METHOD FOR DETECTION AND DIAGNOSIS OF THE AREA OF SKIN DISEASE BASED ON COLOR BY WAVELET TRANSFORM AND A RTIFICIAL NEURAL NETWORK

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Abstract

Many cases of skin diseases in the world have triggered a need to develop an effective automated screening method for detection and diagnosis of the area of disease. Therefore the objective of this work is to develop a new technique for automated detection and analysis of the skin disease images based on color and texture information for skin disease screening.

In this paper, a study of the role of color information in detecting the edges of images was conducted. Therefore another color space (HIS) is implemented. Several edge detection techniques are applied such as Laplace and Perwitt, the results shows that the Laplace operator is more efficient than Perwitt operator in edge detection. Wavelet Transform plays an important role in the image processing analysis, especially in texture recognition of data. For its fine result when using Multi-resolution modeling. The texture image will be entered to Wavelet Mother Function; this will segment the texture into sub bands. These sub bands contain information about the texture, then this information will be entered to feature extraction, the output from them represent the input to the Artificial Neural Network (ANN) which represents powerful tool for handling problems of large dimension.

The idea of combining wavelets and neural networks is proposed to classify images. The output of ANN represents the type of texture.

طريقة كشف وتشخيص مساحة المرض بواسطة التحويل المويجي والشبكات العصبية الأصطناعية

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ألخلاصه

حالات كثيرة من امراض البشرة الموجودة في العالم تتطلب وجود او تطوير طريقة عرض اوتوماتيكية كفوءه لتحديد منطقة المرض وتشخيص نوعه وخاصة الامراض الجلدية لذلك فأن الهدف من هذا البحث هو تطوير تقنية تحديد وتحليل المرض الموجود في الصورة بالاعتماد على اللون ومعلومات النسيج. إن التوجه الأول لهذه الدراسة هو دراسة دور المعلومة اللونية في كشف الحافة للصورة ولذلك تم تبني وتطبيق فضاء اخر للصورة اللونية هو (HIS). عدد من تقنيات . (edge detection) تم استعمالها مثل (laplace and perwit).وقد أظهرت النتائج إن تطبيق (laplace operator)أكثر كفاءة من (Perwit operator)في كشف الحافة.

لعب تحليل الأنسجة دورا" كبيرا" في تحليل وتمييز ألا نسجه حيث تم في هذا البحث أستخدام تحويلات المويجة الذي يقوم بتقسيم النسيج الى اربعة أقسام لكي نستطيع استخراج الصفات التي تحدد نوع النسيج يتم ذلك بواسطة ادخال النسيج على دالة المويجة الام (wavelet mother function) التي تقسم النسيج إلى مجموعة

من الترددات ذات حزم ضيقة العرض في مناطق ذات الترددات الواطئة تحتوي الحزم تحتوي على معلومات عن ذلك النسيج يتم استخلاص الصفات بواسطة ادخال المعلومات على مستخلص الصفات (features extraction) والاخراج من هذه المرحلة سوف يتم إدخاله الى الشبكة العصبية التي تعتبر اداة فعالة لمعالجة المشاكل ذات الابعاد الفعالة الكبيرة وان فكرة الربط بين التحويل المويجي والشبكات العصبية قد اقترحت في هذا البحث لتصنيف الصور وان الاخراج من الشبكة العصبية يمثل نوع المرض(النسيج) او نسبة الشبه من المرض الاصلي.

Keyword
(WT) Wavelet Transform, (ANN) Artificial Neural Network, Segmentation, Border Identification, Features extraction.

List of Abbreviations
ANN: Artificial Neural Network
2D-DWT: 2-Dimential Discrete Wavelet Transform
L: Low pass filter
LL: Low-Low.
N.N: Neural Network
RGB: Red Green Blue.
STD: Standard Deviation
WT: Wavelet Transform

Introduction

Skin diseases are one of diseases that are wide spread. They often strike without warning and have been one of the major killer diseases in the world for the past ten years especially skin cancer. The skin diseases can be prevented if the damage region that leads to the diseases are detected and removed (Ali, 2003).This research is motivated by the fact that the operation and diagnosis of the skin diseases procedure requires expert knowledge and is still mostly manual in nature. In addition, manual diagnosis is influenced by the variability of the human observation that leads to differences in diagnosis (Bulsari, *et al,* 1993).

Image processing techniques have become increasingly important in a wide variety of applications in the medical field, the need for designing and developing the computer–based image processing and diagnosis system has also been increasing and diagnosis system has also been constantly increasing. However, the image processing techniques are mainly applied to many tasks in the area of enhancement and segmentation, the processing and analysis of skin images have gained importance and only a few researchers are working in this area (Hance, et al, 1996). Image processing

and analysis can be applied to skin diseases images in the number of areas, with very good potentials for future clinical applications such as Achieving automatic diagnosis, it is hoped that an intelligent and automated clinical diagnosis and navigation can be carried out with a consistent level of performance with the aid of a computer. This could be possible with software that is capable of image analysis, such as identifying the region boundary and the region classification. These aspects are pursued in the present research work (Harm, et al, 1986).Segmentation refers to the procedure of decomposing on image into regions that each holds some property distant from their neighbors. This is an essential part of image analysis and is a basic requirement (feature extraction) for the identification and classification of objects in image (Katada, 1994). The classification process defines the features in the segmented image constituting a kind of abnormality, for example identifying the tumor. At the end of this stage, all the abnormal areas on the images are marked (Khan, 1996).

Many researches dealing with the texture analysis field are summarized as follows:

(Ali, 2003), uses five groups of gray images, each group consists of five images from the same class in images classification. The research implemented in three stages, the first stage implemented by taking nature textures for five groups, the second stage implemented by taking an image for remote sensing and broken to 16 blocks each block has size (32*32), gray scale), the third stage is implemented by taking 20 samples of new texture for testing the work and we obtain on the results that 19 correct and only one error.

(Bulsari, *et a1,* 1993), in this project, a wavelet based technique is used to extract features that are used to discriminate between different textures seen on remotely sensed image of a forest area. A database created of the textures expected to be found in the image. Wavelet decomposition is done on it. A database of the different types of textures, that were expected to be found in the image, is found. The input image is block processed and the texture recognition system is applied to each block. In the output image, the corresponding block was given specific gray level according to the texture. (Hance, *et a1*, 1996), compare six different color segmentation methods and their effectiveness as a part of finding an algorithm for overall border of skin tumor. They found that principal components transform /median cut and adaptive shareholding algorithms provide the lowest average error and show the most promise for further individual algorithm development.

(Harm, *et al*, 1986), uses image texture in combination white color features to diagnose leukemic malignancy in samples of stained blood cells. They extracted texture micro-edge and "textons" between these micro-edges. The textons are regions with almost uniform color. They extracted a number of texture features from the text ones including the total number of pixels in the text on which has a specific color, the mean text on radius and text on size for

each color and various texts on shape features. In combination with color, the texture features significantly improve the correct classification rate of blood cell types compared with using only color features.

