stage-II. Stage-II separated the meaningful regions of brain portions. In stage-III, wavelet transformation is again used as post-processing tool to generate the brain tumor map from previously obtained brain regions.

Stage-I: *Pre-processing*

In stage-I, the proposed method initially has done a pre-processing technique on MRI brain images. The collected datasets are processed by various wavelet transformations for sharpening the input image. Different types of wavelets like Daubechies (db1 - db5), Coiflets (coif), Morlets (morl), Symlet (sym) and Haar wavelet chosen for comparing the performance of Discrete Wavelet Transform (DWT) in level-1 only. Image decomposition is done by following level from Low-Low (LL), Low-High (LH), High-Low (HL) and High-High (HH). In this, the functions are denoted as approximation coefficient (A), vertical pass (V), horizontal pass (H) and diagonal pass (D). Set approximation coefficients in A equal to zero (A=0) and apply inverse decomposition to obtain a detailed image and its add to the original image. In this stage, image goes to sharpen and produces High-Pass sharpen (HPS) image. Fig.3, shown the preprocess of HPS image building.

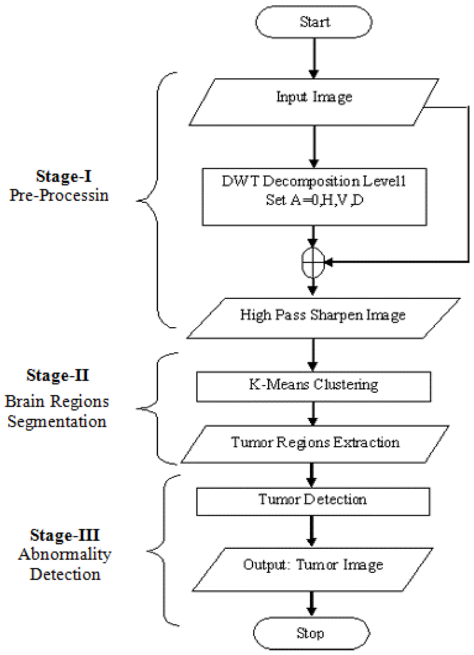

Fig.2. Flow chart for proposed method

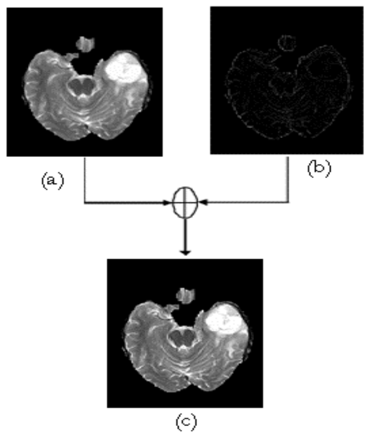

Fig.3. (a) Original image, (b) Detailed image and (c) HPS image

Stage-II: *Tumor Region Segmentation*

The segmenting method is done by as k-means clustering technique on HPS image and classified it into four segmented regions as background (BG), white matter (WM), gray matter (GM) and cerebrospinal fluid (CSF). In the resultant segmentation, tumors appear good in CSF region. Hence the mask of the obtained result of the CSF region is targeted for further processing. The decomposition method using wavelet is applied and decomposed into four sections like (A, V, H, and D) as shown in Fig.4. Next, the approximation coefficient is set to zero as "A=0". Then image converts into inverse processing. Then take the appropriate pixel mask of output image from original CSF region. Finally, take binary mask of CSF region and inverse decomposed detailed image of CSF portion. These two different binary masks intersect successfully and get optimize heuristic solution on CSF portion of tumor region in MRI brain images. Fig.4 has shown the process of tumor extraction from CSF region.

