# Computer Aided Diagnosis of Malignant Melanoma Detection Using FCM Segmentation And Feature Extraction Techniques

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***Abstract-*** *This thesis is mainly used for earlier detection of human skin cancer. Skin cancer is the most deadly form of cancer which destroys a human life. Earlier detection of skin cancer prevents human life. A skin biopsy is a procedure in which a sample of skin tissue is removed, processed, and examined under a microscope. This method gives pain and cause bleeding to the patients. To overcome this problem using dermoscopy images. Computer based diagnosis method is so helpful for earlier detection and reduces the disadvantages of skin biopsy method. Image processing and artificial neural network techniques are used to detect melanoma skin cancer from dermoscopy images. To detect skin cancer region accurately using FCM (Fuzzy C Mean) segmentation and classifying a dermoscopy images using neural networks techniques.*

*Feature extraction techniques are applied to segmented image features are extracted using 2DWT (2D Wavelet Transform) and based on the features classify an image based neural networks. We create GLCM (Gray Level Co Matrix) matrix from processed images and extracts some advanced statistical values. BPN (Back-Propagation Neural) Network is used for classification purpose. It classifies the given data set into melanoma or non-melanoma.*

***Keywords***- FCM, GLCM,malignant melanoma

## I. INTRODUCTION

Skin cancer is the most common form of human cancer if melanoma, basal and squamous cell skin cancers are included. The annual rates of all forms of skin cancer are increasing eachyear, representing a growing public concern. Based on the Cancer Trends Progress Report by National Institute of Health of United States (NIH), it is estimated that nearly half of all Americans who live to age 65 will develop skin cancer at least once. Malignant melanoma, the most deadly form of skin cancer, is one of the most rapidly increasing cancers in the world. Melanoma is now the 7th most frequent cancer in Canada affecting 5,300 people in 2010 and causing 920 deaths and the 5th most common malignancy in the United States. 10710 deaths out of 21,700 incidences are estimated numbers in the United States during 2012. Metastatic melanoma is very difficult to treat, so the best treatment is still early diagnosis and prompt surgical excision of the primary cancer so that it can be completely excised while it is still localized. Therefore, advances in computer-aided diagnostic methods can aid self-examining approaches based on digital images, and may significantly reduce the mortality.

Nowadays skin cancer is the common type of cancer which affects the human skin and destroys the human life. Melanoma is an unwanted tumor which grows in neoplasm of human skin. It can spread very fast to all organs of human body through lymphatic system or blood. Melanoma cancer may appear as malignant or benign form. Benign Melanoma is simply appearance of moles on skin. Malignant melanoma is the appearance of sores that cause bleeding. Malignant Melanoma is the deadliest form of all skin cancers. It arises from cancerous growth in pigmented skin lesion. Melanoma cancer is the deadliest form of skin cancer. Detection of malignant melanoma in its early stages considerably reduces morbidity and mortality. In laboratory treatment, to detect melanoma cancer using biopsy method. A skin biopsy is a procedure in which a sample of skin tissue is removed, processed, and examined under a microscope.

This method gives pain and cause bleeding to the patients. To overcome this problem using dermoscopy images. Dermoscopy is also known as epiluminescence microscopy and it very useful for early detection of malignant melanoma. From this device we can get images and apply image processing techniques then finally classify either cancerous or non-cancerous images. This process is to be termed as computer based diagnosis system. Computer based diagnosis can improve the speed of skin cancer diagnosis which works according to the disease symptoms.

### 1.1 Image Basics

### 1.1.1 Digital Image

A monochrome digital image is a 2 dimensional array of dots arranged in m rows and n columns (Figure 1-2). These dots are called picture elements pixels. Each individual pixel p at location (x,y) can assume a value between 0 and N-1 representing the intensity of light at that location.

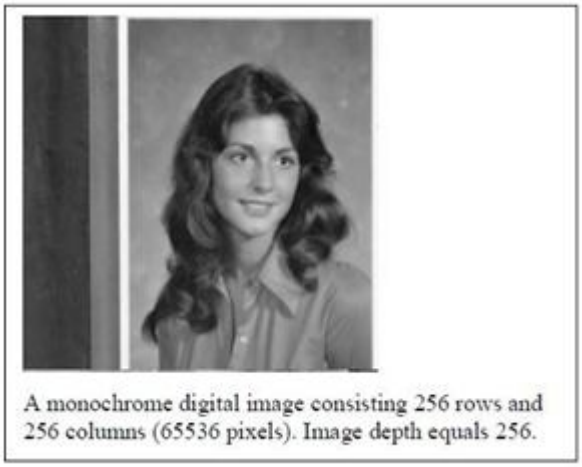


**Fig.1. Monochrome digital image**

### 1.1.2 Image Resolution

Digital images are represented as pixels along the x and the y axes. A picture consisting of m pixels on the x-axis and n pixels on the y-axis has a resolution m x n. Higher the value of m and n, higher the resolution of the image. Higher resolution images depict better quality images, because more image detail is included. More image detail means more information, and therefore a greater volume of data.

### 1.1.3 Image Sampling

Image acquisition devices such as scanners or cameras, have sensors which can take samples from the scene (light reflected from objects). The samples are usually taken in the form of a 2- Dimensional array having m rows and n columns resulting in m x n samples.

### 1.1.4 Gray-Levels

In a monochrome image, if the intensity of light equals 0 the pixel is black and if the intensity of light equals N-1 (where N is usually 2n) the pixel is white while in all intermediatecases the intensity of light is between black and white or grey. Because both black and white are also shades of grey therefore all different intensities that a pixel can assume are called grey-levels.

### 1.1.5 Quantization

Depending on requirement or on the sensitivity of the scanning sensors there is a limited number of grey-levels which each pixel can assume. The number of greylevels which the scanning device distinguishes during analogue to digital conversion is called the quantization levels. Quantization levels in scanners can be set to as small as 2 in which case the image is a black and white or binary image, and it can be set to as large as 1024 or more in case the data is to be analyzed by specialized applications.

### 1.1.6 Neighbors of a Pixel

A pixel p at co-ordinates (x,y) in an image has 8 neighbours surrounding it (Figure 1-3). Four of these neighboring pixels informally called TOP, BOTTOM, LEFT and RIGHT are adjacent to it. These pixels have co-ordinates (x,y-1), (x,y+1), (x-1,y) and (x+1,y) respectively. These pixels are called the 4-neighbours of the pixel or N4. These four pixels are at distance 1 from pixel p i.e. the distance from the center of pixel p at (x,y) to the center of either of these pixels equals 1. The rest of the 4 neighbours of p have diagonal corners touching p. These pixels informally called TOP-LEFT, TOP-RIGHT, BOTTOM-LEFT and BOTTOM-RIGHT have coordinates (x-1,y-1),(x+1,y-1), (x-1,y+1) and x+1,y+1)respectively. These pixels are called Diagonal neighbours of p or ND. The Diagonal neighbours are at a distance of 2 from p. N4 and ND together are called N8 neighbours of p.