(Landeweerd, *et al*, 1978), extracted various first-order statistics (such as mean gray level in a region) as well as second-order statistics (such as gray level co-occurrence matrices) to differentiate different types of white blood cells

System Design Implementation

The developed system works on RGB color images with size 128 x 128 pixel. The system is built with four primary processes these are border identification, features detector, artificial neural network, and final classification.

1- Border Identification

The first process in the suggested system is border identification; color segmentation plays an important role in this subject. Color information is often effective in image segmentation. **Figure (1)** shows the block diagram of Automatic Color Segmentation. The first step is removing the noise from the original color image by using the convolution operator between original image **Figure (2)** and the mean filter **table (1).**

Then convert the RGB image space to HSI image space depending on the following equations.

$$I = (R + G + B)/3 \quad (1)$$

$$S = 1 - 3\min(R, G, B)/(R + G + B) \quad (2)$$

$$H = \begin{cases} \dfrac{G - B}{3(R + G + 2B)} & if \ \min(R, G, B) = B \\ \dfrac{B - R}{3(G + B - 2R)} + \dfrac{1}{3} & if \ \min(R, G, B) = R \\ \dfrac{R - G}{3(R + B - 2G)} + \dfrac{2}{3} & if \ \min(R, G, B) = G \\ undefined & if \ (R = G = B) \end{cases} \quad (3)$$

In the proposed system, border identification process will be explained using practical examples on image of skin cancer with one isolated region as shown in **figure** (3) and **figure** (4) of cancer and multi regions of disease as shown in **figure** (5) and **figure** (6) by using Laplace filter and Perwitt filter. After the above examples we repeat the border process by Lablace only in another disease as shown in **figure (7).**

2- Feature Detecto

Feature detector consists of two stages: - wavelet decomposition and features extraction.

2- A- Wavelet Decomposition

In this procedure, the image data will be analyzed using transform domain techniques based on 2D-DWT. Here the image is handled with1-level, 2-level, and 3-level wavelet decomposition with various multi-resolution sub bands.

In this research a number of skin diseases have been selected. They are (Skin cancer texture and Dermatitis texture), after that we selected (5) samples of images with size (128*128) in RGB space for each one disease from five persons. The analysis stage was started after cutting the lesion (16*16) of disease from all (25) images selected, the textures of the images here are represented by wavelet coefficients using Haar basic function.

2- B- Features Extraction

The features extraction consists of features calculations, features selection and additional processes. The purpose of feature calculations is to obtain those features which preserve the useful information about the image to the largest extent. The aim of feature selection is to determine those principal feature components depending on a certain classification task in order to achieve an effective classification. The output of features detector reflects the information of the image which represents the mean,

standard deviation, and mean of variance for all wavelet sub bands in each image by using the following equations:-

$$Mean = \frac{1}{RS}\sum_{r=0}^{R-1}\sum_{s=0}^{S-1} f(r,s) \quad (4)$$

$$STD = \sqrt{\frac{\sum_{r=0}^{R-1}\sum_{s=0}^{S-1}(f(r,s) - Mean)^2}{R * S}} \quad (5)$$

$$\varepsilon = \frac{1}{RS}\sum_{r=0}^{R-1}\sum_{s=0}^{S-1}\left(f(r,s) - Mean\right)^2 \quad (6)$$

Where:

ε : The Variance.

R: is the number of rows in the matrix.

S: is the number of column in the matrix.

(r): is the value of row.

(s): is the value of column.

f(r, s): is the value of element in the matrix (Mathur, 2002).

But this information is not used directly in image classification; therefore this information is entered to the features selection. The features after selection may not contain enough information about the original image, but must contain the information that is useful to distinguish different classes for image classification. The features of two types of diseases depend on five samples in each disease as shown in **Figure** (**8 and 9**) for the Skin cancer disease. Compute the features values (mean, standard deviation, and variance) for the wavelet sub-bands in each component as shown in **tables (2, 3, and 4).** Calculate the average value of features as shown in **table** (5), therfore ,find the average values of the features in that levels and repeat this processes for all samples (persons) and save the results in file. The results for this processes are shown in **figures (10, 11, 12, 13, and 14)** and **tabels (6, 7, 8, 9, and 10),** while **Figure (15)** explain the dermatitis disease, and one sample is used in wavelet decomposition as shown in **figure (16).**Repeat the same processes above on the dermatitis disease, so that the results are shown in **figures (17, 18, 19, 20, and 21)** and **tables (11, 12, 13, 14, 15, 16, 17, 18, and 19)**. By using the above two examples

of diseases, it can be estimated that the combination of the three features value may be used to decided the type of the disease. The ranges of values for all features in each class of disease as shown in **table (20),** while **table (21)** shows the threshold value for each feature and disease.

Artificlal neural network (classifier)

The above calculated features can be used to train a neural network to work as a classifier for the type of the two mentioned diseases. Neural networks are powerful tools for handling problems of large dimension. Neural network consists of two phases:

1- The Training Phase

The proposed neural network classifier depending on the disease's images is a feed-forward multi-layer net with three inputs and one output, trained by the Levenberg_ Marquardt Algorithm. The input (training pattern) to the net will be the feature values vector which can be computed for each images concerned with the proposed work to make the net learn the characteristics of those images. In the training phase, the net starts with a random set of weights and a training pattern is presented at the input layer which are the threshold value shown in **table** (21). The outputs of the network are then evaluated and compared to the expected output vector for this particular pattern. The resulting errors are fed-back from the output layer and the weights are adjusted, the procedure is repeated for all patterns in the training set and each time the weights are adjusted. The training set is presented iteratively to the net in an attempt to minimize the mean square error. The aim is that, for a low system error, the output vector representing the classification of a particular input pattern should be equivalent to the target output vector. The network continues training with the input patterns until the mean square error value between the value of the desired and target vectors reaches [7.5794e-011] at that point training is stoped, and the weights and all trained network variables will are saved in a file to be used in the testing (classification) stage, The stepes of this phase are shown in **figure (22).**

2- Classiffication Phase

The classiffication phase consist of three processes: wavelet decomposition, feature extracation,

classification

2- A- Wavelet Decomposition

In this process the unknown image will be decomposed using DWT of Haar type into 3 levels.

2- B- Feature Extracation

In every classifcation system, featuers of the image data must be extracated, according to the same way suggested in the proposed system . The data is the color texture of the skin diseases images, all of them of size 16 x 16, the feature extracation will be made for each subband, features vector represents the input image, and consists of three values (mean, standard divation, mean of variance).

2- C- Classification

After the proposd neural network has been trained in phase one, the net can be tested to classify images.both the traininng set and test set contain input / output pattern pairs. While the training set is used to train the network ,the test set is used to asses the performance of the network after training is complet. In the classification phase the feature vector,which results from the above process (process two), will be entered to the trained N.N. (learned), to be tested, the net will give the class for the unknown imag.