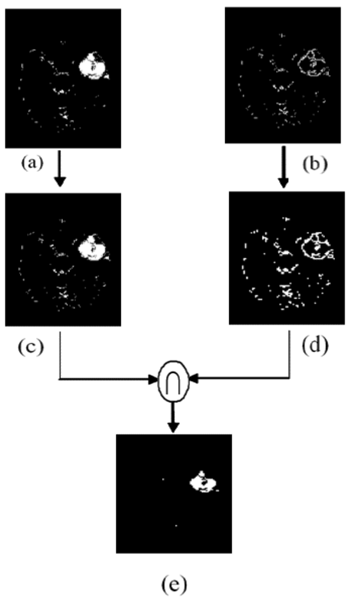

Fig.4. (a) CSF region, (b) After decomposition of CSF region (set A=0), (c) Binary mask of CSF region, (d) Binary mask of after decomposition of CSF region (set A=0) and (e) Tumor region

Stage- III: *Abnormality Detections*

The performance analysis of proposed method used parameters like False Alarm (FA) and Missed Alarm (MA). These parameters are used to check the normal or abnormal detection in MRI brain images. False alarm is an indication when the input scan which does not have a tumor is obtained as abnormal during analysis. Missed alarm is an indication when an abnormal image is not obtained so during the analysis. This proposed method experimented with 5 volumes of datasets. These parameters calculating the tumor not appeared (FA) or missed to detect tumor (MA) in MRI brain images. This proposed method never produced in any FA. However the MA is very less if the tumor presents in good size and contrast.

V. Results and Discussion

Our algorithm was implemented in MATLAB2010 on a PC with Intel Pentium Dual-Core 2.30GHz processor and 2GB RAM. Both qualitative and quantitative validations were used for the performance evaluation.

Experiments were done by taking the MRI brain image and applied the db, coif, morl, sym and Haar wavelet functions on it. The wavelet transform which has wide range of applications such as image sharpening is used in this paper for brain tumor identification. It describes the design and implementation of wavelet transform. The experimental results show that the haar wavelets transform based approach is better for brain tumor extraction process. The segmented images are evaluated using the performance parameters FA and MA.

The sample results are given in Fig.5. The original images are given in column 1, column 2 is db1, column 3 is db2, column 4 is db3, column 5 is db4, column 6 is db5, column 7 is coif, column 8 is morl, column 9 is sym and column 10 is Haar. Table 1 shown db1 MA value as 2.574%, Table 2 shown db2 MA value as 5%, Table 3 shown db3 MA value as 5.2%, Table 4 shown db4 MA value as 5.375%, Table 5 shown db5 MA value as 5.4%, Table 6 shown coif MA value as 4.6%, Table 7 shown morl MA value as 2.974%, Table 8 shown sym MA value as 2.374%, Table 9 shown Haar MA value as 2.174%. The average performances had shown in Fig.6. In the graph, the vertical axis represented the average performance of MA and horizontal axis is wavelet types. The Haar wavelet produces minimum quantity values for BRATS2012 and WBA datasets.

