SKIN CANCER DETECTION USING ARTIFICIAL INTELLIGENCE

A Thesis Submitted

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Electronics and Communication Engineering

By

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STATEMENT OF THESIS PREPARATION

1. Thesis title: Skin Cancer Detection using Artificial Intelligence
2. Degree for which the thesis is submitted: Doctor of Philosophy in ECE
3. Thesis guide was referred to for preparing the thesis.
4. Specifications regarding thesis format have been closely followed.
5. The contents of the thesis have been organized based on the guidelines.
6. The thesis has been prepared without resorting to plagiarism.
7. All sources used have been cited appropriately.
8. The thesis has not been submitted elsewhere for a degree.

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APPROVAL SHEET

This thesis entitled **"Skin Cancer Detection using Artificial Intelligence"** by Mr. Mohd. Firoz Warsi, Regd. No. **16SECE302002**, is approved for the degree of Doctor of Philosophy.

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CANDIDATE'S DECLARATION

I hereby certify that the work which is being presented in the thesis, entitled **"Skin Cancer Detection using Artificial Intelligence"** in fulfillment of the requirements for the award of the degree of Doctor of Philosophy in Electronics and Communication Engineering and submitted in Galgotias University, Greater Noida is an authentic record of my own work carried out during a period from July 2016 under the supervision of Dr. Usha Chauhan and Dr. Ruqaiya Khanam.

The matter embodied in this thesis has not been submitted by me for the award of any other degree of this or any other University/Institute.

Mohd. Firoz Warsi

This is to certify that the above statement made by the candidate is correct to the best of our knowledge.

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ABSTRACT

Malignant melanoma is deadliest form of skin cancer but can be easily treated if detected in early stages. Due to increasing incidence of melanoma, researches in field of autonomous melanoma detection are accelerated. Malignant melanoma is the most severe kind of skin cancer. It can grow anywhere on the body. Its exact cause is still unclear but typically it's caused by ultraviolet exposure from sun or tanning beds. Its detection plays a very significant role because if detected early then it's curable, before the spread has begun. It can be 95% recovered if it is early diagnosed. Melanoma cases are rapidly increasing in Australia, New Zealand and Europe. Australia took highest place in the world with this deadly disease. Early diagnose of melanoma totally depends upon the accuracy and talent of practitioners. So automatic detection of melanoma is highly in demand as computer aided diagnosis methods give great accuracy and they are non-invasive methods for the detection of melanoma. This thesis investigates different methods for melanoma classification. In long run it will offer a source to test new and existing methodologies for skin cancer detection.

The main objective of this thesis is to present detailed investigation for CAD in melanoma detection. Further thesis objective is to improve and build up relevant segmentation, feature extraction, feature selection and classification techniques that can cope up with the complexity of dermoscopic, clinical or histopathological images. Several algorithms were developed during the path of thesis. These algorithms have been used in skin cancer detection but they can be also used in other machine learning applications.

The most significant assistance of this thesis can be summarized as below:

- Developing novel feature extraction technique and optimization of parameters. The proposed work has two stages. In first stage, a new method for color and texture features in one features are extracted with the help of CLCM. This method is known as 3D CTF extraction. This method is applied on 200 images with improved results for skin cancer detection. Second stage is applied with 3D CTF with PCA. This technique is used for dimensionality reduction to improve accuracy of the classifiers.

- Proposing a new model for classification with neural network. This work also has two stages. In first stage feature extracted are fed in to the neural network classifier based on feature extracted without PCA. In second stage extracted features after applying PCA are fed in ANN. Both algorithms are based on back propagation neural network classification. The results show very appropriate analysis and great accuracy for skin cancer images. The first stage is tested onPH2 dataset (publically available) in terms of accuracy, sensitivity and specificity. Extracted combined CTF is fairly discriminative, when it is fed and tested in NN classifier they provide encouraging results i.e. Accuracy = 97.5%, Sensitivity = 98.1% and Specificity = 93.84%. Comparative result analyses with other methods are also discussed. In second Stage For classification of melanoma from Dermoscopic images, a comparison of different types of machine-learning classification algorithms is evaluated, out of which back propagation neural network (NN) classifier outperforms all other and produce best results i.e. Accuracy = 98.5%, Sensitivity = 99.4%, Specificity = 95.0%. Obtained results are even better than benchmarking results of PH2 dataset. Comparisons of results with other similar novel works are also discussed.
- Skin cancer dataset is one of the most important things in melanoma detection. To test and evaluate the system performance PH2 data set is used. PH2 database is freely available for research and benchmarking purpose. This dataset has been built with joint research of Universidade do Porto, Tecnico Lesboa and hospital Pedro Hispaneo in Matosinhos, Purtagal. It has legion areas which are segmented manually; clinical analysis and the marking of structures are by expert dermatologists. They are 8-bit RGB color images with a resolution of 768x560 pixels. This image database comprises a total of 200 Dermoscopic images of melanocytic lesions, containing 80 common nevi, 80 atypical nevi, and 40 melanomas. The PH² database contains medical annotations which are medically lesion segmentation, clinical and histological diagnosis along with the assessment of numerous Dermoscopic criteria. Result obtained presents a very great performance in feature extraction and classification. This work can form a foundation for other more advanced CAD systems in the field of skin cancer detection. This work can be extended for other image processing work in future.

ACKNOWLEDGEMENT

Doing research for the degree of Ph. D. in Galgotias University was quite magnificent and challenging experience for me. In all these years, many people directly or indirectly contributed in shaping up my career. It was hardly possible for me to complete my doctoral work without the precious and invaluable support of these personalities. I would like to give my small tribute to all those people.

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I wish to express my gratitude to Prof. B. Mohapatra, Dean of Department of Electronics and Communication Engineering for his support. I would like to convey my deep regard to Mr. Suraj Kamya for his wise counsel and indispensable advice that always encouraged me to work hard for completion of the thesis.

February, 2022 **Mohd. Firoz Warsi**

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLE

LIST OF PUBLICATIONS

JOURNAL PAPERS

1. **Mohd Firoz Warsi, Dr. Ruqaiya Khanam and Suraj Kamya,** "An efficient 3D color-texture feature and neural network technique for melanoma detection. *Informatics in Medicine Unlocked, 17,* p.100176. 2019.
2. **Mohd Firoz Warsi, Dr. Ruqaiya Khanam, Dr. Usha Chauhan and Suraj Kamya,** "Melanoma classification by 3d color-texture feature & neural network with improved computational complexity using PCA" *International Journal of Medical Engineering and Informatics.* http://dx.doi.org/10.1504/ IJMEI.2021.10035670

CONFERENCE PAPERS

1. **Mohd Firoz Warsi, Dr. Usha Chauhan and Dr. Ruqaiya Khanam,** "Analytical study on melanoma detection using clinical images", In Smart Computing: *Proceedings of the 1st International Conference on Smart Machine Intelligence and Real-Time Computing* (SmartCom2020), 26-27 June 2020, Pauri, Garhwal, Uttarakhand, India (p. 170). CRC Press.
2. **Mohd Firoz Warsi, Dr. Usha Chauhan,** "A comparative analysis of melanoma detection methods based on computer aided diagnose system" *Materials Today*: Proceedings 2021.

CHAPTER 1

INTRODUCTION

The aim of this thesis is to make contribution in the development of automatic detection of skin cancer. This chapter defines motivation followed by outline of problems. After that a short introduction of contents is presented by a chapter by chapter narration.

1.1 PROBLEM AND INSPIRATION

Cancer is a big health issue. Among different type of cancers skin cancer is very dangerous and life taking cancer. In skin cancer Melanoma is a lethal form of skin cancer [1].This cancer is responsible for 75% deaths of all cancers. In America 20 people die every day due to this deadly disease. Estimation of deaths due to melanoma in 2019 is 7230 [1]. Almost 56% deaths of men and 44% of female occur in UK only.

In 2019, U.S has 190,300 fresh cases of melanoma in which 94,800 are noninvasive (in situ) and 95,500 invasive (very dangerous). Invasive melanoma has fifth place in most dangerous cancer for men (56,200 cases) and women (38,250 cases) [1]. Australia and New Zealand are highest occurred melanoma countries. This is more than twice of America. The reason behind this is these countries are close to the equator, so they are more affected by reduced ozone layer and they had population of fair skinned people[2].Skin cancer is of two type Melanoma and Non melanoma. Among them Malignant melanoma is very lethal. Non Melanoma is also very common in the world but it is not deadliest. Non melanoma type cancer is BCC and SCC. Basal cell carcinoma (BCC) is very common in Chinese, Japanese and Hispanics. Squamous cell carcinoma (SCC) is mostly found in African and Asian.

The patients diagnosed with stage I melanoma skin cancer can survive maximum for One-year and The patients diagnosed with stage IV have lowest survival time.. So its early detection is very much important. The early detection of melanoma has survival rate about 98 percent. The rate goes down to 64 percent after the cancer enters in to the blood and 23 % after the disease spread to different organs [2].If the cancer is not spread in the blood vessels it can be removed by surgery. Early diagnostic is very

important and it is generally done by visual methods. Epiluminescence Light Microscopy (ELM) needs an expert to detail the image. Another method is with histopathological image done by pathologist. The pathologist takes biopsy sample from the images and examine under microscope. This also totally depends upon his experience and expertness.

To beat these issues and enhance the accuracy of diagnosis automated system is highly needed. These computational tools support medical experts and create a mathematical method to facilitate melanoma detection. With the help of CAD (computer aided diagnosis) experts can find affected areas and work on them with great efficiency and accuracy.

1.2 THESIS AIM AND CONTRIBUTION

Pathological systems are not very accurate and well versed for skin cancer detection. Since Melanoma skin cancer is very deadly so there is lot of need to enhance the accuracy of diagnose. From last two decades automatic diagnose systems are in work and continuously researchers are trying to make improvements and newness in techniques and algorithm used in skin cancer detection. The common steps involved in Computer Aided Diagnostic with clinical images are preprocessing, segmentation, feature extraction and classification.

The key motivation behind this research work is to give reformed algorithm and expand the application and functionality of existing techniques so that research can be done easily and researchers can experiment with new methods in future.

The motivation is to lessen death rate and increase premature detection of melanoma skin cancer.

The key reason of this research is to improve feature extraction technique so that complexity will be reduced and other is feature selection should be appropriate to make classification accurate. Because extracted feature decide the accuracy of differentiation of melanoma and non melanoma disease.

Second thing is to efficiently train the classifier to improve the performance. This work emphasis on the enhancement of generalized performance of classifiers using labeled and unlabelled data.

This PhD research targets almost all areas of computer aided diagnose with clinical images like extraction, segmentation, selection and classification of features. The results from previous research are compared and pretty satisfactory and encouraging results are obtained.

1.2.1 Contribution of Thesis

The contribution of work is to make people aware from skin cancer and give them awareness about this. Further this thesis gives improved algorithm and technique for skin cancer detection. This research also can be useful in machine learning applications and 3D feature extraction techniques of digital images.

A. Contribution to skin cancer:

- Finding best feature extraction technique to improve classification accuracy. 3D feature extraction technique with color and texture feature combined.
- Proposing neural network model which performs on back propagation technique providing good results in Computer Aided Diagnose Systems.
- Different machine learning techniques are also used to compare with the new work proposed in this thesis.

B. Contribution beyond skin cancer:

- Presenting a survey on all existed computer aided techniques.
- Proposing a feature selection method that can be used in other image processing task.
- Presenting a neural network model that can be trained with data in a complex pattern recognition work.

1.2.2 Formation of Thesis

In chapter 2 skin cancer is defined. In this chapter knowledge of skin cancer its causes and other necessary detail are given. Skin cancer anatomy and symptoms of skin

cancer is introduced followed by their types. Different pathological treatments are discussed and melanoma detection with image analysis is also introduced. In this chapter full knowledge of skin cancer is presented. Although all medical things are not included but it is sufficient to define and understand skin cancers for this research work.

A brief introduction of databases mainly focusing on ph2 database is presented. A brief introduction of Artificial intelligence with ANN is also presented in this chapter. Need of neural network model its application and its contribution in field of skin cancer detection is also discussed. All the neural network techniques are introduced here to enhance the awareness of neural networks.

In chapter 3 the literature review is given. It depicts development of computer aided techniques in field of skin cancer. In this chapter all the phases of image processing like image preprocessing, image acquisition, feature extraction, image segmentation and classification are summarized. All problems and practices related to these techniques are discussed. This chapter represents an overview on research done in field of skin cancer detection. This chapter has created a framework for further research with the help of the results and techniques involved in previous works. Here in this chapter all deficiencies are marked and compared with the other previous works.

In chapter 4 gives details of segmentation techniques. The framework of the suggested segmentation technique is presented. The proposed method of segmentation is discussed.

Chapter 5 provides introduction of features and feature extraction techniques involved in skin cancer detection. Suggested method of feature detection is described in two parts. Part one describes feature extraction with 3 D color texture feature. Second part describes 3D CTF with PCA. Both methods are compared and their experimental results or equations are presented in form of table. The details of 3D feature extraction technique with PCA and feature selection are presented. Theory and feature extraction model with results are presented.

Chapter 6 comes with classification stage. An overview of classifiers in field of automated skin cancer detection is discussed. The proposed classification technique with neural network is discussed with theory and results. The proposed technique is presented in two parts. Part one contains classification with neural network using back propagation technique. Results and relative analysis is done in part one. Part two contains method of classification with ANN using PCA and other six machine learning algorithms. The new effort and its relative study are delivered.

Chapter 7 gives a concise outline of this work and imminent scope of this thesis.

1.3 Summary

The key reason behind this chapter is to present a brief introduction to thesis aim and contribution along with thesis structure and publications.

CHAPTER 2

GENERAL IDEA ON SKIN CANCER AND ANALYSIS TECHNIQUES

2.1 INTRODUCTION

This section aims at giving general idea about skin cancer and structure of skin. This also points out the skin related issues and technical definitions involved to understand the skin cancer. This aims towards the kind of skin cancers and their diagnostic methods used by medical experts. This Chapter also defines CAD system for skin cancer detection with different technique. Since database is a very important part of this study so PH2 database is also discussed in detail. Moreover A brief introduction of Artificial intelligence in the light of Skin cancer detection is presented.

2.2 STRUCTURE OF HUMAN SKIN

Skin has largest area in human body having total area near about 20 square feet. It controls temperature of body and stores its fat, vitamin D and water. It protects body against heat, injury and sunlight.

2.2.1 Types of human skin

Skin has great variation in different body types still skin has two types one is hairy and other is non-hairy. Skin with no hair is found on soles and palms which has thick epidermis. It is deficient in hair follicles and sebaceous gland. It also has encapsulated sense organ in dermis layer. But on the other hand hairy skin has no encapsulated sense organ. It has hair follicles and sebaceous gland as shown in Figure 2.1.

2.2.2 Human skin layers

Skin has mainly three layers

- Epidermis: it is outermost layer. It is mainly made of keratinocytes. These keratinocytes are made from keratin a protein that is present in hair and hand. It provides water proofing and toning of skin. It also protects us from infections.

- Dermis: It is under epidermis and has dense connecting tissues, hair follicles and sweet glands and oil glands with blood vessel. It is also known as corium. Connecting tissues protects body from stress and pressure. The blood vessels provide nourishment and waste removal for epidermis as well as dermis.
- The Hypodermis: it is deepest and thickest layer of skin. It is also known as subcutaneous layer. It contains connecting tissues, lobules of fat and blood vessels. It is just below the skin which provides insulation and padding to the skin. It is shown in Figure 2.2 and 2.3.

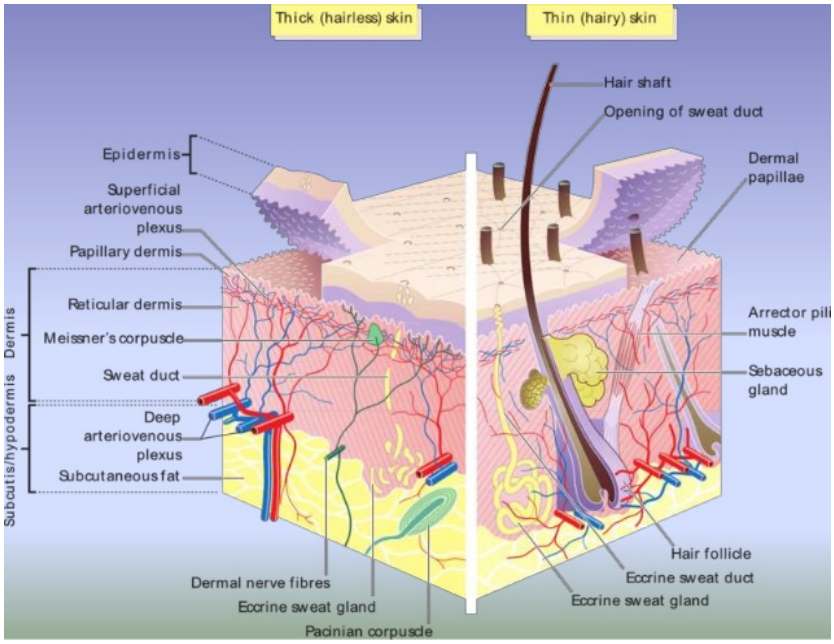


Fig. 2.1 Structure of Human Skin (Source -wikipedia.org)

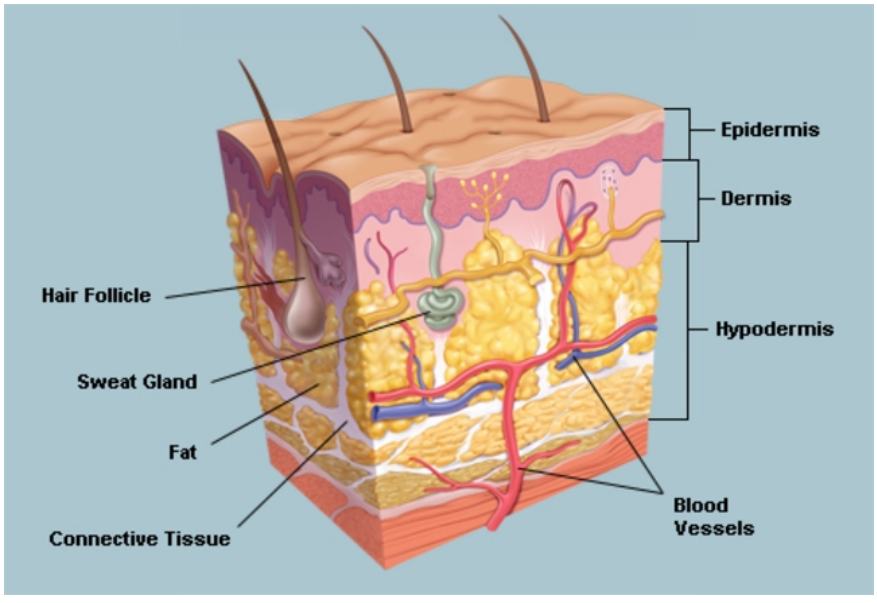


Fig. 2.2 Structure of skin (Source: Webmed 2014)

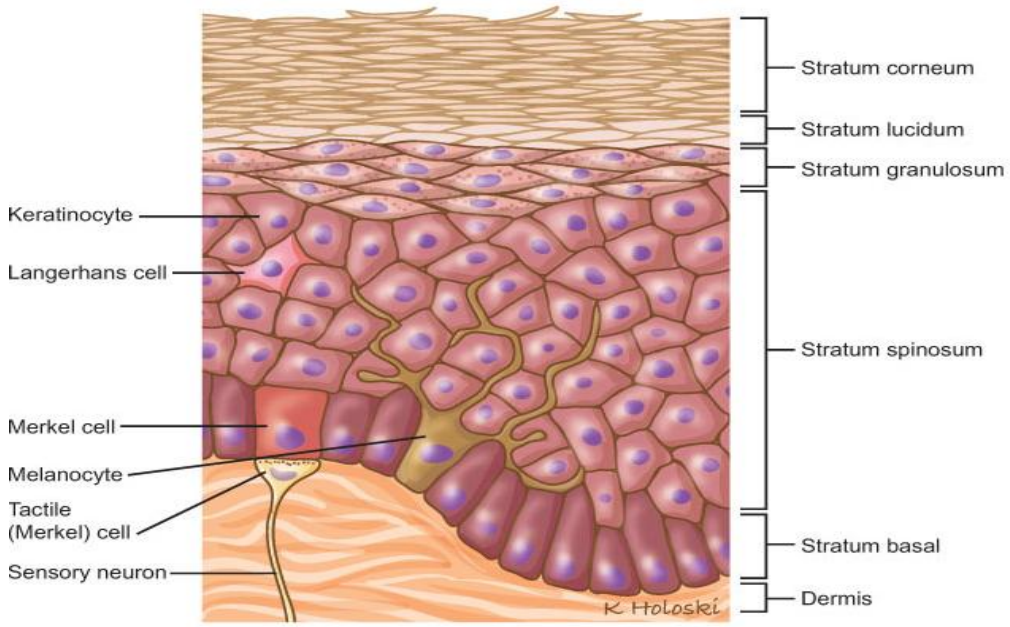


Fig. 2.3 Construction of epidermis (Source: www. headandneckcancerguide.org)

2.3 CANCER

Cells in our body grow and divide for the whole life. But if these normal cells are infected they have uncontrolled and undesirable division. These cancer cells grow in whole body for whole life. Cancer takes birth with these infected cells. After some time this production is out of control and then it can invade in to the other parts of body through blood stream of lymph nodes.

In this world, more than 120 types of cancer are known. The most general types of cancer are lung, breast, colorectal, melanoma, prostate and stomach cancer. Melanoma has large rate of mortality.

2.3.1 Cancer stages

Cancer has basically four stages.

- Stage 0: there is no cancer. There are only abnormalities in cells which can take birth to the cancer. This is known as carcinoma in situ.
- Stage 1: cancer is very weak and it resides in only one area. It is also called early stage.

- Stage 2: cancer is large now and has infected the tissues.
- Stage 3: cancer has infected the lymph nodes and blood stream
- Stage 4: cancer has entered in to the other parts of the body. This is known as metastasis or advanced cancer.

Cancer stages are shown in Figure 2.4

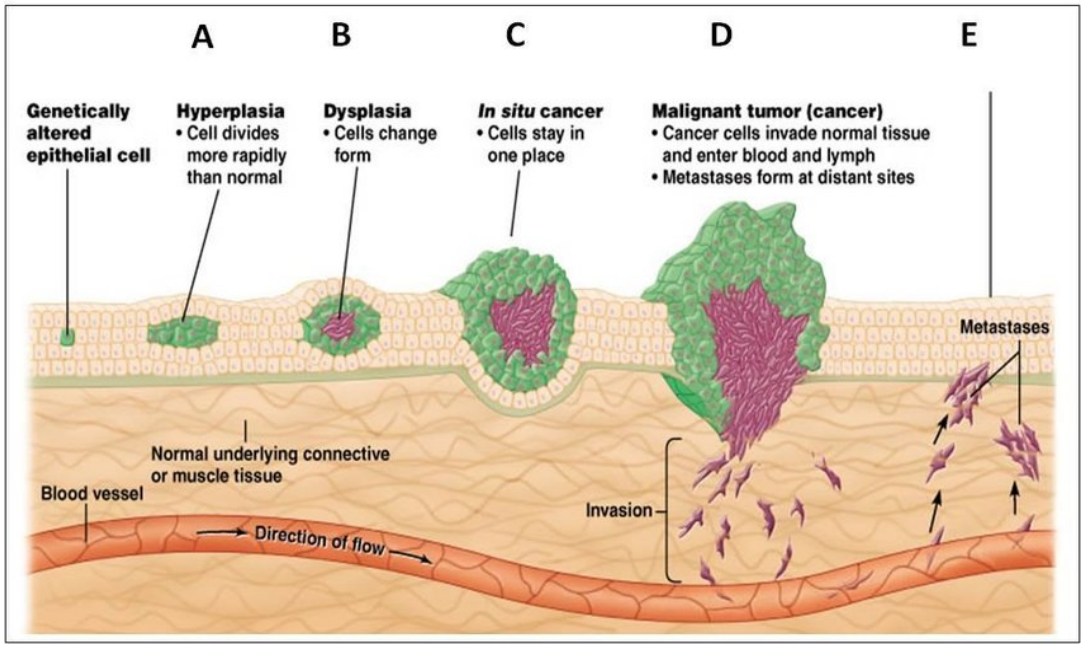


Fig. 2.4 Phases of cancer (source: www.researchgate.net)

2.4 SKIN CANCER

Skin is made of cells that are normally grow and divide to produce more cells throughout our lives. But these cells became infected and cancerous due to the abnormal growth. This abnormal growth is very undesirable and undefined. Due to infection only abnormal cells grow and normal cells die continuously. Skin cells are infected or become cancerous mainly due to the exposure to UV light and due to family history. There are two types of abnormality or tumor in skin Benign and Malignant. Benign is not a cancer. It is like cyst or mole. It does not spread in to the body. They can be removed easily.

