Feature Extraction Based on Wavelet Transform and Moment Invariants for Medical Image

Raniah Ali Mustafa[1] Kawther Thabt Saleh [2] and Haitham Salman Chyad[3]

rania83computer@uomustansiriyah.edu.iq kawtherthabt@uomustansiriyah.edu.iq
haitham@uomustansiriyah.edu.iq

Research Scholar [1] [2] [3]

Department of Computer Science

College of Education

Baghdad

Iraq

_____

ABSTRACT

The objective of feature extraction is to decrease the original data set by measuring definite features, or properties, which recognizes one input pattern from another .The main idea of the proposed system depends on the feature extraction where the system uses two phases the first phase discrete wavelet transform and the second phase seven moment's invariants. In this paper apply two level discrete wavelet transform of medical image; obtain seven bands of texture features are extracted from wavelet coefficients and then apply seven moments invariant for each band where obtain 49 features for each medical image. The proposed system was implemented on a real human MRI dataset, some of them were obtained from the hospitals and the other were obtained from the dataset (Brain-Tumor-Progression), available in the Internet and the proposed system implemented in programing language Visual Basic 6.0.
Key Words: *Feature Extraction, Medical Image, Discrete wavelet transform, Moment Invariants.*
_____

1.   INTRODUCTION

Medical image processing has practiced dramatic increase, and has been an interdisciplinary research field interesting expertise from implemention mathematics, engineering, computer sciences, physics, statistics, medicine and biology. Computer-Aided Diagnostic processing already has become an significant portion of clinical routine. escort by a new development rush in high technology and different imaging way utilize, more challenges appear; for instance, how to analyse and process an important volume of images consequently that high quality information can be created for treatment and disease diagnoses [1].

Along with the fast developments in image processing and pattern recognition methods, computer helped tumours diagnosis attracts further consideration. Many accomplishments with classification technique to define an image depend on metadata as histograms, texture or shape features to afford an accurate definition of an image depend on the image's content employing neural networks to categorize images and classify the tumours [2].

The feature extraction is transformation the image into set of features. Some of the features of a three - or two -dimensional object pattern are the volume, area, etc. which can be measured by counting the pixels. Similarly, the shape of object may be defined by its boundary. The object colour is an extremely significant feature, which can be defined in different colour spaces. The approaches to measure the characteristic are called as feature extraction approaches [3].
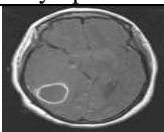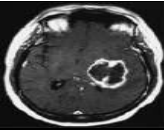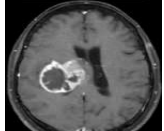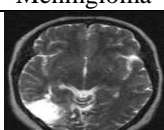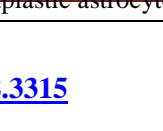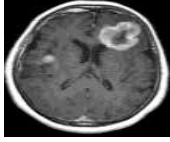
_____

1.1 TUMOR TYPES OF THE BRAIN

Body is creating of many cells. Each cell has definite responsibility. The cells grow in the body and are divided to regenerate other cells. These divisions are actual vital for right roles of the body. When every cell loses the skill of controlling its growth, these divisions are done without any restrictions, and tumor emerges. A tumor is a mass of tissue that grows out of the normal forces control that normalizes growth.

Brain is the essential part of the body. Brain has a very difficult structure. The brain can be affected by a problematic which causes change in its normal behavior and its normal structure. This problematic is identified as brain tumor. It is one of the main causes for the rise in humanity among adults and children. The classification of Brain Tumors is as follows [4]:

A. Benign Tumor i.e. Non Cancerous Tumor: This type of tumor is noncancerous, which is meaning it does not extent or invade the surrounding tissue.

B.   Malignant Tumor i.e. Cancerous Tumor: This type of tumor is cancerous, which is meaning it extents and invades the surrounding tissue. It is classified as secondary and primary tumor.

- Primary Tumors: A primary tumors denote to a mass or tumor that is increasing in the location wherever cancer originated. Most of them are generally effectively treated with procedures as surgery.

- Secondary Tumor (Metastatic): A secondary (Metastatic) brain tumor happens when cancer cells spread to the brain from a primary cancer in additional part of the body. Secondary tumors are approximately three times more popular than primary tumors in the brain.

Table 1.1: Some Types of Tumor in Human Brain

No.	Type of tumor	Description
1	Lymphoma	Primary lymphomas rise from lymphatic cells create in the brain. The classic seaming of lymphoma most frequently is look as a ring.
2	Glioblastoma multiform (GBM)	GBM is most popular tumor of high level astrocytoma and its most malignant tumors. It account about for 30% of all primary brain tumors.
3	Cystic oligodendroglioma	It contains of homogeneous, rounded cells with different borders and clear cytoplasm surrounding a dense central nucleus, also it look like a "fried egg".
4	Ependymoma	Ependymomas are the tumors that rise from ependymal cells in the brain. This tumor is histologically benign but works malignantly.
5	Meningioma	Meningiomas are the most popular benign tumors, accounting for 25-30% of all primary brain tumors. They are more popular in women.
6	Anaplastic astrocytoma	Anaplastic astrocytoma are most popular tumors of

		high level astrocytoma. They may seem as low inhomo-geneous lesions or density lesions or with parts of both low and high densities in the identical lesion.

1.2 MEDICAL IMAGE ANALYSIS

Medical imaging is the method and process utilized to produce images of the human anatomy for medical research, treatment and diagnosis. It is nowadays one of the fastest-growing parts of clinical equipment. The modalities generally utilized to gained medical images are Magnetic Resonance Imaging (MRI), Computed Tomography (CT), X-rays and ultrasound imaging. one of the scanning devices in clinical imaging is MRI which employs magnetic fields to capture images onto movies [5]. Image analysis methods have played an significant role in a number of clinical applications. In general, the applications include the automatic medical features clinical from the image which are then employed for a variety of classification functions, such as differentiating abnormal tissue from normal tissue. basing on the particular classification function, the extracted features may be colour properties, shape properties, or definite textural properties of the image [2].

2. WAVELET TRANSFORM

A "wave" is generally described as an oscillatory function from time or space, as a sinusoid. "Wavelet" expressing of a "small wave", that implicate energy concentrated in time to offer a tool for the analyses of transient, non-stationary, or time-varying phenomena [6]. A wavelet is a mathematical function employed to separate continuous-time signal or a given function into different scale constituents. Figure 1.1 displays the wave (sinusoid) and the wavelet [7].
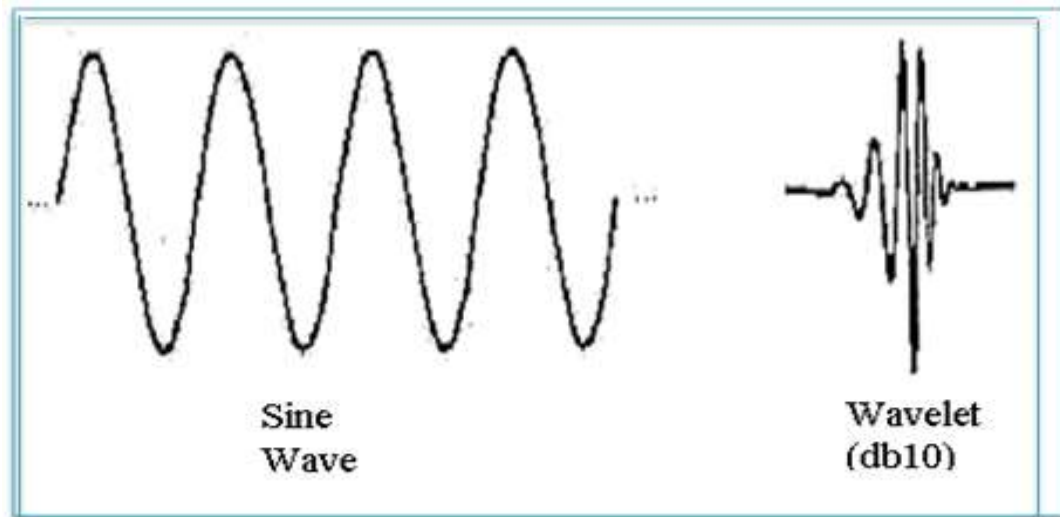

Figure 1.1: A Wave and Wavelet

Wavelet transform (WT) offers robust signal analysis tools, which will be commonly employed within image de-noising, compression, feature extraction, image retrieval applications, detection, and recognition. Wavelet decomposition is the exceedingly spread used multi-resolution method in image processing. Owing to the excellent time-frequency localization distinctive. WT offer a robust mathematical tool. Images have classically locally diverging statistics that outcome of several combinations of unexpected characteristics as edges, of textured regions and of relatively low-contrast homogeneous regions. However similar spatial and inconsistency non-stationary challenge each single statistical definition, the multi-resolution constitutes is more simply handled. WT could be completed successfully for each scale and translation [8]. There are two types of

WT; discrete wavelet transforming (DWT) and continuous wavelets transform (CWT). The major modification among DWT and CWT is that DWT utilizes an clear subset of translation and scale values and CWT utilize each possible translation and scale [6].