Results of Classifier

A- Training Stage

After that find the all probability for a bove set of threshold values in **table (**21) which represent the input to the ANN for diagonous, the outputs from the ANN represent the type of the disease,as shown in **figure (23)**

B- Testing (classification) Stage

After the result from the feature extrication and learning phase we reach to the classification (testing) by taking (29) new samples with size (128*128) color image, for different textures and repeat the above procedure on them the results is only three error and the others are correct (some of result have similar from the original texture). In the final work the results from test stage may be the correct

disease type or may be incorrect disease type or new disease (by adding zero case) using Haar, **table (22)** show the rate of performance of the ANN depends on the following formula:

$$performance\ \ of\ \ ANN\ (\%) = \frac{Number\ \ of\ \ classified\ \ patterns}{Total\ \ number\ \ of\ \ patterns\ \ tested} * 100$$

(7)

$$performanc\ e\ \ of\ \ ANN\ (\%) = \frac{9}{10} * 100 = 90\%$$

(8)

Discussion

All results illustrated in the figures (3, 4, 5, 6, and 7) confirm that the images which are related to the skin diseases only in the Laplace operator. Because Laplace is the best edge detection filter that produces more edge point and the edge is thinner than the edge detection Perwitt filter which are thick and discrete in the two cases (one isolated region or multi regions of disease). Finally, the Laplace filter will be used in the proposed system in border identification process.

The wavelet transform is used as an efficient multi-resolution modeling to transform the image into four small sub images in each depth, the input to Wavelet Transform is an image which contains the region of disease and the output consists of information about the image itself that may be used in another process. This information entered to the features extraction (Mean, STD, and Variance). In the classification of the textures, two groups of skin diseases will be used with properties (16*16, color image) for the medical images that depend on the nature of texture or the shape of lines in the texture.

In the third level, the sub bands are not interesting; this depends on the feature extraction. In this work the sub bands (LL1, LL2, and LL3) are used in mean, standard deviation, and variance. Using the Neural Network in discrimination is very important in this field than the classical method using (if..……then) statement, because it takes the features in each stage and then finds the threshold values to(mean, standard deviation, variance) for all types of diseases and training the network this network takes the output from the feature extraction as a vector. This vector becomes as input for the network this input became standard for all textures (the groups that we

took represent the textures). This for the nature texture network, after that this Neural Network will give the type of each texture, because the output from ANN is approximation and generalization, where the generalization capacity of a neural network is its capacity to give a satisfactory response to an input which is not part of examples or which it was trained. The degree of generalization possible is related to the quality of the result set up by the network.

Conclusions

The proposed system offers high level of classification. From the implementation of the proposed system, it can be concluded that the Laplace filter is powerful tool in edge detection and color segmentation in border stage, and when wavelet transform is used as decomposing, it gives an efficient result in features extraction stage. The statistical measurements (mean, stander deviation, and variance) are useful in texture detection and to reduce the time in process with efficient results, and neural network is very fast detections because the topology of this neural network and the input values from features extraction stage. The proposed system is able to detect many types of distributed diseases with many distributed regions closed together and unable to detect the diseases that have distributed regions separated by distance.

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Table (1) The mean filter

1/9	1/9	1/9
1/9	1/9	1/9
1/9	1/9	1/9

Table (2) Features values of red component.

Level No	Mean	STD	Variance
LL 1	219.0547	29.65183	630.9341
LH1	0.898438	10.18721	96.83447
HL1	1.117188	16.02224	225.3403
HH1	2.210938	8.891678	69.76025
LL 2	438.1094	51.56226	1703.409
LH 2	6.265625	20.58447	375.8623
HL 2	7.515625	15.93672	145.4443
HH 2	-1.82813	15.83396	233.6631
LL 3	876.2188	87.57671	4367.025
LH 3	13.90625	43.11544	1268.346
HL 3	12.59375	51.7438	395.541
HH 3	-13.4688	19.39324	175.0801

Table (3) Features values of green component.

Level No	Mean	STD	Variance
LL 1	162.9531	35.3755	881.6445
LH1	1.1875	10.50605	102.623
HL1	1.390625	16.71623	238.7891
HH1	2.28125	8.780333	67.61914
LL 2	325.9063	62.67295	2490.67
LH 2	7.03125	22.09315	429.8066
HL 2	8.21875	20.26674	243.4395
HH 2	-1.96875	17.32986	278.9512
LL 3	651.8125	104.4025	6155.539
LH 3	16.1875	57.4512	2393.352
HL 3	11	63.21672	370.7031
HH 3	-11.375	27.55676	425.5313

Table (4) Features values of blue component.

level No	Mean	STD	Varia
LL 1	129.0391	38.33782	1072.8
LH1	1.132813	12.36715	144.9
HL1	0.789063	17.25481	251.9
HH1	2.257813	8.7564	67.15
LL 2	258.0781	67.38037	2970.
LH 2	7.765625	26.11887	608.8
HL 2	6.484375	22.6926	315.2
HH 2	-1.57813	18.0004	301.5
LL 3	516.1563	101.3278	6753.
LH 3	18.84375	66.54176	3179.
HL 3	4.09375	78.701	464.9
HH 3	-12.8438	33.10359	542.3

Table (5) Features values of original image.

Level No	Mean	STD	Variance
LL 1	511.0469	103.3652	2585.473
LH1	3.21875	33.0604	344.3613
HL1	3.296875	49.99328	716.0391
HH1	6.75	26.42841	204.5371
LL 2	1022.094	181.6156	7164.268
LH 2	21.0625	68.7965	1414.475
HL 2	22.21875	58.89605	704.1543
HH 2	-5.375	51.16422	814.127
LL 3	2044.188	293.3071	17275.57
LH 3	511.0469	167.1084	6840.793
HL 3	27.6875	193.6615	1231.199
HH 3	-37.6875	80.05359	1142.98

Table (6) Person one

Texture2 of skin cancer	mean	std	variance
total value	306	81	644

Table (7) Person two

Texture2 of skin cancer	mean	std	variance
total value	166	55	490

Table (8) Person three

Textur3 of skin cancer	mean	std	variance
total value	175	56	508

Table (9) Person four

Texture4 of skin cancer	mean	std	variance
total value	258	58	496

Table (10) Person five

Texture5 of skin cancer	mean	std	variance
total value	200	51	500

Table (11) Features values of red component.

Level No	Mean	STD	Variance
LL 1	441.2188	12.98775	131.577
LH1	-1.01563	6.618858	39.0185
HL1	0.734375	7.270821	47.4814
HH1	0.46875	4.644398	19.8681
LL 2	882.4375	19.87094	259.134
LH 2	1.1875	7.740855	54.2988
HL 2	-1.5625	14.29467	167.173
HH 2	1.5625	6.52974	38.5644
LL 3	1764.875	32.10968	365.738
LH 3	5.75	16.90445	26.9726
HL 3	4.9375	10.61176	72.2070
HH 3	4.6875	20.95195	329.238

Table (12) Features values of green component.