On the contrary malignant tumors are deadly. They grow uncontrollably and can spread in to the body. These are melanoma, squamous cell cancer and basal cell cancer. These cancers can invade in to the organs and reproduced even after removal.

The top layer of skin is epidermis. There are three dissimilar types of cells squamous cell, basal cell and melanocyte. In this way we can categorize malignant skin cancer in to three types.

- Basal cell cancer (Basal cell Carcinoma)
- Squamous cell cancer (Squamous cell Carcinoma)
- Melanoma

Figure 2.5 clearly shows skin layers in detail. In right side we can see layers epidermis and dermis and left side we can see three types of cells in epidermis layer. Squamous cells are on the top and Basal cells are in middle and melanocytes are at bottom.

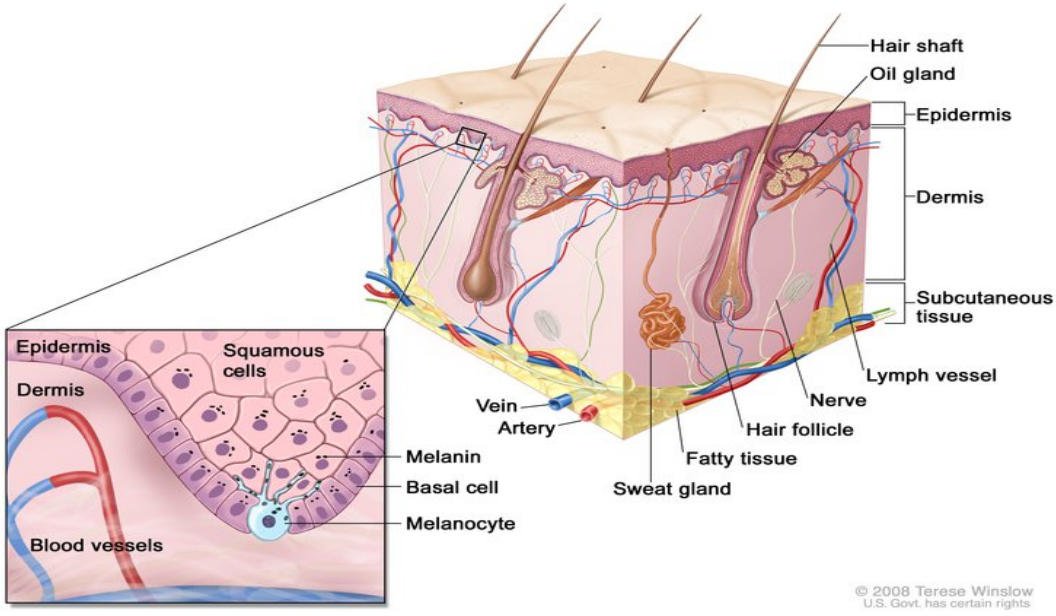


Fig. 2.5 Skin layer in detail (source: visualsonline.cancer.gov)

Skin cancer of malignant type is very dangerous and here brief discussion of SCC and BCC is given. Melanoma is discussed in detail since our research is related to this type of cancer.

2.4.1 Basal Cell Carcinoma (BCC)

BCC generally takes birth when DNA is damaged by UV light of sun. This results in unrestrained growth in basal cells. It is the general and most occurring cancer. It can be seen as shiny bumps, pink scares, and red growth with elevated edges. BCC can itch and bleed. It rarely spread in to the organs as shown in Figure 2.6.

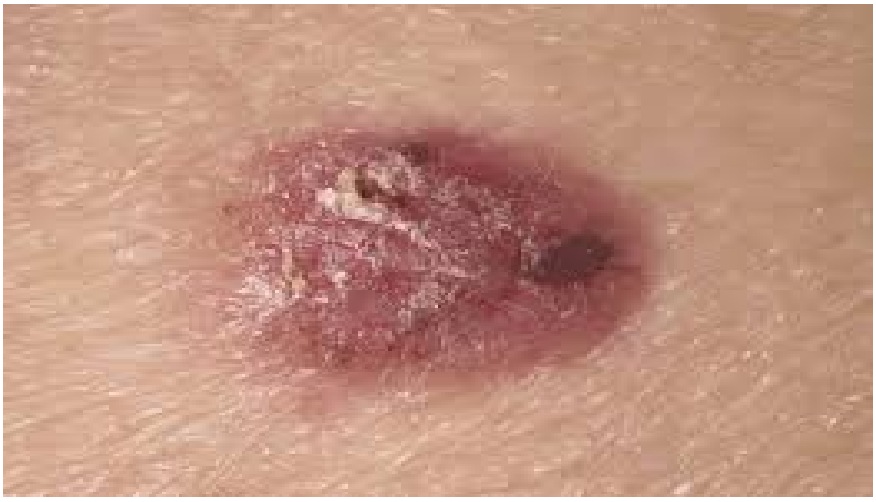


Fig. 2.6 Depiction of basal cell cancer (source: www.msdmanuals.com)

2.4.2 Squamous cell carcinoma (SCC)

This is another most common cancer. In America almost 70000 people are diagnosed with SCC. They are found on the areas of body which are open to the sun like neck head, ear, lips, arms and feet. It nurtures slowly but can spread to the tissues and even in bones. It is like a bump or dome shaped structure. With the effect of SCC skin becomes red, crusty and rough. It May bleed or itch. SCC in one form is presented in Figure 2.7.

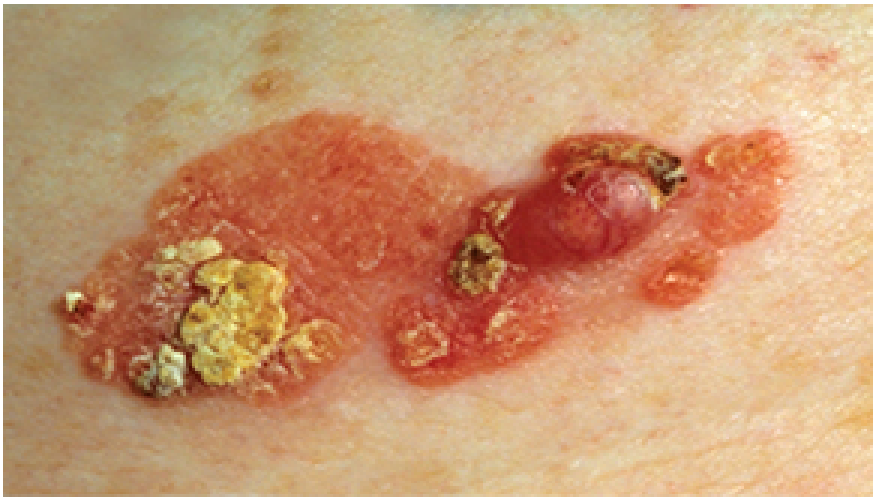


Fig. 2.7 SCC (source: www.webmed.com)

2.5 MELANOMA

Melanoma develops from melanocytes which produce melanin and reside in bottom of epidermis. When there is pigmentation or abnormality in melanocytes tumors are

formed. These tumors are formed due to mutation or abnormal growth of cells. Melanocytes produce melanin that decides our skin color. Melanoma occurs in skin but sometimes also occur in intestine, mouth or eyes. Most of the melanoma cases arise from moles. There are more than eight types of melanoma.

The main cause of melanoma is UV rays of sun or tanning devices. The second cause is genetic disorder and the third is heredity. People having dysplastic nevus syndrome (a multiple mole syndrome) also has a great chance for melanoma. It is most deadly cancer. Highest rate of melanoma is in New Zealand and Australia. Earlier melanoma can be seen as change in shape or color of existing moles. But a nodular melanoma which spread rapidly can be detected as new lump anywhere on skin. At last stage it can ulcerate, itch or bleed. The typical melanoma can be seen in Figure 2.8.

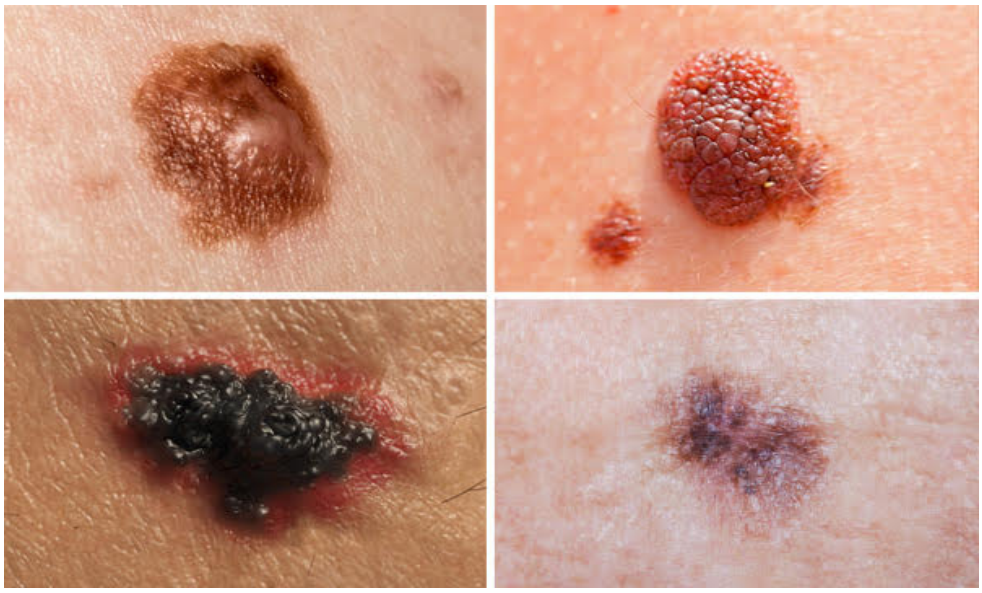


Fig. 2.8 Melanoma (source: www.medpagetoday.com)

Melanoma has five stages.

- Stage 0: it is first stage or it is an early stage. Survival rate is 99.9%.
- Stage 1: melanoma is invaded 1 to 2 mm tumor thickness without ulceration. Survival rate is 90 to 95%.
- Stage 2: it has high risk. Tumor thickness is more than 4mm with ulceration. Survival rate is 50 to 80%.
- Stage 3: it is known as in transit metastasis melanoma. Lymph nodes are affected. Survival rate is 25 to 70 %.

- Stage 4: it is known as distant metastasis with Lactate dehydrogenase (LDH). Melanoma now has invaded the other parts of body. Survival rate is 8 to 20%.

2.6 DETECTION AND DIAGNOSIS OF MELANOMA

Here brief overviews of commonly used skin imaging techniques by medical experts are provided. Algorithm for skin surface diagnose as well as diagnose based on histopathological analysis are also described [3].

2.6.1 Methods for skin lesion imaging

2.6.1.1 Photography

This is simple method. This gives picture of upper surface of skin only.

2.6.1.2 Dermoscopic Imaging

This technique is used to take more detailed image. Image is immersed in oil and then it is exposes to polarized light source. This is done to reduce the reflection and brightening of image. These techniques are superior to the traditional photography.

2.6.1.3 Multispectral Photography

This technique is used for more detailed information from the image. Different types of pigment absorb different type of light. Here we use a narrow band of frequencies of light. So the frequency of reflected wave is calculated and with that frequency we can compare the damaged and undamaged skin.

2.6.1.4 Ultrasound

It calculates the deepness of melanoma. A high frequency wave greater than 30 MHz is sent in to the skin and then if there is melanoma doctor gets exact cut for the surgery.

2.6.2 Diagnosis from Dermoscopic Images

ELM **(**Epiluminescence microscopy) is a method of dermatology in which imaging technique is used to identify the skin lesion. In this method no invasion is done with the skin or body of the patient. From this technique accuracy of diagnose is increased and we can see very tiny morphology of skin. In this method we can increase the accuracy by these factors in the image.

- Liquid immersion
- Angle of incidence of lightening source
- Optical magnification

These methods make it very accurate than the traditional microscopic diagnose. Dermoscopy can help in finding streaks, pigmented network, and dots. A very detailed image can be obtained from dermoscopy. The Figure 2.9 shows the difference between macroscopic and dermoscopic image.

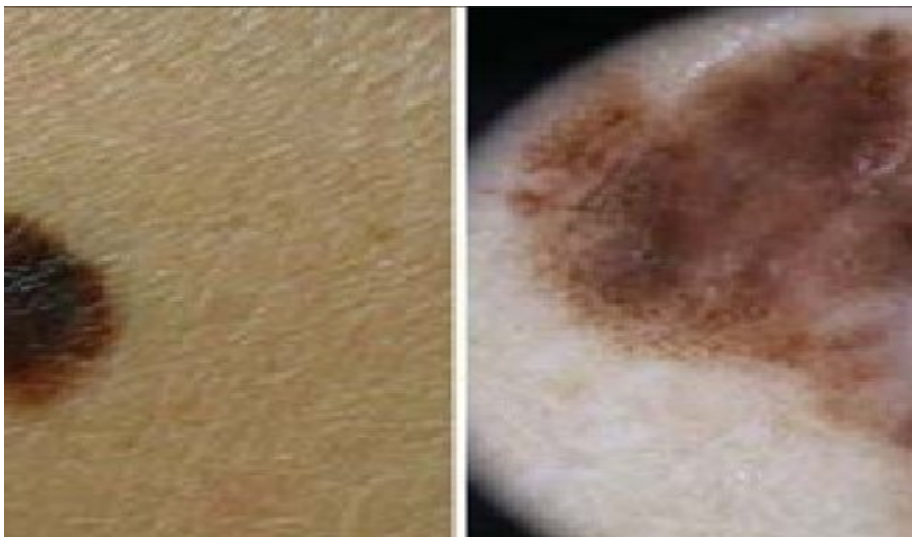


Fig. 2.9 an invasive melanoma (a) Macroscopic image, (b) Dermoscopic image (source: www.researchgate.com)

Researchers have shown that dermatology accuracy is up to 95% [4] while macroscopic accuracy is maximum up to 60%. But there is a drawback of dermatological inspection. If the doctor is inexperienced then this accuracy will be gone to very less or it can be blunder. So for today need it is very essential that we should go with the computers and computer aided techniques should be important. The main aim is early detection of melanoma so that proper removal of the area can

be done by surgery. Except dermatology there are different models that are used in non invasive skin cancer detection for example Raman spectroscopy, confocal microscopy, fluorescence spectroscopy, optical coherence tomography and thermography etc.

Dermoscopy has number of advantages. It enhances the sensitivity for cancer detection. It decreases the benign to malignant biopsy ratio. It can also visualize epidermis structure as well as dermis papillary. It is reported that an experienced doctor with dermatology method can differentiate very well between a malignant and a benign.

2.6.3 Diagnosis Algorithm

To inspect pattern and structure of lesion there are different algorithm like ABCDE rule, Seven point checklist, Menzies method and three point checklist are discussed here.

2.6.3.1 ABCD-E Rule

This is the very first algorithm for early melanoma detection. It was introduced by Stolz in 1994[5]. ABCDE can be defined as-

A (Asymmetry) - Asymmetry in the pattern.

B (Border) - Sudden cutoffs of the affected area at the border.

C (Color) - visualization of different colors on pattern. Six colors can be present like grey, blue, black, white, red, brown, light brown, blue grey and dark brown.

D (Diameter or different structure) – Network of affected structure is present. Structure less area can also be found. Dots and streaks also exist. Diameter greater than 6 mm is dangerous as melanoma patient.

E (Evolution) – The structure, size, color or shape changes day by day. This can be seen in Figure 2.10.

This rule has been proved to be a boon in melanoma diagnosis. It can early detect the cancerous cells of skin. It can differentiate between benign and malignant. ABCD-E has a score value that can be calculated and according to that doctors can identify melanoma and benign [6, 10]. Table 2.1 gives detail for score calculation. Table 2.2

gives the analysis of TDS (Total Dermoscopy Score) value in terms of skin cancer detection.

ABCD-E rule has a benefit for the early detection of melanoma. Early detection is very crucial .According to American cancer society “All cancers can be treated if they are diagnosed in early stage”.

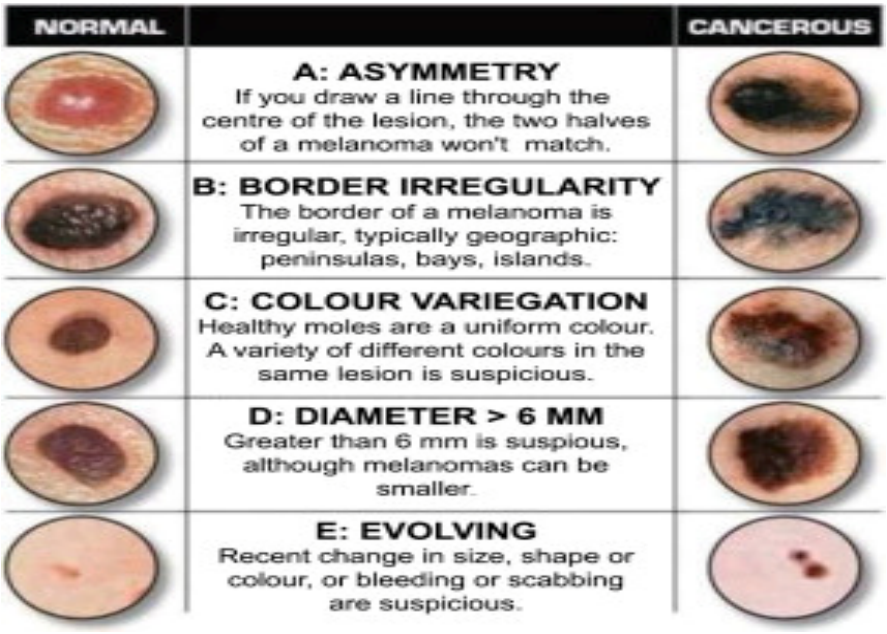


Fig 2.10 ABCD-E rule for skin cancer diagnosis (source- center for excellence in dermatology)

Table 2.1 Calculation of ABCD-E rule

ABCD-E rule criteria	Scores	Weight	Min/Max
Border	0-8	A 0.1	0-0.8
Asymmetry	0-2	A 1.3	0-2.8
Color	1-6	A 0.5	0.5-3
Diameter or different structure	1-5	A 0.5	0.5-2.5
TDS			1-8.9

Table 2.2 TDS Score Meaning

TDS	Meaning
<4.7	Benign
4.7-5.50	Doubtful lesion(surgery is recommended)
>5.50	Highly Doubtful or Melonoma

2.6.3.2 Pattern Analysis

This method identifies the specific patterns [7]. These patterns can be divided in two:

- Global: Nonspecific, parallel, multicomponent, cobblestone and starburst structures
- Local: Pigment Network, Hypo pigmentation, Blotches, Blue-whitish veil and vascular structures. Important structures are explained below

Pigment Network: Pigmentation signifies formation of melanocytic lesion in skin. An image is classified in to three forms typical pigment, absent pigment and a typical pigment network. A pigment network is classified in two forms as shown in Figure 2.11.

- Typical pigment network (TPN)

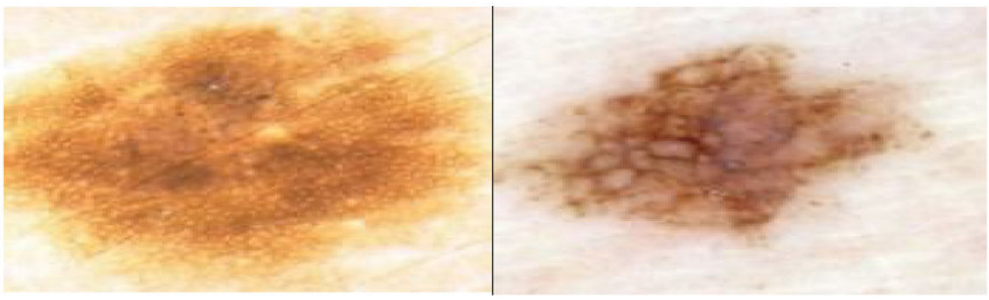
  It is defined as

  "A bright and brown network with tiny, repeatedly spread out holes and cracked lines of network spread repeatedly throughout the laceration and frequently diminishing out at the border".

- A typical pigment network (APN)

  According to work definition

  "A, black, grey and brown system with unequal holes and broad lines".



(a) (b)

Fig. 2.11 Pigment Network (a) Typical (b) Atypical (source- researchgate.net)

The structure is further divided in to darker mesh of network called as 'Net' and lighter mesh known as 'holes'. When 'nets' and 'holes' are identified then several structures and features can be defined for classification.

Blue-White Veil: Dermoscopy defines number of morphological features among them blue white veil is very important. It is irregular and structure less area that has blue pigmentation on while glass like surface as shown in Figure 2.12. This is important for invasive melanoma.

Streaks: It is a kind of linear pigmentation on lesion. They are of two types streaks with bulbous projection known as radial streaming and streaks without bulbous projection is pseudopods. Streaks are local features but they can also be related with global features. For accurate feature extraction streaks are judged only when at the minimum 3 parallel and linear structures are present. The other property of streaks is that they are darker than the neighbor and they are longer than 1%of major axis. Streaks cannot form branches. Figure 2.13 clearly differentiates lacerations with no strain, regular strain (starburst) and irregular streaks.

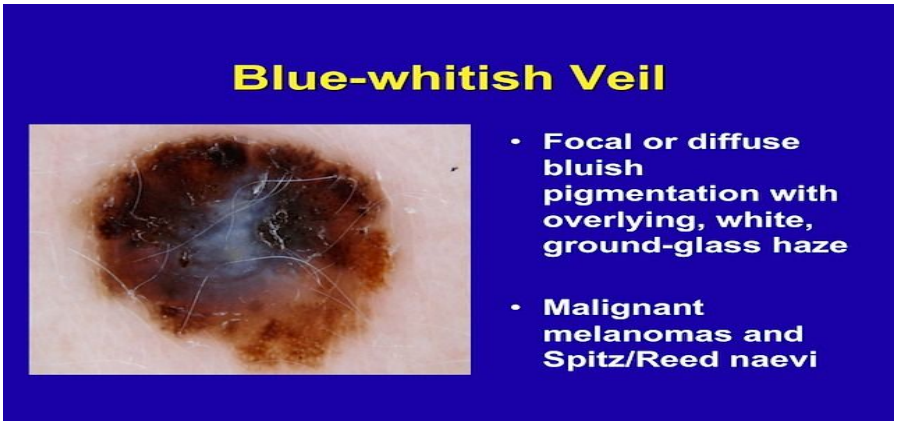


Fig. 2.12 Illustration of blue white veil (Source – pinterest)

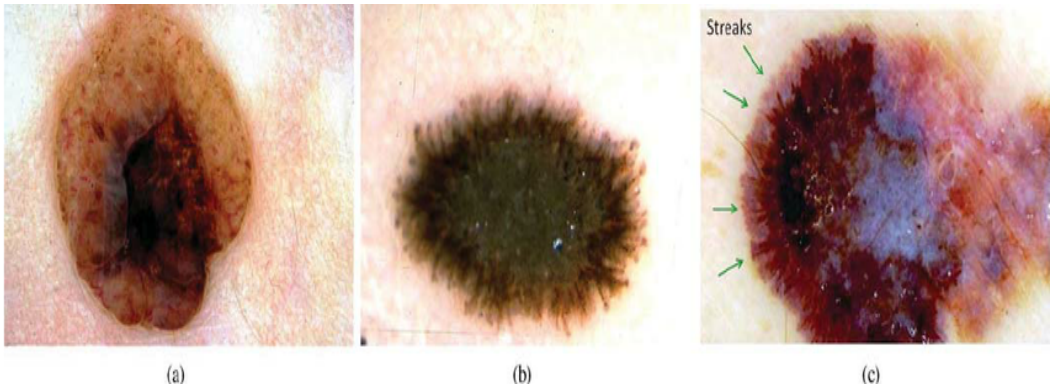


Fig. 2.13 Example of streaks (a) Absent (b) Regular (c) Irregular or melanoma

2.6.3.3 Menzies Method

Since pattern analysis is a method which can be done only by expert doctors. So it was very important to develop a method which should be useful for inexperienced doctors. It was developed by Menzies [8]. This method gives higher accuracy in melanoma detection. It can be understood by Table 2.3 and Figure 2.14.