2.1 HAAR BASIS FILTER

The Haar basis filter contains of Low pass filter (LPF) and high pass filter (HPF) are represented in the following equations (1)-(2):

$$\text{HPF: } \frac{1}{\sqrt{2}} [1 \quad -1], \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots (1)$$

$$\text{LPF: } \frac{1}{\sqrt{2}} [1 \quad 1], \dots \dots \dots \dots \dots \dots \dots \dots . \dots \dots \dots \dots (2)$$

The LP and HP filters are so termed the decomposition filters for they distinct decompose the picture or the picture down to detailed and approximation. The convolution with the band pass filter in a definite direction results in so termed details picture and the convolution with the LPF outcomes in a so termed approximation picture.

LL band (approximation band) is the outcome of implementing LPF in vertical and horizontal directions and its filter gain as follows:

$$LL = \frac{1}{\sqrt{2}}(1 \quad 1)^t . \frac{1}{\sqrt{2}}(1 \quad 1) = \frac{1}{2}\begin{pmatrix} 1 & 1 \\ 1 & 1 \end{pmatrix}, \dots \dots \dots \dots \dots \dots (3)$$

LH band (detail band) is the effect of applying horizontal LPF and vertical HPF and its filter is derived as follows:

$$LH = \frac{1}{\sqrt{2}}(1 \quad 1)^t . \frac{1}{\sqrt{2}}(1 \quad -1) = \frac{1}{2}\begin{pmatrix} 1 & -1 \\ 1 & -1 \end{pmatrix}, \dots \dots \dots .. \dots (4)$$

HL band (detail band) is the result of implementing vertical HPF and horizontal LPF and its filter is gain as follows:

$$HL = \frac{1}{\sqrt{2}}(1 \quad -1)^t . \frac{1}{\sqrt{2}}(1 \quad 1) = \frac{1}{2}\begin{pmatrix} 1 & 1 \\ -1 & -1 \end{pmatrix}, \dots \dots \dots \dots (5)$$

HH band (detail band) is the outcome of implementing vertical and horizontal HPF and its filter is gain as follows:

$$HH = \frac{1}{\sqrt{2}}(1 \quad -1)^t . \frac{1}{\sqrt{2}}(1 \quad -1) = \frac{1}{2}\begin{pmatrix} 1 & -1 \\ -1 & 1 \end{pmatrix}, \dots \dots \dots (6)$$

The transformed bands (LL scaling bands and three wavelet bands HH HL, and LH) can be gained by implementing above filters to every (2×2) adjacent pixel of the entire picture pixel. This method is named Fast Mallat transform algorithm [9]
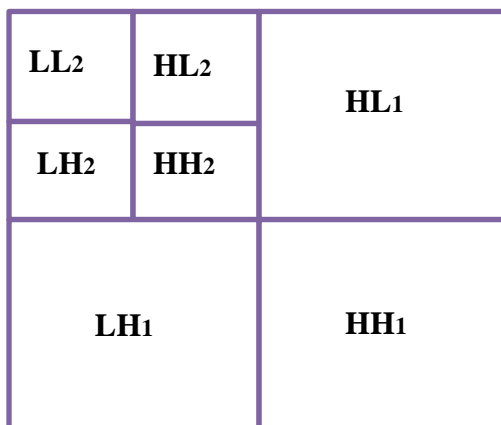
LL2	HL2	HL1
LH2	HH2	
LH1		HH1

Figure 1.2: Two level Wavelet Sub Band Decomposition

2.2 DISCRETE WAVELET TRANSFORM DECOMPOSITION

The DWT for 2-dimensional images $x[m,n]$ can be identically defined through applying 1-dimensional DWT to every dimension m and n independently: $\text{DWT}_n\left[\text{DWT}_m[x[m,n]]\right]$. 2-dimensional WT decomposes a image to "subbands" which are centralized in orientation and frequency. WT is formed through passing the image by sequences of filter bank phases. One phase is demonstrated in Figure 1.3. In which an image is initially filtered in the horizontal direction [10].
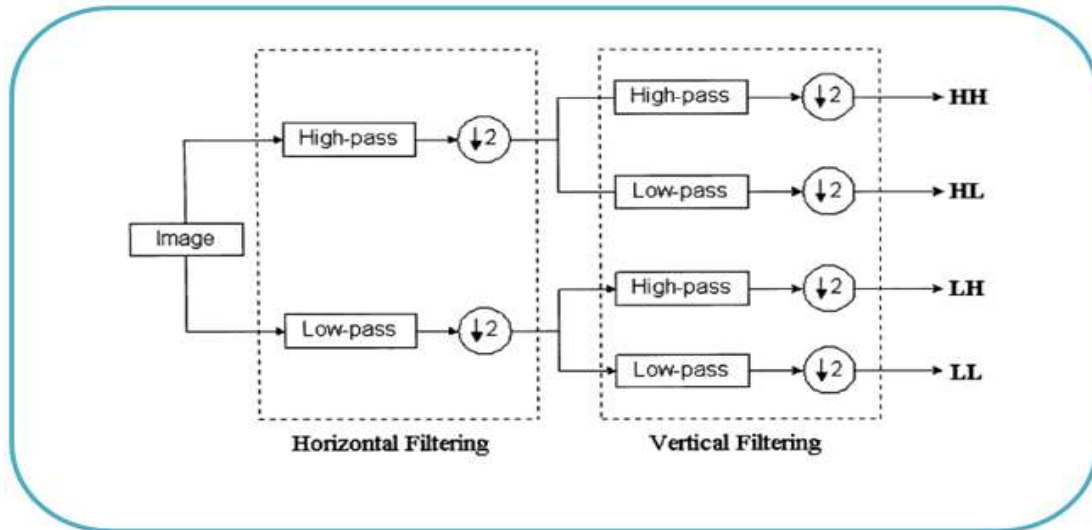
Figure 1.3: Illustration of 2-D Wavelet Transforms

The scaling function (LPF) & wavelet function (HPF) are limited pulsation reply filters. In other words, the output at every point relies just on a limited part of the input. The filtered outputs are then down sampled by a factor of 2 ($\downarrow$2) in the horizontal direction. Those signals are then each filtered through a similar filter pair in the vertical direction. Eventually decomposite the image to 4 sub bands indicated by (LL, HL, LH, HH). Each of those sub bands could be thought of as a smaller version of the image which represents various image properties. The Low-Low is a coarser approximation to the original image. Low High & High Low record the differences of the image along vertical and horizontal directions, consecutive. High offers the high frequency component of the image. 2-Level decomposition could then be conducted on the Low sub band. Figure 1.4 demonstrates two-Level wavelet decomposition [10].