Level No	Mean	STD	Variance
LL 1	229.25	24.80175	204.9131
LH1	-0.40625	6.608601	38.21973
HL1	1.265625	7.741339	52.50684
HH1	0.578125	4.743599	20.65332
LL 2	458.5	45.08483	473.8457
LH 2	3.28125	9.650939	78.61914
HL 2	4.5	19.31386	199.3066
HH 2	2.65625	6.641959	40.65039
LL 3	917	85.20398	483.3477
LH 3	13.9375	8.910726	12.28516
HL 3	25.625	27.07609	440.8945
HH 3	8.1875	29.44601	645.7852

Table (12) Features values of blue component.

level No	Mean	STD	Variance
LL 1	215.0781	21.86434	172.964
LH1	-0.48438	6.497233	36.8808
HL1	1.328125	7.580896	49.5898
HH1	0.546875	4.675772	20.0410
LL 2	430.1563	40.23772	413.478
LH 2	2.6875	8.660013	64.8222
HL 2	3.03125	15.80925	157.443
HH 2	2.25	6.395311	37.8027
LL 3	860.3125	74.58821	669.390
LH 3	11.75	11.07879	4.16406
HL 3	24.75	25.71539	194.070
HH 3	7.0625	26.08849	509.328

Table (13) Features values of original image.

Level No	Mean	STD	Variance
LL 1	885.5469	59.65384	509.4551
LH1	-1.90625	19.72469	114.1191
HL1	3.328125	22.59306	149.5781
HH1	1.59375	14.06377	60.5625
LL 2	1771.094	105.1935	1146.459
LH 2	7.15625	26.05181	197.7402
HL 2	5.96875	49.41777	523.9238
HH 2	6.46875	19.56701	117.0176
LL 3	3542.188	191.9019	1518.477
LH 3	885.5469	36.89397	43.42188
HL 3	55.3125	63.40323	707.1719
HH 3	19.9375	76.48646	1484.352

Table (15) Person one

Texture 1 of Dermatitis	mean	std	variance
total value	527	36	385

Table (16) Person two

texture 2 of Dermatitis	mean	std	variance
total value	676	37	222

Table (17) Person three

Texture 3 of Dermatitis	mean	std	variance
total value	596	54	276

Table (18) Person four

Texture 4 of Dermatitis	mean	std	variance
total value	650	38	237

Table (19) Person five

Texture 5 of Dermatitis	mean	Std	variance
Total value	541	33	228

Table (20) Range values of the diseases.

Disease name	Range of mean	Range of std	Range of variance
Skin cancer	166-306	51-81	490-644
Dermatitis	527-676	36-54	222-385

Table (21) Threshold values of the diseases.

Disease name	threshold of mean	threshold of std	threshold of variance
Skin cancer	226.25	62.5	534.5
Dermatitis	747.5	49.5	337

Table (22) Rate of performance of the ANN.

Disease No.	No. of samples	Number of correctly detected patterns			
		trained	test	classified	Rate of performance
1	10	5	5	5	100%
2	10	5	5	4	80%
Total patterns	20	10	10	9	90%

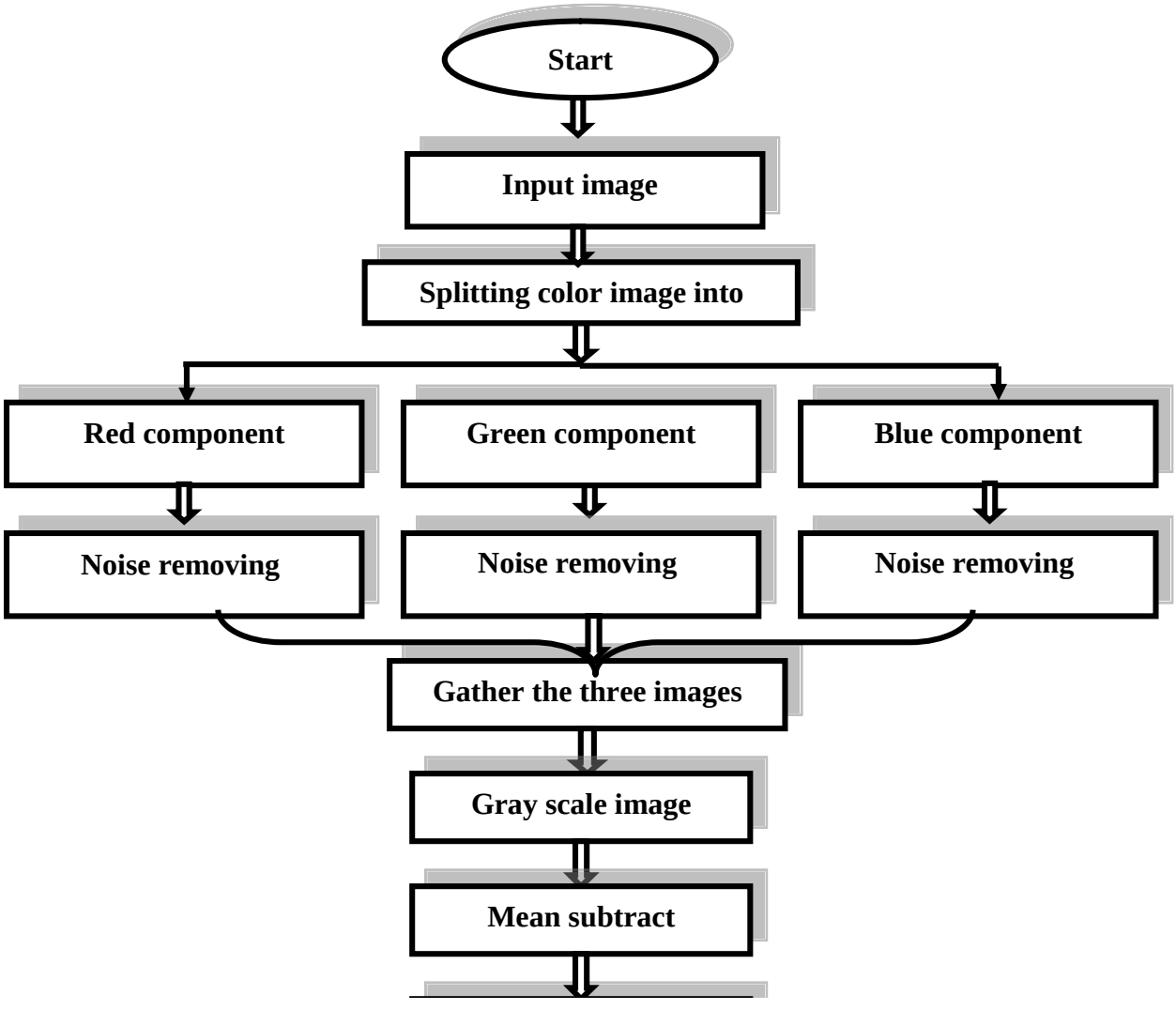
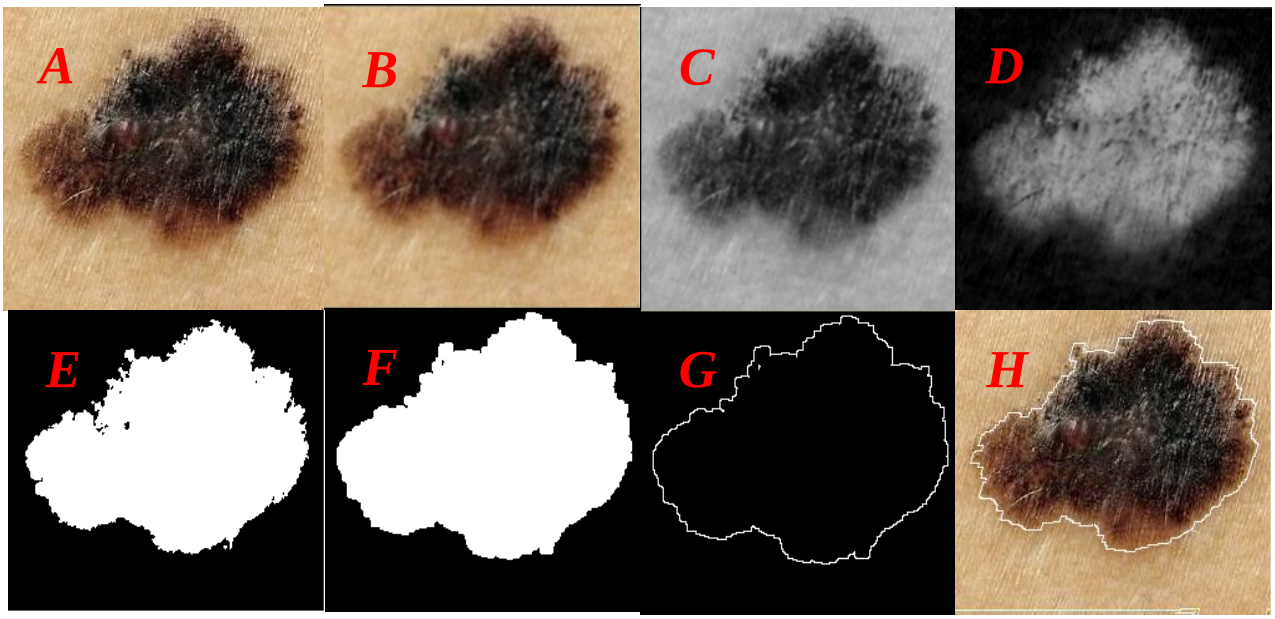


