Sudan University for science and technology

College of Engineering

Biomedical Engineering Department

Research on:

Computer - aided Diagnosis of skin cancer

تشخيص سرطان الجلد بمساعدة نظام الكمبيوتر.

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بسم الله الرحمن الرحيم

﴿أَلَمْ نَشْرَحْ لَكَ صَدْرَكَ ۝١ وَوَضَعْنَا عَنْكَ وِزْرَكَ ۝٢ الَّذِي أَنْقَضَ ظَهْرَكَ ۝٣ وَرَفَعْنَا لَكَ ذِكْرَكَ ۝٤ فَإِنَّ مَعَ الْعُسْرِ يُسْرًا ۝٥ إِنَّ مَعَ الْعُسْرِ يُسْرًا ۝٦ فَإِذَا فَرَغْتَ فَانْصَبْ ۝٧ وَإِلَى رَبِّكَ فَارْغَبْ﴾ ۝٨

صدق الله العظيم

سورة الشرح

اهداء

الى من لايمكن للكلمات ان توفي حقهم... الي من لايمكن للارقام ان تحصي فضائلهم... الى كل من لايسع المجال لذكرهم... نقول لهم:

(لو المرء يهدي فوق طاقته لكان مقدارهم الدنيا وما فيها**)**

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ABSTRACT

In this study, we investigated a computer aided diagnosis system for skin cancer detection problem. Early detection of skin cancer has the ability to reduce mortality and morbidity. There are many diagnostic technologies and tests to diagnose skin cancer. Conventional diagnosis method for skin cancer detection is Biopsy method. It is done by removing or scraping off skin and that sample under goes a series of laboratory testing. To prevent these problems, we are using a neural network system (**NN**) as promising modalities for detection of skin cancer. The different stages of detection involves collection of Dermoscopic images, filtering the images for removing hairs and noises, segmenting the images using region of Interest (**ROIs**), feature extraction using **GLCM** and c1assification using Artificial Neural Network (**ANN**).It c1assifies the given data set into cancerous or cancerous image. The classifiers have been used to classify subjects as normal or abnormal skin cancer images. A classification with a success of **91.6%** has been obtained by the Artificial Neural Network(**ANN**).

المستخلص

في هذه الدراسة، قمنا بالتحقيق في نظام التشخيص بمساعدة الكمبيوتر لمشكلة الكشف عن سرطان الجلد. الكشف المبكر عن سرطان الجلد لديه القدرة على الحد من الوفيات.هناك العديد من التقنيات والاختبارات التشخيصية لتشخيص سرطان الجلد.طريقة التشخيص التقليدية للكشف عن سرطان الجلد هي طريقة الخزعة. ويتم ذلك عن طريق اخذ عينة من الجلد ووضعها تحت الفحوص المختبرية. لمنع هذه المشاكل، نحن نستخدم نظام الشبكة العصبية و طرائق واعدة للكشف عن سرطان الجلد. مراحل مختلفة من الكشف يشمل على جمع الصور من جهازالديرموسكوبي,وتصفيتها عن طريق إزالة الضوضاء والشعر, وتحسين التباين في الصور, وتجزئة منطقة الفائدة(**ROIs**) واستخراج الميزات باستخدام(**GLCM**) والتصنيف باستخدام الشبكة العصبية(**NN**). وهو يصنف مجموعة البيانات المعطاة على أنها صور اورام طبيعية او غير طبيعية وقد نجح في التصنيف بنسبة **91.6%**.

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Introduction

1. 1 general overview

Human Cancer seems as a dangerous disease which is caused mainly by genetic instability and accumulation of multiple molecular alternations. Skin cancer occurs primarily in areas of the body exposed to sunlight, including: the face, scalp, lips, ears, neck, chest, hands and arms. But it can also develop in areas of the body that are rarely exposed to sunlight, such as: the hands, the nails, the spaces between the toes or under the fingernails, as well as in the genital area. There are many types of cancer among which skin cancer are most common. Tumors on the skin can be benign (**not cancer**) or malignant Melanoma (**cancer**). Benign growths are not as harmful as malignant growths . Melanoma is the deadliest form of skin cancer affecting the human skin and gradually spreads whole body. It arises from cancerous growth in pigmented skin area. It is a gradually spreading condition; this begins in the melanocytes (**Types of cells**) in skin **[1].** If the skin cancer is not diagnosed at its early stages, it can cause death of the patient, so early detection of skin cancer is unavoidable. Skin cancer is accounts for more than **50%** of all types of cancers around the

world. Skin cancer is have differing causes and varying degrees of malignancies. Detection of malignant melanoma in its early stages considerably reduces morbidity and mortality. Skin cancer can be cured at very high rates with simple and economical treatments **[2],** if detected at its earlier stages. Presently there is a greater need of automatic diagnosis of skin cancer for masses at an early stage. In this direction, we are explaining you our implemented automation skin cancer diagnosis system. For this we are using images of cancer affected skin of patients. The basic aim of this "automatic cancer detection system" , to have a simple, efficient and automatic skin cancer, detection and diagnosis system with the use of commonly available software for non-experts/clinicians/doctors. This explained automatic skin cancer diagnosis system is implemented in commonly available **software - MATLAB**. Computer aided decision support tools are important in medical imaging for diagnosis and evaluation. Predictive models are used in a variety of medical domains for diagnostic and prognostic tasks. These models are built based on experience which constitutes data acquired from actual cases. The data can be preprocessed and expressed in a set of rules, such as that it is often the case in knowledge-based expert systems, and consequently can serve as training data for statistical and machine learning models.

1.2 Problem Definition and Motivation

The conventional method for skin cancer detection , involving the removal of skin and it undergoes various laboratory tests, this method is time consuming, and The similarities among skin lesions make the diagnosis of malignant cell a difficult task. and also Improper diagnosis of the disease ,such as :-(a person does not have malignant melanoma and was diagnosed with malignant melanoma or versa).

1.3 Objectives of study

The objective of this study Detection skin in human body by Computer Aided Diagnosis (**CAD**) software to assist radiologists in interpreting medical images in skin tumor to provide 'second opinions' and more accurate result by using neural network. and also classify that whether the given input image is Malignant Melanoma or non-melanoma from skin diseases.

1.4 Methodology

Computer-aided diagnosis of dermoscopy images has shown a great promise in developing a quantitative and objective way of classifying skin lesions. computer-aided diagnostic system typically consists of several components .You will know it in Chapter four.

1.5 Thesis Layout

This thesis consists of six chapters.

Chapter one: Provides an introductory view of the project, problem; statement, and concerned objectives of the thesis.

Chapter two: Provides some anatomical and physiological, a quick overview of all the concerned topics and general talking of technique for uses in this project.

Chapter three: Literature Review.

Chapter four: Includes a detailed assembly of the various algorithms and methodologies that have been manipulated and implemented for the achievement of the project objectives

Chapter five: Results and discussion.

Chapter six: Conclusion and Future work.

Chapter two

Chapter two

Theoretical Background

2.1 Skin Biology and Pigmented Skin Lesions

2.1.1 Human Skin Biology

The skin is the human body's largest organ. It covers the entire body ;and its thickness varies from 0.5mm on eyelids to 4mm or more on the palms of hands and the soles of feet **[3].** The skin is our first line of defense. Its primary roles are to protect the body and to maintain the integrity of internal systems. Its other functions are insulation, temperature regulation, sensation, and the production of vitamin D **[3].** Technically, the skin consists of the three layers shown in **Figure 2.1**. the epidermis or top layer, the dermis or middle layer and the hypodermis or bottom layer **[3].**

Epidermis

The outer surface of the skin is called epidermis. The outer layer of the epidermis is comprised of hard, flattened dead cells. The epidermis mainly consists of keratinocytes. The epidermis also contains melanocytes, cells which are responsible for the skin's pigmentation , that provides natural

protection against the sun's rays and Langerhans cells which are part of the immune system. The epidermis is composed of 4 or 5 layers depending on the region of skin being considered: the outermost layer being stratum corneum and then follows stratum lucidum, stratum granulosum, stratum spinosum and stratum basal illustrated in **Figure 2.2**. It is the most visible region under both dermoscopy and naked-eye examination and it is the origin of melanoma **[3].**

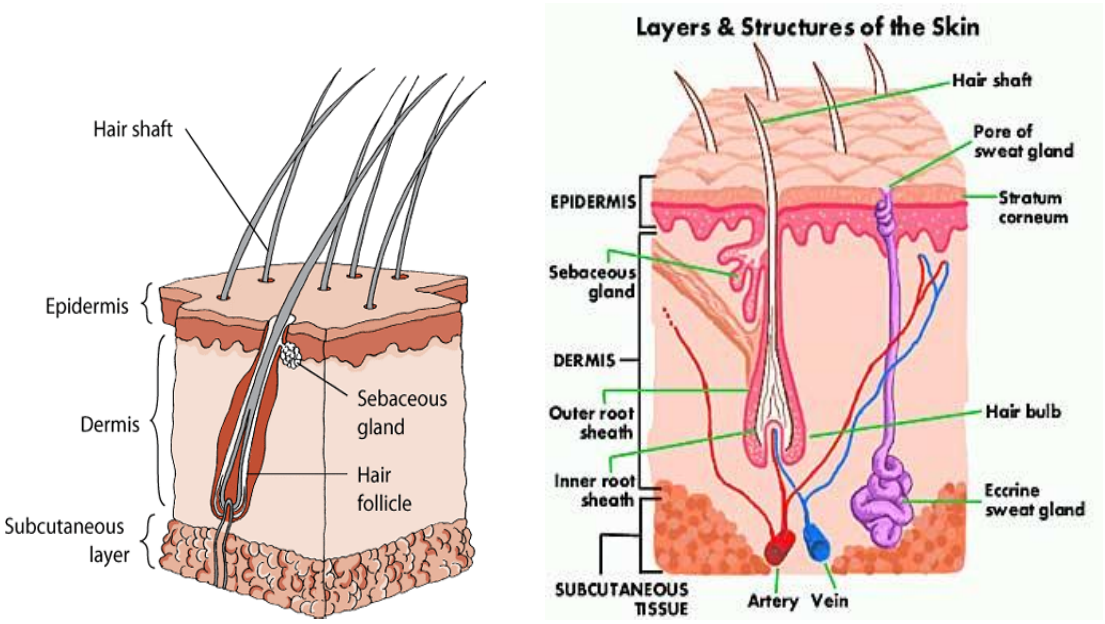


Figure 2.1: Skin structure: epidermis, dermis and hypodermis layers.