(a)	(b)
Figure 1.4: (a) Original Image (b) Two-Level Wavelet Decomposition	
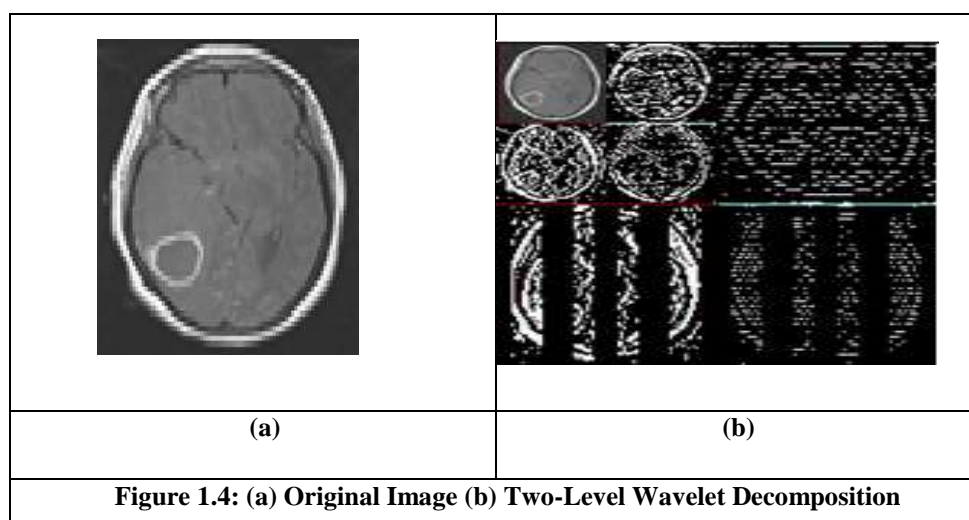
3. MOMENT INVARIANTS

This approach has been widely used to image pattern recognition in a variety of applications because of their unchanged features on picture rotation, scaling, and translation. Moment invariants are helpful for calculating sets of region characteristics that can be utilized for shape recognition. The two dimensional geometric moments of order (p+q) of a function $f(x,y)$ are described in equation (7) [11]:

$$m_{pq} = \sum_{x=0}^{x=N-1} \sum_{y=0}^{y=M-1} x^p \, y^q \, f(x,y), \ldots \ldots \ldots \ldots \ldots (7)$$

Where

$p, q \; 0,1,2, \ldots, \infty$

M: the number of rows, N: the number of columns.

The moments that have the feature of translation unchange are called central moments and are referred by μ_{pq} , they are described as in equation (8) [11]:

$$\mu_{pq} = \sum_{x=0}^{x=N-1} \sum_{y=0}^{y=M-1} (x - \bar{x})^p \cdot (y - \bar{y})^q \, f(x,y), \ldots \ldots \ldots \ldots (8)$$

Where $\bar{x}$ and $\bar{y}$ are the centred coordinates and they are calculated employing equations (9) and (10) [11].

$$\bar{x} = \frac{m_{10}}{m_{00}} , \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots (9)$$

$$\bar{y} = \frac{m_{01}}{m_{00}}, \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots (10)$$

It can be simplify confirmed that the central moments up to the order $p + q \leq 3$,may be calculated by the following equations (11) - (20) and formulas [11]:

$$\mu_{00} = m_{00}, \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots (11)$$

$$\mu_{10} = 0, \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots (12)$$

$$\mu_{01} = 0 , \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots (13)$$

$$\mu_{20} = m_{20} - \bar{x} \, m_{10} , \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots (14)$$

$$\mu_{02} = m_{02} - \bar{y} \, m_{01} , \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots (15)$$

$$\mu_{11} = m_{11} - \bar{y} \, m_{10}, \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots (16)$$

$$\mu_{30} = m_{30} - 3 \, \bar{x} \, m_{20} + 2 \, \bar{x}^2 \, m_{10} , \ldots \ldots \ldots \ldots \ldots \ldots \ldots (17)$$

$$\mu_{12} = m_{12} - 2 \, \bar{y} \, m_{11} - \bar{x} \, m_{02} + 2 \, \bar{y}^2 \, m_{10} , \ldots \ldots \ldots \ldots (18)$$

$$\mu_{21} = m_{21} - 2 \, \bar{x} \, m_{11} - \bar{y} \, m_{20} + 2 \, \bar{y}^2 \, m_{01}, \ldots \ldots \ldots \ldots \ldots (19)$$

$$\mu_{03} = m_{03} - 3 \, \bar{y} \, m_{02} + 2 \, \bar{y}^2 \, m_{01} , \ldots \ldots \ldots \ldots \ldots \ldots (20)$$

Scale unchanged could be got by utilizing normalized central moments η_{pq}, as equations (21) and (22) [11].

$$\eta_{pq} = \frac{\mu_{pq}}{\mu_{00}{}^\gamma} , \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots (21)$$

where

$$\gamma = \left[\frac{(p + q)}{2} \right] + 1 , \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots (22)$$

A seven non-linear absolute moment invariants, computed from normalizing central moments through order three are gotten as equations (23) to (29) [11]:

$$\emptyset_1 = \eta_{20} + \eta_{02} , \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots (23)$$

$$\emptyset_2 = (\eta_{20} - \eta_{02})^2 + 4\eta_{11}^2, \dots\dots\dots\dots\dots\dots\dots\dots (24)$$

$$\emptyset_3 = (\eta_{30} - 3\eta_{12})^2 + (3\eta_{21} - \eta_{03})^2, \dots\dots\dots\dots (25)$$

$$\emptyset_4 = (\eta_{30} + \eta_{12})^2 + (\eta_{21} + \eta_{03})^2, \dots\dots\dots\dots (26)$$

$$\emptyset_5 = (\eta_{30} - 3\eta_{12}) \, (\eta_{30} + \eta_{12})$$

$$[(\eta_{30} + \eta_{12})^2 - 3(\eta_{21} + \eta_{03})^2]$$

$$+(3\eta_{21} - \eta_{03}) \, (\eta_{21} + \eta_{03})$$

$$[3(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2], \dots\dots\dots\dots\dots\dots (27)$$

$$\emptyset_6 = (\eta_{20} - \eta_{02}) \, [(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2]$$

$$+ 4\eta_{11} \, (\eta_{30} + \eta_{12}) \, (\eta_{21} + \eta_{03}) , \dots\dots\dots\dots\dots\dots\dots (28)$$

$$\emptyset_7 = (3\eta_{21} - \eta_{03}) \, (\eta_{30} + \eta_{12})$$

$$[(\eta_{30} + \eta_{12})^2 - 3(\eta_{21} + \eta_{03})^2]$$

$$+(3\eta_{12} - \eta_{30}) \, (\eta_{21} + \eta_{03})$$

$$[3(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2] , \dots\dots\dots\dots\dots\dots (29)$$

4. Normalization Features

An important step between feature extraction and distance computation is feature normalization. Complex image database retrieval systems use features that are generated by many different feature extraction algorithms with different kinds of sources. These feature vectors usually exist in a very high dimensional space. Not all of these features have the same range [12]. The normalization of feature (*f*) is performed using the following equation (30):

$$f\mathrm{norm} = \begin{cases} 0 & \text{if } f \leq \ \mathrm{fmin} \\ \dfrac{f - \mathrm{fmin}}{\mathrm{fmax} - \mathrm{fmin}} & \text{if } \mathrm{fmin} < f < \mathrm{fmax} \\ 1 & \text{if } f \geq \mathrm{fmax} \end{cases} , \dots\dots\dots\dots (30)$$

where *fmin* and *fmax* are *min* and *max* feature values found over all image samples listed in the image database, *form* is the normalized value. The applied normalization process maps the extracted feature values to the range between [0, 1]. [13]

5. THE PROPOSED SYSTEM

The main idea of the proposed system depends on the feature extraction from medical image based on seven moment invariants for each band in two level discrete wavelet transform; texture features are extracted from wavelet coefficients and then using seven moments invariant . To be used for extract features. The proposed system is done in following steps