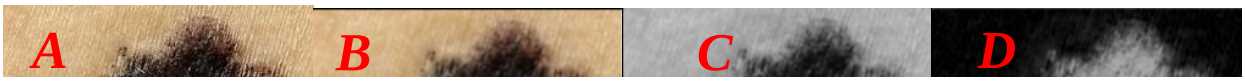
Figure (2) color image.

Example -1-(Laplace Filter)

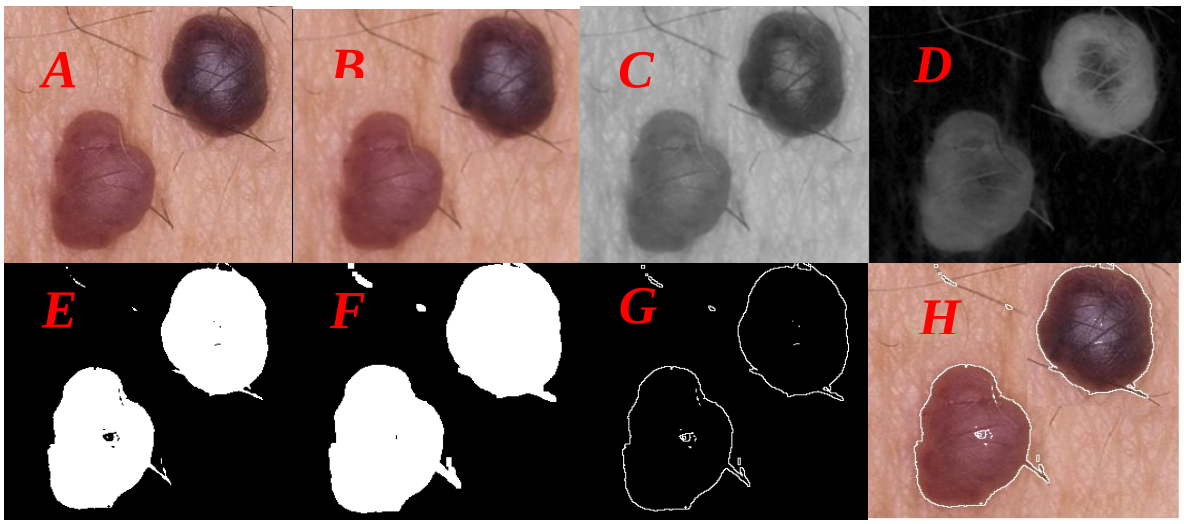


Figure(3): (A)Color original image of skin cancer (B)noise removing (C) image obtain after mapping colors into intensity (D)difference between each pixel in image and the mean of background (E) threshold of difference image (F)filling operator to threshold image (G) Laplace edge detection (H)OR operator between (A)and (G).

Example -2-(Prewitt Filter)

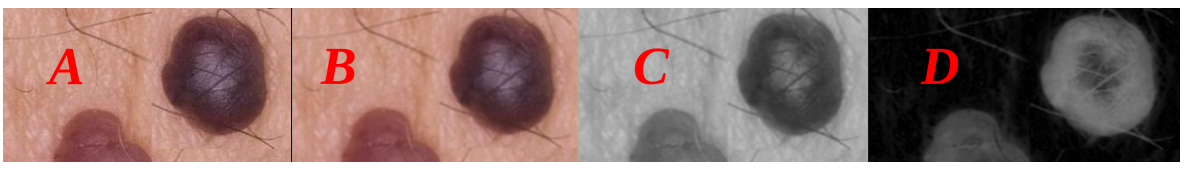


Example -1-(Laplace Filter)



Figure(5): (**A**) Color original image of skin cancer(distributed diseases) (**B**)noise removing (**C**) image obtain after mapping colors into intensity (**D**)difference between each pixel in image and the mean of background(**E**) threshold of difference image (**F**)filling operator to threshold image (**G**) Lablace edge detection (**H**)OR operator between (**A**)and (**G**).