Dermis

Below the epidermis is the dermis which is a thick, supple and sturdy layer of connective tissue. The dermis a dense meshwork of collagen and elastin fibers, two connecting proteins which supports tiny lymph and blood vessels . It

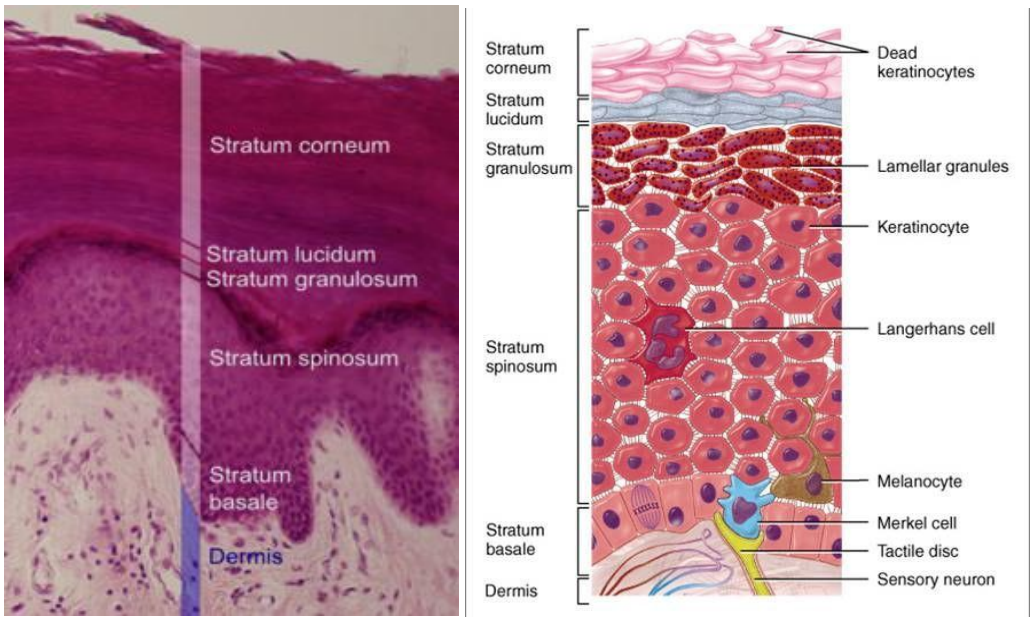
allows the skin as well as the nerves, muscle cells, sweat and sebaceous glands, and hair follicles to breathe and be nourished. This layer contains the special cells that repair the skin, such as the fibroblasts that synthesize the skin proteins like collagen and elastin. The dermis is divided into the papillary dermis, and the reticular dermis **[3].**

Hypodermis

The hypodermis is the deepest layer of the skin, composed primarily of fat. It manages the skin's functions of feeding, excreting and heat exchange. The key cells are fat cells that provide energy, serve as a heat insulator for the body, and act as a shock absorber to protect underlying tissue against mechanical trauma and helps give our skin its resilience. Sweat glands originate in this layer and control the body's temperature by evaporating and cooling the skin surface **[3].**

Melanocytes

Melanocytes are the pigment producing cells in the skin. They are evenly distributed in the skin along the basal layer at the dermo-epidermal junction. Melanocytes produce melanosomes which can be transferred to the surrounding keratinocytes. Melanin is the major pigmentation factor for our skin color due to the variation in number, size and distribution of melanosomes which will be increased if stimulated by UV-radiation or hormones **[3].**



(a) **(b)**

Figure 2.2: Structures of the epidermis layer are shown on the schematic **[4](a)** and histology **(b)** images: the outermost layer is stratum corneum and then follows stratum lucidum, stratum granulosum, stratum spinosum and stratum basal **[5].**

2.1.2 Benign Pigmented Skin Lesions

The purpose of this section is not to give a complete overview of all types of pigmented skin lesions, but to provide a short presentation of the most common lesions. The following sub-sections will briefly review the benign and cancerous skin lesions.

Benign melanocytic lesions

Freckles and lentigo Freckles and lentigines are two benign pigmented lesions that can arise in the skin. In freckles,

there is a temporary overproduction of melanin in skin due to exposure to UV-radiation, while in lentigo maligna there are an increased number of melanocytes in the dermoepidermal junction.

Melanocytic nevi Nevi are lesions which are the result of proliferation of melanocytes at the dermo-epidermal junction. These clusters of melanocytes can either stay at this position or migrate into the dermis where they will be destroyed and disappear. There are variants of nevi with different growth patterns; junctional , compound, dermal, Spitz, Reed, blue nevi and more. The melanocytic nevi are categorized by their location in the skin (junctional nevi locate at the dermo-epidermal junction, compound nevi locate at both the dermo-epidermal junction and the dermis, and dermal nevi located at the dermis), histological patterns and clinical patterns. The majority are totally benign with no, or very limited, malignant potential, although it has been shown that multiple common nevi is a strong risk factor for melanoma. **[6].** For example all Spitz nevi lesions in adults should be excised for histopathologic evaluation **[7].**

Atypical or dysplastic nevi Some nevi lesions have architectural and cytological atypia, and they are called dysplastic nevi, also known as: atypical mole, atypical nevus, Clark's nevus, dysplastic melanocytic nevus. Atypical nevi are defined based on abnormal clinical features (by naked-eyes usually) and dysplastic nevi are defined by abnormal histological features (by biopsies). Atypical nevi are generally

larger than ordinary moles (> 6mm in diameter) and have irregular and indistinct borders. They are often asymmetrical and their color frequently is not uniform and ranges from pink to dark brown; they usually are flat, but parts may be raised above the skin surface **[6,8].** Dysplastic nevi can be found anywhere, but are most common on the trunk in men, and on the calves in women. The clinical importance of atypical nevi lies in their association with increased melanoma risk **[6].** An individual with multiple atypical nevi or a family history of multiple atypical nevi or melanoma has an increased risk of developing superficial spreading melanoma.

Benign non-melanocytic lesions

Seborrhoeic keratosis Seborrhoeic keratosis is a benign, often pigmented, tumour composed of epidermal keratinocytes. These lesions are very common, especially among the elderly, which can be flat but are more commonly verrucous in their appearance. Seborrhoeic keratosis can also resemble melanoma skin cancer in terms of the clinical **ABCD** features, though they are unrelated to melanoma because these are benign non-melanocytic lesions **[8].**

Figure 2.3-e shows an example of a seborrhoeic keratosis lesion. Dermatofibroma A dermatofibroma is a common benign fibrous skin lesion. It is due to a noncancerous growth of dermal dendritic cells.

Dermatofibromas most often occur on the legs and arms. Once developed, they usually persist for years. They appear as

firm-feeling nodules, often yellowbrown in colour, sometimes pink and sometimes quite dark, especially in dark coloured skin **[8].**

2.1.3 Skin Cancer

Skin cancer is by far the most common of all cancers. As discussed in the previous section, skin lesions can have melanocytic and non-melanocytic origins. So, skin cancers can be divided into two major categories as well: melanocytic and non-melanocytic.

Malignant non-melanocytic lesions

The most common non-melanocytic skin cancers are basal cell carcinoma **(BCC)** and squamous cell carcinoma **(SCC),** which are briefly explained in the following sections. Basal cell carcinoma.

Basal cell carcinoma (BCC) is the most common type of skin cancer. BCC arises in cells called basal keratinocytes in the deepest layer of the epidermis. It rarely metastasizes or kills **[9].** However, because it can cause significant destruction and disfigurement, it is still considered malignant by invading surrounding tissues. Statistically, approximately 3 out of 10 Caucasians may develop a basal cell cancer within their lifetime **[9]. BCC** grows by direct extension and appears to rely on the surrounding supportive tissue to grow. Therefore, it does not metastasize through blood vessels or lymphatics **[3, 9].**

Pigmented basal cell carcinoma is a cutaneous condition, a subtype of BCC, that exhibits increased melanization. In some cases, it may be difficult to distinguish deeply pigmented or even non-pigmented basal cell carcinoma from melanoma **[10].** The skin changes caused by this skin cancer depend on the type of **BCC** involved. The most common appearance is of a raised pink or pearly white bump that may have a translucent, rolled, pearly edge and small visible blood vessels **[10].** Pigmented **BCC** may look like a mole with a pearly border.

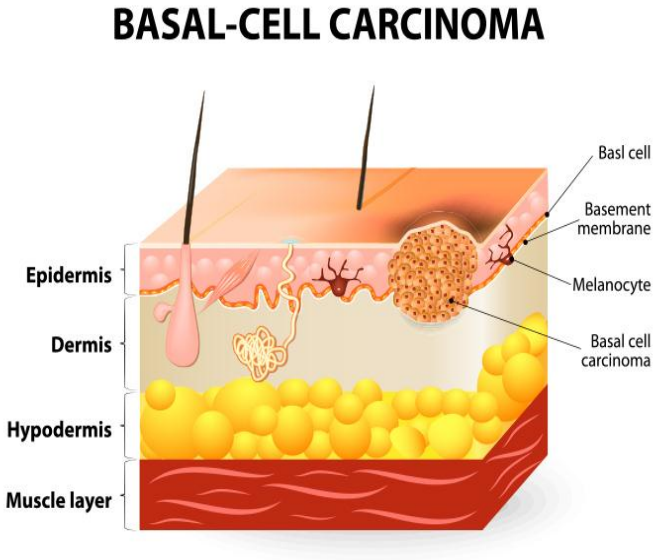


Figure 2.3: An example of basal cell carcinoma.