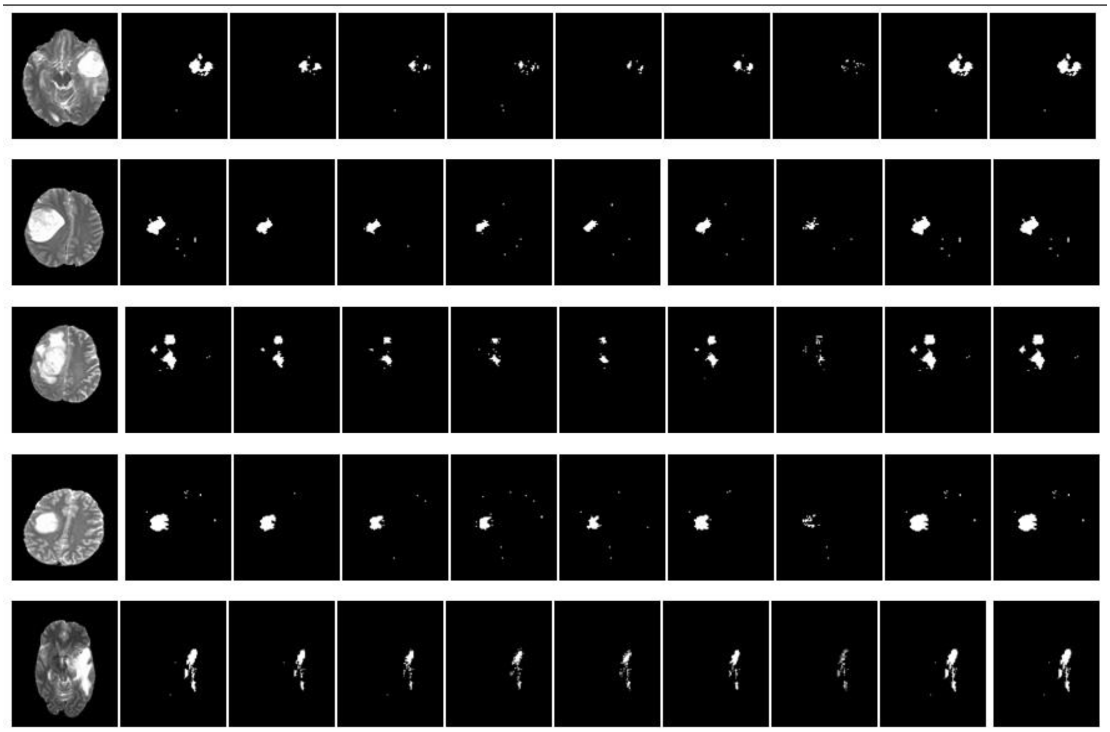

Fig.5. The original images are in column 1, the results of db1 in column 2, the results of db2 in column 3, the results of db3 in column 4, the results of db4 in column 5, the results of db5 in column 6, the results of coiflet in column 7, the results of morlet in column 8, the results of symlet in column 9, the results of Haar in column 10.

Table 1. Daubechies (db1) Wavelet Transform

Vol.	**Total Slice**	**Abnormal Slice**		**FA**		**MA**	
		Actual	*Detected*	*Slices*	*%*	*Slices*	*%*
HG1	176	46-119	52-110	0	0	111-119	5
HG4	176	81-150	86-150	0	0	0	0
HG11	176	64-130	74-125	0	0	126-130	3
LG11	230	115-168	118-166	0	0	167-168	0.87
Vol-1	25	4-15	4-14	0	0	15	4
Average Performance					0		**2.57**

Table 2. Daubechies (db2) Wavelet Transform

Vol.	**Total Slice**	**Abnormal Slice**		**FA**		**MA**	
		Actual	*Detected*	*Slices*	*%*	*Slices*	*%*
HG1	176	46-119	54 - 102	0	0	103 - 119	10
HG4	176	81-150	88 - 147	0	0	148 - 150	2
HG11	176	64-130	75 - 123	0	0	124 - 130	4
LG11	230	115-168	118 - 165	0	0	166 - 168	1
Vol-1	25	4-15	(5 - 14)	0	0	4,15	8
Average Performance					**0**		**5**

Table 3. Daubechies (db3) Wavelet Transform

Vol.	**Total Slice**	**Abnormal Slice**		**FA**		**MA**	
		Actual	*Detected*	*Slices*	*%*	*Slices*	*%*
HG1	176	46-119	54-103	0	0	104 - 119	9
HG4	176	81-150	89-146	0	0	147 - 150	2
HG11	176	64-130	75-120	0	0	121 - 130	6
LG11	230	115-168	117-165	0	0	166 - 168	1
Vol-1	25	4-15	5- 14	0	0	4,15	8
Average Performance					0		**5.2**

Table 4. Daubechies (db4) Wavelet Transform

Vol.	Total Slice	Abnormal Slice		FA		MA	
		Actual	*Detected*	*Slices*	*%*	*Slices*	*%*
HG1	176	46-119	52-101	0	0	102 - 119	10
HG4	176	81-150	87-148	0	0	149 - 150	1
HG11	176	64-130	75-118	0	0	119 - 130	7
LG11	230	115-168	116-166	0	0	167 - 168	0.87
Vol-1	25	4-15	5-14	0	0	4,15	8
Average Performance					0		**5.37**

Table 5. Daubechies (db5) Wavelet Transform

Vol.	Total Slice	Abnormal Slice		FA		MA	
		Actual	*Detected*	*Slices*	*%*	*Slices*	*%*
HG1	176	46-119	52,54-102	0	0	53,103-119	10
HG4	176	81-150	86,88-146	0	0	87,147-150	3
HG11	176	64-130	75-121	0	0	122-130	5
LG11	230	115-168	118-165	0	0	166-168	1
Vol-1	25	4-15	5-14	0	0	4,15	8
Average Performance					0		**5.4**