Example -2-(Prewitt Filter)



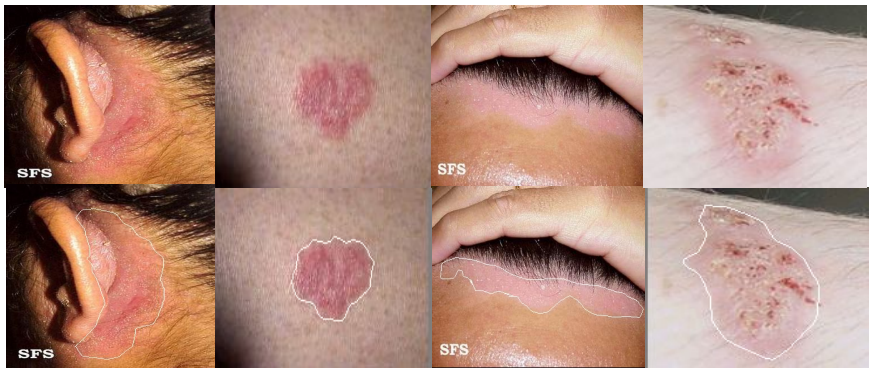


Figure (7) Border identification of dermatitis disease.

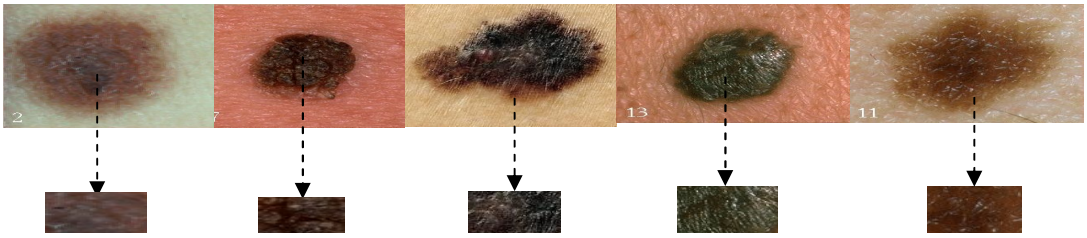
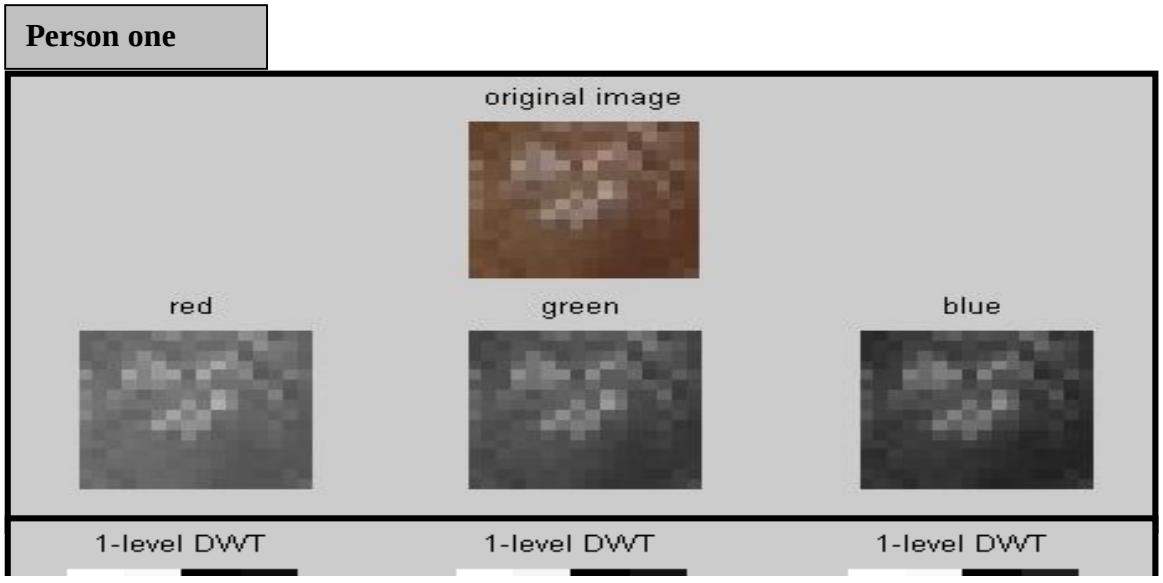


Figure (8) Skin cancer disease (class one).



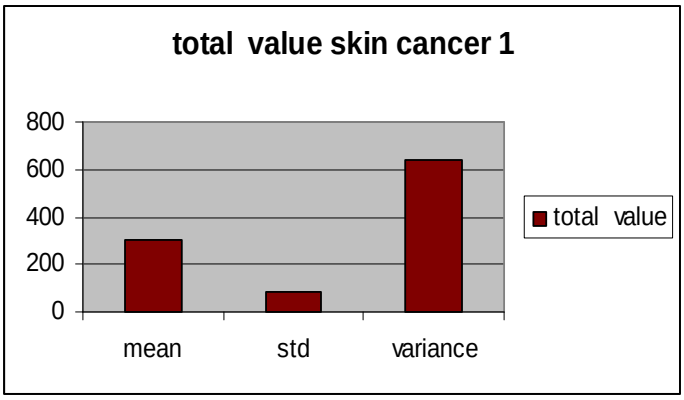


Figure (10) Feature extraction for skin cancer 1.

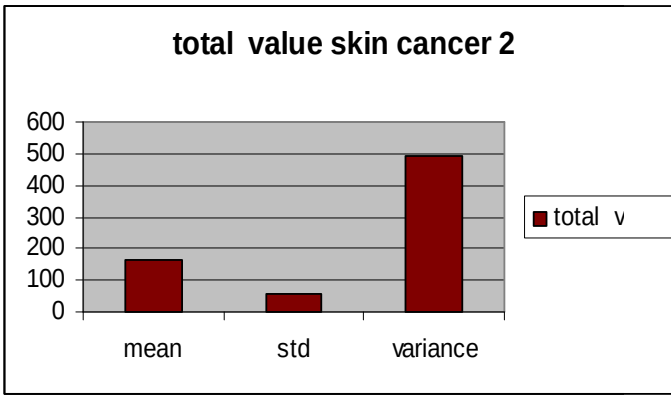


Figure (11) Feature extraction for skin cancer

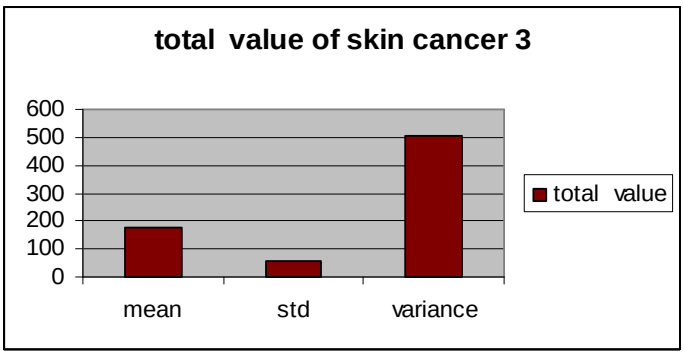


Figure (12) Feature extraction for skin cancer 3.