Squamous cell carcinoma Squamous cell carcinomas **(SCC)** arise from the keratinocytes of the epidermis.**SCCs** begin when the atypical keratinocytes grow through the basement membrane and invade the dermis. When growing only in the epidermis they are considered precancerous, and this condition is called actinic keratosis . More advanced changes

with full epidermal thickness dysplasia but no dermal invasion is called squamous cell carcinoma in-situ, or Bowen's disease. Once an invasive **SCC** has developed it has metastatic potential and can be fatal **[11]**

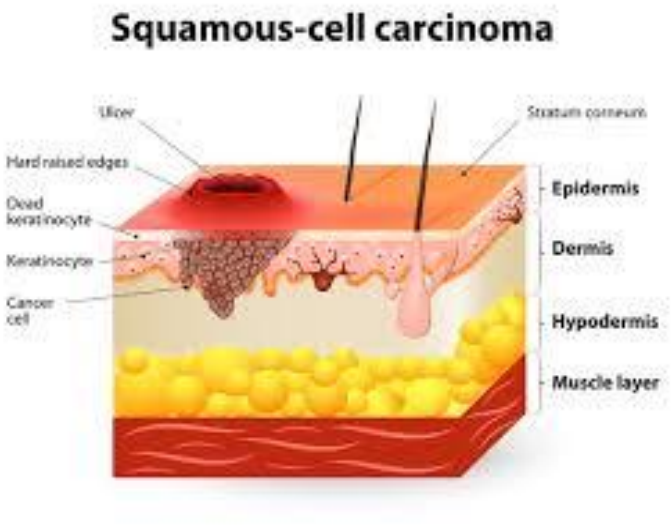


Figure 2.4: An example of squamous cell carcinoma

Melanoma: Malignant melanocytic lesion

Melanoma is a malignant tumor of melanocytes. Melanocytes are cells that produce the melanin, dark pigments responsible for the color of skin. They predominantly occur in skin, but are also found in other parts of the body including the bowel and the eye. Melanoma is less common than other skin cancers. However, it is much more dangerous and causes a large majority of skin cancer deaths since it can spread in the body **[3].** As long as the malignant clone is only growing in the epidermis, the lesion is called a melanoma in-situ. When the malignant melanocytes invade the dermis , the lesion has

become an invasive melanoma (they may have metastatic potential). The level of invasion in the dermis, through to the subcutaneous fat, is measured during histopathologic examination of the tumor after excision. Two measurements are made; the invasion depth according to Breslow is the thickness, in millimeter's , from the stratum granulosum in the epidermis to the deepest invasive melanoma cell **[6].** Another measurement system, called Clark, describes the thickness of a melanoma in relation to its penetration into the skin layers where level I represents intraepidermal growth, i.e. in-situ, level II a few cells in the papillary dermis, level III occupation and expansion of the papillary dermis, level IV invasion of the reticular dermis and level V invasion into subcutaneous fat **[6].**

2.2 Dermoscopy and Clinical Diagnosis

In the **1990s,** light-based visual technologies were adopted to augment the clinical diagnosis of melanoma. Dermoscopy is a noninvasive method that allows in vivo evaluation of colors and microstructures of the epidermis, the dermo-epidermal junction, and the papillary dermis not visible to the naked eye. During a dermoscopy assessment, the pigmented skin lesion is covered with liquid (usually oil or alcohol) and examined under a specific optical system. Applying oil reduces the reflectivity of the skin and enhances the transparency of the stratum corneum. This allows visualization of specific structures related to the epidermis, the dermo-epidermal junction , and the papillary dermis , and it also suggests the

location and distribution of melanin. In the last few years dermoscopes with **LED** light with polarization have been introduced and by using polarized light, immersion liquid is no longer necessary, and some of these instruments do not need direct skin contact. Non-polarized versus polarized light and contact versus non-contact dermoscopy gives somewhat different appearance of the examined lesions in regards to color and visualization of vessels.

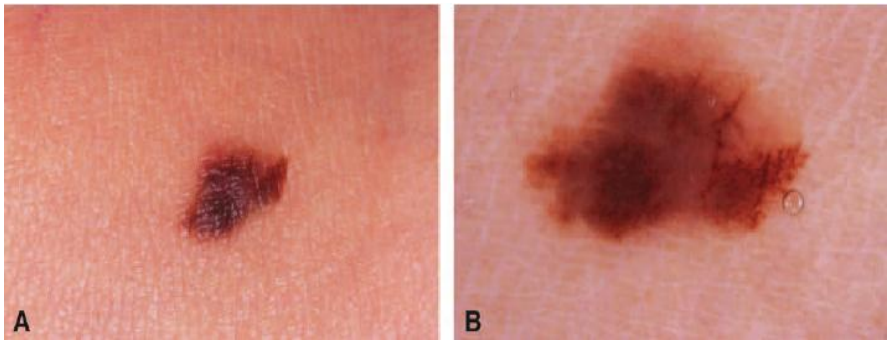
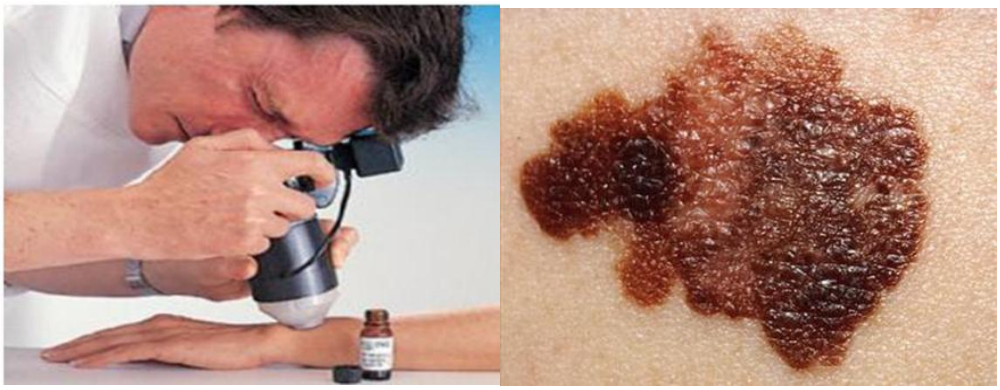


Figure 2.5: **a)** An image of a lesion under clinical view (naked eye). **b)** shows the same lesion under a dermoscope with oil immersion.

Dermoscopy, also known as Dermatoscopy , Dermoscopy, a non-invasive skin imaging techniques, has become a principal tool in the diagnosis of melanoma and other pigmented skin lesions. dermoscopy is a technique for examining the appearance of the skin - ordinary skin as well as moles-to diagnose skin problem . it consist of using a handheld device, dermatoscopes , which combines strong magnification with

good lighting to +/- a polarizing filter to enable your dermatologist to get the best view possible of your skin problem. although dermoscopy can be helpful in all forms of skin diagnosis , it is particularly helpful for the diagnosis of skin cancer, particularly melanoma. Is a high quality digital camera that captures a magnifying glass **10** times and with high evolution (**1024 * 768**) pixels . Illumination was provided by a **150 w** light source .



(a) **(b)**

digital dermoscopes Dermatoscopic image

Figure 2.6: Dermoscopic method

2.2.1 Image Acquisition - Digital Dermoscopes

There are different kinds of dermoscope and they are roughly divided into analogue and digital types. Digital types are easier to take and store dermoscopy images, however analogue types are more widely used. **Figure 2.7** a-e show Heine Delta 10, Heine Delta 20, DermLite III DL3,Dermogenius, and DermLite II Pro , which are analogue dermoscopes. all of them except a

can be attached to a digital camera to provide advantages of digital dermoscopy. DinoLite, Handyscope and DermScope are examples of digital dermoscopes shown in **Figure 2.7** f-h respectively. There is a study in the literature that compares images of a dysplastic compound melanocytic nevus and a thin malignant melanoma under five different handheld dermoscopes (Heine Delta 10 ,Heine Delta 20 , Dermogenius and DermLite Foto 37 with and without glass plate). The magnification was identical in all dermoscopes. The authors show that in the newer dermoscopes, the image quality with regard to color and visible differential structures is distinctly improved compared to the dermoscope (Heine Delta 10) with only one light source **[12].** Three advanced dermoscopes will be reviewed briefly here.

DermLite II Pro

With new advances in technology, dermoscopes have also evolved. DermLite from 3Gen Co. is a dermoscope consisting of a magnifying lens encircled by light-emitting diodes that can be adjusted for polarization. This multi-spectral dermoscope provides color visualization; ranging from white light epiluminescence, surface pigmentation using blue light, superficial vascularity under yellow light, and deeper pigmentation and vascularity with the deeper-penetrating red light frequency. A new version of the DermLite can be used for the evaluation of pigmented lesions and non-pigmented skin cancers, scalp disease, and vascular patterns. The DermLite can be attached to a camera to record images and has a retractable

faceplate for use with immersion oil. DermLite Pro, shown in the **figure 2.7**-d, is one of the most widely used dermoscopes. Recently, the company has provided an iPhone kit that users can snap the DermLite onto their iPhone cameras.

Dino-Lite Pro USB Dermoscope with Polarizer

The DinoLite is a compact digital microscope with USB - PC connectivity. Magnification ranges from 10X to 200X (adjustable single lens) to 500X with white polarized LED lights. The **LED's** light is around the 400 nm spectrum. The polarization feature allows the user to reduce the effect of reflections and glare when looking at highly reflective surfaces. adjustment of the polarization feature is performed by way of a rotating collar, allowing the user to examine objects with varying levels of polarization. **Figure 2.7**-f shows an image of the DinoLite dermoscope.

Handyscope by Foto Finder Systems, Inc.