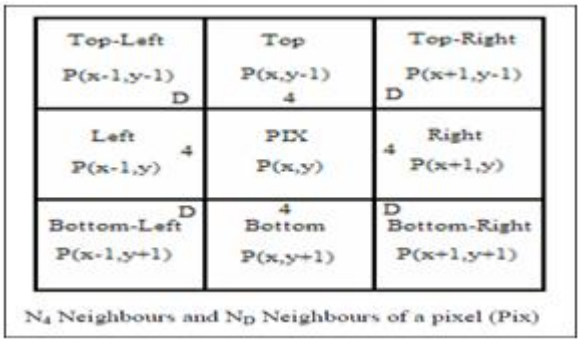


**Fig.2. Neighbours of a Pixel**

### 1.1.7 Raster Scan

An image consisting of n rows and m columns, if scanned one row at a time from top to bottom, and each row scanned from left to right is referred to as raster scan as depicted in (Figure1-4). This is the order of scanning which is used in CRT (Cathode Ray Tube) monitors, where the electron gun focuses the beam at one spot at a time, starting from the top left corner. The gun goes from left to right pixel by pixel

and at the end of the first line moves to the leftmost pixel of the second line and again goes from left to right. Moving in this order when all the rows are drawn the scan is complete. This order of scanning is also used by most of the image processing programs which filter the image pixel by pixel starting from top-left corner pixel and finishing at bottom-right corner pixel.

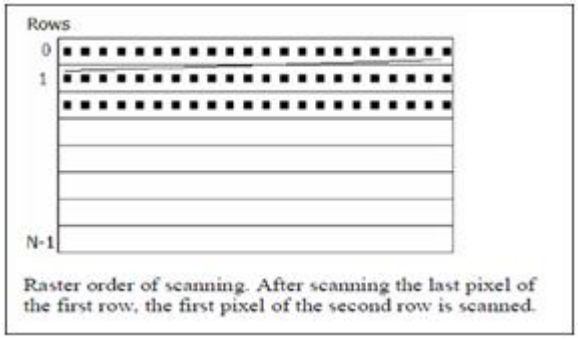


**Fig.3. Raster Scan Order**

### 1.1.8 Types of Images

An image conveys information visually. Historically sketches, heliographs and paintings were used and in the modern ages photographs and video are common. Moreover images can be graphs, charts, sketches, cartoonic characters, vector graphics, Computer aided tomographs, X-ray images, satellite images etc. All of the above kinds of images have their specific purposes. For the purpose of image compression it is useful to distinguish the following types of images.

- **Bi-Level Image:** This kind of image can have only two colors usually black and white. This kind of image is transmitted and reproduced by facsimiles and laser printers. When the resolution of such an image is very high as produced by laser printers it can closely mimic many grey-levels arranging different densities of black dots in regions (half-toning).
- **Gray Scale Image:** Images taken by black and white cameras are grey scale images, where each pixel can assume different intensities. Black has the lowest intensity and white has highest intensity. In between black and white are shades of grey. Because black and white are also considered strongest and weakest shades of grey, all the light intensities including black and white are called shades of grey or grey-levels. In image processing the model used is that of grey-scale images, because it can be generalized to colour images as well.
- **Continuous-tone Image:** All natural images such as those taken by a digital camera are continuous-tone images. A property of these images is that adjacent pixels usually have same or very similar grey-levels. Even if there are sharp edges the transition from one grey-level to the other is not very abrupt. For example (Figure 1-5 a) shows an image (Figure 1-5 b) shows an enlarged portion of the same image showing a sharp boundary (marked in original). Close observation reveals that the transition from one grey-level to the other is not very abrupt.

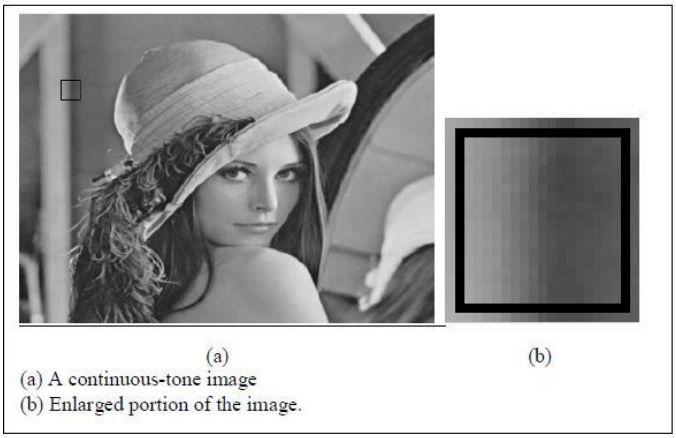


**Fig.4. Continuous-Tone Image**

Discrete Tone Image: This is normally an artificial image. It may have few colors or many colors, but it does not have the noise and blurring of a natural image. Examples of this type of image are a photograph of artificial object or machine, a page of text, a chart, a cartoon, and the contents of a computer screen (Not every artificial image is discrete-tone. A computer-generated image that is meant to look natural is a continuous-tone image in spite of being artificially generated.)

### 1.2 Research Aims

In earlier detection of melanoma cancer use skin biopsy method and it will take more risk and painful to the patients. The research presented in this thesis aims at computer aided diagnosis of melanoma detection based on image processing techniques and overcome the problem of skin biopsy method. To take cancerous image from patients given input to this system for fast and earlier detection of melanoma cancer.

### 1.3Overview of Thesis

Automatic early detection system is a classification system which distinguishes Malignant Melanoma from other skin diseases. This methodology uses Digital Image Processing technique and Artificial Intelligence for the classification purpose. The input to the system is Dermoscopic Images which are in digital format. Usually such images contain noises, so they are undergone Pre-processing. In order to preserve the edges, Post-processing is done. To separate the

cancerous region from healthy skin, segmentation is done. There are some unique features for the cancerous images. Those features are extracted using Two Dimensional Wavelet Transform in MATLAB software. Features are statistical measurements extracted from an image .These features are given as inputs to the Artificial Neural Network based classifier. It uses Back propagation Algorithm for classification. ANN classifies Malignant Melanoma from Benign Melanoma. Thus detecting whether patient is having skin cancer or not .

### 1.4 Contributions

Following are the contributions made during this research

- To overcome the limitation of skin biopsy treatment.
- Earlier detection is most important factor for safe human life so Computer Aided Diagnosis (CAD) of cancer detection is more helpful to the doctors and patients.
- Use FCM (Fuzzy C Mean) segmentation for detect accurate cancerous parts in human skin.
- Extract advanced statistical measurements and GLCM features using 2DWT.
- Use neural networks for fast and easier classification of melanoma and non-melanoma images.