Table 2.3 Definition of Menzies method

Negative Features	1. Symmetry of lesion (Axial and color symmetry of lesion) 2. Presence of only one color	If one of them is present NONMELONOMA
Positive Features	1. Many brown dots 2. Blue white veil 3. Multiple colors 4. Radial Streaming 5. Blue grey dots 6. Pseudopods 7. Scars 8. Brodened Network of lesions	If at least one feature is found MELONOMA

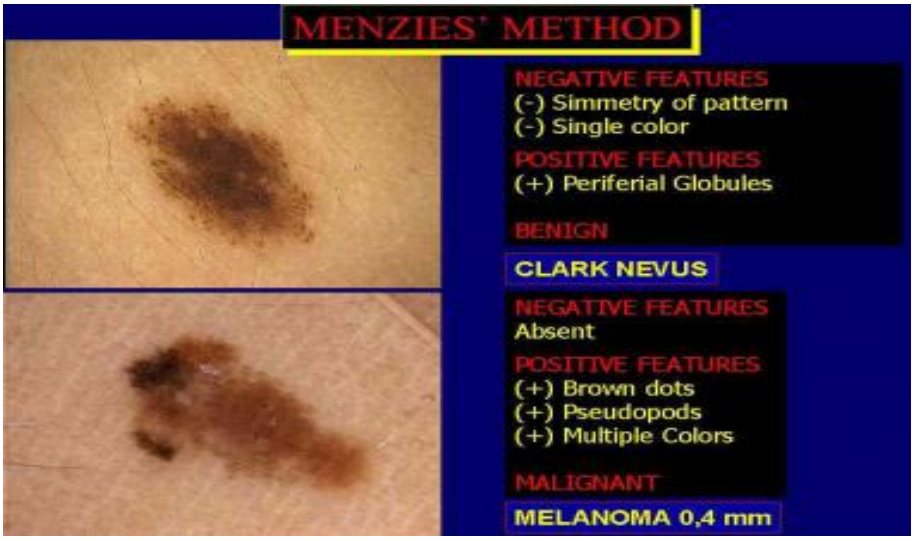


Fig. 2.14 Depiction of Menzies method over cancerous lesion (source- https://emedicine.medscape.com)

2.6.3.4 7 -Point Checklist

This method is introduced with quantitative analysis for melanoma [9]. There are 7 points which are calculated to detect melanocytes lesion. Table 2.4 gives whole idea and calculation for the scoring of melanoma by this method.

Odd Ratios- Increasing probability of each criteria for melanoma.
Seven Point Score- if odd ratio >5 value =2 and if odd ratio<5 value=1.
The odd ratio and 7 point score is calculated by regression analysis and multivariate analysis. Simple addition of the 7 point score can give the calculation of melanoma or non melanoma disease. If 7 point score of an individual <3 there is no melanoma and if the score > 3 melanoma is present.

Table 2.4 Seven Point Checklist

Criteria	Meaning	Ratios (a)	Score (b)
Main Criteria			
Asymmetric Vascular Pattern	Irregular and dotted structure	7.42	2
Blue white veil	Blue dots on glass like surface	11.1	2
Atypical Pigment Network	Irregular holes and blue lines	5.19	2
Minor Criteria			
Irregular Blotches	Irregular and asymmetrical structure	2.93	1
Irregular Dots	Different sized structure and irregular distribution	4.90	1
Irregular Streaks	Finger like projections and bulbous in structure on the edge	3.01	1
Regression Structure	White scars and blue granules	3.89	1

2.7 COMPUTER BASED SKIN CANCER DIAGNOSIS SYSTEM

Computer based melanoma detection is a very important method used now a days. It is far more accurate than dermatologist method.CAD system gives an approach to the finding of lesion and also calculates probability of disease [10],[13]. CAD system is performed on two types of digital images dermoscopic images and no dermoscopic images [11]. After acquisition the images are taken and they are processed to give it in to the computer system as input for the preprocessing task [12]. Figure 2.15 gives the important stages in the CAD of the clinical images.

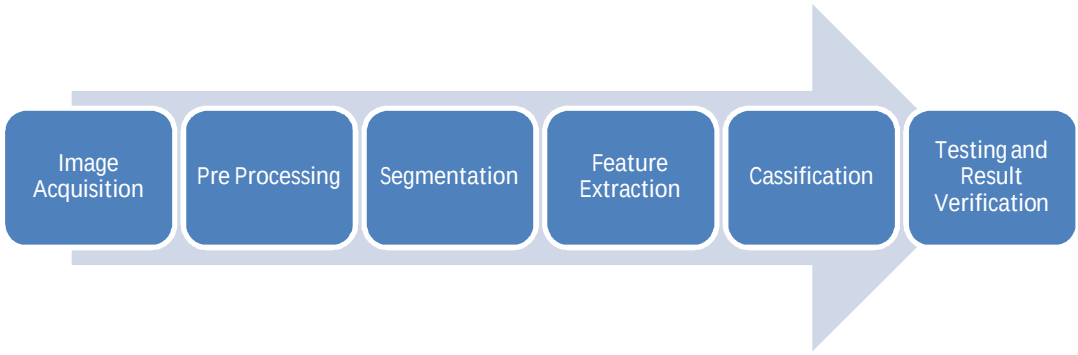


Fig. 2.15 Steps involved in CAD for skin cancer detection

The steps in the CAD of melanoma is described as-

2.7.1 Image Acquisition

Visual inspection of the lesion is not very accurate and so the images taken from the patient with different technique like ultrasound, MRI, OCT, photography and ELM etc re converted in to digital images for further processing . This method is known as image acquisition [12]. Among these techniques described above ELM is main method that is used to get the image of damaged skin. The more advanced technique in ELM like D- ELM and digital dermoscopy analysis (DDA) are also developed to get the desired accuracy in the field of skin cancer detection by computer analysis.

2.7.2 Preprocessing

The preprocessing step starts from the concept how we can differentiate cancerous part from healthy part of skin. The lesion distinguishing from normal part is very difficult as transition between them is very smooth. So it is very important for dermatologist to distinguish between them. Generally dermoscopic images have artifacts such as air bubble, ink spots, gel spots, black frames and some uneven illumination. These artifacts can spoil the detection of skin hairs, blood vessels and texture etc. in a nutshell they can affect border detection task. So preprocessing task is important to smooth the segmentation step by elimination of these useless artifacts and some color transformation. Beside these operations, there are other operations like image resizing, cropping, masking, and hair removal and transformation of different color spaces to grayscale image are also done to correct the image. in this process everything that can damage the image is found , located and erased or masked(filtered).

The most common method to remove artifacts is filtering [13]. Skin lesion is in different colors but these are colors are not very useful in its segmentation so transformation of one color model to other is very common. RGB is converted in to different color model like HIS, KL, CIEL*a*b*etc. color quantization is also a method for color image segmentation [16]. Image contrast is improved to detect the edges of the image for border detection. Histogram stretching, histogram equalization

and mapping are used for this purpose. For high contrast lesion, FFT and high pass filters are generally used.

To remove black frames an iterative algorithm based on HSL color space [13]. Adaptive and median filters are used to remove air bubbles and gel. Hair removal is done by mathematical morphology [14][15]. All these methods discussed in preprocessing are to smooth the work of segmentation and feature extraction.

2.7.3 Segmentation

Segmentation is done so that an image can be easily analyzed. It is used to differentiate lesion part from healthy skin. It is a process to partition a digital image in to the different segments [13]. In this process a label is assigned to every pixel and every pixel with same label exhibit same visual characteristics. So in this way segmented image has partitions in which whole information of an image sustains. Image segmentation is a very important and tough process. This totally depends upon different segmentation techniques.

2.7.4 Feature extraction

It is very difficult to differentiate visually between melanoma and benign. It can be accurate when less and effective features from the lesion are calculated. So this is very essential to identify the essential features out of different features. This technique is well-known as feature extraction. It is done on the segmented image [14].

2.7.5 Classification

Input images are classified or diagnosed whether they are healthy or cancerous. After training and testing is done on classifier then it is used for the classification. For training purpose some images are taken with some special features and model is trained then for testing some new images are tested with new features and according to that performance of classifier is calculated [13]. Classification is judged by two methods. First is discrimination that means how well two data classes are separated and second is calibration that means how close the predictive model is with the real values.

2.7.6 Testing and Result verification (Validation)

Once classifier is trained it is tested with other images of database and then it calculates the execution of model. If the execution of the model or classifier is great then it is validated. To estimate the performance of a classifier the parameters are given in the Table 2.5.

Table 2.5 evaluation parameters of a classifier

S. No.	Evaluation Parameters	Calculation of parameters
1	Specificity	True Negative/(True Negative +False positive)
2	Sensitivity	True positive/ (True positive +False negative)
	Accuracy	(TP+TN)/ (TP+TN+FP+FN)
	FPR (False positive rate)	1-Specificity
	Classification Rate	Quantity of images properly classified/ Total number of images
3	TPR (True positive rate)	Sensitivity
4	Receiver Operating Characteristics	ROC is a graph between TPR and FPR with all their possible combinations or values.
7	True negative rate(TNR)	1-FPR
8	False negative rate (FNR)	1-TPR

TP (True positive) = the quantity of persons appropriately recognized as cancerous

FP (False positive) = the quantity of persons wrongly recognized as cancerous

TN (True negative) = the quantity of persons appropriately recognized as non-cancerous

FN (False negative) = the quantity of persons wrongly recognized as non cancerous.

2.8 DATASET

2.8.1 Skin cancer Datasets

Skin cancer detection in early stage is very important. Several dermoscopy techniques are discussed for the detection of melanoma. But dermoscopy contains visual inspection by doctors or experts so there is a question of time taking and accuracy too. To overcome these issues computer aided diagnosis came in to existence. While

working with CAD images are given in to the machine and then according to the learning algorithm machine learn and then it gives the result after testing. So, digital images or datasets play very important role in CAD system. Evaluation of these images requires a true image database [16]. Table 2.6 gives a detail of some datasets free available for skin cancer detection.

Table 2.6 Summary of publicly available datasets

S. No.	Name of dataset	Properties
1.	Interactive Atlas of Dermoscopy	Number of clinical images = 1,000 Each with at least two images: dermoscopic, and close-up clinical. Fee- 275 euro
2.	Dermofit Image Library	Number of high-resolution images = 1,300 with 10 classes of skin lesions. Fee- 75 euro
3.	MED-NODE Dataset	Number of clinical images =170 (70 melanoma and 100 non melanoma). Fee- freely available
4.	Hallym Dataset	Number of clinical images =125(All BCC) Fee- freely available
5.	SD-198 Dataset	Number of clinical images =6, 584 of 198 skin disease.
6.	SD-260 Dataset	Number of clinical images =20,600 images of 260 skin diseases
7.	Derm7pt Dataset	Number of clinical images =2,000 with 105 images of lesion done with 7 point checklist
8.	The Cancer Genome Atlas	Number of clinical images =793 of skin lesion. Fee- freely available
9.	ISIC Archive Dataset	Number of clinical images =1250 (900 for training and 350 for testing purpose). Fee- freely available
10.	HAM 10000	Number of clinical images =10015 including all type of diagnostic categories. Fee- freely available
11.	BCN20000	Number of clinical images =19424 of skin cancer
12.	Dermatology Atlas	11000 Fee- freely available
13.	Danderm	1900 Fee- freely available
14.	Dermnet	23000 Fee- freely available
15.	DermnetNZ	20000 Fee- freely available
16.	Dermatoweb	7300 Fee- freely available
17.	Dermofit	1300 Fee- freely available

These are some important database that was found in the literature. In this research work, a freely available dataset is used which is known as PH2dataset. This dataset is elaborated in the next section.

2.8.2 PH2 Dataset

This dataset has been built with joint research of Universidade do Porto, Tecnico Lesboa and hospital Pedro Hispaneo in Matosinhos, Purtagal [16][17]. This dataset contains 200 images. In these images 80 images are common navi, 80 atypical nevi and 40 melanomas. They are calculated by tuebinger mole analyzer system. They are RGB color images of 8 bit with 768*560 as pixel resolution of. This dataset has lesser number of melanoma due to two reason first is melanomas show artifacts and not completely inserted in frames and second is actually melanoma cases are actually very smaller .It is free and publically available [17]. If we compared with other databases of machine learning it seems small dataset but annotation is not a simple task. It takes lot of time and effort. All images are manually segmented by expert physician. This database can also be used for experts own training except machine diagnosis. The following parameters are used to evaluate images. Figure 2.16 present a sample of images from PH2 dataset [17].

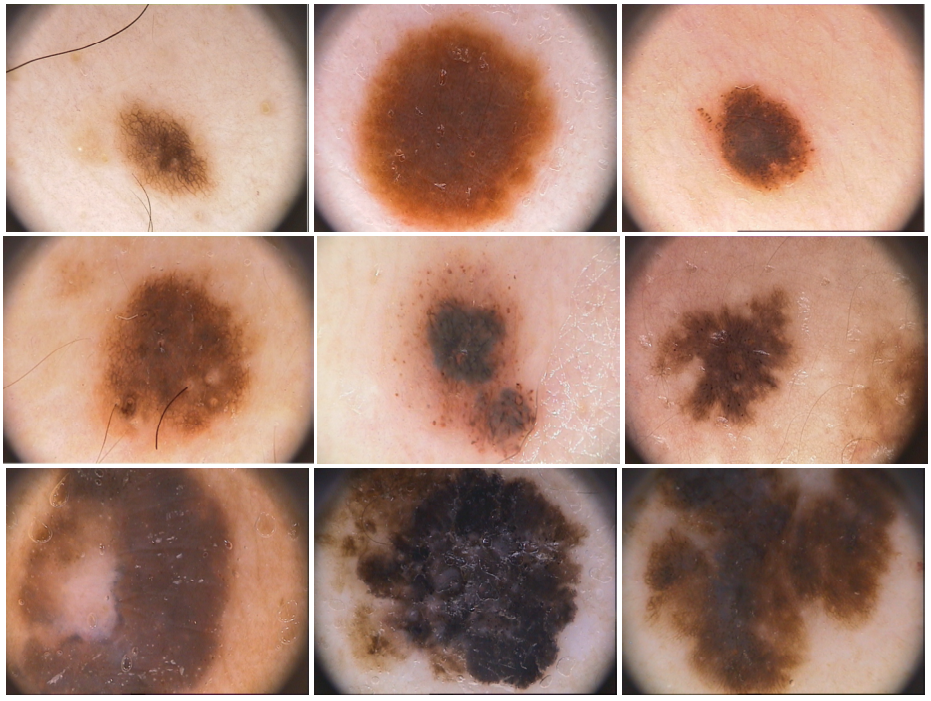


Fig. 2.16 PH2 dataset (First row common nevi, Second row atypical nevi and Third row melanoma)

2.8.3 Physical (Manual) segmentation of the skin lesion

Physical segmentation and annotations are done by experts with a tool named Der-MAT [18]. In this method binary mask is available for each image. Intensity of pixel with value “1” signifies to segmented area and value”0” signifies to framework. Original image and binary mask are same size. Figure 2.17 presents images and its segmented version.

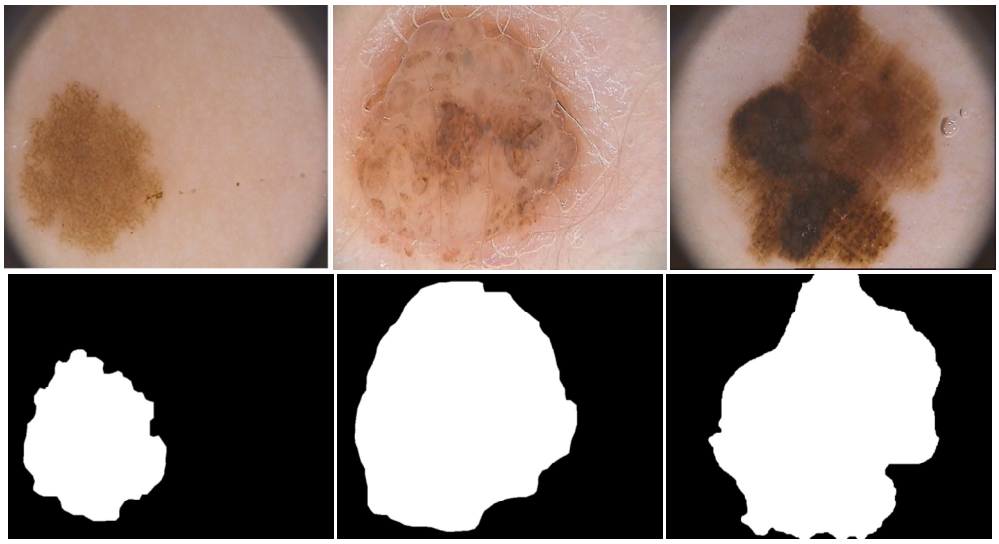


Fig. 2.17 Manual Segmentation of three types of images

2.8.4 Clinical Diagnosis

Melanocytes have two main forms Benign (common and atypical nevus) and malignant .so each image of database is divided in three parts as discussed earlier.

2.8.5 Dermoscopic Criteria

Features available in this dataset corresponds to the relevant diagnose of clinical images. There are lot of feature accessed by this dataset like ABCD rule, Menzies technique and seven point checklist methods.

2.9 ARTIFICIAL INTELLIGENCE (AI)

AI is a research field that gives the solution of difficult problems with the help of human intelligence. This technology has taken birth with the interaction of computer

machines, engineers and other applied sciences [19]. This technology has very wide scope and research area like robotics, machine learning, and computer vision etc.AI has many definitions and also known as Machine intelligence. A perceptive definition of AI is “the study of how to make computers do things at which, at the moment, people do better” [20]. Mainly AI has six areas.

- Machine Learning(ML)
- Computer Vision(CV)
- Robotics
- Automated Reasoning(AR)
- Natural Language Processing(NLP)
- Knowledge Presentation(KP)

Between these ML and CV is most important and major part for the melanoma detection with AI. In this domain AI can be defined as shown in Figure 2.18.

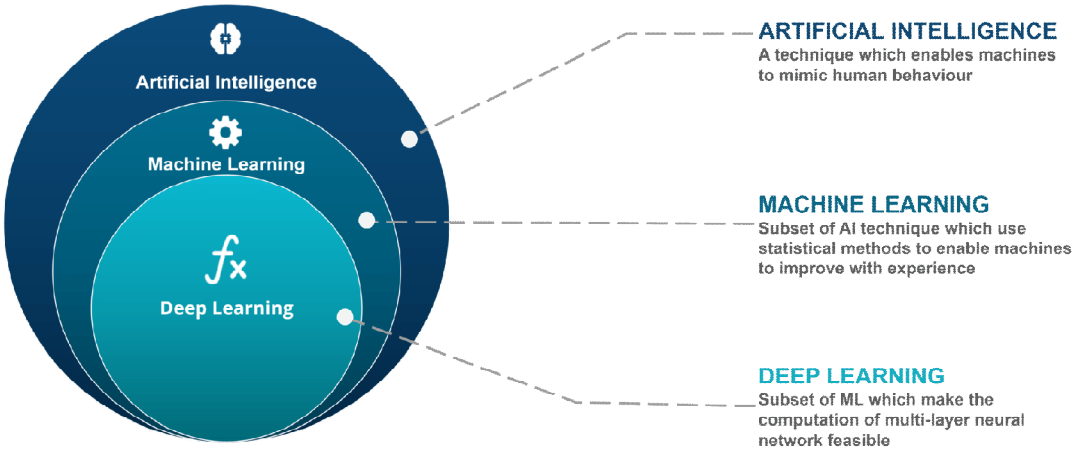


Fig. 2.18 AI with its research fields for Melanoma Detection (source-edureka.com)

From the figure it is clear that machine learning is a subgroup of AI and deep learning is a subgroup of machine learning.

2.9.1 Machine Learning (ML)

Machine learning is study of mathematical and statistical based learning with algorithms. Computer machine use these models to train them and give exact output

with no error. A sample data is given to machine and then machine is trained with the input data. After training, performance of machine is tested and then verified for the desired output [20].

2.9.2 Deep Learning

Deep learning is a part of ML based on artificial neural network. Deep learning involves layers of neural networks. They are RNN (Recurrent neural network) and CNN (Convolutional neural network), etc. They are used for huge database and in almost six fields mention above [21].

2.9.3 ANN

Artificial neural network is most important part of soft computing. ANN is a cluster of artificial neurons connected to one each other creating a very complex structure. Its aim is to behave like human and adapt the changes as human does. Figure 2.19 clearly explains the working and structure of ANN.

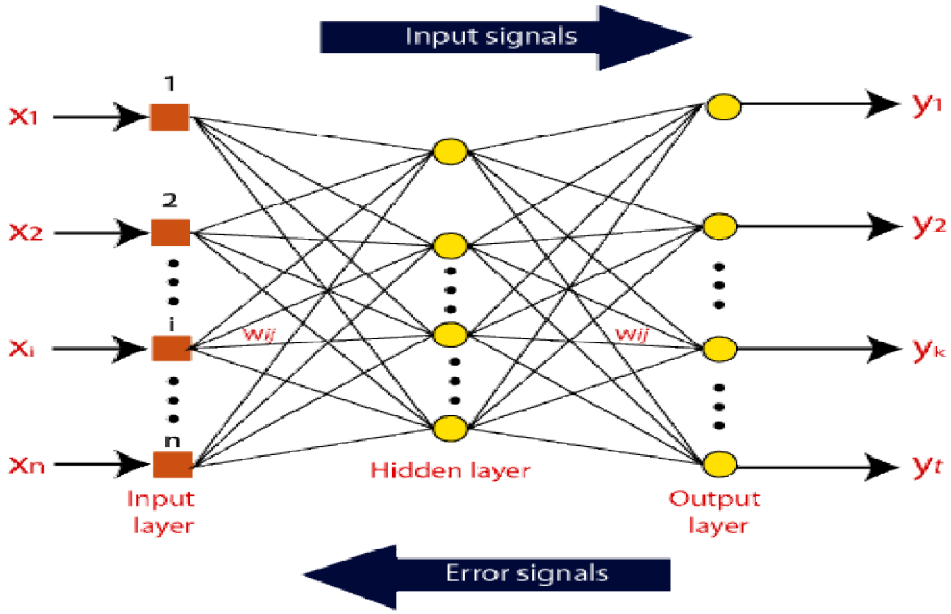


Fig. 2.19 Architecture and Mechanism of ANN

ANN contains number of processing unit known as neurons. There are three layers one layer connected to inputs(x_1, x_2--- x_n) is known as input layer. Secondly there are layers between input and output that is hidden layers and last output layer that is connected to output (y_1, y_2---y_3). Information is propagated between these neurons.

ANN calculates the probability by minimizing a cross entropy error function. Information is stored in form of weights between neurons. According to the error signal these weights are updated for the minimization of error. Since these are iterative processes, machine learns from given example that is known as training. ANN has tremendous capacity to work on complex task and that's why it is very much used in skin cancer detection now a day's [22][23].

This machine learning method has proved itself in last decades in the field of melanoma detection. Various ANN based algorithms are being used. These algorithms are Extreme Learning Machine, Radial Basis Function Network and Back Propagation. Among them Back Propagation (BP) is very famous algorithm for ANN. It was popularized in 1980 with the help of delta rule [24]. Back propagation works in different stages [25].