Handyscope from Foto Finder is a new mobile dermoscope, shown in the **figure 2.7**-g, that allows one to take polarized mole pictures of up to 20X magnification and to save them in the iPhone application **[13].** Handyscope can be used for tele-dermatology, combining latest communication technology of iPhone with a tool for skin cancer screening. Dermoscopy images taken with iPhone camera and the dermoscope attachment can be e-mailed to other specialists for a second opinion. Mobile dermoscopes can provide a good mobility for experts while they are connected to servers through wifi

connections to provide an integrated dermoscopy station.

DermScope by Canfield Scientific, Inc.

The new DermScope from Canfield, shown in **Figure 2.7**-h, is another intelligent dermoscope made for iPhone that addresses all of the important modes of skin visualization including contact and non-contact images with the dual-lighting modes for white light and the cross-polarized light. The DermScope's design has been optimized for iPhone 4 and It has optical zoom of 20x and the viewing field is 15 mm **[14].**

(a) Heine10

(b) Heine20

(c) DermLite III DL3

(d) DermLite(TM)DL100

(e) DermLite II Pro

(f) DinoLite

(g) Handyscope

(h) DermScopeCanfield

Figure 2.7: Figures a, b, c, d, and e show analogue dermoscopes. All of them, except a, are attachable to digital cameras to function as digital dermoscopes. DinoLite, Handyscope, and DermScope are modern digital dermoscopes shown in f, g, and h respectively.

2.2.2 Dermoscopy -Clinical Diagnostic Methods

In this section, the diagnostic algorithm, used is gray Level Co-occurrence Matrix **(GLCM)[1]** .It 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 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 **[15].** 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 | .x, .y) is the relative frequency with which two pixels,

separated by a pixel distance (.x, .y), occur within a given neighbor;hood, one with intensity 'i' and the other with intensity 'j'. This paper presents an application of gray level co-occurrence matrix **(GLCM)** to extract Four features namely, Variance, Energy, Correlation, Homogeneity and Entropy**[15].** The results show that these texture features have fast extraction and high discrimination accuracy. Hence it is used effectively.

2.3 Haralick's Features

The Haralick's texture features are: Energy (**EG**), Correlation (**CO**), Inertia (**IN**), Entropy (**EN**), Inverse Difference Moment (**IDM**), Sum Average (**SA**), Sum Variance (**SV**), Sum Entropy (**SE**), Difference Average (**DA**), Difference Variance (**DV**), Difference Entropy (**DE**), Information measure of correlation-1(**ICO-1**)and Information measure of correlation-2(**ICO-2**).These features can be calculated by using the following equations: Denote *P(i,j):(i,j)* then try in a normalized SGLD matrix Ng is Number of distinct gray levels in quantized image.

$$p_x(i) \sum_{i=1}^{Ng} p(i,j) \dots\dots\dots\dots\dots (2.1)$$

$$p_y$$

$$(j) \sum_{j=1}^{Ng} p(i,j) \dots\dots\dots\dots (2.2)$$

$$p_{x+y}(k) = \sum_{i=1}^{Ng} \sum_{j=1}^{Ng} p(i,j) \dots\dots\dots\dots (2.3)$$

i+j=k, k=2, 3, …….$2N_g$

$$p_{x-y}(k) = \sum_{i=1}^{Ng} \sum_{j=1}^{Ng} p(i,j) \dots\dots\dots\dots (2.4)$$

|i − j|=k, k=0, 1, …….N_g-1

1. Energy (EG)

The Energy feature **(EG)** returns the sum of squared elements in the
SGLD matrix as expressed by the following equation:

$$\text{EG} = \sum_{i}^{Ng} \sum_{j}^{Ng} \{p(i,j)\}^2 \dots\dots\dots (2.5)$$

2. Entropy (EN)

The Entropy coefficient (**EN**) is a descriptor of randomness produces a low value for an irregular SGLD matrix. It achieves its highest value when all elements of the SGLD matrix are equal for an irregular image.
This coefficient is defined by the following expression:

$$\mathrm{EN} = -\sum_{i}^{Ng}\sum_{j}^{Ng} p(i,j)\log(\big(p(i,j)\big) \dots\dots\dots (\mathbf{2.6})$$

3. **Inertia (IN)**

The Inertia (**IN**) also called Contrast feature is a measure of image intensity contrast or the local variations present in an image to show the texture fineness. This parameter is specified by the following equation:

$$\mathrm{IN} = -\sum_{i}^{Ng}\sum_{j}^{Ng} (\mathrm{i}-\mathrm{j})^2\, p(i,j) \dots\dots\dots (\mathbf{2.7})$$

4. **Correlation (CO)**

The descriptor Correlation (**CO**) measures the linear dependence of gray level values in the co-occurrence matrix or describes the correlations between the rows and columns of the co-occurrence matrix. This parameter is specified by the following equation:

$$\mathrm{CO} = \frac{\sum_{i}^{Ng}\sum_{j}^{Ng}(i-\mu_{x)(j-\mu_{y)}\ p(i.j)}}{\alpha_x\ \alpha_y} \dots\dots\dots\dots (\mathbf{2.8})$$

Where μ_x, μ_y, α_x *and* α_y are the means and standers deviations of p_x and p_y.

5. **Inverse Difference Moment (IDM)**

Inverse Difference Moment is also called the "Homogeneity" Mathematically, it can be written as:

$$\text{IDM} = \sum_{i}^{Ng} \sum_{j}^{Ng} \frac{1}{1 + (i-j)^2} \, p(i,j) \ldots\ldots\ldots (\mathbf{2.9})$$

6. **Variance (VA)**

The Variance (VA) is a measure of variation. A variance of zero indicates that all the values are identical. A non-zero variance is always positive: A small variance indicates that the data points tend to be very close to the mean and hence to each other, while a high variance indicates that the data points are very spread out from the mean and from each other.

$$VA = \sum_{i}^{Ng} (i - \mu_x)^2 \; p_x \; (i) \ldots\ldots\ldots\ldots\ldots (\mathbf{2.10})$$

7. **Sum Average (SA)**

$$\text{SA} = \sum_{\text{k=0}}^{\text{2 N}_{\text{g}-2}} \text{kp}_{\text{x+y}} \; (\text{k}) \ldots\ldots\ldots\ldots\ldots (\mathbf{2.11})$$

8. Sum Entropy (SE)

$$SE = -\sum_{k=0}^{2N_g-2} p_{x+y}(k)\, log_{2\, p_{x+y}}(k) \ldots\ldots\ldots\ldots\ldots (\mathbf{2.12})$$

9. Sum Variance (SV)

$$SV = \sum_{k=0}^{2N_g-2} (K - SA)^2\ p_{x+y}(k) \ldots\ldots\ldots\ldots (\mathbf{2.13})$$

10. Difference Entropy (DE)

$$\mathrm{DE} = -\sum_{k=0}^{Ng-1} p_{x-y}(k)\log_2 p_{x-y}(k) \ldots\ldots\ldots\ldots\ldots (\mathbf{2.14})$$

11. Difference Average (DA)

$$DA = \sum_{k=0}^{N_{g-1}} k p_{x-y}(k) \ldots\ldots\ldots\ldots\ldots\ldots (\mathbf{2.15})$$

12. Difference Variance (DV)

$$DV = \sum_{k=0}^{N_{g-1}} (k - DA)^2\, p_{x-y}(k) \ldots\ldots\ldots\ldots\ldots (\mathbf{2.16})$$

13. Information measures of correlation

$$inf1 = \frac{HXY - HXY1}{MAX\{HX, HY\}} \dots\dots\dots\dots\dots\dots (\mathbf{2.17})$$

2.4 Artificial Neural Net Work (ANN)

An artificial neural network **(ANN)** reflects a system that is based on operations of biological neural networks and hence can be defined as an emulation of biological neural systems. ANN's are at the forefront of computational systems designed to produce, or at least mimic, intelligent behavior. Unlike classical Artificial Intelligence **(AI)** systems that are designed to directly emulate rational, logical reasoning, neural networks aim at reproducing the underlying processing mechanisms that give rise to intelligence as an emergent property of complex, adaptive systems. Neural network systems have successfully been developed and deployed to solve pattern recognition, capacity planning, business intelligence, robotics, or intuitive problem related aspects. In computer science, neural networks gained a lot of steam over the last few years in areas such forecasting, data analytics, as well as data mining **[16]. (ANNs)** can be composed of different number of neurons. In chemical applications, the sizes of ANNs, i.e., the number of neurons, are ranging from tens of thousands to only as little as less than ten (1-3). The neurons in **ANNs** can be all put into one layer or two, three or even more layers of neurons can be formed **[17].** It has to be pointed out that data analytics is normally defined as the science of examining raw data with the purpose of drawing conclusions about that information . Data analytics is used in

many industries to allow companies to either make better business decisions, or in science, to verify/disprove existing models or theories. Data analytics differs from data mining by scope, purpose, and focus of the analysis. Data Mining describes the process of discovering new patterns out of very large data sets and does so by applying a vast set of methods that originate out of statistics, artificial intelligence, or database management. The actual data mining task reflects an automatic (or semi-automatic) analysis of large quantities of data and the goal is toextract previously unknown patterns such as groups of data records (cluster analysis), unusual records (anomaly detection), or dependencies (association rule mining). Hence, data mining basically focuses on sorting through large data sets (by utilizing sophisticated software applications) to identify undiscovered patterns and establish hidden relationships (aka extract value). Data analytics focuses on inference, the process of deriving a conclusion that is solely based on what is already known to the researcher. To summarize, a neural network can be described as a highly parallel system that is capable of resolving paradigms that linear computing cannot tackle.

