EARLY DETECTION FOR BREAST CANCER BY USING FUZZY LOGIC

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ABSTRACT

Breast cancer (BC) is one of the important general health problem in the world . There are two types of Breast Cancer; Benign breast cancer and Malignant breast cancer . benign state is poor growing, rarely distributed to other areas of body and also have well- defined edges. Alternatively, Malignant point out has inclination to expand faster which is life intimidating. So, classification of the two state is essential for proper medical diagnosis of a breasts cancer patient. In this paper we suggest a new algorithm to diagnosis the Benign and Malignant cancer where each one (Benign and Malignant) has two types; Begin has two types of tumor adenosis and phyllodes_tumor ,while Malignant has two types also ductal_carcinoma and papillary_carcinoma.

 In this paper we proposed algorithm for diagnosis the Breast cancer where our algorithm has two parts where the first part contain from four steps; the first step is pre-processing step, the second step is for image analysis which used wavelet transform to analysis the images and the third step to extract benefit features which used the results from the wavelet transform to obtain most important numbers of features by using standard division and the fourth step is to know wither the image is Benign or Malignant by using Fuzzy logic to know the two types (Benign or Malignant).

The second part is contain the classified image (Benign or Malignant from first part) this part is for classify the other types of Benign (tumor adenosis and phyllodes_tumor) and Malignant (ductal_carcinoma and papillary_carcinoma), in this part we analysis the images by using GLCM after calculate watershed for the image to know the types of benign. For the Malignant we calculate the colour moment (HSV) then calculate standard deviation and mean to extract the features of each types of cancer, where these features will be as input for fuzzy logic to give the final decision for two types of Begin (adenosis and phyllodes_tumor) and two types of Malignant (ductal_carcinoma and papillary_carcinoma), the results accuracy from our algorithm are 98 %. By using the   data base from http://web.inf.ufpr.br/vr/breast-cancer-database, which contain more than 7000 images.The suggested knowledge-based system can be utilized as a professional medical decision support system to aid doctors in the healthcare practice.

Keywords: *Ductal_Carcinoma , Papillary , Adenosis , Phyllodes , Breast Cancer, Benign , Malignant.*

1. INTRODUCTION

Urbanization and lifestyle changes associated with economic transition have led to a rise in non-communicable diseases. There is currently sufficient evidence to point that cancer is now a significant health concern for most countries within the Eastern Mediterranean Region, malignancies lead in the occurrence of mortality and morbidity. You can find no significant data to point the occurrence of breast tumor based on geographical distribution, however the age- standardized incidence of breast cancers is 12-50 per 100 000 women, with the lowest occurrence in the Islamic Republic of Iran and Pakistan. An increased incidence of breasts cancers (50/100 000) sometimes appears in Middle Eastern and North African countries. However, the comparative frequency of breasts cancer in a lot of the countries in your community is between 15% and 25% of most malignancies diagnosed Based on the Regional Office databases and data from many countries of the spot [1], breasts cancer is the most frequent malignancy in your community, comprising 12%-30% of most cases. So we need for increased community consciousness about breast tumors in your community and the necessity for early diagnosis. .[2]

A histology image research system generally has a mixture of hardware and software and maybe it's put into two consecutive subsystems: (1) composition prep and image creation and then (2)image managing analysis. To lessen the death rate among women two thing are extremely important that are education about breasts cancers and verification that means acknowledgement [3] In This paper we didn't use hardware software of diagnosis .

The paper organized as follows: In Section 2, the research methodology is presented. In this section we also present all methods incorporated in the research method. Section 3 presents Algorithm Suggested . Section 4 presents the results . Finally, in Section 5 the conclusion and present future work.

2. RELATED WORK

Fabio A. Spanhol.et al 2016 [4]. They expose a dataset of 7,909 chest tumor (B.C.) histopathology images obtained on 82 patients, that happens to be publicly available from (http://web.inf.ufpr.br/vri/breast-cancer-database).
The dataset includes both safe and malignant images. The work associated to the dataset is the robotic classification of the images in two classes, which is a very important computer aided id tool for the clinician. For having the ability of evaluate the problem of this activity, they shows some primary results obtained with state-of-the-art image classification systems. The correctness differs from 80% to 85%, exhibiting room for improvement is held. Giving this dataset and a standardized research standard process to the medical community, they desire to assemble experts in both medical and these devices learning field to go frontward towards, this medical program. they survey correctness rates starting from 76% to94% on the dataset of 92 images.

Fatema-Tuz Johra and Md. Maruf Hossain Shuvo 2016[3]. They presented a fresh pipeline for breasts tumor cell recognition and characteristic removal using an wide open origin image examination software called Cell Profiler. They suggested an algorithm for predicated on fuzzy system to classification of the harmless and malignant condition. Comparison using popular achievement variables like precision, awareness and specificity demonstrates our proposed strategy performs much better than the Neural Network (ANN) and Support Vector Machine (SVM) founded classification. The level of sensitiveness , specificity, and exactness of the suggested method is

95.6%, 90.63%, and 94.26% respectively.