1. Read image
2. Feature extraction based on wavelet transform
3. Feature extraction based on seven moment invariants

    In this paper, each steps in the proposed system will explained with the results. The figure 1.5 illustrates the each step for the proposed system.
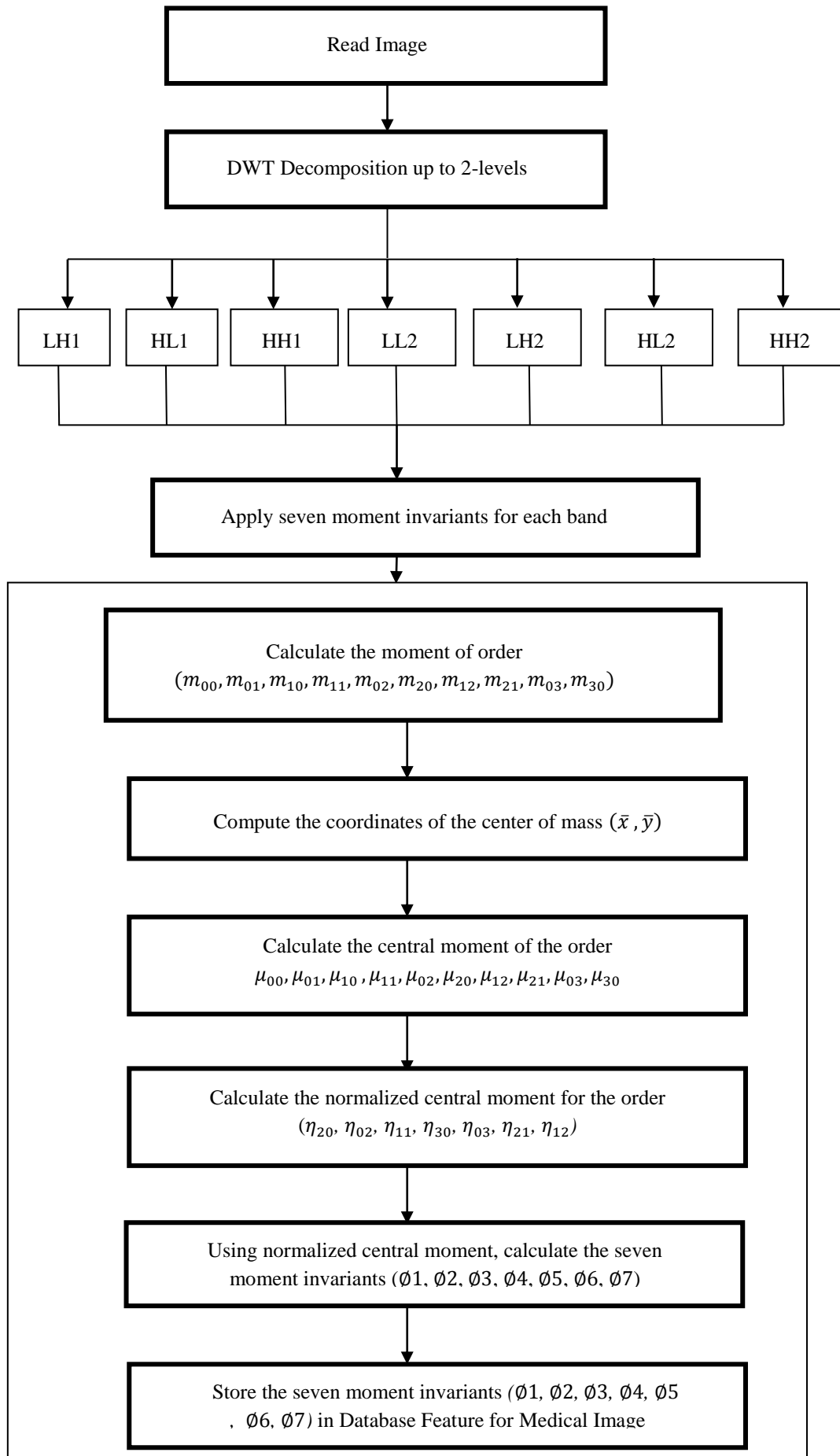
Figure 1.5: The proposed system for Medical Image

5.1 READ IMAGE

Gray-scale images are referred to one-color, images. They contain brightness information only, no colour information. The number of bits used for each pixel determines the number of different brightness levels available. The typical image contains 8 bits/pixel data, which allows us to have 256 (0-255) different brightness (gray) levels.

5.2 FEATURE EXTRACTION

In this section, only the significant information is extracted from the medical image ; The extracted information denotes the necessary features vector to make a distinction between Medical images. The project employs two diverse sets of discriminating characteristic: (i) wavelet transform and (ii) seven moment invariant.

5.2.1 FEATURE EXTRACTION BASED ON WAVELET TRANSFORM STAGE

In this stage, medical image will passing different subphase for the extracted texture features objective, which utilizes for extracted features in moment invariant. A wavelet transform is implemented over these entered images employing Haar filter wavelet decomposition which is implemented the data by computing the averages and changes of adjacent elements. The Haar wavelet operates first on adjacent vertical elements and then on adjacent horizontal elements. The Haar wavelet transform for N elements is calculated as presented see section (2.1).

The purpose of implementing this stage is to extract the factors from the medical image. In this system one image of approximation (low-resolution image) and 6 images of details are gained. Therefore, each medical image is defined by 7 wavelet coefficient matrices, which denote an actual great amount of information (equal to the input image size). The applying of feature extraction process is done employing the steps in the algorithm (1.1).

Algorithm (1.1) Feature Extraction Steps

Input: medical Image.

Output: Extract features vector.

Step1: Read medical image data

Step2: Apply the wavelet transform up to 2- levels of decomposition (which were enough to give a small representation of coefficients) using Haar discrete wavelet transform.

The Haar Basis filter is performed by using that following equation that are mentioned in section (2.1):

$$\text{HPF: } \frac{1}{\sqrt{2}}[1 \quad -1], \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots (1)$$

$$\text{LPF: } \frac{1}{\sqrt{2}}[1 \quad 1], \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots (2)$$

Step6: End.

The problem of reducing the representation of an image to a small number of components carrying enough discriminating information is referred to as *"feature extraction"* .An efficient way of reducing dimensionality and characterizing textural information is to compute a *set of moments*. In this paper, the result for each bands (LH1, HL1, HH1, LL2, HL2, LH2 and HH2 bands) are usually useful to represent characteristics or features of data; it is simple and requires less computation load. See Figure 1.6.

Medical Image (Types of Tumor Image)	Discrete Wavelet transform
Lymphoma	
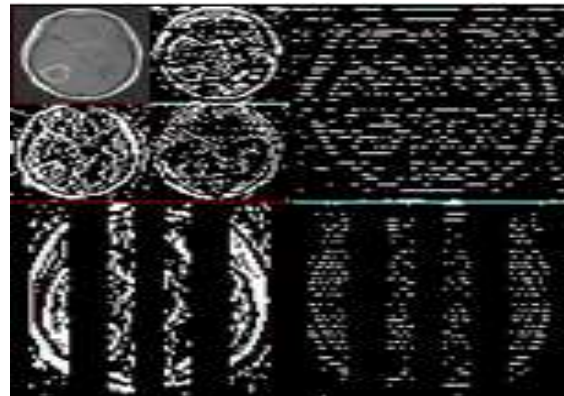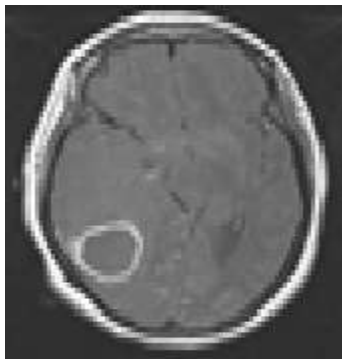
Glioblastoma multiform (GBM)