2.5 ANN – Pros and cons

A neural network can be used to solve linear as well as non-linear programming tasks, as a component of an **ANN** fails, the net continues to operate (based on its highly parallel nature), a neural network learns and does not have to be re-programmed , An **ANN** can be used to solve Classification , clustering, and

regression, related problems. The cons Most **ANN's** require a training phase to operate/function As an **ANN's** architecture differs from microprocessors, **ANN's** have to be emulated. Large **ANN's** require rather powerful HW to run (to accomplish reasonable execution times) .the application of **ANN** In Pattern Classification , Clustering/Categorization , Function approximation , Prediction/Forecasting , Optimization, Content-addressable Memory and Control.

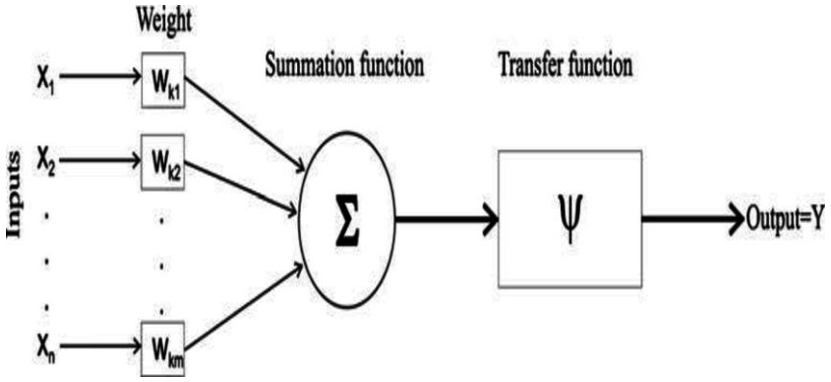


Figure 2.8: simple of ANN

2.6 Modes of Operation

There are two modes of operation in a neural network: training mode and operating mode. Once we complete the training of the network, we test it with sample data different from the training data.

2.6.1 Training mode

Depending on the training algorithm used, we can classify the neural networks into three categories: fixed-weight networks, unsupervised networks, and supervised networks. There is no training required for fixed weight networks, and a training mode is supervised or unsupervised. In supervised training, the training data consists of many pairs of source/target training patterns. The network processes the source inputs and compares its resulting outputs against the target outputs, using the results to adjust its weights. In unsupervised or adaptive learning networks, the training set consists of input training patterns only. Weight updates in these networks often involve moving selected weight vectors closer to the input training vector.

2.6.2 Operating mode

The main difference between training and operating mode is that weights change in training mode but not in the operating mode. We test the neural network in its operating mode.

2.6.3 Testing

A testing set tests the performance of the neural network. The testing set is generally not part of the training set but a representation of the general types of inputs the **ANN** is expected to receive in practice. Apply each testing input to the **ANN** in operating mode and compare the resultant output to the target output. If the network performs well on the testing set, it can be expected to perform well on the general case. The round robin method (leave one out method) is a good example

of training and testing procedure used to evaluate the performance of an **ANN**. In this method we train the **ANN** with all the cases except for one in the database. We apply this case for testing the **ANN** with the trained computer scheme.

2.7 Main Types of Neural Network

The main types of neural networks most commonly used for various applications are feed forward network, Hopfield network, and self-organizing map **(SOM).**

2.7.1 Feed Forward Neural Network

simple neural network type where synapses (connections) are made from an input layer to zero or more hidden layers and ultimately to an output layer. The feed forward neural network type is one of the most common neural networks in use. It is suitable for many types of applications. Feed forward neural networks are often trained via simulated annealing, genetic algorithms, or via one of the propagation techniques. to illustrate, annealing is a term used in metallurgy. If a metal is heated to a very high temperature, the atoms move about at high speeds. Yet, if they are cooled very slowly, they settle into patterns and structures, rendering the metal as being much stronger than before. This principle can be employed as an optimization technique in computer science. More specifically, simulated annealing can be used to aid a neural network to avoid local minima scenarios in its energy function. Simulated annealing basically involves perturbing the independent variables (the ANN weights) by a random value and keeping

track of the value with the least error **[17].** Recurrent ANN's. These types of ANN's incorporate feedback connections. Compared to feed-forward ANN's, the dynamic properties of the network are paramount. In some circumstances, the activation values of the units undergo a relaxation process so that the network evolves into a stable state where these activation values remain unchanged. Examples of recurrent ANN's would be a Kohonen (SOM) or a Hopfield based solution.

2.7.2 Self Organizing Map (SOM)

Neural networks that contains two layers and implements a winner take all strategy in the output layer. Rather than taking the output of individual neurons, the neuron with the highest output is considered the winner. **SOM's** are typically used for clustering related problems where the output neurons represent groups that the input neurons are to be classified into. SOM's may employ a competitive learning strategy.

2.7.3 Hopfield Neural Network

Simple single layer recurrent neural network. The Hopfield neural network is trained via an algorithm that teaches it to learn to recognize patterns. The Hopfield network will indicate that the pattern is recognized by echoing it back. Hopfield neural networks are typically used for pattern recognition.

2.7.4 Simple Recurrent Network (SRN)

Elman or Jordan Style . a recurrent neural network that has a context layer. The context layer holds the previous output from

the hidden layer and then echoes that value back to the hidden layer's input. the hidden layer then always receives input from its previous iteration's output. Elman or Jordan neural networks are generally trained by using genetic, simulated annealing, or one of the propagation techniques. Elman or Jordan neural networks are typically used for prediction related problems.

2.7.5 Simple Recurrent Network (SRN) - Self Organizing Map

a recurrent self organizing map that has an input and output layer, just as a regular **SOM**. However, the **RSOM** has a context layer as well. This context layer echo's the previous iteration's output back to the input layer of the neural network. **RSOM's** may be trained via a competitive learning algorithm (just as a non recurrent SOM). **RSOM's** can be used to classify temporal data or to predict outcomes.

Chapter Three

Chapter Three

Literature review

In 2006,Maryam Sadeghi, segmenting the lesion from the normal skin in the dermoscopy image,and use a graph-based approach to extract the holes and meshes of the pigment network, where cyclic subgraphs correspond to skin texture structures. Each correctly extracted subgraph has a node corresponding to a hole in the pigment network, and the image is classified according to the density ratio of the graph. Our results over a set of **500** dermoscopy images show an accuracy of **94.3%** on classification of the images as pigment network Present or Absent. For analyzing the irregularity of the structure, we locate the network lines and define features inspired by the clinical definition to classify the network with an accuracy of **82%** discriminating between Absent, Typical or Atypical, which is important for melanoma diagnosis. To find streaks in dermoscopy images, filters are applied, and in a similar fashion to fingerprint analysis, orientation estimation and correction is performed to detect low contrast and fuzzy streak lines. A graph representation is used to analyze the geometric pattern of valid streaks, to model their distribution and coverage. We achieved an accuracy of **77%** for classifying dermoscopy images into streaks Absent, Regular , or Irregular

on **945** images; the largest validation dataset published to date. Our contributions will improve automated diagnosis of melanoma using dermoscopy images**.[6]**

In 2011 ,Nima Fassihi, Jamshid Shanbehzadeh, Abdolhossein Sarafzadeh, Elham Ghasemi study presents a novel and accurate method to draw distinction between melanoma and skin lesion. This method is based on segmenting by the use of morphologic operators ;and features extraction by the use of wavelet transform. The first pre-processes the input image by artifact reduction and enhancement. The second segments the image by morphological operators. The third performs image transformation and extracts the features by the use of wavelet coefficients for the recognition phase which is performed by three layer neural network in the final step. The results showed **90** percents accuracy.**[18]**

I n 2012,Yogendra Kumar Jain, Megha Jain presented an the development of a skin cancer screening system that can be used in a general practice by non-experts to classify normal from abnormal cases. The development process consists of Feature Detection and Classification Technique. The features are extracted by decomposing images into different frequency sub-bands using wavelet transform. The output of Discrete Wavelet Transform becomes input to the Classification System which classify whether the input image is cancerous or noncancerous. The classification system is based on the application of Probabilistic Neural Network and Clustering Classifier. The Accuracy of the proposed system is calculated

using different classification techniques on image database of **80** samples (**40** cancerous and **40** non-cancerous images) .For 40 data sets the average accuracy of the proposed system using PNN is **97.5%** where as it is93.5%for Clustering Classifier.**[19]**

In 2013 , Dr. J. Abdul Jaleel , Sibi Salim , Aswin.R.B , study the use Artificial Neural Network based Classification methodology uses Image processing techniques and Artificial Intelligence. Main advantage of this computer based classification is that patient does not need to go to hospitals and undergo various painful diagnosing techniques like Biopsy. In this Computer Aided Classification, dermoscopy image of skin cancer is taken and it is subjected to various pre-processing for image enhancement. The cancer affected region is separated from the healthy skin using Threshold Segmentation. In order to reduce the complexity of classification, some unique features of malignant and benign melanoma are extracted. Such features are extracted using Gray Level Co-occurrence Matrix (**GLCM**) method. These features are given as the input nodes to the Artificial Neural Network. Back-Propagation Neural (**BPN**) Network is used for classification purpose. It classifies the given data set into cancerous or non-cancerous , This Methodology has got 82%. accuracy **[20].**

In2013, Nilkamal S. Ramteke#1 and Shweta V. Jain*2 #1M.Tech Student and #2 Asst. Professor , study the Skin cancer diagnosis system identifies and recognizes skin cancer symptoms and diagnoses melanoma in early stages. A review of skin cancer detection system has been done with the

emphasis of the automated Computer Aided Diagnosis (**CAD**) Digital Image Processing steps, doctors can get very good help from such diagnostic systems. proposing to use **ABCD** rule as its diagnostic accuracy has been reported to be **76%.** A combination of both **ABCD** rules and wavelet coefficients has been shown to improve the image feature classification accuracy by **60%.** At the end, proposing algorithm with relevant processing mathematics for proper, efficient detection of skin cancer**.[21]**