## II. SKIN CANCER - AN OVERVIEW

The skin is the largest organ of the human body as well as our first line of defense. Skin is divided into three layers, viz. epidermis (outer layer), dermis (middle layer) and hypodermis (deepest layer) as shown in Fig.5. The epidermis mainly consists of keratinocytes. It also contains melanocytes, cells responsible for our skin pigmentation, which provides natural protection against sun‟s rays. They are evenly distributed in the skin along the basal layer at the dermo-epidermal junction. Melanin is the major pigmentation factor for human skin color variation. Below the epidermis is the dermis layer, it contains special cells which repair our skin. The hypodermis is deepest layer mainly made from fat and manages feeding, excreting and heat exchange. Fat manages the insulation and sweat glands from this layer controls heat exchange of human body.

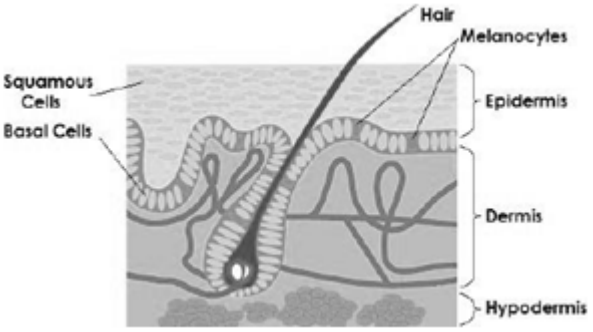


**Fig.5. Structure of the human skin**

### 2.1Types of skin cancer

There are 3 common types of skin cancer, each of which is named after the type of skin cell from which it arises.

1. **Basal Cell Carcinoma:** It is the most common type of skin cancer. It typically appears as a small raised bump that has a pearly appearance. It is most commonly seen on areas of the skin that have received excessive sun exposure.
2. **Squamous Cell Carcinoma:** It is seen on the areas of the body that have been exposed to excessive sun (nose, lower lip, hands, and forehead). Often this cancer appears as a firm red bump or ulceration of the skin that does not heal.
3. **Melanoma:** The malignant melanoma is a highly malignant skin cancer, it grows rapidly and sometimes with different colors and abnormal shapes. Melanoma has its beginnings in melanocytes, the skin cells that produce in the dark protective pigment called melanin.

The melanin is responsible for suntanned skin which acting as a partial protection against sun light. Malignant melanoma, the third most common and the leading cause of death is the second type of skin cancer. Although Melanoma can occur in many organs, the most common form, cutaneous melanoma arises from the melanocytes that are found in basal layer of the epidermis, hair follicles, sebaceous glands and other adnexal structure.

### 2.2Malignant Melanoma

Melanoma often presents as an irregularly bordered, pigmented macule. A melanoma presents numerous shades of color, ranging from tan to brown to jet-black, but they also be evenly colored. Popular or nodular lesions are worrisome for deeper, more invasive disease. Melanoma is the leading cause of skin cancer-related deaths and early detection and diagnosis is the need of present day.

Most of the times, the patches of darker color on the skin represents pigmented skin lesions and is the result of excessive melanin concentration. In benign lesions (e.g. Common nevi), melanin deposits are normally found in the epidermis. In malignant lesions (i.e., melanoma), the melanocytes reproduce melanin at a high, abnormal rate. Due to the penetration of malignant melanocytes into the dermis, they leave melanin deposits there and thus changing the nature of skin coloration. The presence of melanin in the dermis is the most significant sign of melanoma. Melanoma typically grows horizontally within the epidermis. It then penetrates into the dermis. Therefore, accurate diagnosis of malignant melanoma at an early stage, leading to earlier treatment is crucial to successful cancer management and is a crucial issue for dermatologists.

**2.3Skin Biopsy**

A skin biopsy is the removal of a piece of skin for the purpose of further examination in the laboratory using a microscope. Skin biopsies are performed to diagnose a number of conditions.

Several different methods may be used to obtain a skin sample, depending on the size and location of the skin lesion. The skin sample is placed in a solution, such as formaldehyde, or in a sterile container if infection is suspected. In each of these procedures, the tissue is then examined under a microscope. Different techniques are used in different situations. Typically the biopsies are obtained after using local anesthetics to numb the area to be biopsied.

- A shave biopsy takes a thin slice off the top of the skin and can be used to remove superficial abnormal areas (lesions).
- A punch biopsy takes a core (a small cylindrical fragment of tissue from the area of interest) and can be used to diagnose rashes and other conditions.
- Excisional biopsies are usually larger and deeper and are used to completely remove an abnormal area of skin such as a skin cancer. These are not technically biopsies since the goal of this procedure is to remove the whole lesion rather than to remove a small portion to make a diagnosis.

After the biopsy, the skin sample is fixed in special solution, and thin sections of the tissue are cut and placed on microscope slides. The slides are stained for examination by a doctor (usually a dermatologist or pathologist). Sometimes specialized stains are used to examine for antibodies, immune proteins, and other markers of certain diseases. Initial routine biopsy results can be obtained in 48 hours or less, while specialized staining techniques can require a much longer time until final results are available.

**2.3.1 Understanding the Results of Your Biopsy:**

You will not get the results of your biopsy straight away. This usually takes about 2 to 3 weeks. You will go back to see your GP or dermatologist to get the results. If the skin sample contained any cancerous cells, you will need treatment to the area. If you had an excision biopsy, the sample will be closely checked in the lab to make sure a border of healthy skin tissue has been removed all around it. This is called a healthy margin. If not enough healthy tissue has been removed you will need more surgery. This is important because if any cancer cells are left behind, the cancer can continue to grow.

**2.3.2 What are the limitations of biopsies?**

In some cases, the amount of tissue obtained from a needle biopsy may not be sufficient and the biopsy may have to be repeated. This may be particularly true with trying to make a diagnosis of lymphoma. Rarely, less invasive skin biopsy procedures may be unable to detect some lesions or determine the extent of disease present. If the diagnosis remains uncertain after a technically successful procedure, surgical biopsy will usually be necessary.

**2.4 Problem Definition:**

To overcome the limitations of skin biopsy design Computer aided diagnosis based skin cancer detection system. To take the images from a cancerous patients use image processing and feature extraction techniques for fast, easier and painless cancer detection and overcome the problem of skin biopsy method and painless to the patients. Earlier detection and therapy also lead to less morbidity and decreased cost of therapy.. The challenge lies in identifying the lesions that have the highest probability for being melanoma.With highly accurate (75%) diagnosis, there is a need to develop efficient schemes for the clinical diagnosis and to support the dermatologists with computer-aided diagnosis (CAD) systems. The main objective of such systems is to assist the physician in different analysis steps, such as the lesion boundary detection, the quantification of diagnostic features, the classification of lesions, the visualization, the storage, the database management, etc. Detection of skin cancer in the earlier stage is very critical and this thesis proposes and explains the implementation of automatic detection and analysis Skin Cancer from given photograph of patient‟s cancer affected area. The proposed work will help patients/doctors/dermatologist/clinicians for taking further

medical treatment, which will ultimately saves patients valuable time, money and life.