Cystic oligodendroglioma

Ependymoma

Meningioma
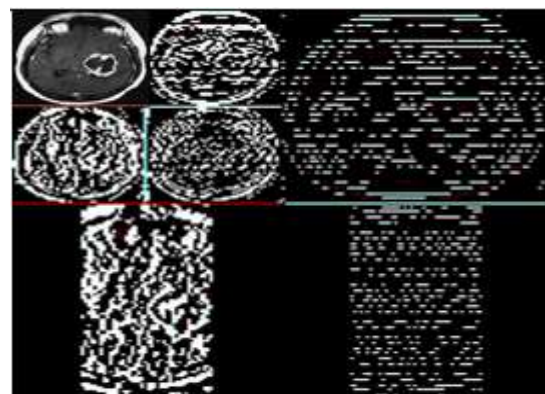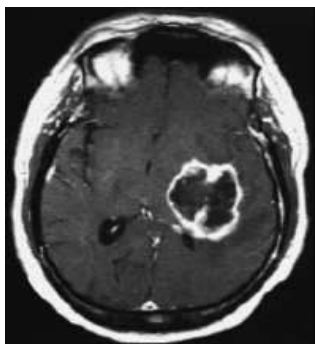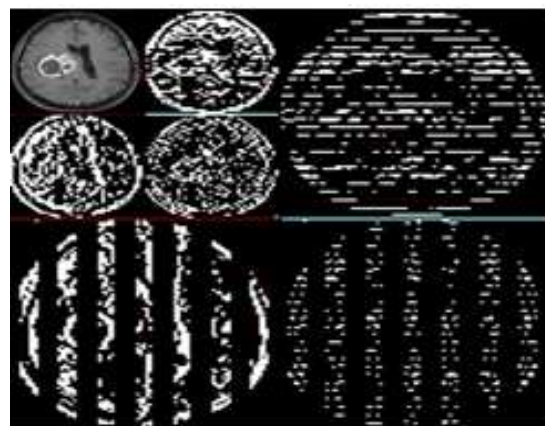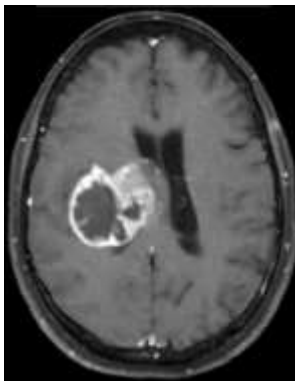
Anaplastic astrocytoma
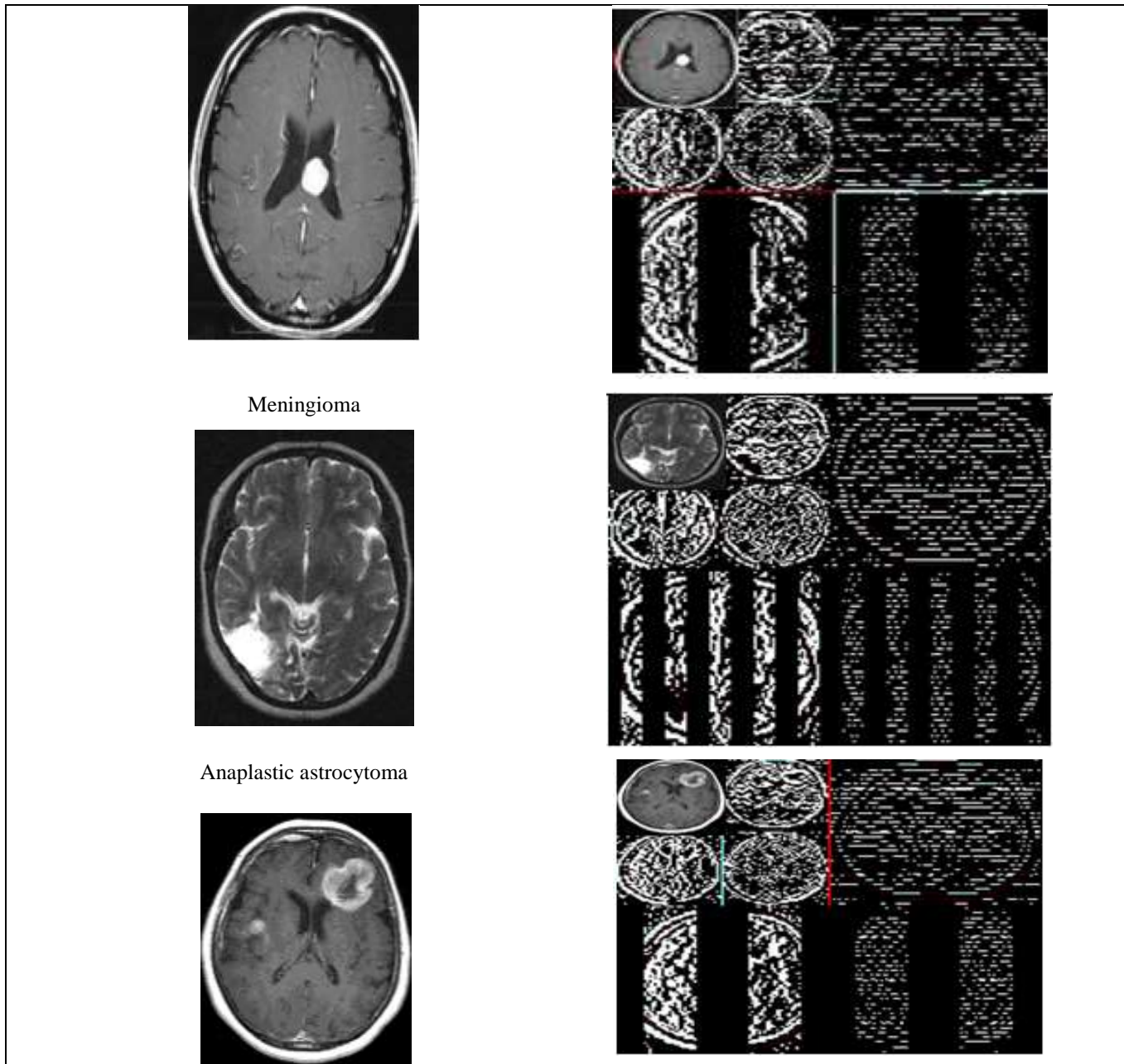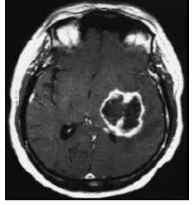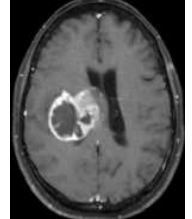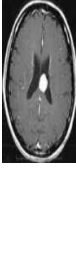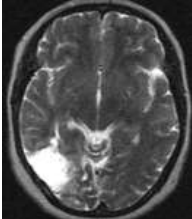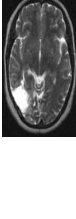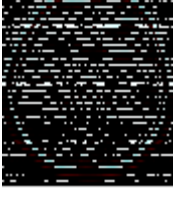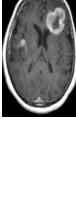
Figure 1.6: Two Level Wavelet Decomposition of Medical image

In this stage, after entered to two levels wavelet transform, it will produce one image of approximation and six image of details and save them. Table 1.2 shows analysis results of bands (LH1, HL1, HH1, LL2, LH2, HL2, and HH2) from some sample medical image database.

Table 1.2: Analysis Results Bands of Wavelet Transform from Sample of medical Image Database

NO.	Medical Image	LH1	HL1	HH1	LL2	LH2	HL2	HH2
1								

5.2.2 FEATURE EXTRACTION BASED ON SEVEN MOMENT INVARIANT STAGE

In this stage will be used the medical image to extract features. The moments' invariant technique will be extract seven values as features; all details are mentioned in section (3). These seven values are extracted from medical image after implement discrete wavelet transform and then seven moment invariants apply for each band (seven bands). The applying of feature extraction process is done employing the steps in the algorithm (1.2).