In 2014,Sarika Choudhari, Seema Biday, the study uses image processing techniques and Artificial Intelligence. The dermoscopy image of skin cancer is taken and it is subjected to various preprocessing for noise removal and image enhancement. Then the image is segmented using Maximum Entropy Thresholding. There are certain features unique for skin cancer regions. Such features are extracted using feature extraction technique – Gray level co-occurrence matrix. These features are given as the input nodes to the neural network. Artificial Neural Network act as classifier and Back-Propagation Neural **(BPN)** Network is used for classification purpose. It classifies the given data set into cancerous or non-cancerous. This Methodology has got **86.66%** accuracy **[22]**

In 2014, SANTOSH ACHAKANALLI1 & G. SADASHIVAPPA2, Dermoscopic images were collected and processed by various Image processing techniques. Cancerous region is segmented from healthy skin this method is called segmentation. The unique features such as statistical and dermoscopy of the

segmented images were extracted using gray level co-occurance matrix. Based on the features and the Total Dermoscop Score range the images were classified as Malignant or non-melanoma. This proposed methodology has got good accuracy of **92%.** By varying the Image processing techniques and training algorithms of Neural Networks, the accuracy can be further improved for this system**.[23]**

In 2015 ,Rashi Goel,Saranjeet Singh , the focus of the study on extraction of features inclusive of contrast, correlation, homogeneity, entropy, radius, standard deviation and perimeter etc. for exact detection of the cancer stage and the post treatment progress could be estimated by the direction and dimensional analysis of parameters. A statistical method of examining texture that considers the spatial relationship of pixels is the gray-level co-occurrence matrix (**GLCM**), also known as the gray-level spatial dependence matrix. The **GLCM** functions characterize the texture of an image by calculating how often pairs of pixel with specific values and in a specified spatial relationship occur in an image, creating a **GLCM**, and then extracting statistical measures from this matrix. A back propagation neural network is suggested for classification of different class of skin cancer by providing sufficient no. of training images to the classifier. The classification results are given in result section of the paper**.[24]**

In 2015,V. Jeya Ramya, J. Navarajan, R. Prathipa and L. Ashok Kumar,The proposed method comprises at first Pre-Processing the images . The wiener filter is used for the noise

removal. Next the **ACM** segmentation method is used to extract the lesion from the Digital camera Image. Thirdly, extracting second order statistical textural **GLCM** features from the segmented skin lesion. Finally classify the lesion as benign or malignant by using **SVM** classifier. Evaluation of the proposed method is done by calculating accuracy, specificity and sensitivity . the system are extracted using **GLCM**. In a classification approach with two; categories (malignant and benign lesions), a sensitivity of **90%,** accuracy of **95%** and a specificity of **85%** is observed. **[25].**

In 2015,TM.Suryapraba , G.Rajanarayanee, Priyanka Kumarihe , the methodology carried out in ;the proposed work is artificial neural network technique. This technique we can use more than one input check the problem. We used feed forward A single stage feed forward neural network classifier containing one input, one hidden and one output layer was predominantly used for lesion classification and sensitivities between 80-90% were reported. The extraction of texture features in the detected cancer has been achieved by using Gray Level Co-occurrence Matrix (**GLCM).**These features are given as the input to the Artificial Neural Network, The results of the artificial neural network techniques were promising as, we got **100%** for sensitivity, **95%** for specificity, and **97.5%** for accuracy. **[26]**

In 2017, Ebtihal AlMansour a , M. Arfan Jaffarb , Shahad AlMansour c,* , study in the analysis of skin images is widely used for assistant physicians to discover the first stage of the

skin lesions disease automatically. One of the challenge the computer science researchers faced when try to develop such system is un-clarity of the exist images such appearing of noise like shadows, low contrast, hairs and specular reflections which complicates the process of detect the skin lesions in that images. the solution of the above mentioned problem has proposed by using the active contour method, but active contour has a major drawback of seed selection where it should start to process segmentation. fuzzy entropy based morphological processing method has been used to find out automatic seed point for active contour. By incorporating this, it can segment the lesion from dermoscopic images automatically. The proposed methodology was tested on standard dataset DermIS and both quantitative as well as qualitative measures was used to check the reliability of the proposed method , we use adaptive contour (snack) segmentation method. Initialization mask is the most important for active contouring methods to feed the seed point required in that algorithm. One way is to select So we used fuzzy entropy technique that gives dynamic and the optimal threshold according to the clusters find out by using well-known method of **FCM** (Fuzzy C-Mean).**[27].**

Chapter Four

Chapter Four

Methodology

The researcher **CAD** system involve following steps as shown in the Computer Aided Diagnosis system .The methods of Skin cancer diagnostic involve The first stage of the entire system concerns loading the image, processing and enhancement. In the second stage, enhanced dermoscopy images that contain abnormal masses and normal masses were passed into a segmentation stage where a variable window size for the region of interest **(ROI)** was taken from the dermoscopy images in order to select a dataset of features for the process of feature extraction. The resulting features were then used to train classifier known as the feed forward back propagation network in order to discriminate the pattern recognition of the masses into two classes; normal and abnormal. The methods of skin cancer diagnostic involve loading skin image, noise removal, features extraction and neural network techniques for image classification. The output can be used for cancer classification. See the following block diagram .

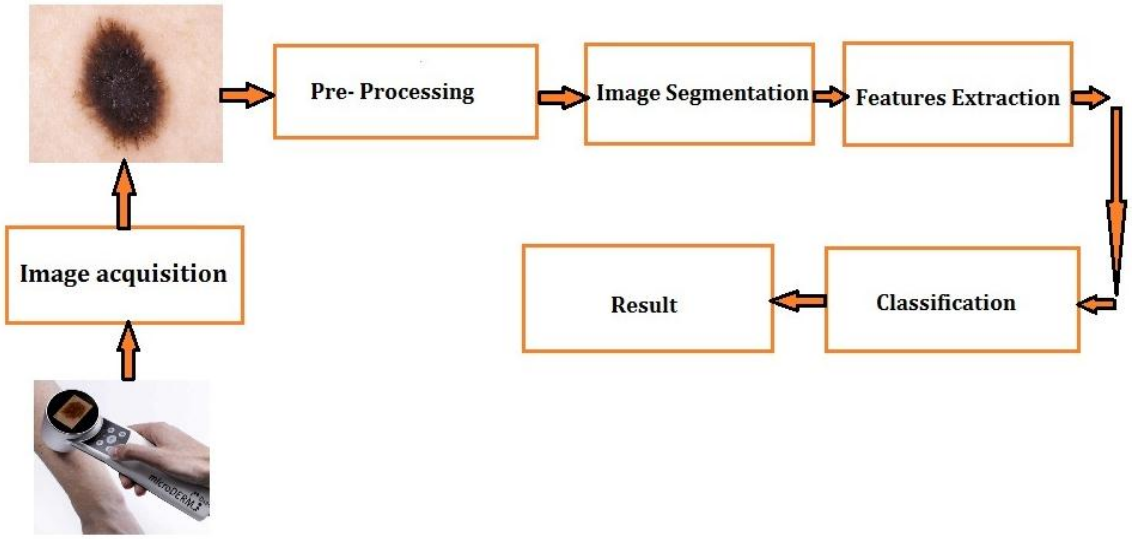


Figure (4.1) proposed methodology of **CAD** system.

4.1 Image acquisition

Image acquisition techniques like dermoscopy are highly dependent on computer technology to generate digital images. At the beginning were collected group of dermoscopy images of the skin provided from hospital. The images were diagnosed by doctors to determine whether the images were normal or abnormal. The dataset consists of digitized skin images**[28].** The database group of images **(119)** with **10** normal, and **109** images abnormal.

4.2 Pre Processing

The acquisition of the digital image of affected skin is the first and primary step in image processing. We are using images taken from Dermoscopy Once image is acquired, then it goes

for pre-processing. In first part of preprocessing digital images of skin cancer, collected in Bitmap or **JPEG** format from different sources are converted to indexed images. It converts the ordinary image to first **RBG** then gray scale . It makes an image suitable for a particular application. the second part of pre-processing involves enhancement of image (Adjust the Image Contrast,change in contrast, resizing the image to **512 X 512** pixels ,hair removal, and noise removal),for smoothing image from noise, Noise is one of the problems of the melanoma and benign images. Among different filters, the wiener filter was chosen because of its efficiency, This type of filter is effective in reducing the effects of Gaussian white noise, as we collected our data set from one source and source of noise depending on the device and condition When analyzing melanocytic lesions, we found the problem of body hair appearing on some images. Thick dark hair may mask part of the lesions and so lead to unsatisfactory results.

Presented here is a method to remove hair from images using a pre-processing program called Dull Razor **[29]. Dull Razor performs the following steps:**

1. It identifies the dark hair locations by a generalized gray scale morphological closing operation,

2. It verifies the shape of the hair pixels as thin and long structure, and replace the verified pixels by a bilinear interpolation, and

3. It smooth's the replaced hair pixels with an adaptive filter.

4.3 Segmentation of region of Interest

Image segmentation and defining the region of interest is an important approach and the most time-consuming part of image analysis and processing, which can divide the images into different parts with certain distinctions .The Segmentation of an image entails the division or separation of the image into regions of similar attribute. The ultimate aim in a large number of image processing applications is to extract important features from the image data, from which a description, interpretation, or understanding of the scene can be provided by the machine. The segmentation of skin tumor from dermoscopy images is an important but time-consuming task performed by medical experts. The accurate segmentation of dermoscopy image into different tissue classes, segmentation determines the Regions of Interest (**ROIs)** in an image. This does not mean that the segmented will try to determine the type of the region, but merely determine the pixels in an image which belong to the same item.

4.4 Features Extraction

In this study, the feature extraction of dermoscopy images is obtained using the Haralick features, Haralick's determine 13 texture features are: Energy(**EG**), Correlation**(CO**), Inertia(**IN**), Entropy(**EN**), Inverse Difference Moment(**IDM**), Sum Average(**SA**), Sum Variance(**SV**), Sum Entropy(**SE**), Difference Average(**DA**), Difference Variance(**DV**), Difference Entropy(**DE**). That well describes the texture of image . The

features can be obtained from it and the diagnosis rule can be designed to exactly detect the cancer area in the skin. This diagnosis rules can eliminate the false detection of cancer resulted in segmentation and provides better diagnosis.