- **Initialize the weights**

ANN with BP consists of three layers. Data given to input flows to the hidden layer and so to the output of ANN. Weights are initialized for further calculation.

- **Output in forward direction**

Response of the network is calculated with the preferred activation function in feed forward manner.

- **Errors Calculations**

Error of the network is calculated with the flow of the network.

- **Updating of error and bias**

After calculation of error weights and bias are updated. This process goes on until right results are achieved.

2.9.3.1 Algorithm to train ANN

Another important thing in ANN is number of hidden layers in the network. There is no rule for that but if we increase the number of hidden layers complexity increases and if we decrease it then accuracy is compromised. In case of skin lesion classification, Feature extraction is very important. If very exact and important features are selected then we can get good results.

Since back propagation is a part of this research and also it is a trade mark algorithm, there have been improvements in this from time to time.
For this study they are following—

- **LM (Levenberg–Marquardt) Algorithm**

LM is very popular in ANN which finds a minimum function as sum of square of linear functions. It is a very robust method to approximate the function [26].

- **SCG (Scaled-Conjugate Gradient) Algorithm**

It is designed by Moller to evade time consuming line search. This algorithm has mixture of LM and conjugate Gradient. SCG acquires nonlinear search technique. So lot of complex problems is solved in less iteration [27].

2.10 ROLE OF AI IN SKIN CANCER DETECTION

Role of AI in field of melanoma detection is very large. It includes dermoscopy, clinical images, confocal microscopy and pathology. But most of the research and current work has been done on dermoscopic and clinical images. Dermoscopic images are repeatedly showing increase in Accuracy, specificity and sensitivity of melanoma detection with proper training of machine. AI has got lot of attention from all aspects of skin cancer detection. There are still lots of potential for AI in field of skin cancer detection.
In future AI will be more accurate and personalized for the doctors. Basic role of AI in this field is to serve doctors and patients.

2.11 SUMMERY

This chapter provides full detail about the basis for the medical treatment in field of melanoma. As Discussed doctors should be aware of the early detection of melanoma so that it can be removed before lethal effect. Several techniques have been mentioned in this regard. In this chapter an overview of all CAD methods for melanoma diagnose is given emphasizing on the role of AI in this field. To complement the work of diagnosis by doctors' bunch of work has been done in the field of melanoma detection with CAD. This will be discussed in next chapter.

CHAPTER 3

LITERATURE SURVEY

3.1 INTRODUCTION

Computer-assisted diagnosis system (CAD) of clinical images has revealed a huge significance in developing a significant approach to classify skin lacerations. A computer- assisted diagnostic system normally has five components: Acquisition of images, Preprocessing of images, segmentation of images, Feature extraction and selection of image and at last is classification done by a knowledge database.

Since there is very low difference among lesions and skin, melanoma and non-melanoma lesions, so a solid framework is needed to expand the precision and proficiency of doctors. Early detection of melanoma in clinical images is like a boon to patients by building survival rate.

Here we present a review of the methods and framework for the premature detection of skin melanoma.

3.2 REVIEW OF THE METHODS AND FRAMEWORK FOR THE EARLY DETECTION OF MELANOMA

Erdem Okur et al. (2018) describes the theorem and technique used for the melanoma detection. Cases of melanoma are increasing day by day with less survival rate. Studies show that only 2% cancers are due to melanoma in the world. But the death rate is 75% from this deadly disease. By USA statistics a person dies with melanoma in every 54 minutes. It is third most dangerous cancer after prostate and breast cancer. Melanoma starts from melanocytes. From epidermis, it can rapidly spread to the dermis by lymph and blood vessels and then it can go any part of the body. So early diagnose is very important. Stage of melanoma can be examined from lesion by checking four parameters.

Tumor thickness, ulceration of tumor, spreading to lymph nodes and spreading to other parts of body. Melanoma stages are also defined to get the precise cure for this deadly disease [28].

Stage0: abnormality in melonocytes in epidermis. There can be cancer. This phase is known as “melanoma in situ”.

Stage1: Formation of cancer. It is of two types.

(A) Stage1A: No ulceration and thickness of tumor >1 mm.

(B) Stage1B: Ulceration with tumor thickness <1mm or no ulceration with thickness between 1mm to 2mm.

Stage2: This is divided in to three stages.

(A) Stage2A: No ulceration and thickness lies between 2mm to 4mm.

(B) Stage2B: Ulceration with 2<thickness<4 or No ulceration and thickness> 4 mm.

(C) Stage2C: Ulceration with thickness>4 mm.

Stage3: lesion thickness is any number with ulceration or not. It is considered as metastasis, it can go up to 2 centimeters from primary tumor. It can spread from lymph nodes and blood vessels.

Stage4: The cancer has entered to all parts of body like liver, kidneys, lung or brain.

According to these stages, strategy of cure for melanoma starts. There are lots of techniques to find the stages and curb them. One is mapping of lymph node in which a material is injected and can be followed by lymph duct. After getting the result, biopsy or removal is done according to the result. CT scans PET scan, MRI with gadolinium and blood Chemistry test (LDH). It is very sad to say that stage 3 and stage 4 are very crucial. It has treatment like Chemotherapy, radiation therapy, immunotherapy and targeted therapy. Since this is deadly disease so we should have proper awareness about its inspection as well cure. ABCDE rule is also very helpful for the early diagnose of melanoma. In this way melanoma is visually inspected but it has very less accuracy up to 60% only. So dermoscopy come in to picture for the accuracy of investigation and detection of melanoma. Dermoscopy was invented in 1663 by kolhaus who investigate lesion from microscope. In 1878 immersion oil is used between lesion and lens to improve accuracy. Then a light source s used with lens system that device is known as Dermascope , in this device a light source with 60 to 100 magnifying lenses are used. Doctors applied a special gel on skin and the see lesion with this device. By this device accuracy was enhanced up to 30% but still there is again it depends upon the experience of doctor or what he sees. So automated detection is very much needed. In early ages there was a problem for CAD system for melanoma detection due to small database and other technical things. But after the

invention of dermoscope now there are lots of database come in to existence (year 2000) to train the machine and get good results. Datasets are PH2, EDRA and ISIC. There are three stages for automatic detection of cancer but these stages are aligned with the clinical inspections.

Stage 1: Lesion Segmentation: This is the first step in melanoma detection by automated system. Lesion segmentation decides the other following steps like feature extraction and classification. It is very important step.in this step lesion is secluded from the image and other artifacts. It results in a binary image in which skin is white and lesion is black. After that to decipher features clinical images are segmented on lesion part. So that features like symmetry, border and regularity can be evaluated easily. There are number of techniques for segmentation.

(A) Thresholding

(B) Clustering

(C) Fuzzy logic

(D) Supervised learning

(E) Graph theory

Among them thresholding is widely used and very much acceptable. It converts grayscale or color images in to binary images. In this work there is a nutshell of thresholding segmentation techniques in Table 3.1.

Artifacts are also a very big problem in melanoma classification. Artifacts can be removed by preprocessing and post processing tasks. There are some examples of artifacts.

(A) Murky corners

(B) Marker ink

(C) Color chart

(D) Ruler marks

(E) Gel foam

(F) Hair

(G) Lightening

(H) Noise

(I) Contrast

Hair removal techniques assembled in this survey are shown in Table 3.2.

Table 3.1 Thresholding segmentation techniques

S. No.	Year	Author	Method of Segmentation
1.	**2011**	Garnavi et al.[29]	Hybrid method with color optimized and clustering algo based on histogram Thresholding
2.	**2003**	Tkalcic and Tasic[30]	XYZ, HSI, RGB, HSV, YCbCr color spaces with hybrid thresholding
3.	**2009**	Yuksel and Borlu[31]	Thresholding with Fuzzy logic
4.	**2008**	Castilo and Menin[32]	Adaptive Thresholding and Otsu method
5.	**2013**	Cellibi et al[33]	Ensemble of Thresholding technique(Thresholding Fusion)
6.	**1995**	Huang and Wang[34]	Similarity Method
7.	**1985**	Kapur et al [35]	Method of Maximum Entropy
8.	**1986**	Kittler and Illingworth[36]	Method of Minimum thresholding
9.	**1979**	Nobuyuki[37]	Otsu's Method
10.	**2006**	Melgani[38]	Thresholding Fusion Method

Table 3.2 Hair removal technique presented

S. No.	Year	Author	Method of preprocessing
1.	**1997[39]**	T. Lee et al.	DullRazor
2.	**2015[40]**	Mendonca et al.	Median filtering for noise reduction and smoothing for hair removal
3.	**2009[41]**	Quintanna et al.	Filtering for Noise removal. histogram and color modification with contrast improvement Methods
4.	**2011[42]**	Weight et al.	Histogram modification. Filtering for Noise reduction. Color rectification and contrast improvement Methods and Otsu method
5.	**2013[43]**	Abbas et al.	Noise removal with filters. Histogram and color rectification and contrast enhancement Methods
6.	**2011[44]**	Wong et al.	Region Merging
7.	**2006[45]**	Iyatomi et al.	Border Expansion and Smoothing

Stage 2: Feature Extraction of Clinical images: After the segmentation of lesions from the image, now it is time to work on the lesion. With the study of lesion we can get the desired features. They are fundamentally global and local. Global features cover the whole lesion while local feature cover a part of lesion like some spot on lesion. The features have three main categories.

(A) Texture

(B) Color

(C) Shape

These features are extracted to get the cancerous skin. Here is a summary of methods widely used for different feature extraction methods in Table 3.3.

Table 3.3 Feature Extraction methods widely used

S. No.	Feature Category	Widely used method
1.	Texture	**1.** GLCM **2.** Histogram **3.** Pixel intensities with neighboring intensities value
2.	Shape	Check symmetry feature of lesion
3.	Color	Clustering method

Output of clinical feature extracted lesion is either a binary mask or pixel value which decide the corresponding feature exits in this or not. These clinical features have different pattern and types. So doctors firstly do visual inspection and then they go for second step that is also visual investigation but it is main investigation. There is Table 3.4 through which visual investigation of first step can be explained.

Table 3.4 visual investigation of melanoma

Dermoscopic Criteria	Symptoms	Type of cancer
Pigment Network-Pseudo-Network	Group of brown interrelated lines lying over surroundings of tan diffuse pigmentation	Melanoma
Aggregated globules	Many, different sized, frequently gathered round or oval structures with different brownish and gray-black shades	Melanoma

Streaks	Bulbous and frequently cramped or finger-like projections at the edge of a lesion	Melanoma
uniform blue pigmentation	Arrangement less blue pigmentation in nonexistence of pigment network	Melanoma
Corresponding shape	Present as melanoma lesions in palms/feet and areas near nose or mouth.	Melanoma
Many milk spot like tumor	Various, different sized, yellow and white circular structures	Acanthotic Nevus
Pimple-like beginnings	Yellow-Brown or black-brown, circular shape plugs in the pores of hair cyst.	Acanthotic Nevus
Brownish structures like smudge	Brownish, soft, grid-like structures with smudge model.	Acanthotic Nevus
Leaf-like structures	leaf-like patterns are formed from brown, gray or blue distinct rounded structures	Basal cell carcinoma
Sore	nonappearance of epidermis frequently linked with frozen blood	Basal cell carcinoma
Red-blue to Red-black uniform areas	Arrangement less uniform red-blue to black -red areas.	Vascular lesion

Second step of investigation is done by different methods. This is known as pattern analysis and is subclasses of features detected in first step. These are listed in following Table 3.5.

Table 3.5 Properties of pattern analysis in literature

Global Features	**Description**	**Analytic importance**
Reticular pattern	Pigmentation casing the majority portions of the lesion.	Benign
Spherical pattern	Many, different shaped, circular arrangments with different color of gray and brown -black	Benign
Brick pattern	Big, directly clustered, sloped globule-like structures	Almost Benign

Regression structures	Spatter-like decolorized blue spot like grains.	Melanoma
Rash	Dark black, brown and gray arrangement less space with asymmetric or symmetric division within laceration	If symmetrical Benign if asymmetrical Melanoma

Mainly three algorithms are used for the second step feature segmentation.

1. **ABCD Rule:** This rule is defined by four parameters A, B, C, D. Table 3.6 defines ABCDE rule.

Table 3.6 ABCDE rule

S. No.	Name	Description	Score	Weight Factor
1.	A =Asymmetry	Asymmetry in Color, Contour and Structure	0-2	1.3
2.	B= Border	Unexpected finish of tint shape at border	0-8	0.1
3.	C= Color	Presence of white, dark-brown, red, light-brown, black and blue-gray.	1-6	0.5
4.	D=Dermoscopic Structures	Occurrences of structure less areas, branch steaks, spots and drop.	1-5	0.5

Z = Score of A * Weight factor of A + Score of B * Weight factor of B + Score of C * Weight factor of C + Score of D * Weight factor of D.

If $Z < 4.75$ then Lesion is normal.

If $4.75 < Z < 5.75$ Lesion can be cut or go under supervision for more time.

If $Z > 5.75$ then Lesion should be removed.

2. **Menzies Method:** This method is well explained in the Table 3.7(a) & (b). It is defined as two features positive and negative. If at the minimum one of the positive features is present, then there is clear indication of melanoma.

Table 3.7(a) Menzies method

S. No.	Negative Features	Description
1.	Regularity of pattern	Pattern is symmetrical along center of lesion across all axes.
2.	Occurrence of one color	Dark brown, black, dark blue, red and Gray.

Table 3.7(b) Menzies method

S. No.	Positive Features	Description
1.	Blue and whitish layer	A part of uneven, arrangement less concurrent blue tint with an overspreading white opacity film.
2.	Many brown spots	Dark and brown spots
3.	Pseudo pods	Rounded and frequently cramp projections created at the border of laceration associated to the lesion figure or tinted system.
4.	Radial streaming	Undistributed or asymmetrical horn-like network at the perimeter of laceration.
5.	Burn-like spots	Zones of white discrete uneven texture.
6.	Outlying Black spots/droplet	Black spots present near rim of lesion
7.	Multiple colors	Dark brown, black, dark blue, red and Gray.
8.	Many gray or blue spots.	Black grains like pattern or pepper like shape.
9.	Expanded network	set of connections fabricated from uneven denser string of the network.

3. 7 Point Checklist: In this method there are 7 different features through which melanoma are defined. It is given in the following Table 3.8.

Table 3.8 7 Point checklist

S. No.	Features	Presentation	Score
1.	Stained structure	Gray and brown net with broad lines	2
2.	Blue or white layer	A part of uneven, arrangement less concurrent blue tint with an	2

		overspreading white opacity film.	
3.	Pattern of blood vessels	Lined and uneven or sprinkled pots.	2
4.	Uneven strip	Black and Brown with round shape or horn like structure. Uneven and disconnected at the rim of laceration.	1
5.	Uneven dots or spots	Brown and Black with round, oval and different shaped shapes unevenly dispersed within lesion.	1
6.	Uneven patch	Gray, Black and brown arrangement less space unevenly Spread within laceration.	1
7.	Imperfect structures	White wound-like decoloring or pepper- like grains in blue color.	1

If overall score >3 it is melanoma.

Comparative Analysis of the Above Described Methods:

This is done with 40 images of same type. The comparison is shown in the Table 3.9 in form of Sensitivity, Specificity and Accuracy.

Table 3.9 Comparison result of images

S. No.	Method	Sensitivity	Specificity	Accuracy
1.	Pattern Analysis	68.4%	85.2%	76.7%
2.	ABCD Method	78%	81%	78.0%
3.	Menzies Method	85%	78%	81%
4.	7- point checklist	82%	74%	77%

Stage 3: Selection of Features and Classification: in this step features are extracted from segmented lesion and then it is given to the input of the classifier. Feature selection is very important as features should be relevant and less in number having all information to reduce complexity. So the features dimensions are also reduced. The following Table 3.10 has a nutshell of feature selection and classification technique for melanoma detection.

Melanoma Detection with Smart Phones: Now a day's smart phones are laced with lot of features and other technical things so melanoma detection is great on that and it

is very much in trend. But its accuracy is still a problem. So it can delay the diagnosis of melanoma.

Table 3.10 feature extraction and classification methods used in literature

S. No.	Year	Author	Method of feature extraction	Method of classification	Result
1.	2007	Celebi et al.[46]	Shape features are extracted by Euclidean Distance Transform. Information based and correlation based feature selection	SVM (radial basis kernel)	Specificity =92.34% and Sensitivity =93.33% on 564 images.
2.	2001	Ganster et al.[47]	122 features reduced to 21. shape and color features are extracted	KNN	Specificity =93% and Sensitivity =87% on 5393 images
3.	2002	Rubegni et al.[48]	48 features were generated with shape color and texture feature.	ANN	Accuracy = 94% on 200 images
4.	2008	Situ et al.[49]	BoF Approach with wavelets and "Gabor-like" filters	SVM	Accuracy = 82.21% on 100 images
5.	2013	S. Arivazhagan et al.[50]	Global and local feature with texture and color.- texture features were generated by Dominant neighbor structure.		Local features dominate global features.

Z. Waheed et al. (2017) presents a resourceful machine learning perspective for the premature melanoma detection from clinical images. This work is divided in to two steps for classification of melanoma.

In first step, different types of color descriptors (that provides definition of color variation and color distribution existing in skin lacerations and texture descriptors (that gives details about texture , smooth or rough surface for different arrangements existing in the lacerations like dots, holes etc.) are extracted from clinical images[51].

In second step, drawn out descriptors are supplied to the SVM classifier to distinguish melanoma from healthy clinical images. In classification step, each clinical image is distinguished as melanoma or non- melanoma image with the help of these extracted color and texture descriptors or features.

To extract color descriptors HSV color space is used that is more close to human perception. HSV stands for Hue (the real color), Saturation (maximum intensity of color) and Value (brightness). This method calculates nine distinct statistical features like Hue (Standard Deviation), Value (max), Hue (in form of mean), Saturation (in form of mean), Value (in form of mean), Saturation (in form of max value), Hue (in form of max value), Saturation (in form of Standard Deviation) and Value (in form of Standard Deviation) by HSV color space. For Texture feature extraction a statistical approach known as Gray-Level Co-occurrence Matrix (GLCM) is used to achieve texture analysis which works with co-occurrence matrix using statistics of neighboring pixels. Grey Level Co-Occurrence Matrix is well known texture Analysis methods. Four different texture features (Correlation, Homogeneity, Energy, and Contrast) are extracted in this method. In this way total 13 statistical features (9 from color extraction and 4 from texture extraction) are extracted.

Second step is classification where 13D feature vectors are formed for every clinical image and put in to database. Here SVM (support vector machine) classifier with 3-folds cross validation is chosen to pick melanoma images from provided database images which depend upon accurate extraction of texture and color descriptors.

Dataset used in this work is PH2 .it is an open access dataset of 200 images having 80 common patch- images, 80 atypical patch- images with 40 melanoma images, adding up 40 melanomas and 160 non-melanomas. Each image has the resolution of 768x560 and 8-bit R-G-B in JPEG format.

Two sets (testing and training) from database are used with 3-folds cross validation SVM classifier. This system is evaluated by calculating Accuracy , Specificity (TNR) and Sensitivity (TPR)on the platform of Weka and MATLAB .Both results from MATLAB and Weka are compared in which MATLAB performs better than Weka. Moreover, Evaluated results are compared by calculating execution of system with the

help of only texture features, only color features, and combination of texture and color features.

Accuracy is calculated for every descriptor group separately and also by adding them. This is inspected that color descriptors only gives 95% accuracy greater than texture descriptors which gives accuracy only 83%. The best performance is attained with the addition of both features sets (color- texture) achieving accuracy 96% for the recommended system.

This paper targets on the work of two feature sets: texture and color. It is establish that color works very much greater than texture with respect to accuracy while together they perform excellent. Uppermost accuracy of 96.1% is attained if both color -texture features are combined. This Suggested system delivers decent result when matched with further methods. It is seen that first-class results are attained with these extracted features to prove the strength of the recommended system**.**

Yanyang Gu et al. (2017) proposed a method based on constrained graph regularized nonnegative matrix factorization and Mahalanobis distance learning for earlier melanoma detection. This method is incorporated with supervised learning and dimensionality reduction of features for both global and local techniques to improve the power of classifier performance. To make an early inspection, doctors generally go with natural treatment that is known as dermoscopy but it totally depends upon dermatologist experience or we can say that it is not precise. So, automatic detection of skin cancer from clinical images is very important. Most computer assisted diagnosis system for skin cancer (CAD) is based on four steps: pre-processing of image, segmentation of image, feature extraction of image and classification of image. Pre-processing of images aim at removing unwanted artifacts and enhances the focal areas in the image. Segmentation is to extract the affected area from image. There are number of feature extraction techniques in CAD such as GLCM, color histogram, LBP, and SIFT etc. After feature extraction, images are converted into vector form to classify but these descriptive vectors have big dimensions of several hundreds. So it is difficult to achieve best classification performance. To curb this problem a novel method proposes a method named as GNMF (unsupervised manifold regularization) to improve the clustering performance [52].

The manifold regularizer constructs a nearest neighbor graph with the help of local interrelations between data points. In GNMF (Graph Regularized Nonnegative Matrix Factorization), an accord graph is built to convert the geometrical details and so a matrix factorization took birth representing the graph structure. Mahalanobis distance learning is introduced in GNMF to improve the clustering performance. Both local and global checks in the data are investigated. At one end, a Mahalanobis distance matrix is supplied to classifier to learn from database that participates to build the local topological space by the sharing of datum and image. Despite this, the features are given as added checks to the matrix of coefficient in a global way.

On given set (PH2 and Edinburg) of skin images, image preprocessing, segmentation and desired image feature selection are done first. All features of the images are converted into vectors after extraction. Here , we employ numerous usually old feature selection and extraction techniques in melanoma recognition research on four features, namely, Local Binary Patterns (LBP), SIFT , Gray-Level Co- Occurrence Matrix (GLCM) and Colour histogram (ClrHst).The overall procedure is distributed into two phases: a training phase and a testing phase. The training phase gets feature information in form of both locally and globally perspectives.

First of all, they applied a Mahalanobis distance learning technique to improve the ability of projected technique from a local viewpoint. In the expected data with low dimensions, the training method increases spaces of data samples between unlike classes while dropping the spaces among cases within similar group. Second, since label checks are added to the matrix of coefficient, the classification skill can be improved from a global viewpoint, where cases of same group are estimated to the same group in novel lesser dimensional space. We obtain a projecting matrix after solving the objective function and leave to the next stage. In the classification stage, the learned projection matrix is used to test data into the same low dimensional space. In a nutshell, a classifier classifies the fresh depiction of the testing sample in the expected subspace. Different types of classifiers are used in this method (CNMF+RF, MCNMF+SVM, CNMF+SVM, SVM, MCNMF+RF, RF) and their performance is compare in form of sensitivity and specificity. The proposed method has given the finest response for datasets (PH2 and Edinburg) with SE=94.43% and SP=81% with

SVM and LBP with PH2, and SE=99.5% and SP=93.68% with RF (random forest) and SIFT descriptors on Edinburgh image library. MCNMF method has significantly performed excellent from all other methods, and feature is not a concern here. After using SVM separately on feature vector on Edinburgh image dataset shows good specificity but sensitivity goes down. The success of the dimensionality reduction technique is demonstrated by the comparison with RF and SVM with raw features. In addition, it can be also observed that this method performs well with the similar RF and SVM classifier.

Datasets also plays important role on the classification results. RF beats SVM with PH2, but SVM works preferable than RF with Edinburgh. That is generally due to the variation of quality of the images between these datasets. In a nutshell, this proposed technique has the great achievement on these datasets as compared to further classification technique.

T Y Satheesha et al. (2017) introduces a computer aided design system which reflects the predictable penetration of skin lacerations for analysis. A 3D skin laceration rebuilding method is presented to compute the expected penetration found from general skin images. With the base of 3D reconstruction of image, 3D shape features as well as texture, color and 2D shape features are took out too. The designed system is applied to inspect basal cell carcinoma, Haemangioma blue blotches, Xanthoma Seborrheic Warts and usual mole lacerations as well as melanoma and in-situ melanoma. This study is based on up to what extreme the cancer and the shape and size of the malignant tumor have reached. Malignant melanoma is described into five phases [53].