## III. PROPOSED SYSTEM

At this stage, the important features of image data are extracted from the segmented image. Feature extraction is a sub-division of improved image into constituent parts or isolation of some aspects of an image for identifying or interpreting meaningful object forms, which includes finding lines, circles or specific shapes and identifying pimples, white heads or black heads, etc. The steps in feature extraction process are shown in Fig 6.

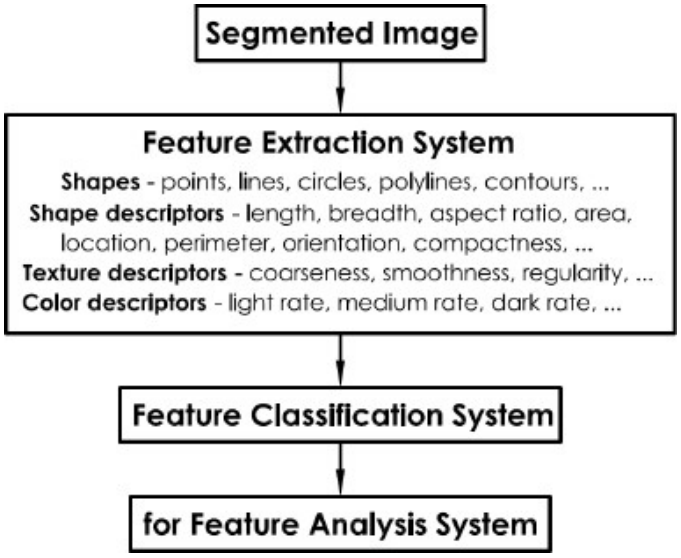


**Figure 6 .Feature Extraction system**

### 3.1.2D Wavelet Transform

Z2D wavelet transform is used for the feature extraction. In this system, 2-D wavelet packet is used and the enhanced image in gray scaled as an input. Bior wavelets at two steps of decomposition are used. At each step of decomposition, the wavelet of primary image is divided into an approximate and three detailed images which show the basic information and vertical, horizontal and diagonal details, respectively. That are depicted as following figure 7.

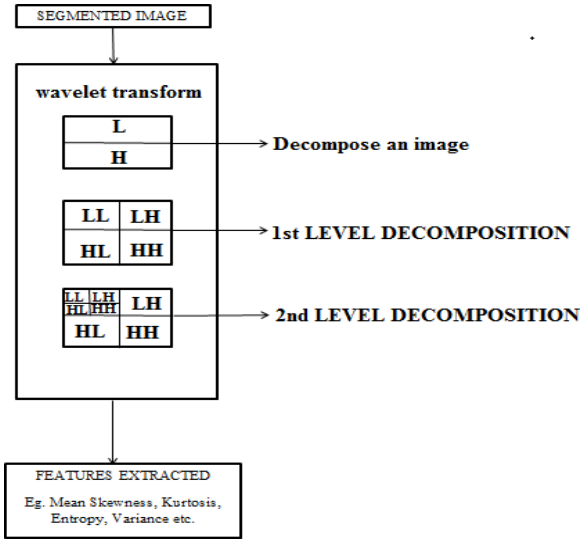


**Fig.7. 2DWT for Feature Extraction.**

Wavelet decomposition allows useful cancer‟s feature to be extracted from the images without clinical knowledge. In this system, 2-D wavelet packet is used and the enhanced image in gray scaled as an input. Assume a digital image sized M x N pixels is transformed by the discrete wavelet as shown in Fig.7 which produced by the level decomposition map that Fig.8 indicates,

The result of the decomposition L and H stand for low and high frequency components. FL and FH represent low-pass and high-pass filters. Perform discrete wavelet transform to the image. LL(0) is the original image. LH(1), HL(1) and HH(1) are the output of high-pass filter that‟s represent the horizontal details, vertical details and diagnosing details. LL(1) represents the approximation with the same size of LH(1), HL(1) and HH(1) that‟s use to perform the second-level decomposition. The images LH(2), HL(2) and HH(2) have finer detail than in LH(1), HL(1) and HH(1). Moreover, the image energy is distributed according to the resolution. Each of these nodes is represent one feature, which then can be used as an input for classification stage. The second level decomposition can generate 16 nodes or features. Two-dimensional wavelet packet returns the coefficients in 2 dimensions matrix. Since there is lack of published articles to comparedifferent wavelet, seven different wavelets are used in this paper followed by same classification test to compare them and find out the best results.

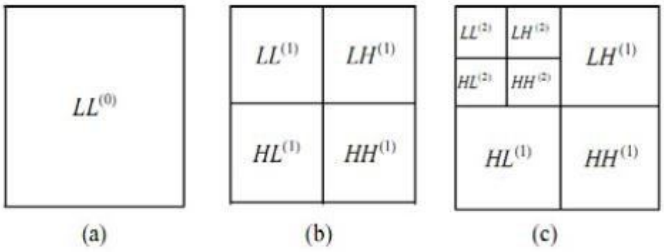


**Fig.8.(A) Original Image (B) First Level Decomposition (C) Second Level Decomposition**

There are some unique features that distinguish malignant melanoma from benign melanoma. Feature extraction extracts the eminent and important features of image data, from the segmented image. It makes the raw data more useful in processing. By extracting features, the image data is narrow down to a set of feature. Feature extraction technique used is Gray Level Co- occurrence Matrix (GLCM).

### 3.2.Extraction of GLCM

In statistical texture analysis, texture features are computed from the statistical distribution of observed combinations of intensities at specified positions relative to each other in the image. According to the number of intensity points (pixels) in each combination, statistics are classified into first-order, second-order and higher-order statistics. The Gray Level Co-occurrence Matrix (GLCM) method is a way of extracting second order statistical texture features. The approach has been used in a number of applications, Third and higher order textures consider the relationships among three or more pixels. These are theoretically possible but not commonly implemented due to calculation time and interpretation difficulty.

A GLCM is a matrix where the number of rows and columns is equal to the number of gray levels, G, in the image. The matrix element P (i, j | Δx, Δy) is the relative frequency with which two pixels, separated by a pixel distance (Δx, Δy), occur within a given neighborhood, one with intensity „i" and the other with intensity „j". The matrix element P (i, j | d, ɵ) contains the second order statistical probability values for changes between gray levels „i" and „j" at a particular displacement distance d and at a particular angle (ɵ). Using a large number of intensity levels G implies storing a lot of temporary data, i.e. a G × G matrix for each combination of (Δx, Δy) or (d, ɵ). Due to their large dimensionality, the GLCM"s are very sensitive to the size of the texture samples on which they are estimated. Thus, the number of gray levels is often reduced. GLCM matrix formulation can be explained with the example illustrated in Fig.18 for four different gray levels.

| neighbour pixel value ---> ref pixel value: | 0 | 1 | 2 | 3 |
|---|---|---|---|---|
| 0 | 0,0 | 0,1 | 0,2 | 0,3 |
| 1 | 1,0 | 1,1 | 1,2 | 1,3 |
| 2 | 2,0 | 2,1 | 2,2 | 2,3 |
| 3 | 3,0 | 3,1 | 3,2 | 3,3 |

**Fig.9. GLCM Calculation**

Here one pixel offset is used (a reference pixel and its immediate neighbor). If the window is large enough, using a larger offset is possible. The top left cell will be filled with the number of times the combination 0,0 occurs, i.e. how many time within the image area a pixel with grey level 0 (neighbour pixel) falls to the right of another pixel with grey level 0(reference pixel). The enhanced image in gray scaled is given as input.