Mitko Veta . et al 2014[5] They released for non-experts. It begins with a synopsis of the cells prep, staining and slide digitization techniques accompanied by a conversation of different image finalizing techniques and applications, which range from analysis of tissues staining to computer-aided prognosis, and prognosis of breasts cancers patients. They used ER(estrogen receptor) and PR(progesterone receptor) receptor statuses are customarily dependant on counting the ratio of favorably stained nuclei. If this ratio is above a predefined threshold (10% in European countries and 1% in America) the tissues is described positive. **Benzheng Weil .at el 2017** [13] they propose a novel breasts tumor histopathological image classification method predicated on profound convolutional neural systems, called as BiCNN model, to handle the two-class breasts cancer tumor classification on the anthological image. This profound learning model considers course and sub-class product labels of breast cancer tumor as previous knowledge, which can restrain the length of top features of different breast cancer tumor pathological images. Furthermore, a sophisticated data augmented method is suggested to match tolerance whole slip image identification, which can full reserve image border feature of cancerization region. The copy learning and fine-tuning method are implemented as an best training technique to improve breast cancers histopathological image classification exactness. The test results show that the suggested method brings about an increased classification precision (up to 97%) and shows good robustness and generalization, which gives successful tools for breasts cancer clinical prognosis.

Mahmoud Al-Ayoub . et al 2016 [6]. The study presents an acceleration way for the segmentation of the mammography images predicated on the GPU. To be able to provide an improved recognition for the malignancy tumor, they use a improved version of the most frequent algorithm for image segmentation, which is the Sole Go away Fuzzy C-Means (FCM) algorithm. The strategy applied to a couple of mammogram images to tell apart between malignant and harmless cases. Additionally, the machine is executed on GPU parallel processor chip as well as the original CPU to be able to compare the performance of both implementations. The suggested execution on GPU offers a fine speedup in comparison to its serial execution on CPU.

Fatima S. Ahadi .at el 2017 [7] they implement a Mamdani-Type fuzzy inference system to predict a benign or malignant state. The results show that the

optimized fuzzy inference system can handle the complicated cancer prediction problem with higher accuracy

3. METHODOLOGY

We use Efficient methods for analysis the images such as wavelets transform , watershed technique , GLCM ,and colour moment (HSV) to find the features that is the key of diagnosis which used in Fuzzy logic after find the specific feature by using standard deviation (STD) , Energy , and mean for find the feature vector.

3.1 Wavelet Transform

The wavelet transform was proposed by the French mathematician Morlet J. et al. The wavelet transform has become a powerful signal processing tool based on Fourier transform, which has been developed and perfected by many scholars. Its theoretical basis is invariance under translation and extension, which allows the signal to be decomposed into sub-bands (time and frequency) without losing the information of the original signal [8]. According to the Mallat pyramid decomposition algorithm, the wavelet decomposition of two-dimensional image is realized quickly. After the wavelet decomposition of digital images, a series of sub-bands after decomposition is shown in Fig.1. In Fig.1, CAi is the low-frequency coefficient of layer i for wavelet decomposition. And the CH_i, CV_i and CD_i are the horizontal, vertical and the diagonal direction detail component of the i-layer after decomposition separately. [8]
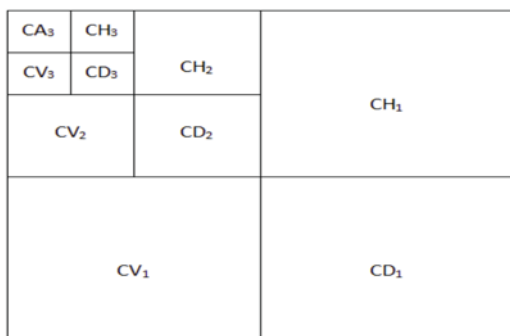

Fig. 1 Schematic diagram of tertiary wavelet

To understand the wavelet transform, let us recall the definition of convolution of a time function f (t) with a kernel g(t): [8]

$$\psi(t) = \frac{\emptyset_{1.0}\,(t) - \emptyset_{1.1}\,(t)}{\sqrt{2}}$$

$$= \emptyset(2t) - \emptyset(2t - 1) \quad ..(1)$$

And set

$$\psi_{0,n}(t) = \psi(\, t - n) = \frac{(\phi)_{1,2n}(t) - \phi_{1,2n+1}(t)}{\sqrt{2}}$$

$$for\ n = 0\ ,1\ ,..\,N - 1. \,...(2)$$

Then the set $\{\psi_{0,n}\}_{n=0}^{N-1}$ is an orthonormal basis for W_0 , the orthogonal complement of $\mathcal{V}_0$ in $\mathcal{V}_1$. Discrete wavelet transform : the space $\mathcal{V}_1$ can be decomposed as the orthogonal sum $v_1 = v_0 \oplus w_0$ where W_0 ai the orthogonal complement of $\mathcal{V}_0$ in $\mathcal{V}_1$,and $\mathcal{V}_1$ therefore has the two bases

$\phi_1 = (\phi_{1,n})_{n=0}^{2n-1}$ and $\phi, \psi) = (\phi_{0,n})_{n=0}^{n-1}, (\psi_{0,n})_{n=0}^{n-1}$,(3)