Phase 0: It is the first phase defined to as in situ melanoma.
Phase 1: The tumor in this stage expands into the skin but only in epidermis layer. This stage is 100% curable.
Phase 2: Melanoma malignancy is 2mm - 4mm in shape and shows like ulcer but does not go to blood vessels or other parts of the body. Sub groups are 2A, 2B and 2C depending on the depth of ulceration.
Phase 3: Tumor is more than 4mm deep and in form of ulcer but has gone to the blood vessels and still not spread in other parts.

Phase 4: The ulcer is greater than 4mm deep and has expanded to different body part and blood vessel.

This phase has high mortality and very expensive. So it can be seen that the tumor depth is a dangerous constraint for detection and recognition of the cancer phase. The 3D reconstruction allows estimating the relative penetration of the key tumor which is very helpful to detect melanoma earlier. The image dataset is divided in to testing and training sample data. Image segmentation is done to get the desired region or skin laceration area to be diagnosed. The skin lesions are extracted using image segmentation methods. The projected system uses an adaptive snake segmentation technique to get area of interest from a set of images. A deepness map is constructed from the 2D skin image. Penetration map is applied for structuring a 3D model of the skin image. Structure from motion Stereo vision, depth from focus, depth from defocus etc. are used to inexact penetration allowing for multiple images. Penetration map acquired is well to the aid for 2D surface to activate 3D surface renovation. The 3D surface is signified as building tensors. A feature set having 2D shape, 3D shape, color- texture are extracted for every image. R-G-B color space is taken for evaluation of color features. The mean and variance of each channel(R, G, B) is computed. A feature selection is done from extracted features by decision making. For texture descriptor extraction the segmented lesion is first transformed to grey scale pattern. Haralick-features are applied to get the texture properties in form of equation. Energy, homogeneity and correlation are computed. 2D shape features are Shape, border and asymmetry descriptors in the projected computerized assisted system. In totality, 11 two dimension shape features are calculated from the skin lesion images after segmentation. On the other hand, the minimum, maximum, and average depth feature is obtained from the three Dimensional skin laceration rebuilt. 3 affine moment and 7 Hu invariants are also taken for the characterization of 3D shape features of the skin lesion.

In the planned computerized assisted system 2D shape, 3D shape, color and texture features of skin lesion images are extracted.

Classification is the last stage of this work. The anticipated system adopts multi group classification techniques for choice making, enhancing its capability to classify a large

range of skin laceration images. In the present research work three unlike type of classifiers i.e. AdaBoost, SVM, and the newly bag-of features (BoF) classifiers are applied. There are two phases involved in Classification: training and testing. Training and testing is done on two databases PH2 and ATLAS. They are open access database. PH2 has 200 images used for 4 type of lesion and ATLAS has 63 images used for 8 type of lesion in this work.

Output of the projected scheme with every classifier separately is calculated using the feature extraction and selection. A total of 4 experiments for each classifier for every dataset are passed out. For classification AdaBoost advanced bag of features and SVM classifiers are used. Evaluation is done with the ATLAS and PH2 datasets. Responses with other classifiers like AdaBoost, BoF, SVM classifiers and feature combinations are presented. An outcome show that insertion of 3D shape features projected (which adds the expected depth descriptor) improve execution aiding precise diagnosis of different types of lesion. SVM gets best classification scores as SE= 96.1% and SP=97.2% with PH2 dataset. The SVM classifier results SE= 98.1% and SP=99.1% with ATLAS image dataset is recorded. The depth evaluation method projected in this paper is novel. Depth evaluation performance is calculated on a group of 23 skin images from ISIC archive dataset. The growing results of the comparative projected penetration verify correctness of the projected 3Dimensional reformation technique for easy emerging melanoma. In future work we can calculate penetration approximation accuracy using clinical data and apply new techniques to neutralize errors.

Amir Reza Sadri et al. (2017) proposed a method based on a fixed grid wavelet network (FGWN) for early recognition of melanoma from clinical images. The distinctiveness of this method can be explained in this way the (i) FGWN has no need of gradient algorithms for its structure. (ii) A new regressor selection technique construct FWGN know as D-optimality orthogonal matching pursuit (DOOMP), and (iii) Proposed FGWN is reliable to the entire CAD system. The DOOMP algorithm optimizes the system model estimation capability and also improves the model competence and strength. Then FWGN is used to construct CAD system to perform processing task: image enhancement, image segmentation, and image classification. The proposed study presents an algorithm that build a specific FGWN with three

layers, one inputs, output and one hidden layer, (a i/p × o/p FGWN). The construction of this mechanism is particularized by the subsequent phases. First, a linear map is used to normalize the input data [54].

Then after choosing a suitable mother wavelet, a wavelet lattice is formed. The big dimensions of this procedure are lessened and efficient wavelets are chosen. This is done through the projected regression based classification algorithm, D-optimality orthogonal matching pursuit (DOOMP). When the FGWN is built, the DOOMP algorithm is used to estimate the weights of the model and to optimize the network construction. The formation of wavelet framework gives WN formed by a regression equation which is linear in parameters. This regression is solved by the conventional orthogonal least squares (OLS) algorithm. Although OLS is a competent method, but the analytical charge of this method is too pricey. In this study, to conquer this issue, OMP (orthogonal matching pursuit) is useful to give the same results as OLS in a reduced amount of time. Furthermore, to optimize model competence and strength, they introduce a altered cost function formed on the D-optimisation. The dataset used in this work has 1039(528 as MM and 511 non melanoma) clinical images collected from other parts of the human body. These images are 24 bit RGB, with a pixel resolution of 485 × 716.

The CAD system proposed in this paper has five general stages. (i) Acquisition (ii) Preprocessing (iii) Segmentation (iv) Extraction and Selection of features (v) Image classification.

After the skin image is developed, image enhancement is done. Here to remove hair algorithm based on the suggested FGWN (3 × 1) is applied. Database has only 54 images (5.2%) having dark wide hairs that can be problem in segmentation process and so in classification stage. On these dataset of images, a novel double level hair exclusion process is applied. Firstly, the proposed FGWN detect hair pixel and then these pixel values are substituted by the median value of the neighboring local non-hair skin pixels (3 × 3 block with its center as hair pixel). In this paper we have also calculated accuracy and PSNR from DULL RAZOR method as well as our proposed system. The projected hair removal algorithm attains great performance (%Dull-Razor: DA= 89.8, PSNR=89.1, %proposed FGWN: DA=90.3, PSNR= 89.2).

The second step is segmentation. For segmentation of skin images, the R-G-B value of pixel for these images becomes inputs for FWGN (3 × 1). A novel method with an FGWN working on OLS algorithm is introduced for the skin lesions segmentation. This paper is also benefitted by the planned FGWN working on DOOMP algorithm to segment the border of the skin laceration. Segmentation with the help of DOOMP algorithm is quicker than ordinary least square method, but both implementations have identical accuracy. At last, the result of the model is segmented images.

After the segmentation stage, feature extraction is done. In order to illustrate and signify the color properties for pixels, auto-correlogram and color histogram are used. First, second, third and fourth-order color moments, peak value, and median value are calculated from color histogram in RGB, HSV, L a b space. Further for texture feature extraction GLCM and wavelet are used. To extract shape feature, area , perimeter, solidity etc. are calculated. In total 441 features (185 texture-related, 246 color-related, and 10 shape-related features) are dig out from the laceration and its border. To decrease Analytical time and enhance classification correctness, a descriptor selector is applied.

The feature selection algorithms has following steps: (i) ReliefF algorithm, which is very much immune to noise and powerful to feature exchanges (ii) FCBF (fast correlation-based filter) evaluates feature–feature correlations and feature–class and give an efficient method to grip feature error in feature selection (iii) FS (Fisher score) chooses descriptors that allocate alike values for the same category samples and different values for different category samples (iv) MRMR (minimum-redundancy-maximum-relevance) algorithm chooses features jointly distant far from one another, whereas they have good connection to the variables for classification and (v) chi-square set is worked as a check of freeness to evaluate whether the class label is free from a particular descriptor.

Final step is classification .In the classification experiments, 200 skin lesions dataset were divided into two discrete training and testing subsets. The data for training has 60 percent of 200 free images and the left over subset used as the testing data to evaluate classification for the desired descriptors. This study shows that ReliefF

feature selector offers satisfactory results (Mean of accuracy =87.14%, RR= 78.8**)**. Lastly, these selected descriptors are fed to a FGWN (10 × 1).

Classification is the ultimate step in the diagnosis method. The dig out features is utilized to detect whether the laceration is malignant or normal. The projected model is examined on 1039 clinical images and the estimation process is done having numerous metrics. This algorithm is compared with four methods that had been effectively used in lots of classification models: AWN, k-NN, MLP and the Support Vector Machine (SVM).

The MLP has 3-layered multilayer neurons with a buried layer, ten inputs and an output. In k-NN, K = 12 neighbors gives the most consistent results for numerous selection methods implemented in the MATLAB software. AWN parameters are initialized with some random values and then optimization is done by backpropagation technique. This approach can increase the computational time. Moreover, A SVM classifier based on kernel formed with Gaussian radial basis function is applied using MATLAB software.

The estimation process is done calculating four parameters accuracy, sensitivity, specificity and precision. All models and algorithms are applied on MATLAB 7.12. Proposed FWGN method gives satisfactory result compared to other classifiers which can be presented in terms of sensitivity= 92.61**,** Specificity= 91.00**,** Accuracy= 91.82**,** Precision= 91.40. Further computational time for each image from FWGN is also less than other technique.
Hair removal time = 63 seconds, Segmentation = 118 sec, Classification = 185 seconds. ROC (The Receiver Operating Characteristic) curve also tells the response of a classifier in form of AUC. Value of AUC for this system is 0.994.

In a nutshell, this method converts network in to a function of linear in the parameters rather than a gradient (SCG, CG etc.) algorithm. This method has easy arrangement, and fast running time to make it a good choice for designing CAD systems for skin cancer detection.

Adria Romero Lopez et al. (2017) proposed a new technique to classify lesion in skin medical images with the use of neural networks. This method gives a deep learning model to differentiate between cancerous and non cancerous skin images obtained from dermoscopy. Melanoma is a very lethal skin cancer and the clinical accuracy is very less to classify this type of cancer near about 65 to 80%. But we are using CAD then it can improve up to 50% more[55]. This work is introduced to determine melanoma or benign from a skin lesion with the help of deep learning.

This research uses convolution neural network architecture known as VGGNet (Very Deep Convolution. Network for Large-Scale Visual Recognition) developed by Visual Geometry Group of the University of Oxford. VGGNet16 architecture is shown in figure. In this work VGGNet16 is used as it is compatible and perform well with all datasets. It has 16 weight layers and 224x224 pixel RGB image is given as input layer of network. It has 5 convolution blocks with 2D convolution layer operation. ReLU (Rectified linear unit) is stimulation function and all buried layers are set with ReLU. Special pooling is done with special pooling or merging layer. The model is connected with classification block with three completely attached layers.

The final output layer is modified for binary classification. Activation function is also modified in to sigmoidal function. First of all image preprocessing is done to make image suitable for working. It is done in four further steps.

(A) Pixel values are normalized between [0,1].

(B) Cropping the image to aspect ratio.

(C) Resize the image to attain size of 224*224 pixels as prescribed.

(D) Data Augmentation is done to improve accuracy of model and to avoid over fitting. It is done as size rescaling, horizontal shift, horizontal flipping and zooming.

The VGGNet can be used in three different ways or in this work it is modeled as three different methods. In this research these three methods are used for the classification on Dermofit Image Library, Dermnet, International Symposium on Biomedical Imaging (lSBI) and ISIC dataset.

Method 1: In this method back propagation technique is used for classification. Model is loaded with random weights and then it is trained for multi epochs. After each epochs model learn features and if there is any error it again starts from back layer and then try to reduce the error in classification. This model has very good accuracy in smaller datasets. In this work it is also considered as a basic method for the comparison to the others.

Method 2: This model is trained on larger dataset like ImageNet. This model is initialized by weights from VGG16.For training a learning transfer method is used. This method involves training of data with fixed feature extractor like pre-trained ConvNet. This pre-trained model trains the new dataset and freezes all convolution blocks.

Method 3: This method also contains a learning transfer method. It retrains the top of the network as well as applies a fine tuning to the network with back propagation. In this work lower layers are freeze as they have generic features but training of top layers is done due to their great performance in extraction of more specific feature. This model is initialized with weights from ImageNet dataset.

Implementation Platform: To run this model, Keras a deep learning framework based on python environment has been used. Keras allows user to create their network followed by sequence which is linear stack of layers. Moreover its function in library permit user to build and transform network layers. It also provides update solution of daily challenges for deep learning researchers.

Datasets: In this work**,** Skin lesion analysis was done on ISIC dataset. Total number of images are 1279 (900 training images and 379 test images) both malignant and benign.

Results: In this work both training and testing is done on ISIC datasets. Responses are calculated in terms of loss, sensitivity accuracy, and precision for each method. Epochs for three methods are given in Table 3.11.

Table 3.11 Number of epochs

S. No.	Methods	Number of Epochs
1.	Method 1	20
2.	Method 2	50
3.	Method 3	20

For training dataset Method 2 has best value of terms Loss = 0.1203,Accuracy = 95.95% , Sensitivity = 0.9621 Precision = 0.9560.
For testing dataset method 3 gives outstanding performance. Loss = 0.4337, Accuracy = 81.33%, Sensitivity = 0.7866, Precision = 0.7974.

The proposed approach performs with great results - particularly, a value of sensitivity = 78.66% and a a value of precision =79.74%. They are considerably greater than the present state of this dataset (50.7% and 63.7%, correspondingly.

Nazia Hameed et al. (2016) review the methods used in computer assisted diagnosis system (CAD) and study present methods in different steps of these systems. Statistical data and outcome from the highest significant and fresh implementations are examined and described. The achievement of new work depend on distinct constraints like accuracy, segmentation, analytical time, dataset, color features, noise and hair removal technique, feature extraction and classification techniques etc. are compared. According to the study skin has the largest area of body having near about 20 foot square area. There are three layers in skin: Epidermis, Dermis and Hypodermis.

The skin has very important work to assist human body to control changes in temperature, defend the inside body parts from jerks and the ultraviolet rays, bacteria and allows the feelings of contact, warmth, and cold. Skin cancer is of widely two kinds: benign and malignant. Benign is common nevi but malignant is dangerous form of cancer and it is incurable if it penetrates in to dermis layer of skin. It can enter to the other organs of body if not diagnosed early. This survey found that approximately 100,000 new patients of malignant melanoma are diagnosed each year and roughly 2400 patients died due to this deadly disease.UK cancer research says that about 14,500 melanoma patients were diagnosed in the year 2013 and prediction

is that they will go high in coming year. Steps involve in a computer diagnose system is very common. They are Pre-processing, Segmentation, Feature extraction and Classification of image [56].

Pre-processing is very first and crucial step in CAD system in skin cancer detection. The key reason of this stage is to eliminate noise. Clinical images contain some dirty backgrounds such as brown or black frame, gel used in taking image, hairs in image, air bubbles, skin lines and blood vessels. These unwanted noise make a problem in segmentation, feature extraction and classification. This result in losing of accuracy and high computational complexity. So in this paper many techniques like resizing, hair removal, and contrast refinement, filtering is used and compared.

Abbas presented a morphological techniques and Derivative of Gaussian for hair detection as well as fast marching inpainting method for hair repairing on 100 images resulting 3.21 error rates. He proposed another technique morphological technique based on edge detection and Gaussian Filter with its first derivative and matching mechanism and for hair detection and fast marching inpainting method for hair repairing on 100 skin images giving 93.2% accuracy.

Maglogiannis and Delibasis suggested novel model for the hair finding and removal. Hair detection was done with Laplacian of Gaussian (LoG), bottom-hat and Logsobel operator. As hair repair technique interpolation was used. They did not use original images but they generate them with the artificial hairs with hard brown , black and diminished brown colors. They found accuracy= 92.68%, Sensitivity= 84.80% and Specificity = 88.36%.

Toossi suggested model for noise removal based on Wiener filter worked on grey scale. Canny edge detector with morphological processes is used to identify hairs. Afterwards repairing was done using MRCTIP (multi-resolution coherence transport in-painting) on 50 original images getting accuracy of 88.3%.

Zhou used Steger's algorithm and 2D second order Gaussian Partial Derivation as hair detection method and in-painting technique based on exemplar was used to patch-up hairs in 460 images.

Korjakowska uses HSL color space and detect hair with top-hat transform and unsharp masking. Repairing was done by Values calculated by neighborhood pixels on 50 images with accuracy of 88.7%.

Segmentation is to distinguish the lesion from unaffected skin. Accurate segmentation is a very hard and important task. According to the researchers, there is segmentation can be categorized as following: region based segmentation Threshold based segmentation, segmentation based on color, segmentation based on Discontinuity, segmentation based on Soft Computing. Soft computing is most emerging and precise technique for segmentation. Feature Extraction plays very important role in diagnose of melanoma. Features are of different type: Texture, color, shape, dermal, histogram etc. For color extraction, color spaces are used as L*u*v*, RGB, CIE L*a*b*, CIE.

HSL (Hue Saturation Luminance) and HSV (Hue Saturation Value). ABCDE descriptors consists of A= Asymmetry, B= Border irregularity, C= Color and D= Diameter and E= Evaluation. Like this Dermal features represent, skin bounciness, skin resistance, epidermis volume and bone densities. At last, standard deviation, Mean value, skewness entropy and kurtosis are calculated from histogram descriptors. After extracting features classifiers are used to find out melanoma from clinical images. Classification methods are of two types: Clinical and Computer aided. ABCDE rule, Menzies method, 7 point checklist are examples of clinical classification. Classification by CAD has a wide range. For CAD, ANN (Artificial neural networks), SVM (Support vector machine), KNN (k-nearest neighbors) and decision trees algorithms are mostly used. In all of them dataset is divided in to two parts one is to train the system and the other is for testing. After that mostly calculated parameters are Accuracy, Sensitivity, and Specificity to classify the infected images. It is very difficult to compare all the CAD techniques for classification because they all are distinct and depends upon number of images taken, computational time etc. According to survey SVM is highly used (47%) and neural network (21%). In this survey it is resulted that SVM is the well-known and its investigative accuracy ranges from 60%-97%. This paper has also highlighted three open source datasets for researchers.

PH2 Database: 200 images [80 atypical, 80 typical and 40 melanomas], DermIS and DermQuest, ISIC dataset. In a nutshell, there will be excellent methods and freely offered datasets for the new researchers in such a manner that they will be able to control this lethal disease.

J.C.Kavitha et al. (2016) introduced a method for melanoma classification using color and texture descriptor extraction. These extracted descriptors are used for classification of cancerous image with the help of SVM.

This work has three steps like the other image processing tasks. First is segmentation: Adaptive thresholding technique is used for segmentation. In Adaptive thresholding input is typically a grayscale image, in its easy execution; outputs are a binary image demonstrating segmentation. A threshold is evaluated for every pixel present in image dataset. Threshold value for each single pixel is evaluated with the help of interpolating the results of the sub images. Second step is feature extraction. It is divided in to two parts: Texture and color descriptors extraction. The color descriptors evaluation is done with the help of histogram method using color space like RGB, HSV and OPP. Color is very important feature in detection of cancerous image. This is due to the fact that color of effected area is changed. An R-G-B color model is a preservative color model. A specific R-G-B color model has three chromaticity: Red, Green, and Blue with added primary colors, that can create any chromaticity with the triangle of colors as defined by R-G-B model.. The disadvantage of RGB color space is its non uniformity, depends upon image acquisition. So to reform the drawbacks different color models are used. OPP has strengthened edges [57].

HSV has three features 1. Hue: it signifies color of color space, (from 0 degree to 360 degrees). Saturation is the quantity of gray shade in given color, (0 to 100 %). Dropping the saturation tending to zero is to put further faded gray effect. From these color spaces 3D histogram is formed generating 8*8*8= 512 color bin. Histogram is well known method for color extraction. In image processing, the histogram is normally referred as a graph of the pixel intensity values and their frequencies. Histogram is a chart which shows the number of pixels in an image v/s every intensity value in given image. In this way color feature vectors are formed and ready to go to

classifier. Texture feature have very important role in feature extraction and classification. Texture is a measure of the inconsistency of the intensity of a surface, counting properties such as roughness or smoothness, hardness and regularity. The three principal methods are set to define texture are statistical, structural and spectral. Here in this work statistical method is used for texture descriptor evaluation. The statistical texture extraction has three methods: First order, second order and higher order statistics. Gray Level Co-occurrence Matrix (GLCM) is a technique to evaluate texture features by second order statistics. GLCM is evaluated by the connection between two adjacent pixels, a neighbor pixel and a reference pixel. A GLCM is defined as a matrix with the number of columns and rows equivalent to the count of gray levels in the given image. The different eight textural features out of 14 features some of them as correlation , homogeneity, energy, entropy, dissimilarity, maximum probability, contrast and inverse difference moment are calculated with GLCM matrix.

These 8 features are given to the input to classifier like color features. The classifier is SVM-RBF which is applied on 150 images. 150 images are divided in to training and testing datasets 100 for training and 50 for testing the system. Support vector machines are based on supervised learning algorithms. It uses a different kind of learning model applicable for the purpose of classification. Classifiers performance is tested on three factors Accuracy, Sensitivity and Specificity. This work has proved that if color-texture features are taken together for classification, we will get enhanced accuracy. Classification with GLCM: Accuracy =76%, Classification with RGB: Accuracy = 92, Classification with HSV: Accuracy = 92%, Classification with OPP: Accuracy = 89%. But Classification with RGB and GLCM: Accuracy = 93.1% as well as highest sensitivity = 88.2%.

Lei Bi et al. (2016) introduced a new method of melanoma detection. In this method, MLR (multi-scale lesion-biased representation) and JRC (joint reverse classification) are introduced to classify cancerous images from dermoscopy images. MLR has been used to adequately characterize skin lesions and JRC is used to classify malignant melanoma and benign lacerations with smallest amount of sampling errors. The work is classified in to three steps: Hair removal, MLR, JRC[58].

In first step hair removal and other artifacts are removed from the images. For hair detection, multiple hair formats with three directions (0 degree, 45 degree and 90 degree) are used. Identified hair pixels were replaced by pixels without hair extracted from near pixels.

Second step is to create histograms to present skin lesion accurately. So in segmented area, a border box is created to summarize the skin laceration. Here in this work, twelve directions (Ranging from 0 degree to 330 degree with an increment of 30 degree) and 4 values of Gaussian blur filter with values as {0, 1, 2, 4} are adopted. Then for feature detection, Scale invariant feature transform (SIFT) features having good discriminative ability is used. To extract SIFT feature HSV color model is used. HSV color model on the laceration area results in total of 384 dimensions with the blotch size as 24×24. Extracting SIFT descriptors from dissimilar images, the visual word *w* was generated by K-means clustering. Then multiple histograms for each image are generated based on similarity of visual words. To represent one image 48 histograms are produced. The BoW Coding is used to construct histograms.

Third step is to classify the images and that is done with JRC. Histograms are collected in to a single set. Then this set is divided in to two sets (D_1 and D_2). The classifier is trained on D_1 and Q (Unlabelled histograms from MLR).A Linear kernel is selected for better accuracy and number of iterations was set to 5 having good computational efficiency as well as robustness.

To accomplish the work The PH2 public dataset with 200 dermoscopy images (160 non-cancerous and 40 cancerous) is adopted. Images in the dataset are 768×560 pixel resolution and 8-bit RGB color images.

As a result 4 parameters are calculated and compared to the other similar recent work. Accuracy = 92.1%, Sensitivity = 88%, Specificity = 93.3%, BAC = 90.31%. In this way this method acquires high accuracy in the classification of melanoma with clinical images in comparison to the other methods with same art.