Algorithm (1.2) Feature Extraction Steps

Input: medical Image

Output: Hu's Moment for each medical image

Step1: Read madical image data

Step 2: Get image width (**For** i=0 to image.width -1)

　　　Get image height (**For** j=0 to image.height -1)

Step 3: Calculate the moment of order $(m_{00}, m_{01}, m_{10}, m_{11}, m_{02}, m_{20}, m_{12}, m_{21}, m_{03}, m_{30})$ from equation (7).

Step 4: Compute the coordinates of the center of mass by using equations (9) and (10).

Step 5: Calculate the central moment (denoted by μ_{pq}) by using equation (8) of the order

　　　$\mu_{00}, \mu_{01}, \mu_{10}, \mu_{11}, \mu_{02}, \mu_{20}, \mu_{12}, \mu_{21}, \mu_{03}, \mu_{30}$ and for easy calculation use equations (11) to (20).

Step 6: Calculate the normalized central moment (denoted by η_{pq}) by using equation (21) and (22) for the order ($\eta_{20}, \eta_{02}, \eta_{11}$,

　　　$\eta_{30}, \eta_{03}, \eta_{21}, \eta_{12}$).

Step7: Using normalized central moment calculate the seven moment invariants (∅1, ∅2, ∅3, ∅4, ∅5, ∅6, ∅7), equations (23) to

　　　(29).

Step 8: Store the seven moment invariants (∅1, ∅2, ∅3, ∅4, ∅5 , ∅6, ∅7) in Training database feature for medical image.

Step 9: If there are more medical image, repeating the steps from (1-8) for all medical images.

Step 10: End.

In this stage, after analysis medical images in two level wavelet transform will be applied to normalized central moment to obtain seven moment invariants of ($\emptyset_1, \emptyset_2, \emptyset_3, \emptyset_4, \emptyset_5, \emptyset_6, \emptyset_7$) feature vectors extraction for each band (seven band) and save them in training database features (TRDBF). Table (1.3) shows results of extracted features (Before normalization) for sample of medical image database.

Table 1.4: Result of Extracted Features for sample of Medical Image Database (Before Normalization)

	Features						
	$\emptyset_1$	$\emptyset_2$	$\emptyset_3$	$\emptyset_4$	$\emptyset_5$	$\emptyset_6$	$\emptyset_7$
LH1	0.319139595003979	1.1232350620857E-03	2.83473496312047E-04	2.59233280139565E-06	-1.72258940274752E-09	8.49003048041991E-08	2.84689461007154E-11
HL1	0.390501581892102	1.57097483311013E-03	1.02690867292295E-04	1.7324990668161 6E-05	-6.9814478310683E-08	-6.71954328477067E-07	6.18712860454209E-10
HH1	0.543182127493015	3.372840477963 22E-04	4.76860907304783E-04	4.4702658402935 7E-05	4.43132264461421E-06	-2.71702633494392E-07	3.49363151359528E-09
LL2	0.734091696755431	4.14731135858739E-02	8.07698933553286E-04	0.00415545487913 7	1.16400411919949E-05	8.27245636425744E-04	-5.76242072077209E-06
LH2	0.202381142215875	7.89692175242363E-04	7.10975680759436E-05	2.8287945525156 8E-06	-2.76759767129675E-08	-6.93282451723336E-08	3.70503470575524E-11
HL2	0.196477544182135	1.31279485386223E-03	2.18017474603248E-05	1.3205126313478 6E-06	-1.55688349808676E-08	-3.93098962408772E-08	-2.70577478543619E-13
HH2	0.233692835098198	2.14427881368654E-03	1.66330034589102E-04	3.5243016671107 6E-05	5.41514032642168E-11	7.70738498948925E-07	-2.65254481108465E-09

In this sub stage, after seven moment invariants feature vector extraction normalizing (f_{norm}) will be performed by finding maximum (f_{max}) and minimum (f_{min}) values for each feature for sample in the Training database Features (TRDBF). Table (1.5) shows results of extracted (f_{max},f_{min}) for features vectors for sample medical image database.

Table 1.5: Result of Extracted (f_{max}, f_{min}) for Features from sample of medical Image Database

	Features						
	$\emptyset_1$	$\emptyset_2$	$\emptyset_3$	$\emptyset_4$	$\emptyset_5$	$\emptyset_6$	$\emptyset_7$
f_{max}	0.734091696755431	4.14731135858739E-02	8.07698933553286E-04	0.004155454879137	1.16400411919949E-05	8.27245636425744E-04	3.49363151359528E-09
f_{min}	0.202381142215875	3.37284047796322E-04	7.10975680759436E-05	2.59233280139565E-06	-6.9814478310683E-08	-6.71954328477067E-07	-5.76242072077209E-06
	$\emptyset_1$	$\emptyset_2$	$\emptyset_3$	$\emptyset_4$	$\emptyset_5$	$\emptyset_6$	$\emptyset_7$
f_{max}	0.233692835098198	2.14427881368654E-03	1.66330034589102E-04	3.52430166711076E-05	5.41514032642168E-11	7.70738498948925E-07	2.70577478543619E-13
f_{min}	0.196477544182135	1.31279485386223E-03	2.18017474603248E-05	1.32051263134786E-06	-1.55688349808676E-08	-3.93098962408772E-08	-2.65254481108465E-09

After finding maximum (f_{max}) and minimum (f_{min}) values for each features for all samples in the Training database Features (TRDBF) process normalization will be applied. Table (1.6) shows results of extracted features for sample of medical image database.

Table 1.6: Result of Extracted Features from Sample of Medical Image Database (After Normalization)

	Features						
	$\emptyset_1$	$\emptyset_2$	$\emptyset_3$	$\emptyset_4$	$\emptyset_5$	$\emptyset_6$	$\emptyset_7$
LH1	0.641	0	0.5509	0.0101	0.3844	0.0005	1
HL1	0.3538	0.03	0.0429	0.0035	0	0	0.9995
HH1	0.2196	0.0191	0.2883	0	0.0058	0.0009	0.9994
LL2	1	1	1	1	1	1	0

LH2	0	0.011	0	0.0001	0.0036	0.0007	0.9994
HL2	0	0	0	0	0	0	1
HH2	1	1	1	1	1	1	0

Figures (1.7), (1.8), (1.9), (1.10) ,(1.11), (1.12) and (1.13) show the strong features extracted from seven moment invariant by comparison among features ($\emptyset_1, \emptyset_2, \emptyset_3, \emptyset_4, \emptyset_5, \emptyset_6, \emptyset_7$) for sample medical image.

Figure 1.7: Comparison among seven moment invariants ($\emptyset$1) of discrete wavelet transform

Figure 1.8: Comparison among seven moment ($\emptyset$2) of discrete wavelet transform