The discrete wavelet transform (DWT) is the change of coordinates from
basis ϕ_1 to the basis (ϕ, ψ) . if

$$g_1 = \sum_{n=0}^{2n-1} c_{1,n}, \emptyset_{1,n} \in v_1 \quad (4)$$

$$g_0 = \sum_{n=0}^{N-1} c_{0,n}, \emptyset_{1,n} \in v_0 \quad (5)$$

$$e_0 = \sum_{n=0}^{N-1} w_{0,n}, \psi_{0,n} \in w_0 \quad (6)$$

And $g_{1=}g_0 + e_0$ then the DWT is given by [8]
$$c_{0,n} = (c_{1,2n} + c_{1,2n+1})/\sqrt{2} \qquad ....(7)$$
$$w_{0,n} = (c_{1,2n} - c_{1,2n+1})/\sqrt{2} \qquad ....(8)$$

3.2 Standard Deviation (STD)

After decomposing the images using Wavelet Transform, we can extract some important features using Mean, Standard Deviation. The mean is implemented as follows [9].

$$mean = \frac{1}{RS} \sum_{r=0}^{R-1} \sum_{s=0}^{S-1} f(r, s) \qquad ...(9)$$

The Standard Deviation (STD) is implemented as:[9]

$$STD = \sqrt{\frac{\sum_{r=0}^{R-1}\sum_{s=0}^{S-1}(f(r,s) - mean)^2}{R \times S}} \quad ..(10)$$

3.3 HSV Color Space

HSV colour space represents colors in conditions of Hue (or colour-depth), Saturation (or colour-purity) and depth of the worthiness (or colour-brightness). Additionally it is known as HSB (Hue, Saturation, Brightness) or HSI (Hue, Saturation, Intensity). Hue identifies shade type, such as red, blue, or yellow. It requires worth from 0 to 360 (but it is normalized to 0-100% in a few applications). Saturation identifies the vibrancy or purity of the color. It takes values from 0 to 100%. Finally, Value aspect identifies the lighting of the color. It requires the same range as the saturation (0-100%). [10]

The conversion from RGB to HSV is defined by the following expressions (Eqs. (11), (12) ,(13),(14) and (15)) :

The R,G,B values are divided by 255 to change the range from [0-255] to [0-1]:

$$R' = \frac{R}{255} \quad , G' = \frac{G}{255} \quad , \quad B' = \frac{B}{255} \quad ......(11)$$

$$Cmax = max(R', G', B'), Cmin = min(R', G', B'), \Delta = Cmax - Cmin..(12)$$

Hue calculation:

$$H = \begin{cases} 60° \times (\frac{G'-B'}{\Delta} \bmod 6), & if\, Cmax = R' \\ 60° \times \left(\frac{B'-R'}{\Delta} + 2\right), & if\, Cmax = G' \\ 60° \times \left(\frac{R'-G'}{\Delta} + 4\right), & if\, Cmax = B' \end{cases} \quad .(13)$$

Saturation calculation:

$$S = \left(\begin{cases} 0, & if\, Cmax = 0 \\ \frac{\Delta}{Cmax}, & if\, Cmax \neq 0 \end{cases}\right) \times 100\% \quad ..(14)$$

Value calculation:

$$V = (Cmax) \times 100\% \quad ..(15)$$

3.4 Grey Level Co-Occurrence Matrix (GLCM)

Using GLCM for extracting Gray various texture features. GLCM is also called as Gray level Dependency Matrix. It is defined as "A two dimensional histogram of gray levels for a pair of pixels, which are separated by a fixed spatial relationship." GLCM of an image is computed using a displacement vector d, defined by its radius δ and orientation θ [11].

3.4.1 Energy:

This is a measure of local homogeneity in the image. Its value is high when the image has very good homogeneity. In a non-homogenous image, where there are many gray level transitions, the energy gets lower values. The measurement of energy is given by:[12]

$$Energy = \sum_{i=1}^{Ng} \sum_{j=1}^{Ng} p(i,j)^2 \quad ...(16)$$

Where Ng is greatest level in gray level image, P (i,j) is GLCM matrix .

3.5 Watershed

In digital image handling, watershed is dependent on the three-dimensional image, and two will be the coordinate, another is grey level. Based on the idea of geography, there are three tips in the image: (1) Locality lowest point; (2) When a drop of water placed on the positioning of a point, the water must fall on a single minimum point. (3) Once the water reaches some point on the positioning, it will stream several such minimum amount point with the same likelihood. Then, for the least value of a specific region, the group of points which satisfy the condition (2) will be called the minimum amount "watershed" or "catchment basin",, and the set of points which satisfy the condition (3) and form together will be known as the "watershed." In the process of digital image, , the goal of the watershed algorithm [13] is to get the watershed and the watershed line in the image. [13] .

3.6 Fuzzy Logic

Fuzzy logic examines human thinking and represent this thinking as mathematical rule to applies it to conduct problem solving and decision making. Verbal rules and variables used in the human decision-making process are fuzzy, unlike the precise, numeric nature of computer logic. These verbal terms are represent mathematically as membership functions. The decision-making in fuzzy logic using symbolic verbal phrases rather

than numeric values and can produce best results depend on indefinite verbal knowledge like humans. If a system's behavior can be modelled by rules or requires very complex nonlinear processes, fuzzy logic can be applied to this system. Mamdani's fuzzy inference method is the most commonly used fuzzy inference system. [14]

Fuzzy rule-based systems consist of three main steps; Fuzzification, Inference and Defuzzification. In the fuzzification step, the crisp input and output variables are defined and mapped to linguistics variables. Once the input and output variables and the corresponding membership functions are defined, a system of rules composed of IF-THEN statements is designed and the fuzzy inference takes place, producing a fuzzy output set. The output is then defuzzified during the defuzzification step to produce a crisp output value - the prediction . For our case, Range between (0-5) and (10-16) was used to represent the output which is the probability Malignant or Benign respectively [14]. And Range between (20-30) and (50-60) was used to represent the output which is one of the types of Benign breast cancer ,   And Range between (80-100) and (120-150) was used to represent the output which is one of the types of Malignant breast cancer .