Lequan Yu et al. (2016) proposed a novel method to find out malignant melanoma from dermoscopic images. In this method to meet the challenges, an extremely deep

convolutional neural network (CNNs) for melanoma recognition is introduced. This method was also analyzed with other existing methods whether small-level manually-fed descriptors or CNNs with depthless models (very few number of layers). But this technique significantly deeper network (more than 50 layers) has obtained more affluent and more discriminative features for more precise detection [59]. To work deeper models precisely, a set of arrangements was prepared to make sure efficient training or learning for less training data. The over fitting and degradation problems are very common when a network includes deep structure. So residual learning is applied to cope with these demerits. This method can make certain that this network will perform great with deeper network. Then, a fully convolutional residual network (FCRN) was built for precise segmentation of skin laceration, and a multi-scale related instruction integration plan was added to enhance the capacity. Finally, a two-stage framework is organized: The projected FCRN (Segmentation) and other deeper residual models (Classification). The proposed framework is broadly trained and tested on Skin Lesion Analysis towards Melanoma Detection Challenge dataset (ISBI 2016).

Recently convolutional neural networks (CNN) are authenticated to be a boon to the researchers for skin cancer detection. But, a good result is not that easy as it seems to be. If we evaluate with normal image task troubles, the learning data of clinical methods is generally very restricted. That’s why it is hard to efficiently train deeper networks with a huge amount of variables or parameters. Large amount of parameters increase system complexity too. Another confront is the difference in their own interclass. Medical image analysis work is generally much minor than that in different image processing jobs (for example interclass difference between tree and bike is much larger than the interclass difference between melanoma and non-melanoma lesions).

The proposed method can be understood in three steps: 1) a very deeper and convolutional network (FCRN) with the incorporation of a multi-scale contextual information integration scheme for precise skin lesion segmentation is introduced. This multi-scale contextual information integration scheme is added to enhance the capacity of the network. 2) The performance of networks with different depths are compared and it has been confirmed that very deep and effectively trained CNNs can

be used to solve difficult medical image investigation jobs, even with limited learning data.

FCRN (Fully convolutional residual network) for lesion segmentation is based on residual blocks having input and output both as an image and an equal shaped estimated score mask. FCRN can make pixel- wise predictions that are highly recommended in segmentation. So while testing we can easily get mask for segmentation with a single forward propagation. Each single pixel is considered to be an independent training sample due to pixel-wise operation. Therefore, the quantity of same learning samples is enhanced to a great extent. This is supportive to train extremely deep neural networks with a huge amount of variables and parameters with less training data. When a layer in FCRN layer increases or becomes deeper, the size of interested field becomes larger and the descriptor maps are more able to capture global and relative descriptors of skin lacerations. So integrate multi-scale appropriate instruction is proposed in FCRN. Particularly, the many skin laceration estimated maps are generated by introducing dissimilar stages of descriptors in FCRN, and then combine these estimated maps with an adding technique by the subsequent deconvolutional layers.

Consequently, the calculated prediction maps train both global and local descriptors of skin cancer. So calculation becomes more precise and correct. Proposed FCRN network consists of 16 blocks in down-sampling way. Every block contains one 3*3 convolutional layer two 1*1 convolutional layers, 3 batch stabilization layers and 3 layers of ReLU. The network results in the ultimate estimated map with the equal size of the input image by summing a 8*up-sampling deconvolutional layer on topmost of the merged 8-pixel stride estimated map. So, the skin laceration probability matrix map integrating multi scale relative descriptors are created after the Softmax layer. In the above summing scheme, pixel-wise fusions are used for addition. After getting the skin laceration matrix probability map, the last skin lesion filters are created by assigning a threshold (0.5).

Training process of FCRN is done by cropping sub image from every image in smallest rectangle with lesion region. Then another cropping is done with same

dimensions. Total pixels on these clipped sub-images are used as sample data to make FCRN learn. Every pixel is considered to be training sample.

For Skin cancer classification, a deeper network is constructed depending upon the segmentation performance. The construction of the model of the proposed FCRN has an pooling layer of 7*7 and 16th blocks to take out the global deep residual features. Two classifiers SVM (support vector machine) and Softmax are used to get two predictions and then by averaging they give final results. Both the classifier is trained separately in a back-to-back way with the proposed residual network.

Evaluation is performed on ISBI 2016 (a public challenge dataset of Skin Lesion Analysis towards Melanoma Detection). This dataset is collected from the International Skin Imaging Collaboration (ISIC) Archive1, well known database. In this work, 900 among total images as training samples and 350 as testing samples are taken. This work was implemented with C++ and Matlab software. Stochastic gradient descent (SGD) method was adopted to learn the network.

For the segmentation evaluation the work has calculated SE (Sensitivity), AC (Accuracy), SP (Specificity), JA (Jaccard index) and DI (Dice coefficient). Segmentation results tell us that there is a limit between quantity of neural network layers and neural network performance for each application. FCRN of 50 layers gives outstanding results.
FCRN-50, AC = 0.949, DI = 0.897, JA = 0.829, SE = 0.911, SP = 0.957 whereas FCRN of 101 gives worst results.

Results on the multi-scale contextual integration scheme are also compared in which FCRN of 8 layer has got very good results. FCRN8 AC =0.949, DI =0.897, JA =0.829, SE = 0.911, SP = 0.957. Moreover Segmentation results on ISBI 2016 were very good. In this work top 10 work has been compared for the result the results got AC =0.953, DI =0.910, JA = 0.843, SE =0.910, SP =0.965.

Result for different classifiers is also a milestone in this work. If only Softmax is used then AUC = 0.790 and SP= 0.934 that is highest but if fusion is considered (SVM + Softmax) AC= 0.855, AP=0.624 and SE=0.547 higher than other two classifier.

In a nutshell, this method mainly deals two techniques: segmentation and classification. The two steps are connected to form an automatic structure. Extremely deeper CNNs can make features with great categorization strength, and so will progress in the achievement of both technique segmentation as well as classification in comparison to much shallower networks. Additionally a new FCRN adding a multi-scale related instruction integration method was formed for precise skin cancer segmentation. Proposed method was learned, trained and tested on ISBI 2016 (challenge dataset of Skin Lesion Analysis towards Melanoma Detection).

Cristofer Marín et al. (2015) propose software which can detect melanoma in early stage. Since malignant melanoma is hard nut to crack, its early detection is very much needed. The detection of melanoma is very rare in rural or remote areas due to lack of money and other means. This work introduces low cost software to detect melanoma from dermoscopic images. This is based on ABCDE rule, image processing and ANN. Melanoma is caused due to abnormal tissues of skin. It first lies in epidermis but if it is not seriously taken it can go to the other body parts and then it is impossible to cure it. There are lots of symptoms of malignant melanoma. Basically melanoma is of two types malignant and benign. Malignant melanoma is deadliest form of skin cancer. It can happen spontaneously or in form of changing moles on skin. This change can be of shape, color or texture. First these types of cancers are detected by dermatologist by ABCDE rule that is very accurate and popular among doctors. It is a great tool for melanoma detection. This work corresponds to software based on ABCDE rule followed by image recognition and artificial neural network. Here three layers of ANN is used .At input data is given and output tells us whether it is cancerous or not. The hidden layers are trained by adjusting the weights of neural network [60].

First of all the dermoscopic images are taken in which both melanoma and non melanoma images are present. Then the images are cleaned like hair removal, noise reduction and segmentation. Then it is given to the ANN for training and after training it is tested for the results. The software used two tools “Trainer” and “Detector”. This is developed on MATLAB Version R 2013B. In ANN, programming is not done very first but system is trained or learned through model and then it is validated.

This work contains six steps.

Step 1: Uploading of Images in ANN Trainer- images of good resolution and out of noise is captured at distance of 8 cm. the images are also free from brightness and shadows for good accuracy. 50% of malignant melanoma and 50% of non melanoma images are uploaded to justify the classification.

Step 2: Selection of Infected Part in ANN Trainer - Infected part is selected by rectangle from whole image to reduce interference and hair on the skin. The nevus is then separated from the original image.

Step 3: Conversion from RGB to Binary Format in ANN trainer –The image is changed in to grayscale then in binary format. So that it can be converted in to matrices. Now image can be processed with no trouble and smaller in size.

Step 4: Training of ANN – In this step NN is trained with the images. Features from the images go as input to ANN and then they are stored as variable and then processed image are kept in another variable. Then a model of neural network is created and stored in a file.

Step 5: Validation of ANN- In this step validation of the stored network or model is done to confirm the accuracy.
If training is not done properly it is retrained and then it is again validated. The ANN trainer is shown in the Figure 3.1.

Step 6: ANN Detector- In this step the trained and validated model of ANN is tested on the images to calculate accuracy that lies between 0 to 100%. The ANN detector is also shown in the Figure 3.2.

Table 3.12 Comparison of tests

Number of tests	No of images	Sensibility	Sensitivity
First test	48 nevi	76.06%	87.18%
Second test	30 nevi	76.75%	87.74%
Third Test	50 nevi	76.89%	87.82%

These results also show in Table 3.12 that as numbers of images are increased performance of software is also increased. Here is a graph between confidence level and number of images which shows that increasing number of image performance of software is also increased.

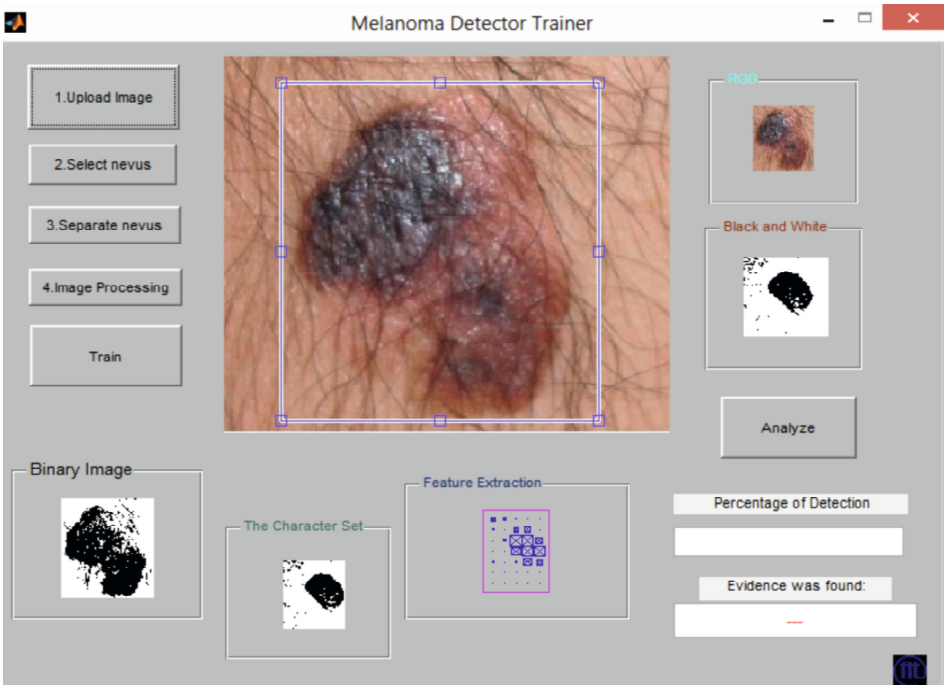


Fig. 3.1 Melanoma Detector Trainer

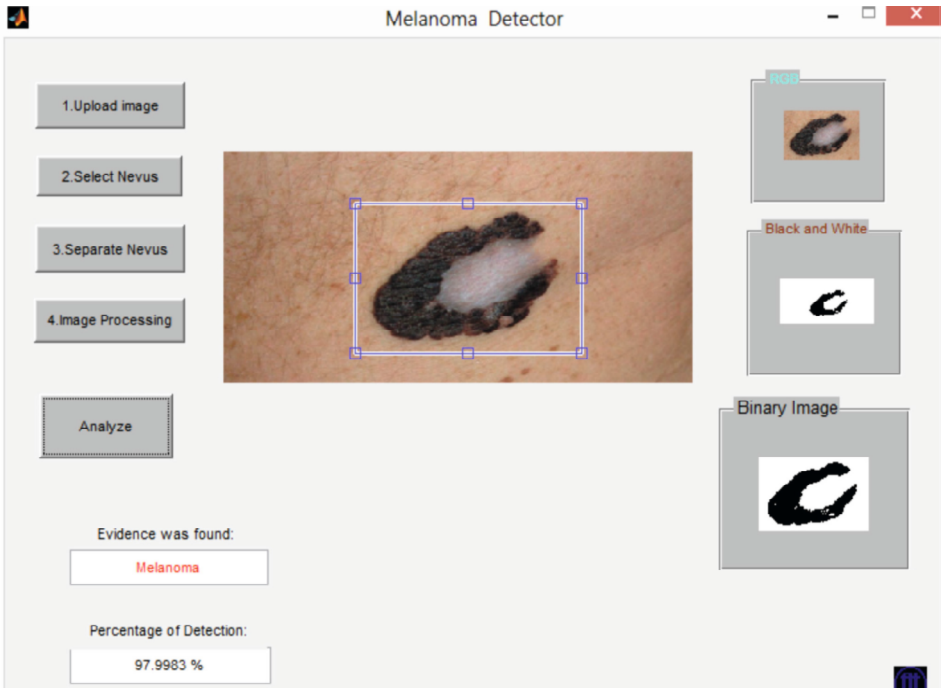


Fig. 3.2 Melanoma Detector

Omar Abuzaghleh et al. (2015) presents a new technique for melanoma detection and skin burns in real time systems. Since malignant melanoma is very deadly skin cancer, author proposes a system on cell phone which has two parts. First one is to check people from sun burn. A unique equation is introduced for the calculation of time to burn the skin. Second is CAD based melanoma detection in which all the image processing is done starting from image acquisition to classification [61]. This will apply on moles and will examine whether moles are benign or malignant.

In this way this work can be categorized in two ways:

1. An alert time for skin burn based on equation model.

2. A Dermoscopic method to analyze benign and malignant melanoma.

Real Time Alert System: Due to sunburn or overexposing to the skin cancer can take place. Repeated sunburn increases the risk of cancer. Sun exposure can make skin dry, wrinkled, create dark spots and all these symptoms can cause melanoma. So the right time that a skin should be exposed to the sun is very essential. To overcome this real time model is created for calculation of time to expose with sunlight. An equation has been derived to calculate TTSB (Time to Skin burn). This equation is dependent on UV light and other atmospheric conditions. This model has different result for different type of skin. This model is based on mobile phones. So GPS in phone tells that UV and altitude of the user and other details like type of skin, cloudy weather, sandy environment ,shady environment etc. are manually fed. The Table 3.13 below shows UV exposed time according to the skin type. This model has been validated with the data given by National Weather Service Forecast. All TTSB values go correct with the span of data given by National Weather Service Forecast.

Table 3.13 Time to burn skin according to skin type at UV index

Skin Type	Time to burn skin at UV index 1 in minutes
1	67
2	100
3	200
4	300
5	400
6	500

Dermoscopic Analysis of Image: The analysis is based on early detection of melanoma. This is based on smart phone operations. In this work moles are classified in to three groups: benign, atypical and melanoma with the help of two classifiers. The user will click the photo of lesion and this lesion will be processed to classify it. Image processing and classification is done on server end so internet is needed for that. This app does not contain very much processing on device side.
The work can be explained in these steps.

Image Acquisition: This is a very first step of image processing. Here image is captured very carefully so that image preprocessing work like hair removal, noise removal, blurring all tasks can be done very easily and with good accuracy. For this purpose here 5s apple phone is used having 8 megapixel camera. A dermoscopic device is also attached with iPhone to take enhanced picture for the convenience.

Preprocessing: In this step image is made clear without any hair or lumps. This is very important task as all accuracy of segmentation depends upon this task. If hair remains in the image it will lead to the error. For this purpose a bank of 84 filters are used. These filters are output of the subtraction of Gaussian filter to isotropic filter. After removal of hair with mask image is again reconstructed.

Segmentation: Before feature extraction segmentation is very much needed. It separates the lesion part from the whole image. This work is done in 10 steps.
Step 1: The RGB color image is converted in to grayscale image.
Step 2: Then a two dimensional Gaussian filter having size 9*9 and sigma = 0.5, is created. The image is filtered from this filter.
Step 3: A global threshold technique named as Otsu is applied. Here intensity image is converted in to binary image,
Step 4: In this step white corners in the image is removed with the help of special mask. Every white pixel in corner is replaced by black pixel.
Step 5: Now the irregular edges due to threshold are smoothened with the help of morphological operations. For this purpose a method like radial breakdown using periodic lines is applied and a CD like structure is generated.
Step 6: After that Erosion followed by dilution is done.
Step 7: The holes in binary images are filled by an algorithm.

Step 8: An active contour algorithm is applied for the segmentation of 2D gray image using Sparse-Field level-set method. Output of the image is binary now having background black and foreground white.

Step 9: In this method all small objects are removed. It is done by area opening in which all the small objects are determined by the area and objects only having pixels less than 50 is eliminated.

Step 10: At last the disk structure that has been created in earlier step is used to execute open and close operations. After that the image is again masked for the preservation of corners.

Feature Extraction: Features are the parameter that exhibits the property of image and if they are perfectly extracted classification accuracy is very high. In this work five different feature sets with four special features sets are calculated.

1. **2-Dimensional FFT (Fast Fourier Transform):** Here 4 factors are calculated.

(A) Cross correlation of 1st coefficient for 1st 20 rows and column of FFT2.

(B) First coefficient of FFT2.

(C) The Standard deviation of firs1st t 20 rows and column of FFT2.

(D) The mean of 1st twenty rows and column of FFT2.

2. **2-D-Discrete Cosine Transform:** Four parameters are calculated.

(A) Cross correlation 1st coefficient of 1st 20 rows and column of DCT2.

(B) First coefficient of DCT2.

(C) The mean of 1st twenty rows and column of DCT2.

(D) The Standard deviation of 1st twenty rows and column of DCT2.

3. **Difficulty Descriptor Set:** This contains 3 features.

(A) Mean of ROI intensity value.

(B) Median of ROI intensity value.

(C) Mode of ROI intensity value.

4. **Color Descriptor Group:** Color descriptor also plays important role in extraction of information from image. Three color channels R, G, B is used here and their 3D

histogram is created. 3D histogram is converted in to 2D histogram and 64 bins are generated.

5. **Pigment Network feature Set:** Pigments are another source of melanoma**.** They are generated by melanocytes in basel cell. For a cancerous skin they look like a net of brown thin streaks upon brown border. Extraction of pigmented network is done by segmentation of lesion from whole image using 12 directional filters. Here five parameters are calculated to define the extraction of pigmented network.

A: Stained Area vs. Laceration Area Ratio: This is a ratio between pigment area and lesion area.

B: Stained Area vs. Occupied Net Area Ratio (f2): It compares pigmented area with totally occupied system area.

C: Total Quantity of Holes in The Stained Network (f3): This parameter evaluates the total quantity of holes in stained network.

D: Total Quantity of Holes in The Stained Network vs Laceration Area Ratio (f4): This is the ratio between numbers of holes with lesion area.

E: Total Quantity of Holes in The Stained Network vs. Occupied Net Area Ratio (f5): This parameter calculates ratio of number of holes with filled network area.

6. **Laceration Shape Feature:** to display the lesion shape feature in a good manner a best fit eclipse is used. It is a base for calculation of irregularity.

7. **Laceration Location Feature:** lesion location is evaluated by angle between lesion and major axis of eclipse.

8. **Laceration Border Feature:** This distance plot is used to capture the oscillation and the angle of movement of the laceration margin.

9. **Laceration Strength Design Feature:** lesion intensity pattern is calculated by average gray intensity.

10. **Laceration Deviation Design Feature:** the deviation of pattern is calculated by pixel gradient method.

Classification: In this work three classifiers A, B, C are used.

1. **First Classifier (Classifier A):** This classifier has one level. This classifies image in three categories atypical melanoma, benign and malignant melanoma.
2. **Second Classifier (Classifier B):** This classifier has two levels. Level one classifies abnormal lesion and level two classifies malignant melanoma.
3. **Third Classifier (Classifier C):** This classifier has two levels. Level one classifies melanoma and level two classifies atypical or abnormal images.

Data Base and Experimental Results: All the classifiers used are SVM with radial basis function kernel. For this work PH2 database is taken which has 200 images in which 40 melanoma, 80 benign and 80 are a typical. These images are having resolution of 768*560 with 8 bit RGB format. The planned work compares three type of classification. Among them classifier B perform very well and results can be understood from the following Table 3.14.

Table 3.14 Comparison of classifiers

Type of Classifiers	Accuracy to Classify Benign images (%)	Accuracy to Classify Atypical images (%)	Accuracy to Classify Melanoma images (%)
Classifier A	93.5	90.4	94.3
Classifier B	96.3	95.7	97.5
Classifier C	88.6	83.1	100

Deepika Singh et al. (2014) presents different diagnostic techniques called as Seven Point checklist, Menzies scale method, Pattern Analysis method and (ABCD) rule based method for early detection of skin cancer. A thorough study of different edge finding in image segmentation task and other segmentation technique are proposed. Analysis is performed on number of dermoscopic images and found that preprocessing by Otsu method (Thresholding) and canny edge detector and gives the finest result. In clinical diagnosis approach Menzies Method has important role. It has nine positive features and two negative features. It says if there is any negative feature it is not a melanoma but if it has one or more positive feature it is melanoma skin [62]. It is discussed in Table 3.15 and 3.16.

Table 3.15 Menzies method properties

Negative features (Non Malignant)	Positive features (Malignant)
Symmetry of lesion (Across all axes symmetry)	Blue and Whitish mole (An uneven and shapeless area of convergent blue pigmentation)
Presence of single color (Should be one color)	Multiple Brown dots
	Pseudo pods (Crimped projections at edges)
	Finger designed wing at the border of a laceration, irregularly spread around the laceration.
	wound like white asymmetrical extension
	Black spots or blob
	Multiple 5·6 colors (Dark Brown, Gray, Blue, Tan Black and Red).
	many blue· gray spots (black or gray spots)
	Expanded grid (Expanses of wide lace).

Second method is seven point checklists that have a scale from 1 to 7 points. For major melanoma “2” points, for benign “1” point and for malignant skin “3” or more than that is required.

Table 3.16 Criteria of 7 point check list

Criteria	Points
[Major criteria] A characteristic net pigmentation A characteristic model Blue and white shield	Two Two Two
[Minor criteria] uneven strips Uneven coloring uneven acnes or blobs Parts of Reversion	one one one one
Score	If total<=3 then it is non -melanoma, If total >=3 then it is melanoma

The third one is TDS (Total dermoscopic value) score based on ABCD rule. It is represented by a formula

$$[TDS = 1.3*A + 0.1*B + 0.5 * C + 0.5*D],$$

where A implies asymmetry, B implies border, C implies color and D implies diameter.

If TDS > 5.45 Then it is malignant melanoma. The parameters like specificity and sensitivity are used to calculate the accurateness of method.

Specificity= (True Negative)/ (True Negative) + (False Positive)

Sensitivity= (True Positive)/ (True Positive) + (False Negative)

Further this study talks about the CAD diagnosis system in which there are four basic steps: Image acquisition, preprocessing, segmentation and classification.

Image acquisition: Digital image of tissues are obtained by cameras, scanner etc.

Image preprocessing: it is very important step. Here image is made to be consistent on its characteristics. Numerous tasks come under this category. In this work following hierarchy has been followed for preprocessing task.

1. Hair removal by median filter.
2. Conversion from RGB to grayscale.
3. Noise removal.
4. De blurring.
5. Contrast enhancement.
6. Conversion in to binary (by threshold).
7. Edge detection (using canny method).

Edge detection has been specified in this work. There are a variety of methods to execute edge finding and they are broadly categorized in Gradient based edge detection and Laplace based edge finding. Canny gives the best result among the entire edge recognition algorithm because it enhances edge finding in noisy situation and also improves S/N ratio.

Image Segmentation: Used for better detection of objects and for getting appropriate features to differentiate from different items to the border. Segmentation divides an

image into its essential objects. In this work different techniques for segmentation has been discussed and compared.

Segmentation Based on Region: This technique divides an image into areas according to characteristics such as shapes, color or texture etc.

Watershed Transform Segmentation: To separate near about touching or exactly touching objects in an image is very hard nut to crack in image dealing tasks. The watershed transform is a solution to this difficulty. It is used with distance transform by a function *bwdist.*

Otsu Segmentation Algorithm performs image thresholding based on clustering. In this model, it is presumed that image has two types of pixel or it has bimodal histogram and then computation of best threshold sorting for two modules is done. In this method, a threshold which minimizes the interclass variance is found out. Interclass variance is defined as biased addition of variances of two groups.
In a nutshell, this work concludes that ABCD rule is widely and frequently adopted and gives promising results. Canny edge detection is a very good method giving great results. Moreover if canny edge algorithm is applied with Otsu segmentation algorithm gives great results.