The MATLAB code used for the GLCM is q1 = imread ('Jerry.jpg');

w1 = rgb2gray (q1);

e1 = imresize (w1, [128 128]); r1 = graycomatrix (e1);

disp (r1);

t1 = imhist (e1);

figure, imshow (e1), title ('transformed gray Jerry .jpg in gray');

The output will be an 8*8matrix which is a GLCM of input image. GLCM is a matrix where the number of rows and columns is equal to the number of gray levels. The GLCM is a tabulation of how often different combinations of pixel brightness values (gray levels) occur in an image. The GLCM is a powerful tool for image feature extraction by mapping the gray level co- occurrence probabilities based on spatial relations of pixels in different angular directions. The features extracted based on GLCM are: Contrast, Correlation, Energy, Mean, and Homogeneity.

A homogeneous scene will contain only a few gray levels. It provides GLCM with only a few but relatively high values. Contrast is the measure of contrast or local intensity variation. Correlation is a measure of gray level linear

dependence between the pixels at the specified positions relative to each other

The Features extracted using the wavelet transform are: Mean, Standard deviation,Mean Absolute Deviation, Sum of Absolute difference, Skewness, kurtosis, entropy, contrast, correlation, energy, homogeneity, moment, and variance.

**3.3 Extract Texture Features Of Image**

Gray Level Co-Occurrence Matrix (GLCM) has proved to be a popular statistical method of extracting textural feature from images. According to co-occurrence matrix, Haralick defines fourteen textural features measured from the probability matrix to extract the characteristics of texture statistics of remote sensing images. Proposed work use following features explained as below

**Entropy**

Entropy shows the amount of information of the image that is needed for the image compression. Entropy measures the loss of information or message in a transmitted signal and also measures the image information.

**Correlation**

Correlation measures the linear dependency of grey levels of neighboring pixels. Digital Image Correlation is an optical method that employs tracking & image registration techniques for accurate 2D and 3D measurements of changes in images. This is often used to measure deformation, displacement, strain and optical flow, but it is widely applied in many areas of science and engineering. One very common application is for measuring the motion of an optical mouse.

$$\text{ENTROPY} = \sum_{i=0}^{Ng-1}\sum_{j=0}^{Ng-1} -P_{ij} * logP_{ij}$$

**Image Moment**

$$\text{Correlation} = \frac{\sum_{i=0}^{Ng-1}\sum_{j=0}^{Ng-1}(i,j)p(i,j) - \mu_x\mu_y}{\sigma_x\sigma_y}$$

In image processing, computer vision and related fields, an image moment is a certain particular weighted average (moment) of the image pixels' intensities, or a function of suchmoments, usually chosen to have some attractive property or interpretation. Image moments are useful to describe objects after segmentation. Simple properties of the image which are found via image moments include area (or total intensity), its centroid, and information about its orientation.

**MAD(median absolute deviation)**

In statistics, the median absolute deviation (MAD) is a robust measure of the variability of a univariate sample of quantitative data. It can also refer to the population parameter that is estimated by the MAD calculated from a sample. For a univariate data set X1, X2, ..., Xn, the MAD is defined as the median of the absolute deviations from the data's medianThat is, starting with the residuals (deviations) from the data's median, the MAD is the median of their absolute values.

$$\text{MAD} = \text{median}_i\left(\left|X_i - \text{median}_j(X_j)\right|\right),$$

**Mean**

The mean is the average of the numbers calculated “central” value of a set of numbers.

**Skewness**

Skewness is asymmetry in a statistical distribution, in which the curve appears distorted or skewed either to the left or to the right. Skewness can be quantified to define the extent to which a distribution differs from a normal distribution.

Kurtosis

The height and sharpness of the peak relative to the rest of the data are measured by a number called kurtosis. Higher values indicate a higher, sharper peak; lower values indicate a lower, less distinct peak.

## IV. ARITIFICIAL NEURAL NETWORK

One type of network sees the nodes as artificial neurons“. These are called artificial neural networks (ANNs). An artificial neuron is a computational model inspired in the natural neurons. Natural neurons receive signals through synapses located on the dendrites or membrane of the neuron. When the signals received are strong enough (surpass a certain threshold), the neuron is activated and emits a signal though the axon. This signal might be sent to another synapse, and might activate other neurons.

The complexity of real neurons is highly abstracted when modeling artificial neurons. These basically consist of inputs (like synapses), which are multiplied by weights (strength of the respective signals), and then computed by a mathematical function which determines the activation of the neuron. Another function (which may be the identity) computes the output of the artificial neuron (sometimes in dependence of a certain threshold). ANNs combine artificial neurons in order to process information.

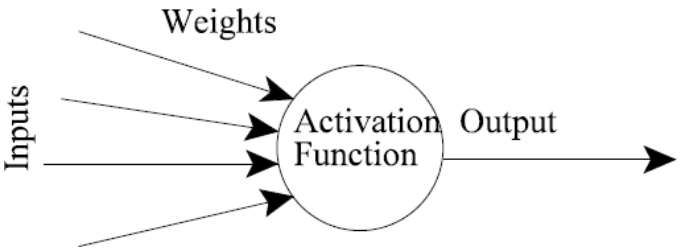


**Fig.10. Artificial Neuron**

The higher a weight of an artificial neuron is, the stronger the input which is multiplied by it will be. Weights can also be negative, so we can say that the signal is inhibited by the negative weight. Depending on the weights, the computation of the neuron will be different. By adjusting the weights of an artificial neuron we can obtain the output we want for specific inputs. But when we have an ANN of hundreds or thousands of neurons, it would be quite complicated to find by hand all the necessary weights. But we can find algorithms which can adjust the weights of the ANN in order to obtain the desired output from the network. This process of adjusting the weights is called learning or training. The number of types of ANNs and their uses is very high. Since the first neural model by McCulloch and Pitts (1943) there have been developed hundreds of different models considered as ANNs. The differences in them might be the functions, the accepted values, the topology, the learning algorithms, etc. Also there are many hybrid models where each neuron has more properties than the ones we are reviewing here. Because of matters of space, we will present only an ANN which learns using the back propagation algorithm (Rumelhart and McClelland, 1986) for learning the appropriate weights, since it is one of the most common models used in ANNs, and many others are based on it. Since the function of ANNs is to process information, they are used mainly in fields related with it. There are a wide variety of ANNs that are used to model real neural networks, and study behaviour and control in animals and machines, but also there are ANNs which are used for engineering purposes, such as pattern recognition, forecasting, and data compression.