4.   THE PROPOSED ALGORITHM

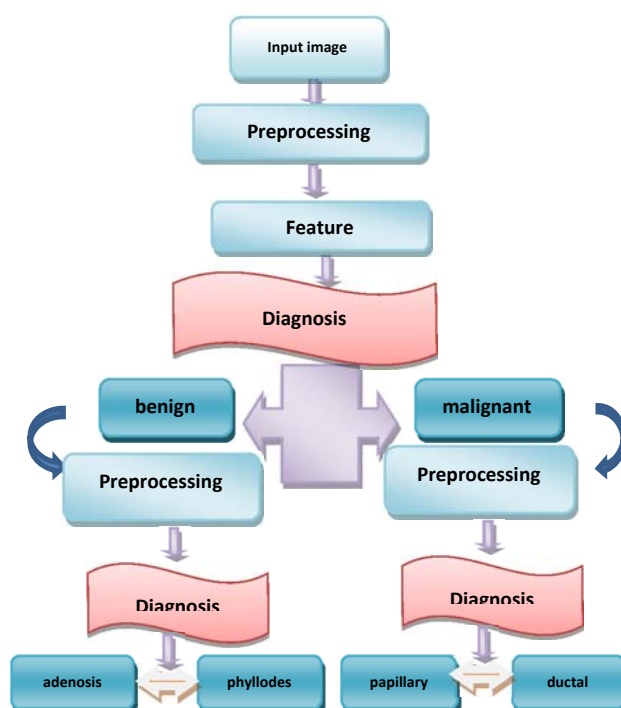Our proposed algorithm is consisting of six steps as shown in Figure 2

Figure 2 : The Algorithm flowchart

4.1   Step One Is Image Acquisitions:

By collect the images database from internet (http://web.inf.ufpr.br/vr/breast-cancer-database) which is contain more than 1000 images we used 120 for training (60 Benign images and 60 Malignant images) , and 40 image for testing.as shown in Figure 3.
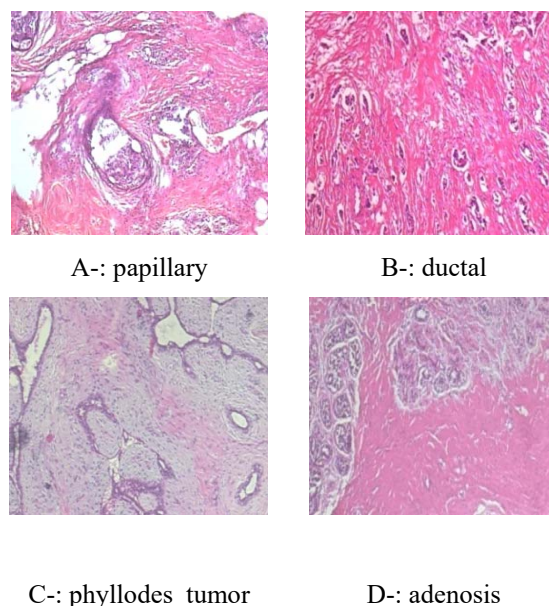

A-: papillary   B-: ductal

C-: phyllodes_tumor   D-: adenosis

Figure 3: (A and B) Malignant images , (C and D) Benign images

4.2 Step Two Is Pre-Processing:

1.   the pre-processing is starting by transform a histology colour image into grey scale image ; where the color image contain matrix with three color values for each pixel; Red (R), Green (G) and Blue (B), as shown in in Figure 4.
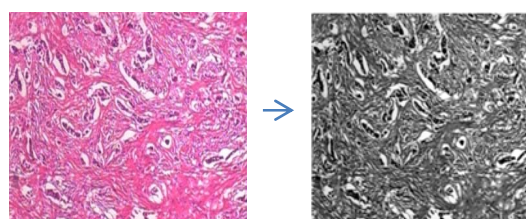

Figure 4: transform a histology image to grey scale image

2.   stores all numeric variables as double-precision floating-point values that are 8 bytes (64 bits). These variables have data type (class) double. as shown in algorithm 1.

algorithm 1: Preprocessing

input: original image

output: enhanced image

step1: convert original image into gray scale

$$\Upsilon = 0.299R + 0.587G + 0.114B. (17)$$

step2: convert resulted image into double image

End

4.3 Step Three Is Feature Extraction :

1. Calculate CA1,CA2, CD2 and CA3   (the approximately parts of HWT for three levels respectively); as shown in Figure.5.
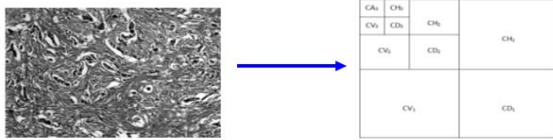

Figure 5: HWT for three levels

2. Calculate STD1, STD2 , STD3 and STD4 for CA1, CA2 , CD2 and CA3 respectively. There are four features will obtained (std1, std2, std3, and std4) which be the inputs for the fuzzy logic, as shown in algorithm 2.