Miroslav Benco et al. (2014) have researched the arrangement of color with texture features in texture classification. A vigorous descriptor is created for the extraction of color- texture descriptors. Gabor filters and GLCM (grey level co-occurrence matrix) are applied for the texture feature extraction in experiments. SVM (support vector machine) is applied for the texture classification. In the first approach, GLCM is applied with the color channels (HSV and RGB) in the color image getting huge increase of precision for color texture extraction by GLCM. So, the GLCM is applied directly on the color image for calculating probability matrices. In this work, thirteen directions neighborhood system is planned and matrix probability equations are presented. This method is recognized as CLCM (color-level co-occurrence probability matrix), an influential method for color texture classification [63].

Texture feature is very powerful for CBIR systems .texture feature can be solved with gray scale values. But color feature gives more precise results. GLCM is second order statistical method to estimate image properties. It depends upon reference pixel and its neighborhood pixel (pair of pixels). They are represented as joint probability matrices between pair of pixels at "d" distance apart with some direction (θ).

The Gabor filters (GF) acquire a group of segmented images which signify a definite measurement and direction element of the unique texture for image.

In first work, texture features are extracted from color images. Color image representation (RGB) which is three dimensional are analyzed with 2D matrix. So the feature vectors are combined as –

$$FV = [(C1), (C2), (C3)]$$

where $C1$, $C2$, $C3$ are 2D matrix for particular color channel (HSV, RGB).

In RGB space it is named as CGLCM-rgb and for HSV it is named as CGLCM-hsv.

In the next experiment, GLCM matrices are extracted directly on color images and modified to CLCM. In color image, a pixel on its position is a vector, which is represented by three values. These three values correspond to the individual color in color spaces and make a three-dimensional representation of the pixel. 4 simple GLCM equations are modified in to 13 new equations to analyze the color image as a 3D CTF representation. All neighborhood pixels has distance =1 and orientation from 0 degree to 135 degree.

Classification and evaluation was done with SVM very well-known method and widely used. In this study, SVM classifier with an RBF (radial basis function kernel) and a 5-fold cross validation method created on LIBSVM (library for support vector machines) was applied. Best model parameters are obtained by PSO (particle swarm optimization) method. Evaluation was done by calculation F1 that is combination of "Precision" and "Recall".

$$F_1 = 2PR/(P+R)$$

where P = Number of correctly detected textures /(Number of correctly detected textures + Number of incorrectly extracted textures) and R = Number of correctly detected textures /(Number of correctly detected textures + Number of textures not extracted) and F is the quantity of incorrectly extracted textures ,C is the quantity of correctly perceived textures and M is the quantity of textures not extracted. If P and R are both high only then F1 will be high.

For experiments evaluation two databases the Vistex database and Outex TC-00013 database (MIT Mediam Lab) were used. From Vistex database 32 images are considered 16 images for learning and 16 for testing with resolution of 64*64). In Outex TC_00013 database 1360 color images of 128*128 resolutions are used. The greatest response for GLCM (grey-level texture descriptor) was derived by Gabor Filter (GF), getting F1 near about 80% for both databases. The maximum accuracy for color- texture recovery was obtained by CLCM.

Application of CLCM-RGB gives P= 93, 27, R =92, 65 F1 =92, 42 for Outex TC_00013 database and CLCM-HSV gives P =92, 57, R = 91, 52, F1 = 90, 97 for Vistex database**.** The investigational results verify that the projected CLCM technique got an F1 value just about 40% superior to the simple GLCM technique, representing greater than 90% accomplishment in color- texture extraction.

Catarina Barata et al. (2013) addresses two separate technique for melanoma detection first is global method and other is local method. Color and texture feature are also tested to verify the classification of melanoma [64].

Global Method for Melanoma Classification is defined in three steps: segmentation, color or texture feature extraction and classification.

Segmentation is done by adaptive thresholding in which first histogram computation is done. After that peak is detected and the next and final step is threshold estimation and segmented image is created.

Feature Extraction has done by extracting color descriptor only, texture descriptor only and by both of them.

Texture Descriptor Extraction is done by using two gradient histogram. First RGB image is converted in to gray level image. Image gradient is calculated by Gaussian filter and gradient vector for every point is calculated by Sobel operator. Then the magnitude and orientation of histogram is calculated. Melanoma and non melanoma has different value of magnitude and orientation of histogram.

Color Feature Extraction includes six color spaces (HSV, HIS, CIE, La*b*, L*uv, RGB). Color distribution is characterized with a set of three color histogram. Here discrepancy between melanoma and non melanoma features is clearer.

Global System for Lesion Classification consists of statistical classifier used on image data base (PH2 database). 3 classifiers are used in this study: SVM classifier, AdaBoost classifier and kNN classifier. Dataset has 176 dermoscopic images that have 25 melanomas and 151 non melanomas. Every group of descriptor classifiers are first trained and then tested for great performance. Value of parameters in feature extraction as well as in classification has been changed for performance evaluation of classifiers. Number of bins in histogram is changed for feature extraction variation. For Knn classifier number of neighbors (k) and distance (dist) are changed. Three different distances have been taken: Kullback–Leibler, Kolmogorov and Euclidean. The best performance for Knn classifier is SE = 96% and SP = 79% with L*uv color model and SE = 100% and SP = 72% with opp.

For SVM classifier, two different kernels are used for testing: linear and Gaussian radial basis function (RBF). Best results are obtained from RBF-SVM by combining gradient magnitude in texture feature and opp. Color model with SE = 92% and SP = 72%.

AdaBoost classifier can train a classifier from weak classifiers. It removes the features that do not take part to develop classifier performance. This work also shows that best results are achieved with small number of features.

In this work ,weak classifiers used for training: $W \in \{2, 100\}$. This gives the best result with HSV and HSI color model: SE = 96% and SP = 80%. Moreover with single text feature (gradient magnitude) the best results are: SE = 96%, SP = 59%.This study also shows that if we vary value of W classifier performance will be changed and if two features are taken classifier selects bins from color histogram only since color feature has more discriminative information.

Local Method for Melanoma Detection: This is presented by BoF (Bag of features). BoF represents them by image patches. At first a set of key points are defined in

image. Then these points are defined by feature vectors that contain local information of image. Key points are nodes of regular size of grid in image. Size and shape of image mask is equal to the size of lattice. Each dermoscopic image mask is defined with color- texture feature. Color histogram and gradient histograms are used to characterize patches. The steps are same as in global classification system. First we will evaluate features with same database. Algorithms have been implemented using stratified tenfold cross validation. Training of classifiers is done with feature vectors. First set of features for training is taken then by K-means algorithm, feature sets are approximated by prototype (visual words). After training, all feature vectors are classified in nearest prototype and each feature vector is labeled. Histogram counts the occurrence of prototype for each of the training images. Histogram has visual words with bins or rather it is a descriptor vector that defines the image. Feature extraction and classification depends on number of parameters. These parameters are grid size, quantity of histogram baskets and the quantity of prototype for feature extraction. For classification, kNN classifier is used considering three distances (Kullback–Leibler, Kolmogorov and Euclidean). In classification numbers of neighbors are varied. In this way 44928 configurations are produced and ten classifiers for training. BOF with texture feature gives best result as SP = 45% and SE = 95%. Color features give better result SP = 75% and SE = 100%. The texture with color feature gives SP = 79% and SE = 98%. In these classifiers best distance for features is Kullback–Leibler divergence. In the figure, it is shown how value of SP and SE vary with best combination of texture and color features with different values of visual words k. This is evident that ‘k’ has significant role in the performance of classifiers.

If we compare global and local classification systems, both achieve good results but local features with BoF produce good output. In every case color feature work superior to texture. Moreover results show that for computation local features are slower than global features.

In a nutshell, we can conclude that performance of color feature is better than texture alone (SE = 93% and SP = 85%). Best results from global system produced SE = 96% and SP = 80% while best results from local method gives SE = 100, SP = 75%.

S. Binu Sathiya et al. (2014) presents a review paper on technology and methods to detect early melanoma. Since melanoma is a deadly cancer, it has been a center of study for all researchers. Here in this paper author has tried to summarize all techniques used in the earlier time. Authors have taken 15 papers and represent a nutshell in her paper. According to the American cancer society melanoma is increasing very fast and it has a very toxic form. If it is treated early then life survival rate can be good otherwise after a certain period of time it is deadly. It is very dangerous because it spread in to the dermis from epidermis and then it can also spread in to other part of the body through the lymph [65].

It can be detected by dermoscopic methods like ABCDE method.

A for asymmetry: If the lesion is not symmetrical then it is a symptom of melanoma.

B for border: If lesion border is disturbed then it is again a symptom of melanoma.

C for color: Change in color also takes to the cancer.

D for diameter: Diameter greater than 6 mm can be melanoma.

E for evolution: If texture of mole is changing with respect to time then it can be melanoma.

Like ABCDE there are lots of dermoscopic methods by which melanoma can be detected but their accuracy is not very good. So CAD operated systems for melanoma detection is in great use. Images from the patients are diagnosed by computer aided software and accuracy can be improved. In this study author has collected such researches for the future researches. It has been described in the Table 3.17.

Gerald Schaefer et al. (2013) propose a unique technique for melanoma detection with multiple classifier system. This work contains the following steps [80].

1. **Segmentation:** This is done by automatic border detection algorithm. Border detection is accurate technique which provides accurate information about features like irregularity, border abnormality and border cutoff. Except this extraction of features like unusual stain networks, blobs, a blue and whitish area highly depends on border detection accurateness. Edge detection is done by JSEG algorithm. In preprocessing, smoothing and color quantization is done and then after thresholding, a rough outline of the lesion is created. After that unwanted areas like background or isolated areas are removed and rest areas are merged.

Table 3.17 Summery of Researches

S. No.	Author	Year	Preprocessing	Segmentation	Feature Extraction	Classification	Accuracy
1.	P. Ramya[66]	2014		Done with k means (k=3) clustering and LRRS algorithm			Good detection
2.	Nikhil Cheerla et al. [67]	2014	Hair and pigmentation are removed	K means algo for color segmentation and LBP for texture segmentation	ABCD	NN classifier	SE>97% SP>93%
3.	Feng-YingXie et al. [68]	2012		Adaptive clustering algorithm based on SGNN	Assymmetry, eccentricity, BDR, color diversity and texture correlation are calculated	NN classifier	Accuracy=93.2%
4.	Nidhal Khadhal et al. [69]	2014		Adaptive thresholding, Otsu method, Fuzzy C-means clustering and k-means clustering			Accuracy=98.2%
5.	Nadia et al. [70]	2013	Noise and unwanted signal from median filter and morphological operations	Region growing technique	ABCD rule followed by TDR value		Accuracy=92%

6.	Mrinal Mandal et al. [71]	2013		Mean shift algorithm with LRRS and LDED			SE=80% PPR=70%
7.	R.Garnavi et al. [72]	2010		Histogram Thresholding,color clustering and spatial segmentation	ABCD Rule, Menzies method, 7 Point checklist method	Shape,color, texture	Accuracy=97%
8.	John Breneman [73]	2012	Global image binarisation by otsu method	With DoG and SVM	ABCDE descripter		hopeful
9.	Binamrata Baral et al. [74]	2014		Neuro-fuzzy model		ANFIS Neural network	Segmentation with good accuracy
10.	NimaFassihi et al. [75]	2011	Image enhancement and noise removal by median filter	Segmentation by perwit,canny,sobel and Robert and zero cross operators	Wavelet Decomposition (Means and variance are calculated)	NN classifier	Accuracy=90%
11.	Mohammed Messad et al. [76]	2014	Gaussian refinement and morphologicaloperations	Unsupervised algorithm for segmentation	A,B,C and D are calculated	NN Classifier	TDR increasing and FPR decreasing in result
12.	Md. Khaled et al. [77]	2013	Karhunen-Loève (KL)	Segmentation by ROI and SRM	Wavelet Decomposition and curvelets	NN classifier with back propagation	Accuracy for wavelet=58.44%. Accuracy for curvelets=86.57%

13.	Narmadha et al. [78]	2014	Dust , noise and hair are removed by bilinear methods	Level set segmentation algorithm and LRRS		SVM classifier	SE=80% PPR=70%
14	Rahil Garnavi et al. [79]	2012		Texture feature are extracted by wavelet decomposition	Gain ratio method for feature selection (23features)	SVM, naïve Bayes and random forest , logistic model	Accuracy=91.1%

2. **Feature Extraction**: Feature like color, shape and texture are extracted. In total number of shape feature vectors are 11, color feature vector is 354 and texture descriptor vectors are 72 for every image. It is clear by the following Table 3.18.

Table 3.18 Description of shape, color and texture features

S. No.	Feature	Description
1.	Shape	**(A).** Aspect ratio of lesion **(B).** Lesion area **(C).** Two irregularity features **(D).** Solidity **(E).** Maximum lesion Diameter **(F).** Eccentricity **(G).** Hardness **(H).** Equivalent diameter
2.	Color	**(A).** Mean with Standard Deviation of three channels in RGB, CIEL*u*v*, HSV, and color models. **(B).** Differences of standard and mean deviation from the unlike image areas for all color models. **(C).** 2 color asymmetry descriptors each for Red Green and Blue channels. **(D).** Centroidal distances for each channel of all color spaces **(E).** CIEL*u*v* $L1$ and $L2$ histogram distances between the different image regions
3.	Texture	**(A).** Energy **(B).** Maximum probability **(C).** Inverse difference **(D).** Entropy, **(E).** Moment **(F).** Correlation of the normalized GLCM **(G).** Contrast

3. **Classification:** Multiple classifier system is used which overcome the weakness of individual classifier. Classifiers for melanoma detection maps feature space to the

labels given to classifier. To avoid class imbalance, classifiers are trained on balanced object spaces. Construction of MCS includes following steps.

- **Space Partitioning:** Numbers of subspaces are created for minority class (melanoma) objects and under sampled majority class object (benign). Random sampling method is used to create subspaces. Subspaces now have smaller and equal number of objects randomly chosen from dataset. After random sampling, minority objects are removed from training set.

- **Classifier Construction:** On these subspaces, a classifier is trained to construct group of classifiers. Subspaces are the base of classifiers. SVM classifier with polynomial kernel is used. Feature selection for subspaces is done by correlation based feature filter. it separates feature classes and pair of features.

- **Classifier Selection:** Complimentary models are generated by trimming of classifiers based on diversity. Since all classifiers can provide different advantage to the group, so it is done with lot of care. Classifier selection has done by fuzzy measures of diversity. A fuzzy membership function is defined for a given object. This function is given to Shannon function. Shannon function checks for its fuzziness, giving output in form of [0, 1] where zero indicates identical classifiers and one indicate to highest possible diversity.

- **Classifier Fusion:** classifier fusion is very important as it is accountable for decision making. Here discriminate functions are used for making decisions. So neural fuser with one layer is taken for each of the class and is trained with quick prop algorithm. Support function of each classifier is given as input and output is biased support of every classes.

To find the results, data of 564 skin lesions is used from three universities sample.

1. Sydney Melanoma Unit
2. University of Naples and University of Florence
3. University of Graz

These images are true color images with 768×512 pixels resolution. Among 564 images 476 are non-melanoma and rest 88 are melanoma. In this work, a single SVM classifier, SVM with SMOTE, SMOTE bagging, SMOTE boost, IIvotes and Easy Ensemble are used. The Output is calculated via specificity, accuracy and sensitivity as shown in Table 3.19.

Table 3.19 Comparison of results from different classifiers

Classifier	Accuracy	Sensitivity	Specificity
SVM	26	93	83
SMOTE Bagging	92.54	93.06	92.98
SVM+SMOTE	91.34	92.25	92.10
SMOTE Boost	91.85	92.89	92.73
Easy Ensemble	91.85	92.89	92.73
IIvotes	93.05	93.56	93.48
Proposed ensemble	98	94	93.73

From the above table it is clear that SVM accuracy alone is not good. But SVM with SMOTE performance is better. Further performance is improved by using ensemble classifiers. Ensemble classifiers give the better classification results. The proposed model gives highest accuracy (93.76%), Sensitivity (93.84%) and Specificity (93.83%). Moreover it is also proved from this model that proposed method outperforms statistically. In this way, this method proves that if we craft ensemble classifiers with care, it will give great result for lesion classification.

Catarina Barata et al. (2012) proposes an automatic detection technique for pigmented network in dermoscopy images**.** As it is shown in Figure 3.3 this work involves the following steps [81].

- **Preprocessing:** In this step mainly two operations are done.

1. **Detection of Artifacts:** Two types of artifacts are detected (Reflection and Hair). So they are converted in to grey color level. Then reflection artifacts and hair artifacts are detected by using histograms. The reflection artifacts come from

acquisition process where gel is applied to the body part to take the images. The reflection artifact detection is done by thresholding algorithm. Hair artifacts have same type of shape as pigmented network. So here also pool of directional filters (N=60) is used having mask dimensions of 41*41. A threshold value (0.06) is given to the output to detect the hair artifacts from the images.

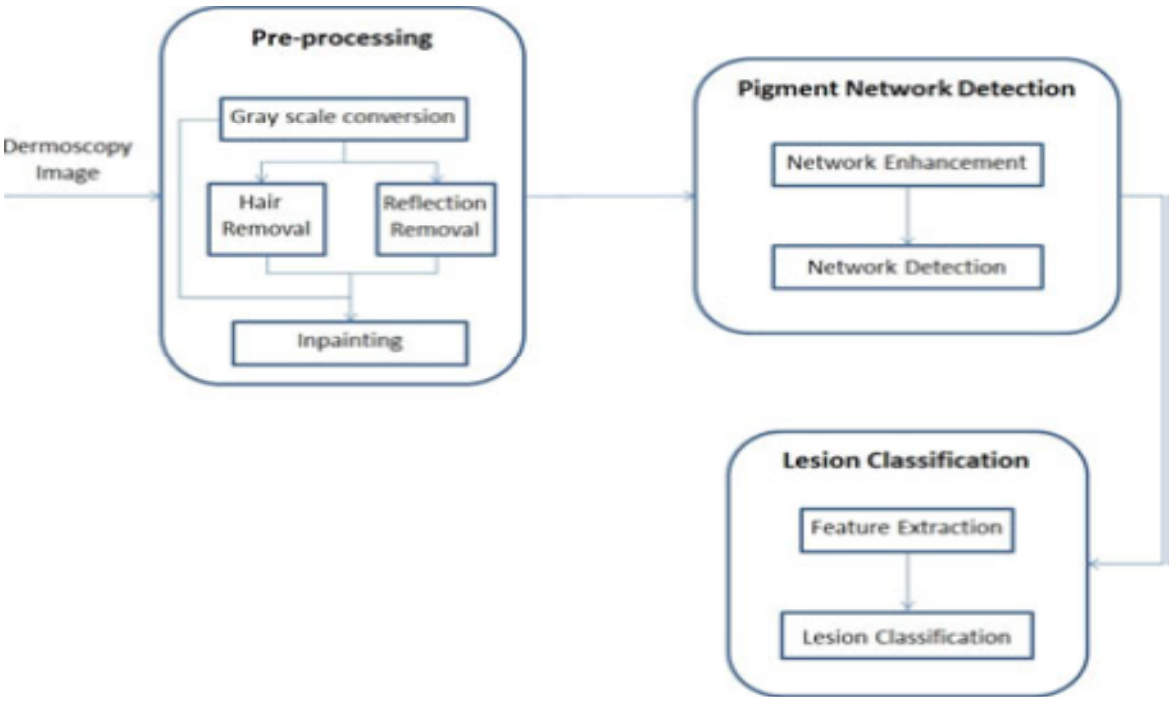


Fig. 3.3 Overview of the detection system

2. **Removal of Artifacts:** After the detection, grey level images are multiplied with mask and gap is generated. To fill the gaps interpolation is done also known as impainting.

- **Segmentation:** This is done in two steps.

1. **Network Enhancement:** lines linked with the pigmentation are made sharp comparative to background. First images from preprocessing are filtered by bank of filters (mask size=11*11) and threshold is applied to get pixels responsible for pigmentation. These filters work on 2-D Gabor filter , matched filters and linear filters.

2. **Network Detection:** since pigmented area has set of connected lines, so topological relations in pixels are considered. Connectivity can be identified with help of component analysis in which eight connectivity criteria is used. In this way all connected components are identified and then a threshold is given in form of area. If connected region area is greater than threshold it is a pigmented network. Output of pigmentation detection is a "Net Mask" which is a merger of all linked areas.

- **Feature Extraction:** Binary labels are assigned to the image. These labels are set of feature that identifies whether it is pigment or not. Features used in this work are in form of density and regular distribution.so total 5 features are extracted.

1. **Network/Laceration Ratio:** This calculates area of detected network with area of whole lesion in form of ratio.

2. **Network /Regions Ratio:** This is the ration between area of detected network and pigment network regions- mask.

3. **Quantity of Holes:** This has holes of total detected area.

4. **Holes per Laceration Ratio:** This value calculates ratio of quantity of holes with area of laceration.

5. **Holes per Region Ratio:** This value calculates ratio of quantity of holes with area of stained network.

- **Lesion Classification:** Five features described above are used to train the classifier. Classifier with boosting algorithm is used to select exact feature. The Algorithm is tested on PH2 database having 200 images in which 112 are normal and 88 are pigmented. They have resolution of 765*573 with BMP and JPG format. Results are acquired with 10-fold CV method. The output of this system is also matched with the binary ground truth G_T by two techniques.

1. **Pixel Detection Statistics: A** Binary mask for detected area is compared to G_T and Accuracy, Specificity, Sensitivity are calculated. For threshold value = 700 SP =84.5% and SE= 58.6% and for threshold value = 900 SP = 84.5% SE = 58.6%.

2. **Region Detection Statistics:** Each region in pigmented network is compared with G_T and Accuracy Specificity, Sensitivity are calculated. For threshold value = 700 SP =79.4% and SE= 89.7% and for threshold value = 900 SP = 82.1% SE = 91.1%.

William Henry Nailon et al. (2010) proposes fractal method for texture feature extraction. This property is directly related to the pixel intensities. It is defined by the variation in intensities of pixels within the spatial coordinates. Texture analysis is used for segmentation, classification and synthesis. Machine based texture analysis is very important as human eye cannot discriminate two textures having higher order statistics difference. To do texture extraction first of all image is considered in 3D surface [82]. Then texture analysis is done by using statistical methods.

1. **First Order Statistical Texture Analysis:** This is done with image histogram**.** Histogram is a plot between grey levels of an image and there probability of occurrence. The descriptors that describe the texture of image are entropy, coarseness, mean, variance, skewness, kurtosis and energy.

2. **Second Order Statistical Texture Analysis:** In this technique**,** co-occurrence matrix for pixel intensity is calculated known as GTSDM (Grey tone spatial dependence matrix). It is calculated as probability of finding a grey level at position 'i' to the next pixel at distance'd' and angle 'a' and at position 'j'. Since value of 'a' can be (0, 45, 90,135) in this way every pixel has 8 nearest neighbor. After calculation of matrices 14 features in form of Angular Momentum, contrast and Correlation have been calculated.

3. **High Order Statistical Texture Analysis:** In this analysis, GLRLM (Grey Level Run -Length) is used. In this method, information is contained on run of that grey-level. It is defined by seven descriptors and analogous to the GTSDM.

Fourier Power Spectrum: Fourier transform is a two dimensional transform. It is a good tool to study the texture properties. So it is a boon to the image description and enhancement. Power spectrum in Fourier series has periodicity and directionality of texture feature. To extract texture features, mainly two techniques are used here, Ring and Wedge filter.

Fractal Texture Analysis: Fractal texture analysis means description of the shape of natural objects like clouds, mountains etc. It describes the irregularity of texture of the surface. It can be understood by self-similarity. Self-similarity means an object can be divided in to smaller copies of itself. This concept divides the fractal in two parts random and deterministic.