**4.1Back Propagation Algorithm**

The back propagation algorithm (Rumelhart and McClelland, 1986) is used in layered feed- forward ANNs. This means that the artificial neurons are organized in layers, and send their signals "forward", and then the errors are propagated backwards. The network receives inputs by neurons in the input layer, and the output of the network is given by the neurons on an output layer. There may be one or more intermediate hidden layers. The back propagation algorithm uses supervised learning, which means that we provide the algorithm with examples of the inputs and outputs we want the network to compute, and then the error (difference between actual and expected results) is calculated. The idea of the back propagation algorithm is to reduce this error, until the ANN learns the training data. The training begins with random weights, and the goal is to adjust them so that the error will be minimal. The activation function of the artificial neurons in ANNs implementing the i back propagation algorithm is a weighted sum (the sum of the inputs x multiplied by their ji respective weights w)

$$A_j(x^1,w^1)=\sum^{n}_{i=0} x_i w_{ji} \qquad (1)$$

We can see that the activation depends only on the inputs and the weights. If the output function would be the identity (output=activation), then the neuron would be called linear. But these have severe limitations. The most common output function is the sigmoidal function:

$$O_j(\bar{x},\bar{w}) = \frac{1}{1+e^{A_j(\bar{x},\bar{w})}} \qquad (2)$$

The sigmoidal function is very close to one for large positive numbers, 0.5 at zero, and very close to zero for large negative numbers. This allows a smooth transition between the low and highoutput of the neuron (close to zero or close to one). We can see the output depends only in the activation, which in turn depends on the values of the inputs and their respective weights. Now, the goal of the training process is to obtain a desired output when certain inputs are given. Since the error is the difference between the actual and the desired output, the error depends on the weights, and we need to adjust the weights in order to minimize the error. We can define the error function for the output of each neuron

$$E_j(\bar{x},\bar{w},d) = \left(O_j(\bar{x},\bar{w}) - d_j\right)^2 \qquad (3)$$

We take the square of the difference between the output and the desired target because it will be always positive, and because it will be greater if the difference is big,

and lesser if the difference is small. The error of the network will simply be the sum of the errors of all the neurons in the output layer

$$E(\bar{x},\bar{w},\bar{d}) = \sum_j \left(O_j(\bar{x},\bar{w}) - d_j\right)^2 \quad (4)$$

The back propagation algorithm now calculates how the error depends on the output, inputs, and weights. After we find this, we can adjust the weights using the method of gradient descendent

$$\Delta w_{ji} = -\eta \frac{\partial E}{\partial w_{ji}} \quad (5)$$

This formula can be interpreted in the following way: the adjustment of each weight will be the negative of a constant eta (0) multiplied by the dependence of the i previous weight on the error of the network, which is the derivative of E in respect to w. The size of the adjustment will depend on 0, and on the contribution of the weight to the error of the function. This is, if the weight contributes a lot to the error, the adjustment will be greater than if it contributes in a smaller amount. (5) is used until we find appropriate weights (the error is minimal). If you do not know derivatives, don‟t worry, you can see them now as functions that we will replace right away with algebraic expressions.

If you understand derivatives, derive the expressions yourself and compare your results with the ones presented here. If you are searching for a mathematical proof of the back propagation algorithm, you are advised to check it in the suggested reading, since this is out ofthe scope of this material. ji So, we “only” need to find the derivative of E in respect to w . This is the goal of the

Back propagation algorithm, since we need to achieve this backwards. First, we need to calculate how much the error depends on the output, which is the derivative of E in respect j to O (from (3)).

$$\frac{\partial E}{\partial O_j} = 2\left(O_j - d_j\right) \quad (6)$$

$$\frac{\partial O_j}{\partial w_{ji}} = \frac{\partial O_j}{\partial A_j}\frac{\partial A_j}{\partial w_{ji}} = O_j(1-O_j)x_i \quad (7)$$

And then, how much the output depends on the activation, which in turn depends on the weights (from (1) and (2)):

And we can see that (from (6) and (7)):

$$\frac{\partial E}{\partial w_{ji}} = \frac{\partial E}{\partial O_j}\frac{\partial O_j}{\partial w_{ji}} = 2\left(O_j - d_j\right)O_j(1-O_j)x_i \quad (8)$$

And so, the adjustment to each weight will be (from (5) and (8)):

$$\Delta w_{ji} = -2\eta\left(O_j - d_j\right)O_j(1-O_j)x_i \quad (9)$$

We can use (9) as it is for training an ANN with two layers. Now, for training the network with one more layer we need to make some considerations. If we want to adjust ik the weights (let‟s call them v) of a previous layer, we need first to calculate how the error depends not on the weight, but in the input from the previous layer. This is easy, we would i ji just need to change x with w in (7), (8), and (9). But we also need to see how the error of ik the network depends on the adjustment of v. So

$$\Delta v_{ik} = -\eta \frac{\partial E}{\partial v_{ik}} = -\eta \frac{\partial E}{\partial x_i}\frac{\partial x_i}{\partial v_{ik}} \quad (10)$$

Where

$$\frac{\partial E}{\partial w_{ji}} = 2\left(O_j - d_j\right)O_j(1-O_j)w_{ji} \quad (11)$$

And, assuming that there are inputs u into the neuron with v (from (7)):

$$\frac{\partial x_i}{\partial v_{ik}} = x_i(1-x_i)v_{ik} \quad (12)$$

If we want to add yet another layer, we can do the same, calculating how the error depends on the Inputs and weights of the first layer. We should just be careful with the indexes, since each layer can have a different number of neurons, and we should not confuse them. For practical reasons, ANNs implementing the backpropagation algorithm do not have too many layers, since the time for training the networks grows exponentially. Also, there are refinements to the backpropagation algorithm which allow a faster learning.

### 4.2 Artificial Neural Network Classifier

This classifier is used for distinguished an image into cancerous or non-cancerous skin. For the classification purpose Artificial Neural Network (ANN) is used in proposed system. Generally Feed forward multilayer is used and Back Propagation Network (BPN) algorithm is used for training. Back-propagation neural network is one of the most common neural network structures, as it is simple and effective. The hidden and output layer nodes adjust the weights value depend on the error in classification. The modification of the weights is according to the gradient of the error curve, which points in the direction to the local minimum. BNN is benefit on prediction and classification but the processing speed is slower compared to other learning algorithms. In Matlab initially formulate the data set and classified into trained data and test data. Then train the network and calculate the output then check error value. Update the weights and network is back propagated for train the network. Train the network recursively until the error value is minimized. In the proposed system the neural network structure as following figure.