Algorithm 2 : Image Analysis

Input: gray image

Output: features extraction

Step1: Finding Haar wavelet to three level .(HWT)

Step2: Calculate CA1, CA2 , CD2 and CA3 for three levels.

Step3: Calculate STD1, STD2 , STD3 and STD4 for step2 respectively.

End

4.4 Step Four Is Diagnosis :

The objective of diagnosis step is to distinguish between malignant and benign melanoma, after obtaining features vector. In our algorithm , fuzzy logic is used for distinguishing between malignant and benign breast cancer (B.C.) in First phases , Algorithm (3.3) describes the steps diagnosis As shown in Figure 12.

Algorithm 3 : Diagnosis

Input: Features vector

Output: type of cancer (benign or malignant)

Step1: four input fuzzy logic will be the features vector(STD1, STD2 and STD3 and STD4).

Step 2: build fuzzy logic (two rules) ,   as shown in Figure 6 and Table 1.

Step3: one output form fuzzy logic (Benign or Malignant) .

Table 1: Fuzzy Rules

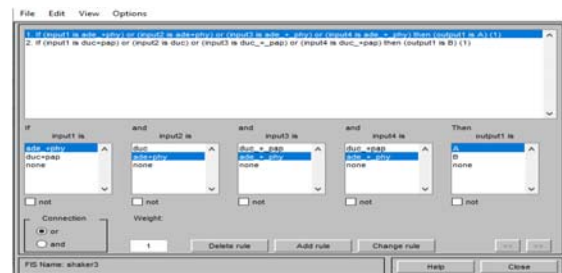| No	Rule
1	IF (input1 is duc+pap) OR (input2 is duc) OR (input3 is duc_+_pap) OR (input4 is duc_+pap) THEN (output1 is B)
2	IF (input1 is ade_+phy) OR (input2 is ade+phy) OR (input3 is ade_+_phy) OR (input4 is ade_+_phy) THEN (output1 is A)

Figure 6: Input Rules

4.5 Step Five Separate The Benign And Malignant Types :

The second stage is also contain from many steps to separate the Benign and Malignant types; The results from first phases will be Benign or malignant, so we need to separate each types of cancer (two types of Benign and two types of malignant) as illustrated in Algorithm 3.4 and 3.5
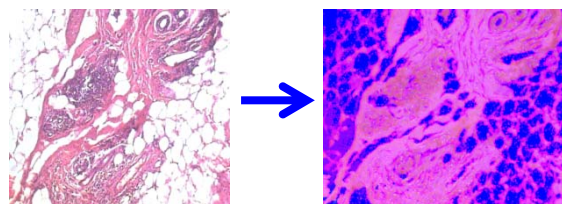
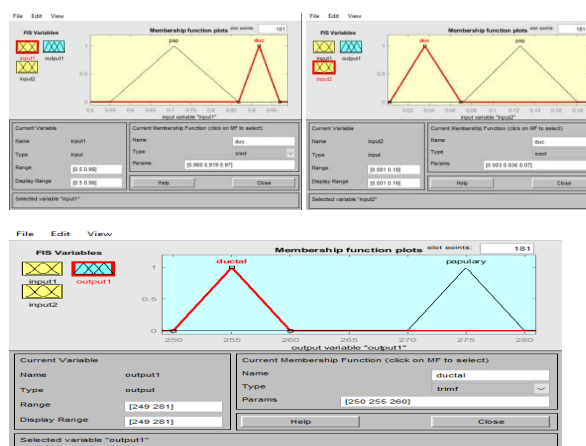| Algorithm 4 : Detecting breast cancer (malignant image) |
|---|
| **Input**: malignant image
 Output: one types of malignant (ductal_ carcinoma or papillary_ carcinoma) |
| **Step1:** Re-read the original image(which is diagnosed as Malignant) by convert **a** histology coloured image into colour moment (HSV) as shown in Figure 7

 Step2: Creates the structuring morphological element of discoid shape with radius=1 , then expands the image using the morphological element (discoid shape).

 Step3: Calculate the mean and STD for H, S and V of HSV image. Where the results shows that only two features mean of (H) and STD of (H) gives best results from others which will be inputs into the fuzzy logic .

 Step4: The two inputs are mean of (H) and STD of (H)) from (step 3) will build two rules of fuzzy logic for diagnosis and one output (ductal_ carcinoma or papillary_ carcinoma). as shown in Figure 8 and Table 2.

 End |

Figure 7: transform a histology image to color moment (HSV) image

Figure (8): Inputs and Outputs types of Malignant Mamdani model

Table (2): Fuzzy Rules

No	Rule
1	IF (input1 is duc) OR (input2 is duc) THEN (output1 is ductal)
2	IF (input1 is pap) OR (input2 is pap) THEN (output1 is papulary)

Algorithm 5 : Detecting breast cancer (benign image)
Input: benign image   **Output**: one types of benign (Adenosis or Phyllodes)
Step1: Re-read the original image (Benign) by convert a histology colour image into grey scale image.   **Step2**: Find the edges of image by using a two-dimensional filter 'sobel' .   **Step3**: Apply morphological opening of the image through the element morphological structuring. And performs the morphological reconstruction image, then expands the image using the

morphological element (discoid shape) .