4.5 Pattern Recognition and Classification

This stage of the study concerned with the detection of masses and their classification into either, normal or abnormal Therefore, a total of **119** dermatoscopic images comprising **10** normal and **109** abnormal cases were taken into consideration.

4.5.1 Skin image classification based on ANN

Neural networks are widely used in pattern classification since they do not need any information about the probability distribution and the a priori probabilities of different classes. **ANN** classification system mimics the human reasoning and in some cases, it gives the decision for more than one class to show the possibilities of other diseases. For Skin dermoscopy image classification, as normal or abnormal, we used a Back-propagation neural network (**BPNN**) to classify inputs into the set of target categories (normal or abnormal) based on feature selection parameters. **BPNN** is a supervised learning method which is a non-linear generalization of the squared error gradient descent learning rule for updating the weights of the artificial neurons in a single-layer perception, generalized to feed-forward networks. **ANN** is a branch of artificial intelligence (**AI**). It can imitate the way in which a human Skin works in processes such as studying, memorizing, reasoning and capable of performing massively parallel computations for data processing and knowledge representation. One advantage of the neural network approach is that most of the intense

computation takes place during the training process. Once the **ANN** is trained for a particular task, operation is relatively fast and unknown samples can be identified. Generally, an **ANN** can be defined as a system or mathematical model that consists of many nonlinear artificial neurons running in parallel and may be generated as one-layered or multilayered. Most **ANNs** have three layers: input, output, and hidden. The function of the hidden layer is to intervene between the external input and the network output in some useful manner, An **ANN** structure is shown in (**figure 4.2**). Feed forward multilayer neural network **(FFNN)** is dominantly used. The back propagation algorithm has been used in the training of the **FFNN.** Two kinds of signals are identified in this network: The function signals (also called input signals) that come in at the input of the network, propagate forward (neuron by neuron) through the network and reach the output end of the network as output signals; The error signals that originate at the output neuron of the network and propagate backward (layer by layer) through the network.

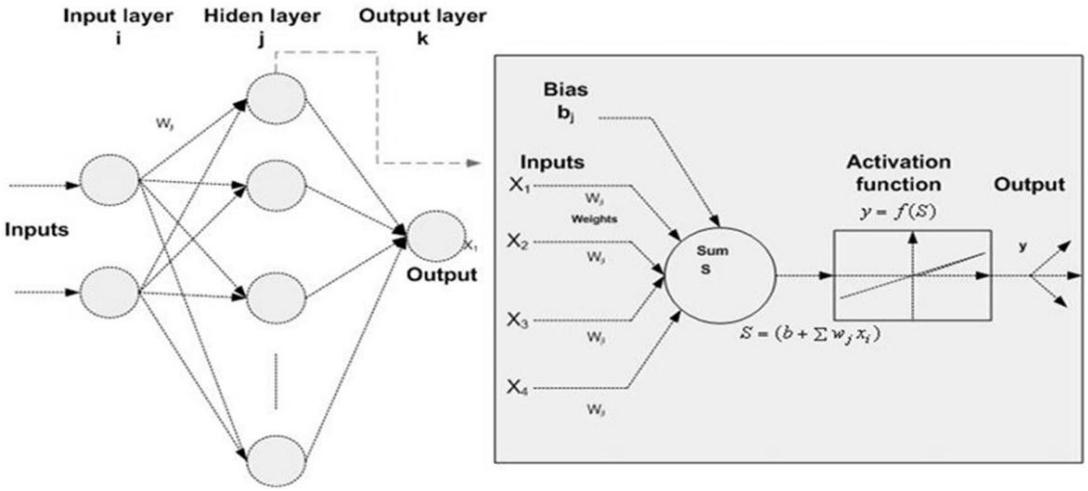


Figure 4.2. Artificial neural network (ANN) architecture.

The output of the neural network is described by the following equation:

$$y= F_0(\sum_{j=0}^{M} W_{oj}\ (F_h(\sum_{i=0}^{N} W_{ji}\ X_i))) \ldots\ldots (4\text{-}1)$$

Where W_{oj} represents the synaptic weights from neuron y in the hidden layer to the single output neuron, X_j represents the ith element of the input vector, F_h and F_0 are the activation function of the neurons from the hidden layer and output layer, respectively, W_{ji} are the connection weights between the neurons of the hidden layer and the inputs. The learning phase of the network proceeds by adaptively adjusting the free parameters of the system based on the mean square error E, described by **Eq (4-2)** between predicted and measured path loss for a set of appropriately selected training examples:

$$E=\frac{1}{2}\sum_{i=1}^{M}(y_i - d_i)^2 \ldots\ldots (4\text{-}2)$$

Where y_i is the output value calculated by the network and d_i represents the expected output. When the error between network output and the desired output is minimized, the learning process is terminated and the network can be used in a testing phase with test vectors. At this stage, the neural network is described by the optimal weight configuration, which means that theoretically ensures the output error minimization.

Chapter Five

Chapter Five

Result AND discussion

5.1 Results

The first stage of the entire system concerns loading the image, processing and enhancement. In the second stage, enhanced Dermoscopy images that contain masses and without masses were passed into a segmentation stage where a variable window size for the region of interest **(ROI)** was taken from the Dermoscopy images in order to select a dataset of features for the process of feature extraction. The resulting features were then used to classifier known as the feed forward back propagation network in order to discriminate the pattern recognition of the masses into two classes; normal and abnormal. With the skin cancer system fully developed using **MATLAB**, the means to evaluate the efficacy of the methods and algorithms used, is crucial. A total of **119** samples of Dermoscopy skin images containing masses have been compiled for this project **109** skin images which contain tumor cases, **10** skin images which contain without tumor cases.

5.2 Image acquisition and preprocessing

The algorithm where implemented based on **119** Dermoscopy

skin images consisting of **10** normal and **109** abnormal (malignant and benign tumors)from a real human Dermoscopy skin dataset .These images were collected from **VIP-lab** website.

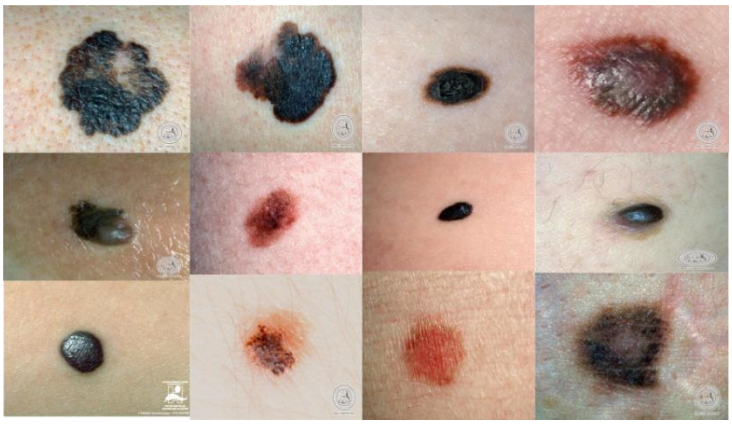
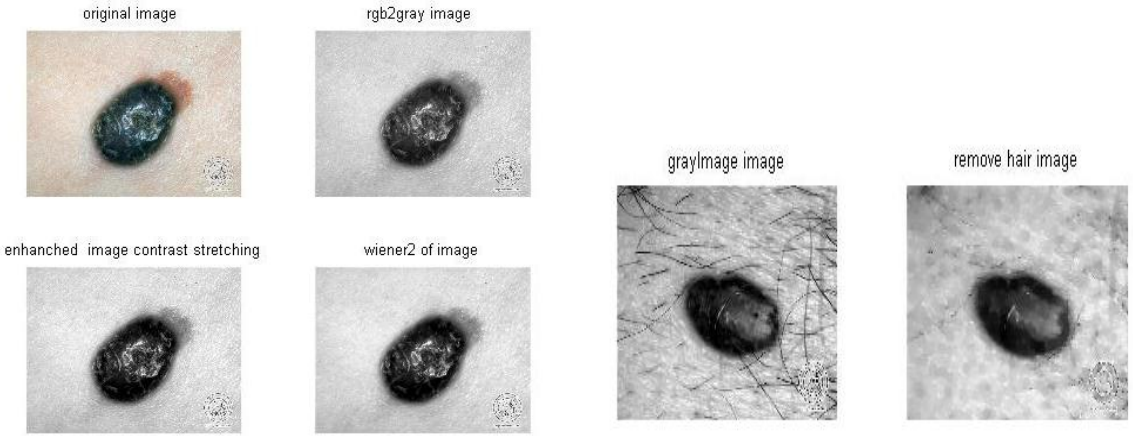


Figure (5.1): sample of dermatoscopic image

Machine & image specification .

A pre-processing stage should be considered to enhance the quality of the Dermoscopy skin before segmentation, feature extraction and classification. Image processing and enhancement stage is the simplest categories of medical image processing. This stage is used for reducing image noise, highlighting edges, or displaying digital images. Some more techniques can employ medical image processing of coherent echo signals prior to image generation. The enhancement stage includes resolution enhancement; contrast enhancement.

These are used to suppress noise and imaging of spectral parameters. For achieving best possible diagnosis it is necessary that the medical image should be sharp and noise free. In this work noise is removed by using adaptive filter . using pixel wise adaptive Wiener filtering, using neighborhoods of size m-by-n to estimate the local image mean and standard deviation , If the variance is large, it minimally smoothest the image. If the variance is small, it performs more smoothing, **Fig. 5.1** shows the image enhancement with the **wiener filter**. After this stage the medical image is converted into standard image without noise(**Gaussian white noise**).