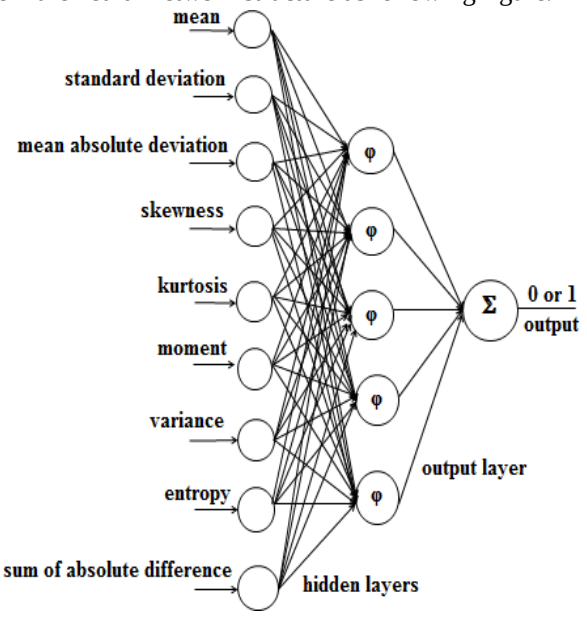


**Fig.11. Structure of Neural Network in Proposed System**

The classification is done in Neural Network Simulation software – NERURAL LAB. First stage is the Network layer setup. Then Network is trained using known data set of both benign and malignant melanoma cases. Many epochs of training are repeated until Mean Square Error is less than a desired Value. Once training is completed, datasets for classification are given to the network. Fifty Malignant and Benign Melanoma Features are given for Classification. The output of the classifier is either 0 or 1. One represents cancerous (Malignant) condition and Zero represents Non-cancerous (Benign) condition. Here the classification is done after optimizing Mean Square Error in NEURAL LAB. After train the network, decision making can be performed. In this proposed methodology, thirteen features were given as input to a multilayer feed forward network. There is one hidden layer with two hidden neurons. Output layer with one output neuron. Activation function used is linear function, which gives an output of 0 or 1. Zero represents non- melanoma or benign condition and one represents cancerous or melanoma condition. NEURAL LAB tool is used in Matlab software used for ANN classification. It is ANN simulation software which gives good results in classification. The network is trained using known values of Malignant and Benign Melanoma features. Many epochs of training are repeated until Mean Square Error isless than minimum value. Then data for classification is given as input to classifier. Cancerous condition and Zero represents Non-cancerous condition.

## V. RESULTS AND EVALUATION

### 5.1Image Processing

In image processing the image can be used various preprocessing techniques for prepare an image in a correct format in skin cancer detection system. Skin cancer images are collected from various resources from online. The sample images are depicted as following figure.

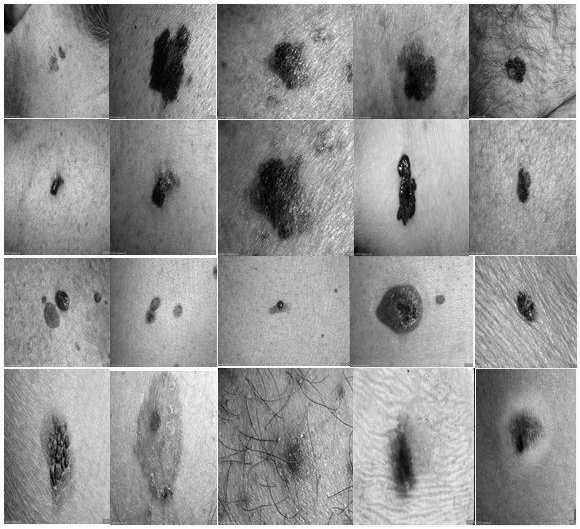

**Fig.12. Input images**

In proposed work using median filtering, histogram equalization, region highlighting, border filtering, noise removal techniques for prepare good quality for detect skin cancer systems. Here compare the input cancerous image for histogram equalization used in proposed work described as below figure.

To evaluate the segmentation results four different matrices used that are the Hammoude distance (HM), the true detection rate (TDR) and the false positive rate (FPR) are area based metrics. Compare to the other segmentation methods FCM has 95.47% in TDR .

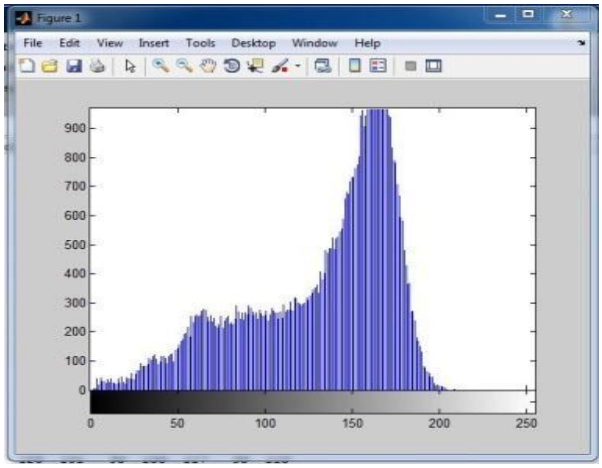


**Figure 13.Before histogram Equalization**

rate (FPR) are area based metrics. Compare to the other segmentation methods FCM has 95.47% in 13

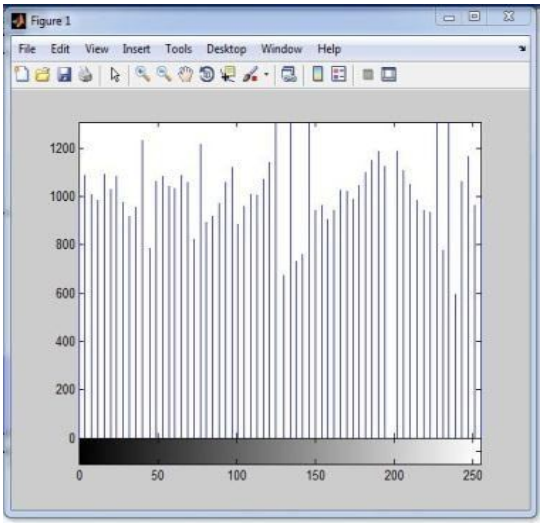


**figure 14.After Histogram equalization**

### 5.2Feature Extraction

In proposed work bior wavelet using into an image extracting a features are given input to the neural network system . The „bior5.5" wavelet found it provided the highest accuracy that achieved 88.5%[4]. On the other hand, the daubechies wavelet („db1" and „db10") has the most stable experimental record during the testing. It proved that Biorthogonal is advance for the image reconstruction and decomposition. The results of comparing different types of wavelets followed by ANN as a classifier displayed in table 1.

The following table shows the results of classification. Each table has statistical measurements such as mean, standard deviation, variance, entropy, moment, mean absolute deviation, contrast, correlation, energy, entropy, homogeneity, Skewness, kurtosis and sum of absolute difference. Based on these measurements neural networks classified as melanoma and non-melanoma images. Here the sample images have measurements based on feature extraction as follows and image can be extracted in Matlab as follows.