Step4: Find the image complement and extracts the regional maximums , then dilation to avoid marker and fragmentation removes smaller 5-pixel markers from the image.

Step5:convert image into binary then find the watershed algorithm by final the boundaries of the marker. Which will convert the binary Colour watershed label image, as shown in figure (9,10).

Step6: apply GLCM onto grey scale image the resulting of previous operations   after histogram   implementation on image . There are 16 features from GLCM these 16 features will build 16 rules of fuzzy logic   and there are only one output (adenosis or phyllodes_tumor)   as shown in Figure (11) and Table (3).
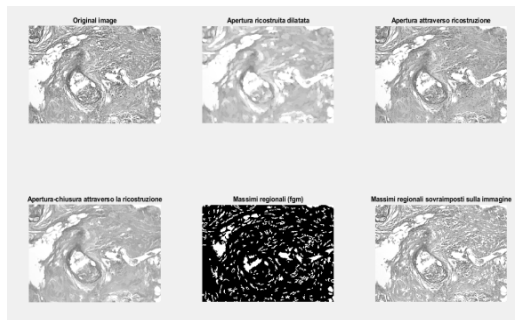
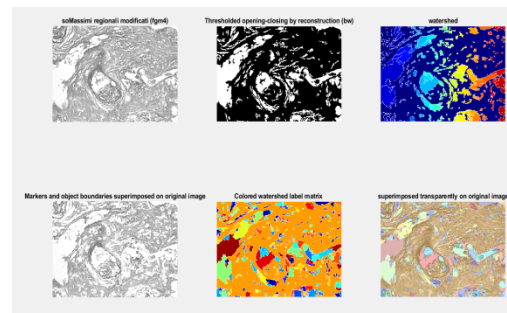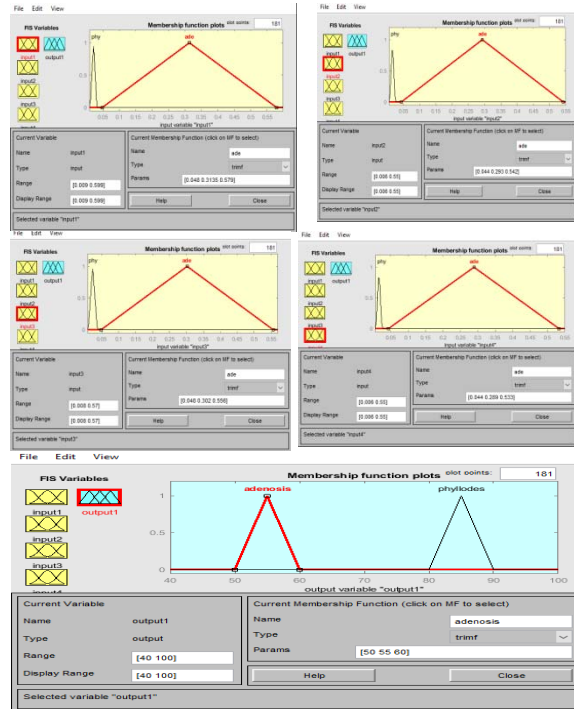**End**

Figure (9): watershed operations part2

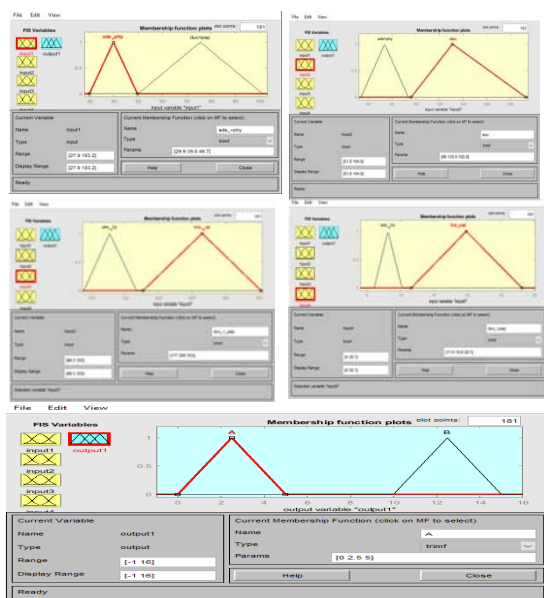*Figure (10): watershed operations part2*

Figure (12): Inputs and Outputs for(Benign , Malignant) Mamdani model

Figure (11): Inputs and Outputs for(Benign , Malignant) Mamdani model

No	Rule
1	IF (input1 is ade) OR (input2 is ade) OR (input3 is ade) OR (input4 is ade) THEN (output1 is adenosis)
2	IF (input1 is phy) OR (input2 is phy) OR (input3 is phy) OR (input4 is phy) THEN (output1 is phyllodes)

Table (3): Fuzzy Rules

5. RESULTS

In this section, we discus several concepts needed for our new algorithm . In This paper we use histopathology images for diagnosis the breast cancer through check the images if it is Benign (BC) or Malignant (BC) then classify each types of Benign with two types (adenosis and phyllodes_tumor) and Malignant with two types also (ductal_carcinoma and papillary_carcinoma). by use wavelet transform algorithm in   first two steps of our algorithm then use GLCM and colour moment(HSV) in step three   to the end, the features extracting for each step will be input to fuzzy logic to know the final decision, there are four features used as four inputs of fuzzy logic which give the final results (Benign or malignant) in first two steps and there are six features used as six inputs by calculate (MEAN , STD) for (H)of colour moment (H, S, V) for diagnosis the two types of Malignant and (energy $(A0°)$, energy

$(A45°)$, energy $(A90°)$, energy $(A135°)$) for diagnosis the two types of Benign.