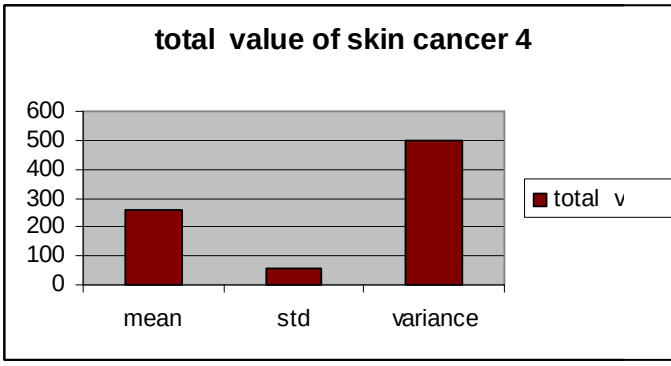
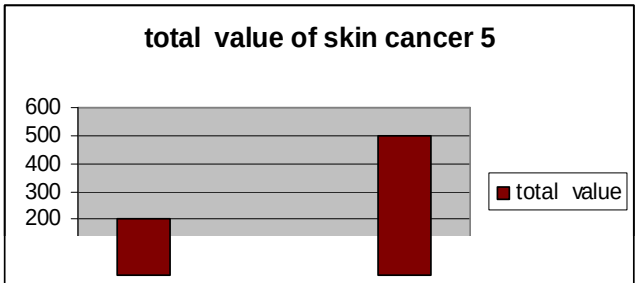


Figure (13) Feature extraction for skin cance



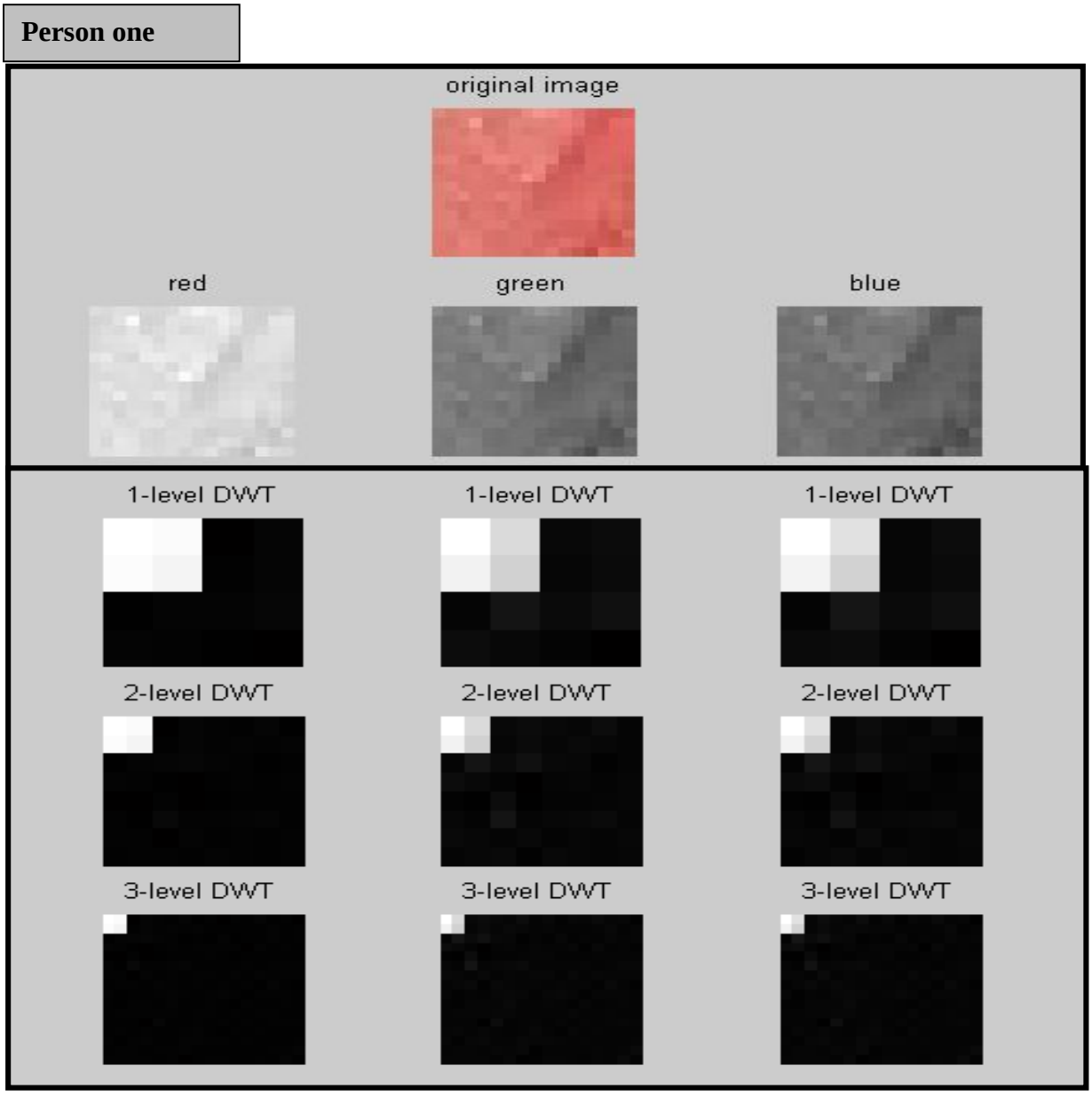


Figure (16) 3-Level of DWT.

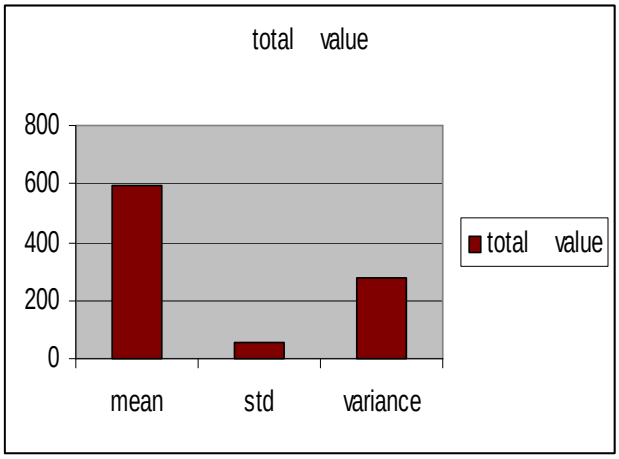


Figure (19) Feature extraction for dermatitis 3.

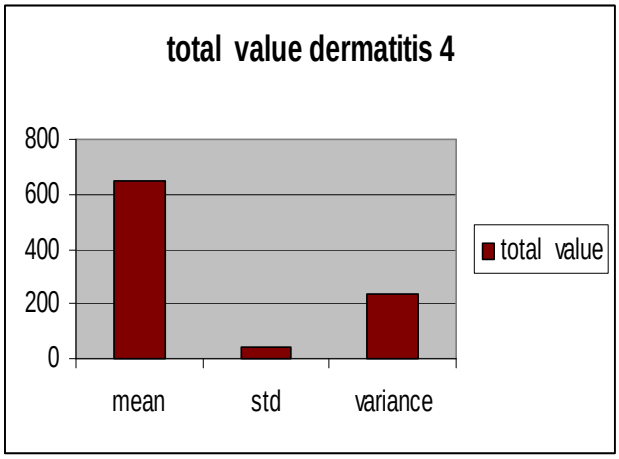


Figure (20) Feature extraction for dermatitis 4.