(a) **(b)**

Figure (5.2): (a) enhanced image contrast stretching and noise removal by wiener filter, **(b)** remove hair image

5.3 Pattern Recognition and Classification

5.3.1 Segmentation

Focus on the suspicious area using the **imcrop tool**. This process paints the rest of the Skin image that is useless and focuses the window only on the selected area. The output of the segmentation processes was classification and obtain appropriate accuracy.

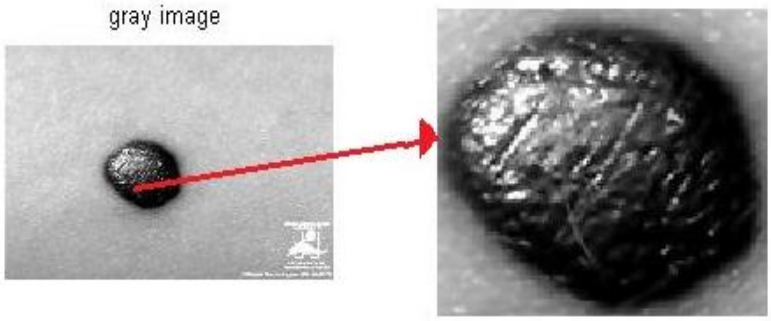


Figure (5.3): segmentation (**ROI**)

5.3.2 Feature extraction

Based on adjusted and segmented images produced in stages **1** and **2**, a set of features are extracted from each image. We then apply our reduction algorithm on these features. Before the classification model can be built, meaningful features of the **ROIs** delineated during the process of segmentation, need to be extracted and used as input in the classification process. The **Haralick** features were used in our developed technique (**mentioned in Section 4.4**) for feature extraction. Then the Best features were selected and used as input in the

classification for high accuracy. Four features not used in the classification were excluded [Sum Variance(**SV**), Energy(**EG**), Information Co-ocurrence(**1&2**),contrast].

5.3.3 Classification

The final procedure of the proposed system is to confirm the suspicious region and determine if it is a true nodule utilizing features obtained from previous stages neural networks (**NN**). The Artificial Neural Networks (**ANN**) Feed-forward back propagation network is good for binary classification.

5.3.3.1Performance measures

Sensitivity (SE) : The sensitivity of a test is the ability of the test to identify correctly the affected individuals Proportion of persons testing positive among affected individuals.

$$SE=TPTP+FN \text{ ..... (5.1)}$$

Specificity (SP): The specificity of a test is the ability of the test to identify correctly non-affected individuals Proportion of persons testing negative among non-affected individuals.

$$SP=TNFN+TN \text{ .... (5.2)}$$

Positive Predictive Value (PPV): Is the proportion of abnormal cases correctly identified .

$$\text{PPV=TPTP+FP ..... (5.3)}$$

Negative Predictive Value (NPV): Is the proportion of benign cases correctly identified.

$$NPV = \frac{TN}{FN + TN} \quad \ldots\ldots (5.4)$$

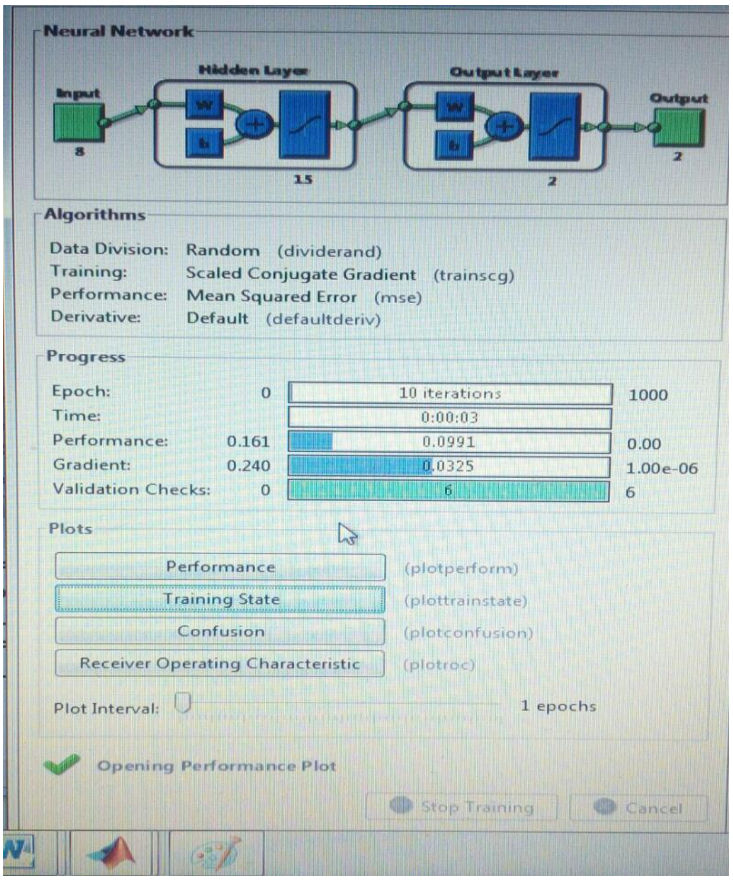


Figure (5.4): Neural Network Training

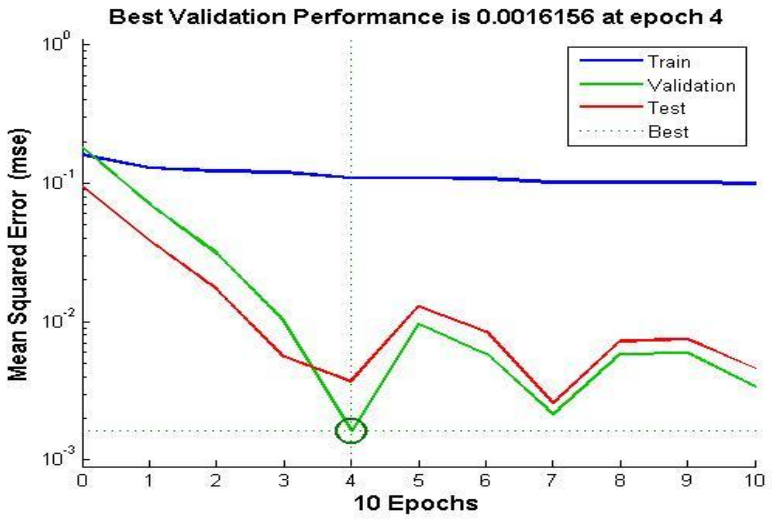


Figure (5.5): plot perform (**TR**) plots the training, validation, and test performances given the training record **TR** returned by the function train.

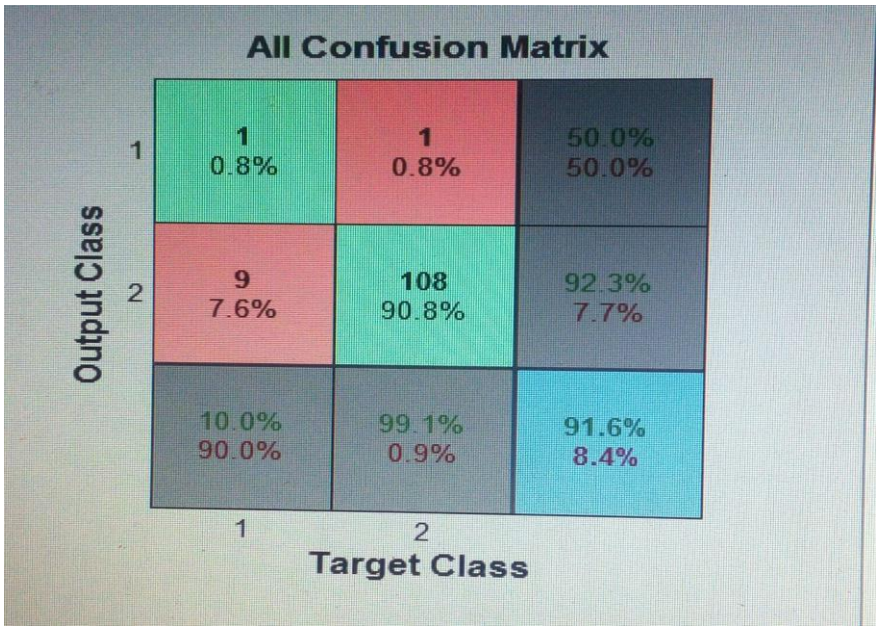


Figure (5.6): classification of images using **ANN**

The accuracy in **Figure (5.6)** is the overall evaluation of the classifier for the pattern recognition and classification of the tumors. Therefore, the proposed system has successfully been able to discriminate between Abnormal and normal tissue with a precision level of **91.6%.**

Chapter SIX

Chapter SIX

Conclusion and Future work

6.1 Conclusion

In this research, the computer assisted skin cancer detection system is proposed. It proves to be the best diagnostic method of traditional biopsy method. **PC-based** skin cancer detection is more beneficial to patients, which patients can detect skin cancer without going to hospital or without the help of a doctor. It saves a lot of time for patients. The diagnostic methodology uses digital image processing techniques and artificial neural networks to classify malignant melanoma from benign melanoma. Dermuscopeic images were collected and processed by various image processing techniques. Unique features of fragmented images have been extracted using **GLCM**. Based on the features, the images were classified as malicious or benign. This classification system has a good accuracy of **91.6%.** By changing image processing techniques and classifications, the accuracy of this system can be improved. For more accurate results.

6.2 Future work

There are several future directions which might further

Improve the **CAD** systems for skin Dermuscopeic images,

(1) The acquisition of large databases from different institutions with various image qualities for clinical evaluation and improvement in the **CAD** systems

(2) Improve the classification accuracy by extracting more efficient features and increasing the training data set.

(3) There is still much room for additional researcher to utilize other machine learning techniques and integrate them into a hybrid one system.

(4) Further experiments and evaluation are therefore desirable to establish whether the proposed approaches have generic applications.

(5) One of the problems that we have encountered is the problem of illumination in image .when process this problem allows the use of better techniques in the segmentation phase to obtain high accuracy.

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والله ولي التوفيق