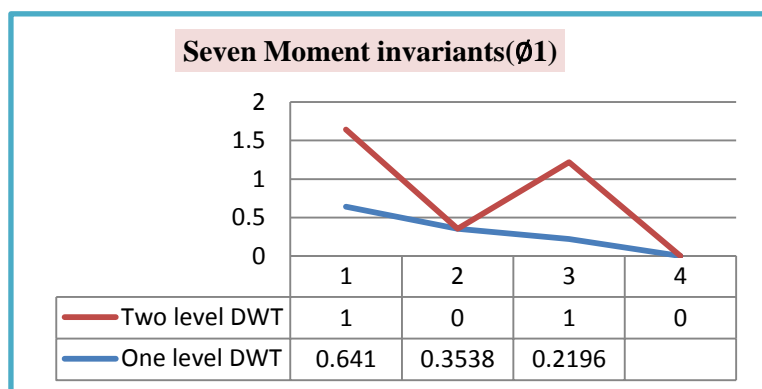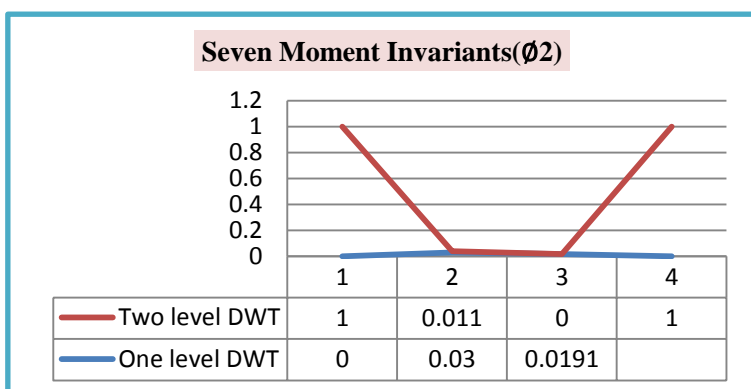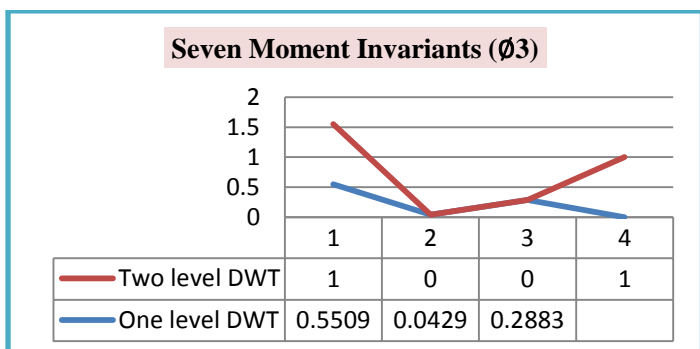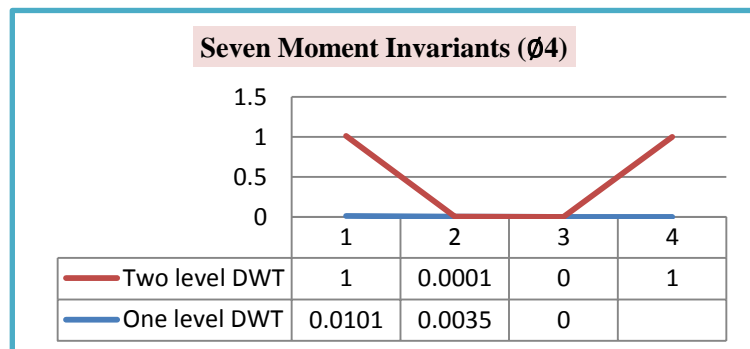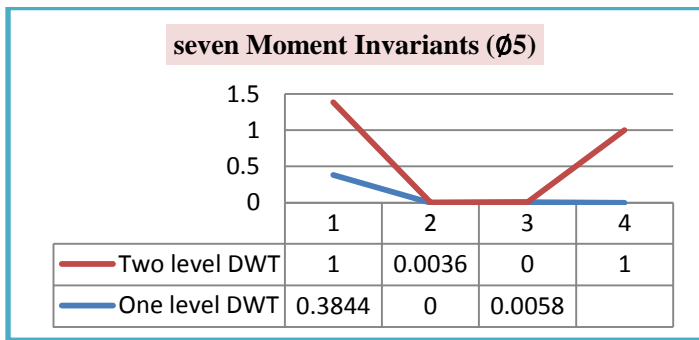**Figure 1.9: Comparison among seven moment invariants ($\emptyset$3) of discrete wavelet transform**

Figure 1.10: Comparison among seven moment ($\emptyset$4) of discrete wavelet transform

seven Moment Invariants (∅5)

	1	2	3	4
Two level DWT	1	0.0036	0	1
One level DWT	0.3844	0	0.0058	

Figure 1.11: Comparison among seven moment invariants (∅5) of discrete wavelet transform

Seven Moment Invariants (∅6)

	1	2	3	4
Two level DWT	1	0.0007	0	1
One level DWT	0.0005	0	0.0009	
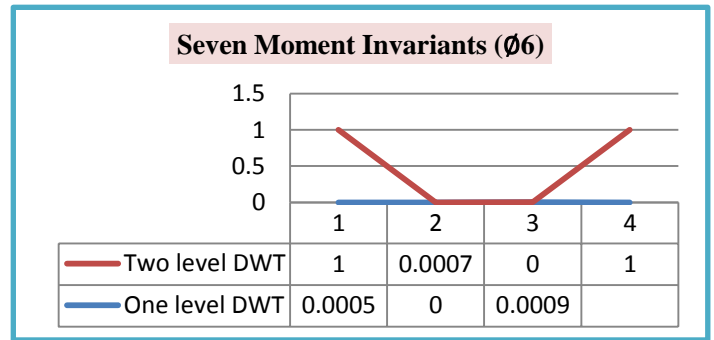
Figure 1.12: Comparison among seven moment (∅6) of discrete wavelet transform

Seven Moment Invariants (∅7)

	1	2	3	4
Two level DWT	0	0.9994	1	0
One level DWT	1	0.9995	0.9994	
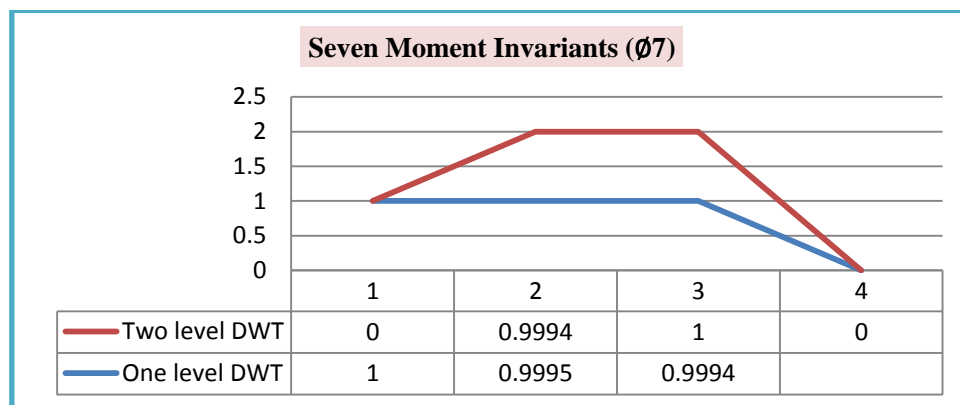
Figure 1.13 Comparison among seven moment invariants (∅7) of discrete wavelet transform

6. THE COLLECTED DATA

In this system proposed six types of tumors and the normal case of brain MRI image were used. Figure (4.3) presents the samples of this types of brain MRI Images. The proposed system was implemented on a real human MRI dataset, some of them were obtained from the hospitals and the other was obtained from the dataset (Brain-Tumor-Progression), available in the Internet from this types of tumors. The number of collected images are 140 they are gray level image with 8 bit (pixel value 0..255) and the type of them are: BMP, JPEG, and PNG. With various image sizes.

Lymphoma	Glioblastoma multiform	cystic oligodendroglioma

| Ependymoma | Meningioma | Anaplastic astrocytoma |

Brain-Tumor-Progression
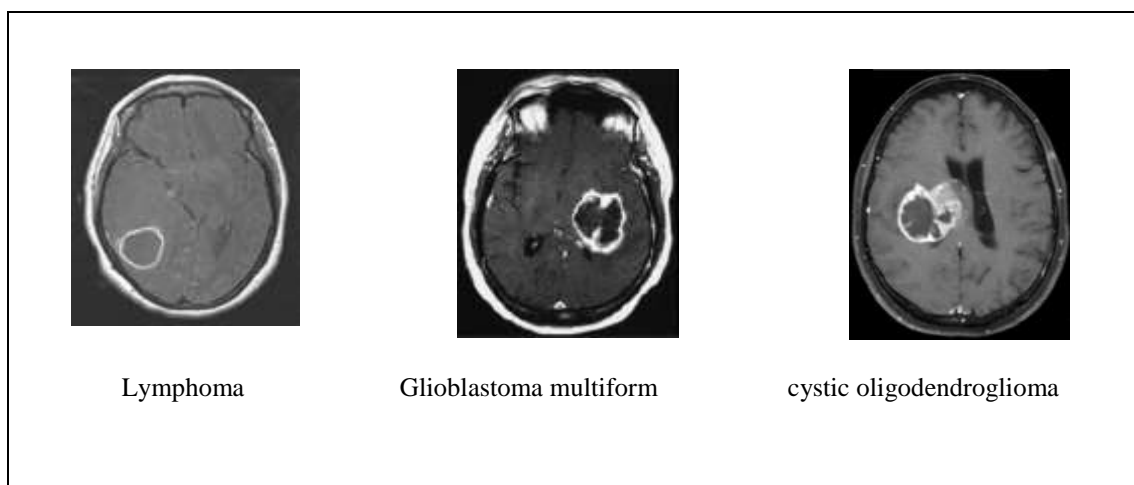
Figure 1.14: Samples of different types of brain MRI images.