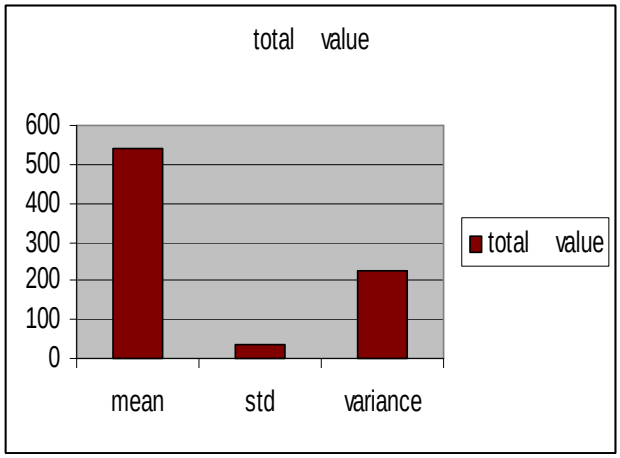
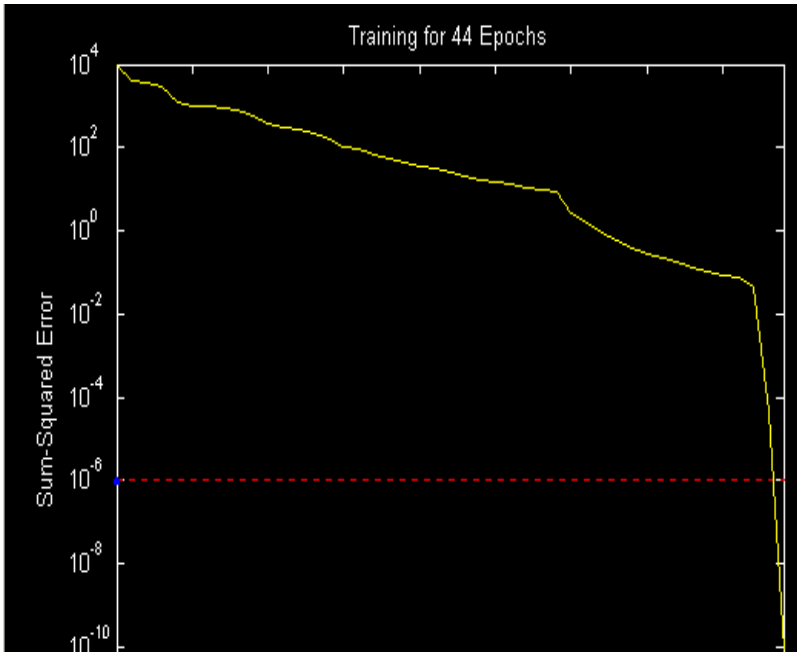


Figure (21) Feature extraction for dermatitis 5.



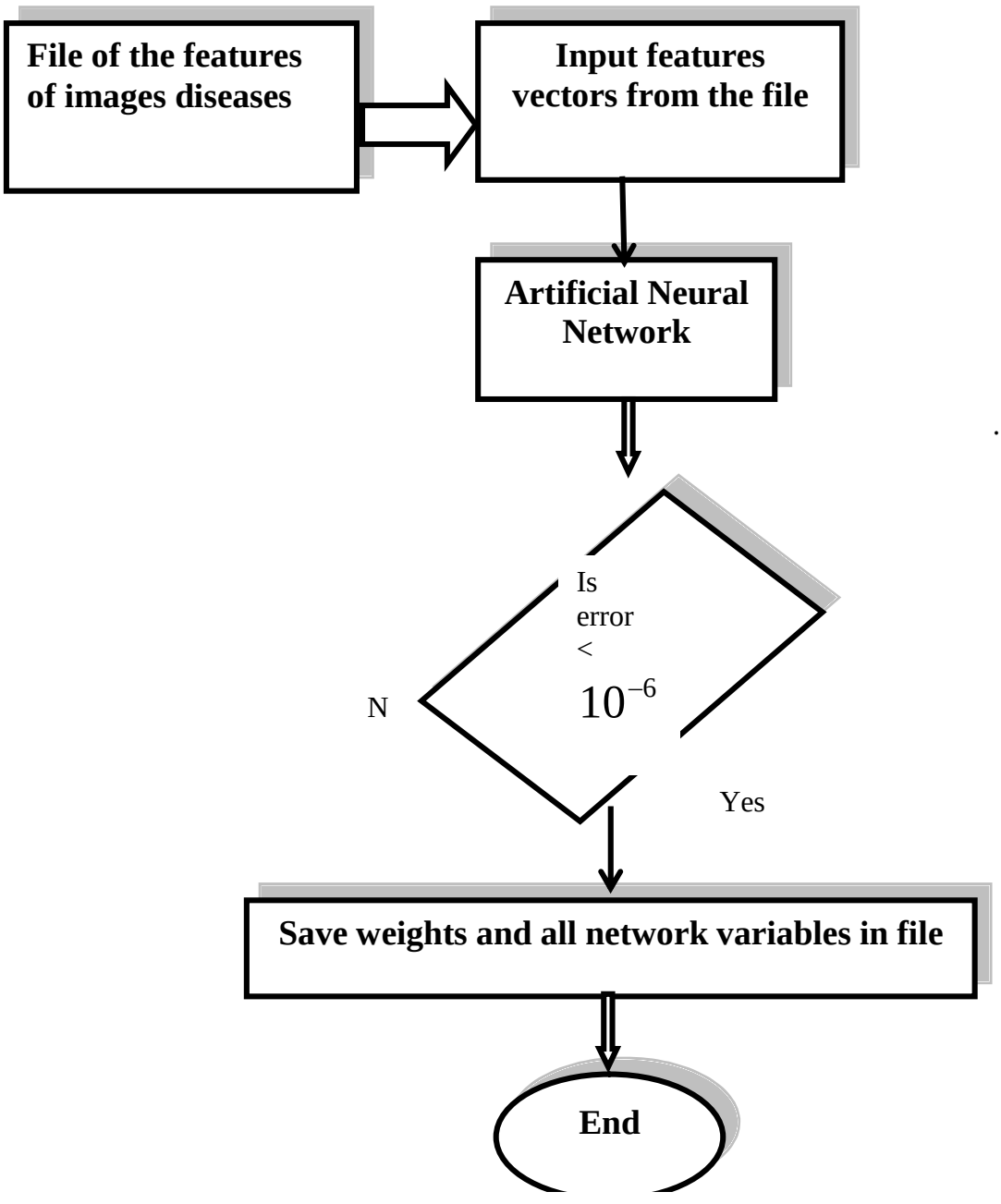

File of the features of images diseases
Input features vectors from the file
Artificial Neural Network
Is error < 10^{-6}
N
Yes
Save weights and all network variables in file
End

Figure (22)
Block diagram of the training stage