There four features in step two (classify Benign and Malignant)which calculate by STD1, STD2 , STD3 and STD4 for CA1 , CA2 , CD2and CA3 of three levels WT respectively , as shown in Table (4 and 5). There are six features from steps three   as shown in table (6 , 7 , 8 and 9)

Table (4).STD For Benign

Image No.	STD1 CA1	STD2 CA2	STD3 CA3	STD4 CD2
1	43.63146	81.3981	144.2333	8.366293
2	37.67848	69.13245	118.6775	8.067114
3	35.47462	66.36621	117.4697	6.592461
4	37.28117	70.91358	128.7396	6.059023
5	37.75304	70.2219	122.6454	7.511251
6	40.72568	75.18213	128.9053	8.678011
7	40.92783	75.20538	129.4749	9.10601
8	38.8137	71.01208	120.7492	8.928726
9	38.97185	71.32115	122.0768	9.014804
10	39.36198	71.96632	121.364	9.09672
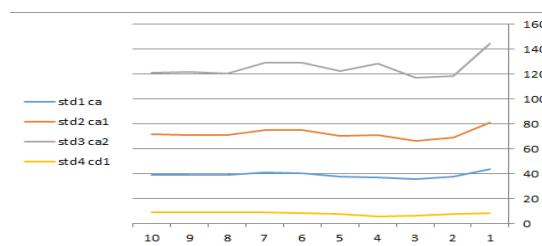
Figure 13 : Benign

Table (5). STD For Malignant

Image No.	STD1 CA1	STD2 CA2	STD3 CA3	STD4 CD2
1	99.56281	184.3522	319.3109	22.30879
2	98.53386	179.1271	302.6923	24.91326
3	90.35643	157.2049	243.9512	28.12394
4	91.66428	165.576	279.0232	24.82369
5	92.89925	164.9793	264.8339	25.65492
6	59.85532	107.7856	181.6433	16.2245
7	67.52448	124.2312	219.1201	16.09513
8	73.81036	141.7642	266.9144	12.50924
9	69.40446	120.1879	190.222	22.51926
10	92.65795	173.5048	315.3208	20.23946
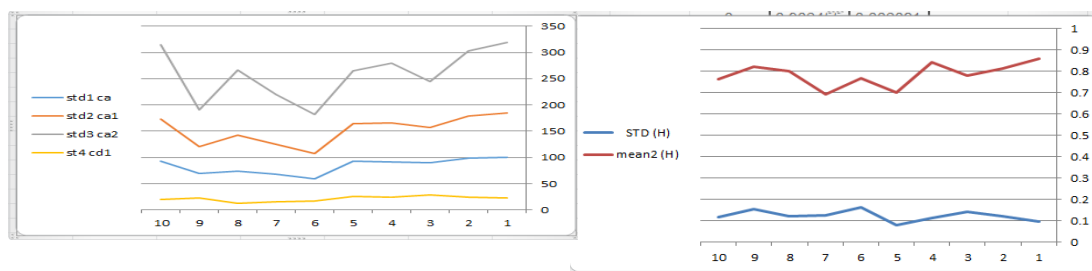
Figure 14 : ma lignant

Table (6). (mean2 (H), STD (H))   For malignant(ductal_carcinoma)

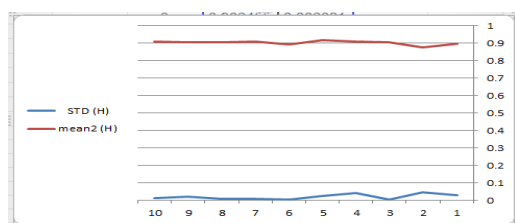| Image No.	mean2 (H)	STD (H)
1	0.896701	0.031082
2	0.878165	0.044246
3	0.906455	0.006081
4	0.909259	0.042167
5	0.917552	0.026798
6	0.891837	0.003962
7	0.907903	0.006694
8	0.905304	0.007464
9	0.907001	0.020096
10	0.908558	0.013844

Figure 15 : ductal_carcinoma

Table (7). (mean2 (H), STD (H))   For Malignant (papillary_carcinoma)

Image No.	mean2 (H)	STD (H)
1	0.8581105	0.0971186
2	0.8137186	0.1216032
3	0.7814398	0.1422598
4	0.8420075	0.1145205
5	0.700039	0.0810016
6	0.7695641	0.1642349
7	0.6943092	0.1252418
8	0.8012199	0.1203206
9	0.8214097	0.1551491
10	0.7621288	0.1175079

Figure 16 : papillary_carcinoma

Table (8).STD For Benign(adenosis)