7. CONCLUSIONS

From The practical part of this work, the following conclusions can be drawn:

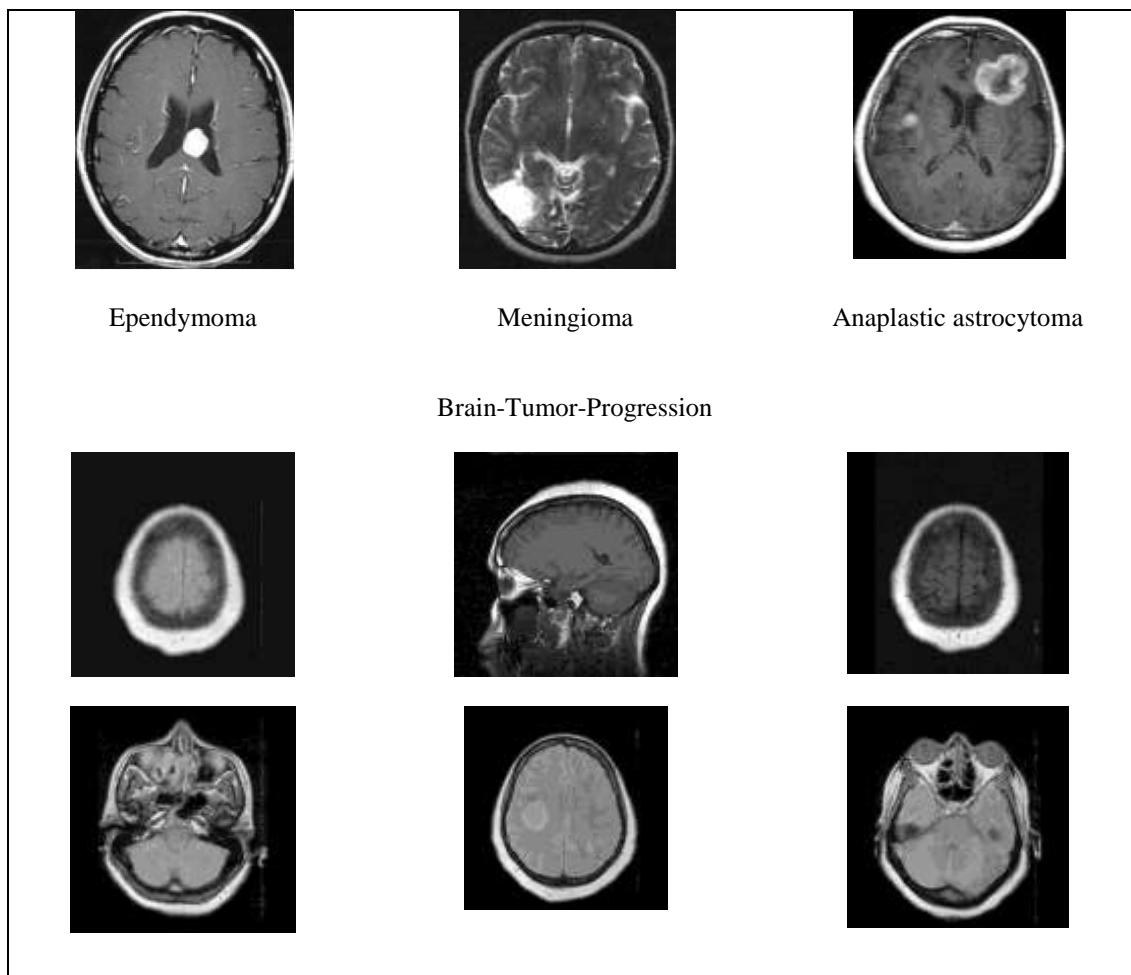1. The proposed system is applicable to different sizes and types of image formats such as BMP, JPEG, and PNG file format.

2. Using the wavelet transform to extract texture features leads to good outcomes because this technique is strong to extract texture features from medical image .The wavelet transform employed for feature extraction which shows robustness against secondary variances in the image sample (i.e. scaling, lighting conditions, and noise).

3. The seven moment invariant utilized for feature extraction displays robustness because of invariant features on scaling, translation, and rotation image.

4. We utilized normalization to implement to features which were extracted from seven moment invariant to achieve the objective to reducing the features size.

8. SUGGESTIONS FOR FUTURE WORK

During the development of this work, many recommendations come to mind. In this context some ideas may be considered for further work on the proposed method:

1. The use of other types of brain tumors, or other parts of human body.

2. Use of other Neural Network algorithm such as, probabilistic Neural Network, Markov Models Using back-propagation neural network and Using swarm intelligent model with back-propagation algorithm. Also I suggest using genetic algorithm. For the purpose of discrimination for tumors

REFERENCES

[1] H. Zhu, "Medical Image Processing Overview", University of Calgary, pp. 1-27, 2003.

[2] AL-Taiyy A., "Medical Image Classification Using Kohonen Neural Network", M.Sc Thesis, Informatics Institute for Postgraduate Studies at the Iraqi Commission for Computers, September, 2006.

[3] T. Acharya, A. Ray, "Image Processing: Principles and Applications", A John Wiley & Sons, New Jersey, 2005.

[4] H. Khotanlou, "3D Brain Tumors and Internal Brain Structures Segmentation in MR images", Ph.D. Thesis, Ecole Nationale Supérieure des Télécommunications, 2008.

[5] N. Abdullah, U. Ngah and S. Aziz, "Image Classification of Brain MRI Using Support Vector Machine", Imaging Systems and Techniques (IST), IEEE International Conference, pp. 242-247, May, 2011.

[6] S. Bharadwaj and M.Vatsa, and R. Singh, " Aiding Face Recognition with Social Context Association Rule based Re-Ranking", IIIT-Delhi, India, 2014.

[7] R. Kapoor, P. Mathur, "Face Recognition Using Moments and Wavelets", International Journal of Engineering Research and Applications (IJERA), ISSN: 2248-9622, Vol. 3, Issue 4, pp. 82-95, Jul-Aug 2013.

[8]"Color Spaces", Apple Computer, Inc., 2006, Web Site: http://developer.apple.com/documentation/mac/ACI/ACI-3.html

[9] G. R. Kumar, G. A. Ramachandra and G. Sunitha, "An Evolutionary Algorithm for Mining Association Rules Using Boolean Approach", IJCES International Journal of Computer Engineering Science, Volume1 Issue 3, December 2011.

[10] B.L. Zhang, H. Zhang and S. S. Ge, "Face Recognition by Applying Wavelet Subband Representation and Kernel Associative Memory", IEEE Transactions on Neural Networks, Vol.15, No.1, January 2004.

[11] M. Mercimek, K. Gulez and T. V. Mumcu, "Real Object Recognition Using Moment Invariants", Sadhana, Vol. 30, No. Part 6, pp. 765–775, December, 2005.

[12] C. Nastar, M. Mitschke, and C. Meilhac," Efficient Query Refinement For Image Retrieval", In Proceedings of IEEE Conference on Computer Vision and Pattern Recognition, June 1998.

[13] I. N. Ibraheem, "Color Models Indexing for Content Based Image Retrieval System", Ph.D. Thesis, Department of Computer Sciences of the University of Technology, 2009.