**Table.1. ANN Classification Test with Different Wavelet**

| Wavelet | Training | Validation | Testing | Total |
|---|---|---|---|---|
| Db1 | 98.3% | 48.9% | 73.1% | 85.6% |
| Db10 | 100% | 48.1% | 73.6% | 86.9% |
| Bior1.3 | 100% | 51.1% | 68.4% | 85.7% |
| Bior5.5 | 100% | 53.6% | 77.4% | 88.5% |
| Coif3 | 100% | 57.1% | 69.1% | 86.5% |
| Sym4 | 99% | 44.4% | 68.7% | 84.5% |
| Sym7 | 73.7% | 40.8% | 53.5% | 64.4% |

Based on the above table values the melanoma and non-melanoma can be differentiated described as below chart.

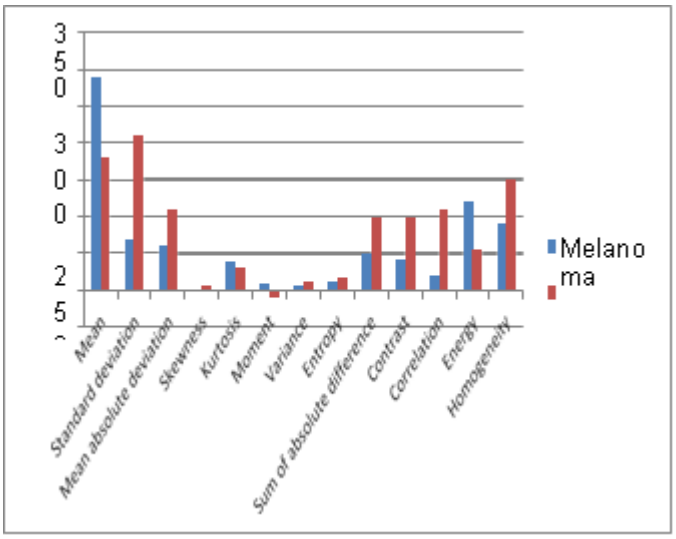


**Fig.13. Comparison between melanoma and non-melanoma with Feature extraction values**

From a chart the 13 features are in a particular range based on the range neural network classified an image into cancerous or non-cancerous image.

### 5.3Artificial Neural Network

The classification is done in Neural Network Simulation software – NEURAL LAB. Then Network is trained using known data set of both benign and malignant

melanoma cases. Many epochs of training are repeated until Mean Square Error is less than a desired value. Once training is completed, datasets for classification are given to the network. Fifty Malignant and Benign Melanoma Features are given for classification. The output of the classifier is either 0 or 1. One represents cancerous (Malignant) condition and Zero represents Non-cancerous (Benign) condition. Here the classification is done after optimizing Mean Square Error in NEURAL LAB. In our experiments, two dermoscopic image sets with 75 images used to evaluate the proposed method. The set of 75 dermoscopic images were taken from three different resources, and contained 45 melanoma images and 30 non-melanoma images. Using this data sets in our work to test the system for detect misclassifications.

The obtained results were compared with the clinicaldiagnostic results of a dermatologist. The confusion matrix shows the errors in the classification. There were 7 misclassifications. The accuracy of this proposed system is 84%.Also the classified outputs are obtained in the MATLAB window. It is shown in figures.

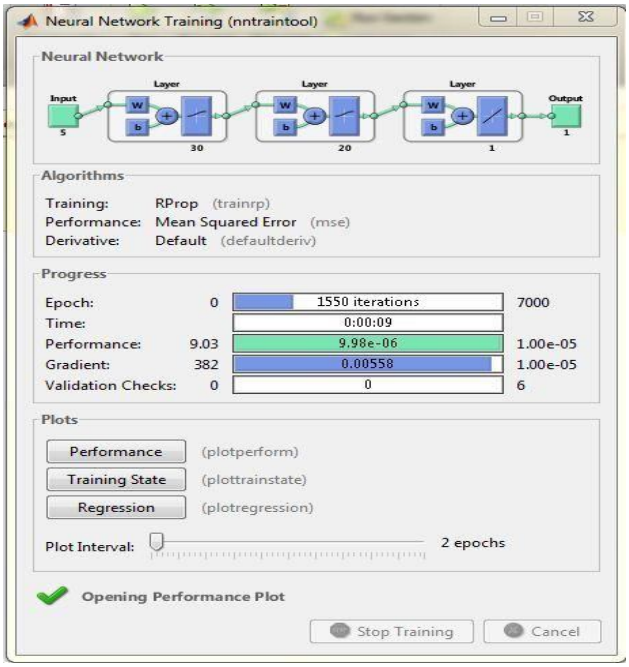


**Fig.14. ANN training in Matlab**

A confusion matrix is a matrix for a two-class classifier, contains information about actual and predicted classifications done by a classification system.. In Matlab neural network toolbox provide this function for measure the neural network classification. This proposed work use neural network for classification got 84% accuracy.

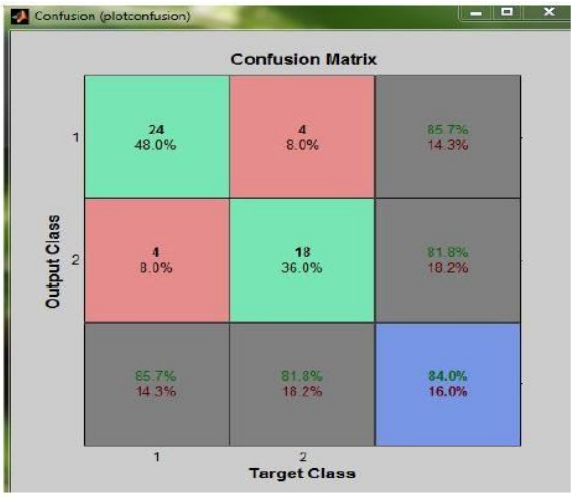


**Fig.15. Confusion matrix showing results of classification**

## VI. CONCLUSION

Early skin cancer diagnostic system using computer based techniques is more efficient than the conventional Biopsy methods. The cost involved as well as the time taken for detection is less in this proposed methodology. An economical, optimized and painless Artificial Intelligence based skin cancer diagnosing system is developed and proposed. It proves to be a better diagnosis method than the conventional Biopsy method. By using this methodology, patient can diagnose skin cancer without going to hospitals. It saves considerable amount of time of patients as well as doctors. Also the cost involved in this method is low. The diagnosing technique used Digital Image Processing Techniques and Artificial Neural Networks for the classification of Malignant Melanoma from benign melanoma. ANN based classifier proved to be very efficient in decision making as well as pattern recognition applications. The dermoscopic images were used for classification.

The images were subjected to various image processing techniques. ANN is used for classification purposes. The unique features of the segmented images were extracted using 2-D Wavelet Transform. Based on the features, the images were classified as Cancerous and Non-cancerous. This methodology has got good accuracy also. By varying the Image processing techniques and Classifiers, the accuracy can be improved for this system. The proposed system has an accuracy of 86%, which is much higher than that of conventional methods. This system seems to be very usefulness to Dermatologists, Doctors, Clinicians and Masses for early detection of skin cancer for further treatment. This system is simple, easy-to-use, intuitive, cheap, fast and an accurate tool. This system will be a great help in early

detection of malignant melanomas for faster, cheaper and efficient treatment.

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