Table 6. Coiflet Wavelet Transform Type 1

Vol.	Total Slice	Abnormal Slice		FA		MA	
		Actual	*Detected*	*Slices*	*%*	*Slices*	*%*
HG1	176	46-119	52-103	0	0	104-119	9
HG4	176	81-150	88-148	0	0	149-150	1
HG11	176	64-130	68-123	0	0	124-130	4
LG11	230	115-168	115-165	0	0	166-168	1
Vol-1	25	4-15	5-14	0	0	4,15	8
Average Performance					0		**4.6**

Table 7. Morlet Wavelet Transform

Vol.	Total Slice	Abnormal Slice		FA		MA	
		Actual	**Detected**	**Slices**	**%**	**Slices**	**%**
HG1	176	46-119	52-113	0	0	114-119	3
HG4	176	81-150	86-150	0	0	0	0
HG11	176	64-130	74-125	0	0	126-130	3
LG11	230	115-168	117-166	0	0	167-168	0.87
Vol-1	25	4-15	5-14	0	0	4,15	8
Average Performance					0		**2.97**

Table 8. Symlet Wavelet Transform Type 1

Vol.	Total Slice	Abnormal Slice		FA		MA	
		Actual	*Detected*	*Slices*	*%*	*Slices*	*%*
HG1	176	46-119	52-111	0	0	112-119	5
HG4	176	81-150	86-150	0	0	0	0
HG11	176	64-130	74-127	0	0	128-130	2
LG11	230	115-168	118-166	0	0	167-168	0.87
Vol-1	25	4-15	4-14	0	0	15	4
Average Performance					0		**2.37**

Table 9. Haar Wavelet Transform

Vol.	Total Slice	Abnormal Slice		FA		MA	
		Actual	*Detected*	*Slices*	*%*	*Slices*	*%*
HG1	176	46-119	52-113	0	0	114-119	3
HG4	176	81-150	86-150	0	0	0	0
HG11	176	64-130	74-125	0	0	126-130	3
LG11	230	115-168	117-166	0	0	167-168	0.87
Vol-1	25	4-15	4-14	0	0	15	4
Average Performance					0		**2.17**

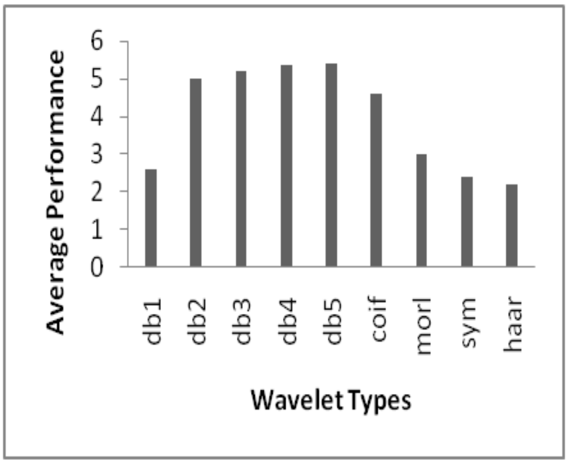

Fig.6. Performance of proposed method

VI. Conclusions

The proposed work is brain tumor detection using wavelet transformation and k-means clustering. This work classifies the given MRI datasets into normal and abnormal slices. This work detected the tumor portion of the brain which is present in CSF region. This work provides an effective result that helps to locate abnormalities in brain MRI images. The advantage of this proposed method is it took minimum MA to detect the tumor in brain images and never produces any FA. The experimental study used in this method is done on 5 volumes of datasets like BRATS2012 and WBA. There is no more FA for entire datasets and minimum MA, 2.174% from Haar wavelet. This shown that the proposed method attained minimum alarm values by Haar wavelet while compared other wavelet transformations. The proposed method is very efficient for detecting and extracting the tumor regions from MRI brain images. In future, increase the number of datasets and parameters for enrich the proposed method. The performance would be compared for their segmentation time with existing methods.

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