Image No.	Energy a1	Energy a2	Energy a3	Energy a4
1	0.31564	0.30764	0.320645	0.307528
2	0.38988	0.38103	0.394251	0.380613
3	0.38984	0.38076	0.39351	0.379236
4	0.29501	0.28767	0.299229	0.286296
5	0.54998	0.54262	0.556284	0.533915
6	0.49371	0.48345	0.502557	0.479568
7	0.4282	0.41964	0.429567	0.418053
8	0.16577	0.16149	0.168277	0.160703
9	0.23156	0.22813	0.23333	0.225815
10	0.48737	0.48089	0.491402	0.476215

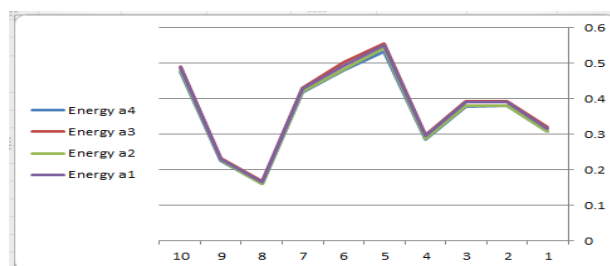*Figure 17 : Benign(adenosis)*

Table (9).STD For Benign(phyllodes_tumor)

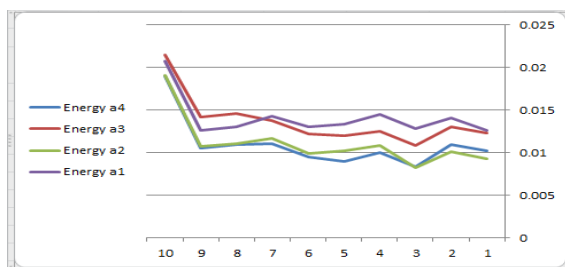| Image No.	Energy a1	Energy a2	Energy a3	Energy a4
1	0.01264	0.00924	0.01233	0.01024
2	0.01409	0.01012	0.01304	0.01098
3	0.01285	0.00822	0.01087	0.00836
4	0.01446	0.01088	0.0125	0.01002
5	0.01337	0.0102	0.01199	0.00896
6	0.01308	0.00993	0.01219	0.00952
7	0.01428	0.01164	0.01374	0.01105
8	0.01301	0.0111	0.01463	0.01092
9	0.01262	0.01076	0.0142	0.01057
10	0.02074	0.01914	0.02144	0.01903

Figure 18 : Benign(phyllodes_tumor)

6. COMPRESSION OUR ALGORITHM WITH OTHERS

There are many researches in diagnosis Breast cancer or detection , so that there are difference result and difference accuracy of researches . Table.10 shows the difference between our proposed algorithm with other researches algorithms.

Researcher	Accuracy
Fatema-Tuz Johra .at el Shuvo 2016[3]	95.6%
Benzheng Weil .at el 2017 [13]	97%
Fabio A. Spanhol.et al 2016 [4].	94%
Our proposed algorithm	98%

7. CONCLUSION

It is important to work in the field of early detection of breast cancer by using histological images because of the multiplicity of devices used in obtaining histological images and their accuracy, in addition to the distortions that occur during the conservation and storage phase of microscopic microscopy. Through the proposed algorithm and the conclusions reached, we recall the following conclusions:

1. In our algorithm we used Discrete Wavelet Transform with three levels each level has four parts, the total number of parts are 12 separate parts; (CA1 , CH1 , CV1, CD1 , CA2 , CH2 , CV2 , CD2 , CA3 , CH3 , CV3 and CD3) but the experiments shows that CA1 , CA2 , CD2 and CA3 are the best parts will give the best feature for diagnosis whither the cancer is Benign or malignant.

2. For recognition and diagnosis the two types of Malignant based on color features in general, the color model (HSV) that led to higher recognition results in color images. through used colour moment for each part of HSV (H, S, V respectively), and calculate (Mean , STD) for each part (H, S, V respectively), will collect six features (Mean for H , STD for H, Mean for S , STD for S, Mean for V , STD for V) but the experiments shows that (Mean for H and STD for H) give the best features to diagnosis the two types of Malignant.

3. For recognition and diagnosis the two types of Benign Brest cancer based on GLCM with 16 features Distributed by using (contrast , energy , correlation , homogeneity in $0°, 45°, 90°, 135$) but the experiments shows that (energy (in $0°$), energy (in $45°$) , energy (in $90°$), energy (in $135°$)) are the best ones which give the best features for diagnosis the two types of Benign.

4. Different kinds of statistical features are used such as Entropy, Mean, Moment and Standard Deviation but the experiments shows that the best ones are STD , Energy and Mean .

5. We hope that work can lead to more specialized medical decision support systems to help the patients to discover malignant and benign Breast Tumor in early cases. As such, we have identified several areas of future work that would benefit the breast cancer detection researches:

a) The improvement of the suggested online breast tumor recognition system to build self-detection system for the patients.
b) Use the same technique to diagnose other types of breast cancer using histological images.
c) Experience this technique in categorizing other tissue images for other types of cancers (not only Breast cancer).
d) This technique is used the same types of images but with different scale of the microscope zoom (2X, 6X, 10X, 15X, ….etc.) used to visualize the tissue.

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