Estimation of fractal involves number of methods that are described in this study and they are as follows

1. **Box-Counting Method:** The box-calculating method follows self similarity in which it can be divided in to smaller parts. This subpart characterizes random structure with fractal tools.

2. **Korcak Fractal Analysis:** This technique work with intersection profile of surface of image. To calculate the fractal dimensions a horizontal plane is passed through the 3D surface in vertical direction and fractal dimensions are calculated. The points above the surface and plane are called islands and below them are named as lakes. A threshold technique is applied to measure area of island and lake. Then a log -plot is drawn between different lakes or islands and their area. In this graph a straight line is found. The gradient of this straight line is considered to evaluate fractal dimensions.

Feature extraction, Selection, and Classification: In previous segment features are obtained on which image will be processed further. So we have both features which are relevant and non-relevant also. To lessen the dimensionality of data, lessening of feature is done so that accuracy will be improved and problem of over fitting should not come. Here two methods for feature reduction SFS (sequential forward search)

and SBS (sequential backward search) are used. K-means algorithm is used for classification purpose.

Sequential Forward Search Algorithm: This feature reduction method is based on bottom-up strategy. First of all with collection of features and their subset is created a selection .Then a criterion function 'J' is defined. Now iterations are done and after every iteration the feature that has maximum value of J is summed in the feature collection. So in this way selection criterion function is optimized giving good accuracy and only relevant features are added. The desired function will be J(X) = min (E) where E is minimum probability of error. This technique also has some disadvantages like nesting and discrimination of two features which separately gives minute discrimination but together gives very good result.

Sequential Backward Search Algorithm: It has more computation than SFS**.** It adopts top-down methodology and after every iteration one feature is removed having smallest value of selection criterion function. It has complexity and expensive. It also has nesting problem.

Classification: classification is done with k-means algorithm. This technique is based on clustering. Clusters are defined as similar points, groups or classes. Here in this work features are clustered on specific image region. First of all observations are partitioned. Algorithm work according to the similarity and moves from one cluster to another to classify the object. This can be understood by an example. Let number of clusters are N. For k means algorithm we need three steps.

Step 1: If there are N observation like y= {y1, y2, y3------y_{Nc}} and they are to be classified in different classes Ω = {Ω_1, Ω_2, Ω_3---------- Ω_N}. Algorithm starts with observations in to N cluster and mean value of each cluster is calculated with Euclidian distance.

Step 2: Each observation with closest mean is assigned in observation y.

Step 3: After updating mean vector for each cluster, step 2 is repeated until change in cluster mean does not occur.

Biomedical Image Analysis Case Studies: case study is explored for texture extraction in medical field.

Case Study: This case study is for the treatment of cancer. Radiation oncologist visualizes the tumors and according to that radiation is passed to cure the disease tissue. So the accuracy depends upon the visualization of Gross tumor volume. This work is proposed to differentiate between cancerous part and other healthy regions obtained from CT images with the help of texture analysis method. Here CT scan images of eight bladder patients were acquired. 7 patients are scanned with 3mm thickness and 1 with 5 mm thickness. Repeated CT scans are done to permit matching of same area on every image. Image descriptors were calculated on the basis of 1st order histogram (bins=7), 2^{nd} order GSTM (bins =14) higher order GRLM (bins =5) and box counting fractal approach with bins =1 .So in this way , 27 features were used to work on the image. Classification was done first with 27 features using SFS then secondly best three features are found for the classification. The best of three features technique calculated by the sequential forward search feature extraction shows mark able difference between the three image groups.

This result say after eliminating features with little biased power, classification has been improved. Except this, current method also presents the effectiveness of texture analysis to classify desired region.

Ilias Maglogiannis et al. (2009) review the different methods to recognize visually the features of skin lesion and define the. Then extraction of features was also discussed for the classification for melanoma with dermoscopic images. Skin has different layers but in epidermis contains melanocytes that produce melanin which absorb blue part of UV light.so it save skin from harmful UV rays. Dermis is the second layer contains fiber, blood vessel and made of collagen fiber as shown in Figure 3.4 [83].

Skin lesion looks like a patch of color on skin. It is mainly due to excess melanin production. Common nevi or benign is normal and found in epidermis. In malignant lesion melanin production is higher but when they stay in epidermis it is not so

harmful that is said “in situ”. But when this melanin goes in to dermis it is very dangerous and changes the color of skin as shown in Figure 3.4.

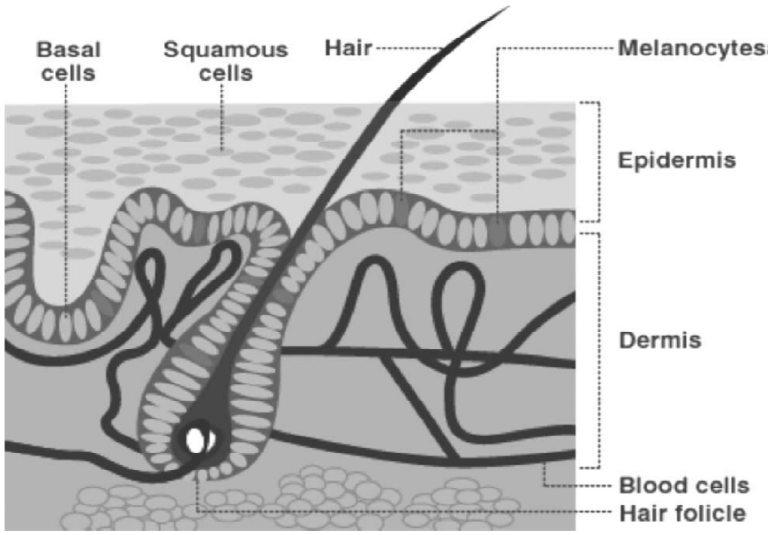


Fig. 3.4 -Skin Anatomy

Computer aided skin cancer detection has these steps.

1. **Image Achievement:** This is the very first step and here lesion image is captured for the processing. There are lots of techniques used for this purpose. Here is a table which gives the whole information about the acquisition technique according to the survey. Figure 3.5 clearly shows the difference between melanoma and non cancerous lesion. Table 3.20 defines method for melanoma detection by acquisition methods.

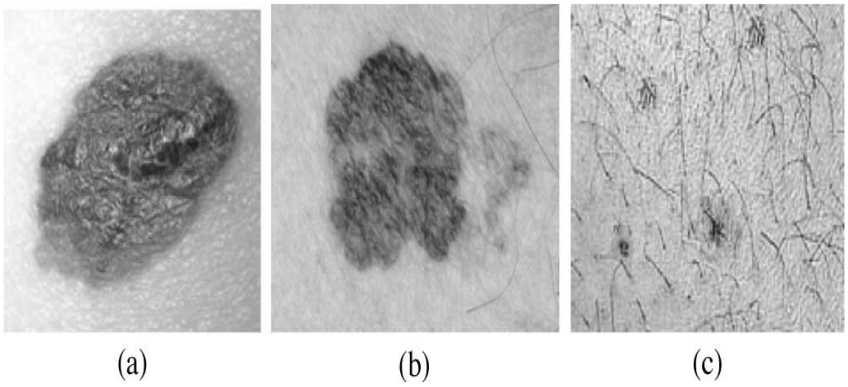


Fig. 3.5 Difference between benign and melanoma lision (a) typical melanoma, (b) dysplastic nevus, and (c) nondysplastic (common) nevus

Table 3.20 Acquisition techniques

S. No.	Acquisition Technique	Detection
1.	Epiluminence microscopy (ELM or dermoscopy)	Melanoma
2.	Transmission Electron Microscopy (TEM) using neviscope	Melanoma
3.	Still CCD Camera	Wound curing
4.	Raman Spectra	Melanoma
5.	Video microscopy	Melanoma
6.	UV illumination	Melanoma
7.	Tissue microscopy	Melanoma
8.	Video RGB Camera	Ulcer , Tumor, hair, scars, burns, Melanoma

2. Image Pre processing

3. Image Segmentation

4. Feature selection and Extraction: To choose and extract feature it is very necessary to know about features in melanoma detection. Features are visual cues. lot of features are used to diagnose melanoma from skin lesion. Feature should be :

(A) High TPR

(B) High SE

(C) High SP

(D) High TNR

(E) High Area under ROC

(F) Lowest false negatives

According to this survey there are five main methods to diagnose melanoma on early stages.

(A) ABCD Rule: it has four features.

Asymmetry: The laceration is divided by two axes with lowest possible asymmetry.

Border: border information is obtained by image segmentation. Laceration is divided in 8 pie shaped sections and then it is seen whether any sharp or cut off is present on periphery or border of lesion. Here lesion is separated from healthy skin. Mostly used

methods are Adaptive thresholding, JSEG algorithm based segmentation, Region growing thresholding and color transformation from one model to another. Except these AI methods like fuzzy borders are used for feature extraction. Other methods are edge detection segmentation. They are done by edge detectors. Hybrid methods involve color transformation and edge detection both. Active contour or snake is used for border detection. Most important features in this category are.

1. The maximum diameter
2. The area
3. The border abnormality
4. The symmetry distance (SD)

   CIRC = 4Aπ/p2

   Where A= area of examination part and p is parameter.
5. The variation of the distance of the boundary laceration points from the centroid.
6. The circularity index (CIRC)
7. The thinness ratio

Color: Number of colors and color properties of a lesion is investigated. These colors are black, brown, dark brown, white, red, and slate blue. A color image generally contains three channel Green, Red, and blue. Color descriptors are extracted on RGB Color Channel and others like UV (YUV) chrominance components, magenta, cyan, yellow (CMY), hue saturation value (HSV), Y(luminance) or various merger of all.

Differential Structures: In this category dots, pigments, streaks and globules are extracted.

Pattern Analysis: This is to specify specific patterns. These can be global or local.

Menzies Method: It is defined for negative (pattern symmetry, just one color) and positive features (light bluish white cover, numerous brownish dots, pseudo pods, depigmentation, blobs, several colors, several blue or gray dots, widened network). If at the minimum one positive feature among all features is present, then there is clear indication of melanoma.

Seven-Point Checklist: This method depends upon seven criteria to diagnose melanoma**.** These criteria are related with color, texture and shape characteristic like

stained web of dark blue and white veil, different blood pattern, uneven stripes, rough dots or blobs, rough marks, and deterioration structures.

Texture Analysis: Texture is defined as smoothness or roughness, of surface. Texture parameter calculation is to identify their properties and measure them. Texture features and their analysis method come in two categories: Statistical and Structural. lattice aperture waveform set (LAWS) and Neighboring gray-level dependence matrix (NGLDM) are two methods for texture identification and extraction.

Dissimilarity: It is a feature defined as

$$d = \sum_{i,j=0}^{N-1} P_{i,j} |i - j|$$

Where "i" represents row value and j represents column value. N is total number of row and column and p is pixel intensity.

Angular second moment (ASM):

$$ASM = \sum_{i,j=0}^{N-1} i P_{i,j}^2$$

GLCM Mean: It represents the how many times of one value of pixel is in arrangement with a specific neighbor pixel value.

$$\mu_i = \sum_{i,j=0}^{N-1} i P_{i,j} (i - j)$$

Standard deviation for GLCM: Deviation of the value about mean.

$$\mu_i = \sum_{i,j=0}^{N-1} i P_{i,j} (i - j)$$

The following illustration gives us right information about uses of different technique in feature extraction as shown in Figure 3.6.

Feature Selection: Selection of feature is a very important task in melanoma detection. According to the number of features selected classification is defined. For example too much features go to bad results. So features should be well defined and up to the mark. There are a lot of feature selections techniques are used in literature.

- Sequential forward floating selection (SFFS)
- Generalized sequential feature selection (GSFS)
- Leave-one-out (LOO)

- Cross-validation (CV)
- Principal component analysis (PCA)
- Heuristic strategies
- Genetic algorithms
- Sequential backward floating selection (SBFS)

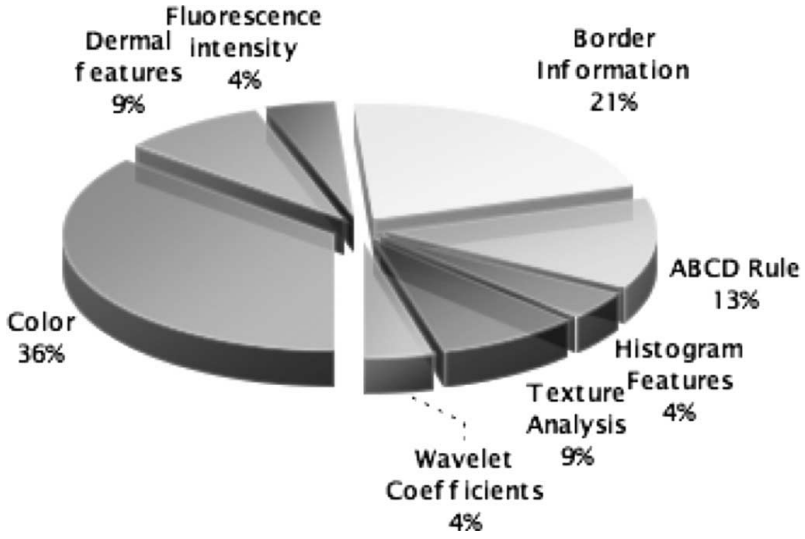


Fig. 3.6 Sketch of the feature extraction systems used in literature

Classification Methods: There are a number of methods involve in classification of lesion. All of the methods involve two basic steps.

- **Learning Step:** In this phase machine learned by the extracted feature set from the digital images. From the given images some images are taken and machine automatically learn after feeding the features in it. In deep learning there is no need to feed the features manually. According to the paper there are lots of techniques to make machine learn. But we can introduce them like this. These methods are also shown in the Figure 3.7.

(A) Neural Network: It is a net of connections between input and output with weight and bias. They are designed to minimize error and they are very good with large dataset. They are little complex but gives great accuracy and results.

(B) SVM: This is another method for the classification. This is commonly used for big datasets. it is depend on support vectors which are calculated by determining hyper plane to minimize the error with the use of a cost function.

(C) Statistical Methods: This is also very classical method. Covariance matrices, Gaussian distribution and discriminant analysis is used in these methods.

(D) ADWAT Method: Tree-structure based on the adaptive wavelet-transform based classification uses statistical analysis and threshold based criteria to classify the images.

Testing: In this step trained classifiers are tested for the classification. From the whole data almost 80% is used for learning and rest 20% is for testing. Responses are calculated in form of TPR, FPR, Accuracy, sensitivity and specificity. There are more terms that define the classification of skin lesions. ROC and AUC curves are very important in the final depiction of classifier performance.

Different Classifiers performances for Skin images: This segment explains the different classifiers for skin lesion classification on Weka (open source platform). The classifiers used are given in tables. The database used in this work is from Vienna Hospital. This dataset has 3639 images. 972 are dysplastic, 2598 are non dysplastic and rest is melanoma. Another dataset is small having 26 melanoma and 42 nevus from general hospital, Athens.

Feature extraction, Selection and Application: Here three different features like border, color and texture is applied. For these three techniques of feature extraction are used with different type of classifiers. These techniques are CFS, PCA, and GSFS.

From the above analysis it is evident that right feature collection and use of different algorithms can decrease difficulty but the response of model is not always good and extremely goes with the classification technique.

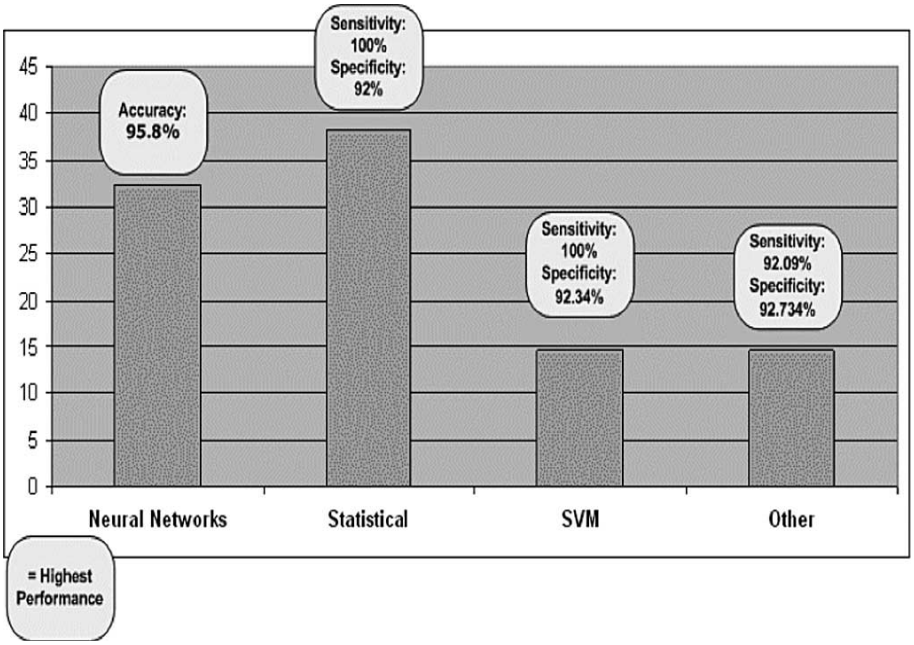


Fig. 3.7 Classification method vs their performance for existing classification systems.

Achievements and Results: In this study three types of experiments are conducted.

1. Detection of melanoma with nevus
2. Classification between dysplastic and non dysplastic
3. Classification between all three classes.

3.3 SUMMARY

In this chapter background of research work in field of skin melanoma detection is provided. A review of all techniques in computer system diagnosis like Preprocessing, Segmentation, Feature extraction, selection and Classification are discussed. The statistics and results in the researches have been discussed. This research analysis creates the foundation of methods projected for getting more improvement in all the processes. The shortcomings in different processes of CAD are also discussed during the study of literatures. In the next chapter more effective and proposed algorithms will be discussed for the improvement in the field of melanoma detection.

CHAPTER 4

THESIS CONTRIBUTION TO SEGMENTATION METHODS

4.1 INTRODUCTION

This chapter represents the segmentation phase of CAD in melanoma detection. The main aim of segmentation is to extract the affected area or desired region from whole image. Different Segmentation techniques are also presented. Background behind the proposed system of segmentation is presented. After that proposed system technique has been described in detail.

4.2 IMAGE SEGMENTATION

Image segmentation is a very important stage in digital image processing. It can also be said as a part of image compression [84]. An image is subdivided in to different segments or its constituent parts or objects. Each part of the image has some kind of information. It can be in form of color, texture and intensity [85]. Segmentation technique takes a single value, assigned to each pixel. Due to this value, one region is easily differentiated from the other regions. The discrimination is done according to the features like texture, color and intensity. The method of differentiation totally depends upon the problem domain. Segmentation is stopped when region of interest has been isolated from the digital input image.
Image segmentation in a broad manner can be classified in two parts.

4.2.1 Local Segmentation

This type of segmentation is done on the subpart of an image. This technique involves the segmentation of a small part of the digital image.

4.2.2 Global Segmentation

Global segmentation stands for segmenting whole image.

4.3 IMAGE SEGMENTATION TECHNIQUES

Image segmentation techniques can be mainly divided in two parts according to Figure 4.1.

4.3.1 Layer formed Segmentation Methods

This technique is used for the segmentation to define the shape mask and explain the appearance. This method calculates class labels and object instance labels [86].

4.3.2 Block formed Segmentation Methods

This technique is based on different features of an image. It can be in form of texture, color or intensity (pixel).this is a simplified method of segmentation. In this approach an image is divided in different blocks and each block follow exact object boundaries [87]. Block based segmentation can be divided in three parts. These are all based on discontinuity and similarity. Figure 4.1 represents the different type of segmentation techniques.

4.3.2.1 Edge or Boundary Based Methods (Based on discontinuities)

Edge detection is a very basic step for segmentation. Background of an image is separated from the object of an image in this technique. Detection is done by the change in intensities or grey values. Edges are formed between two regions [88]. Edge detection is done in three steps. First is filtering for the noise removal. Second is enhancement in which image is enhanced with respect to the changes in neighborhood intensities. Third is detection which is done by different methods.

4.3.2.1.1 First Order Differential

Roberts, Prewitt and Sobel operator come under this category. Robert detection is based on cross operator which does a quick and simple task with the help of spatial gradients. Prewitt detection is based on the calculation of magnitude and direction of

edge with 3*3 kernal masks. Sobel detection is based on one kernel of 3*3 rotated by 90 degree.

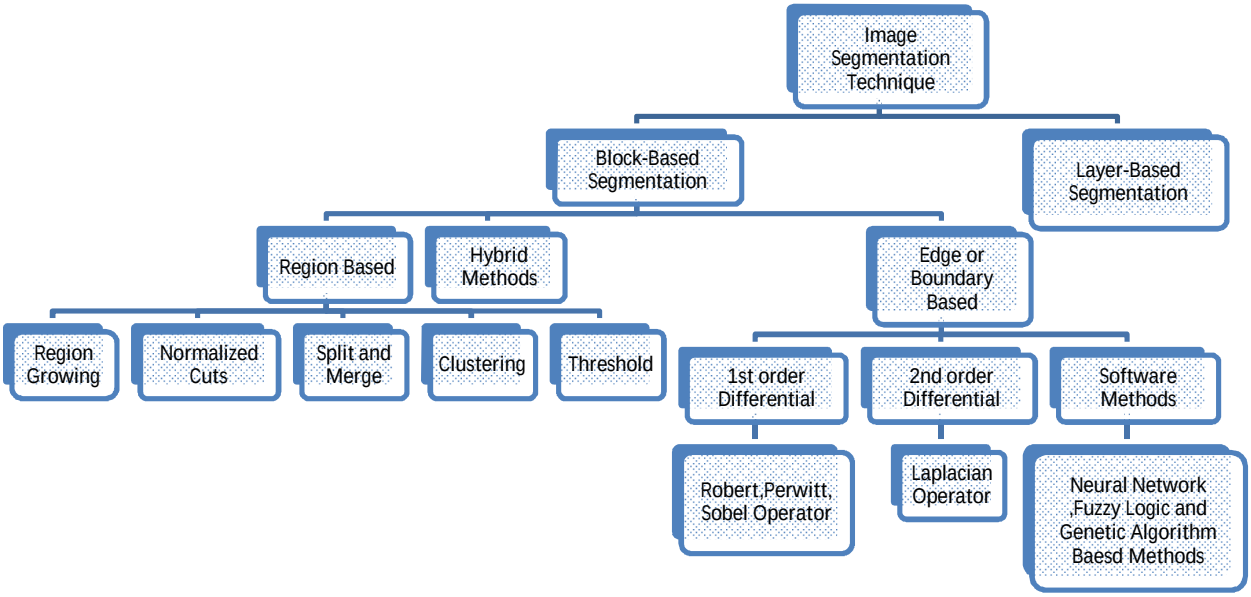


Fig. 4.1 Image segmentation Methods

4.3.2.1.2 Second Order Differential

It is based on Laplacian of Gaussian and Laplacian operator and [89]. Laplacian is 2-Dimensional measure of second spatial derivative. Laplacian operator detects edge and noise and when it is convoluted with Gaussian kernel it is known as LoG.

4.3.2.1.3 Software Methods

4.3.2.1.3.1 Fuzzy Logic based segmentation

Grayscale image is converted in to fuzzy image or pixels of an image are divided in to fuzzy sets. Fuzzification function with different morphological operations gives very good results. Fuzzy-k means and fuzzy-c means are mostly used in segmentation [90].

4.3.2.1.3.2 Genetic Algorithm Based Segmentation

It works on evolution theory. There are three steps in this technique.

1. Selection
2. Crossover
3. Mutation

Fuzzy Genetic Algorithm function is used for the operation [91].

4.3.2.1.3.3 Artificial Neural Network Based Segmentation

ANN is considered as pattern recognition tool in a broad way. These are based on neurons which work according to the weight, bias and interconnection between layers. These neurons signify the pixel [92]. This system has three parts.

1. Input layer
2. Buried layers
3. Output layer

This method involves the classification of pixels using ANN functions and techniques. Image is trained with the help of neurons and then the other images are tested based on learning rule. There are some important neural networks used in segmentation like BPNN, Hopfield, FFNN, MLP, MLFF, SOM, and PCNN [93].

4.3.2.2 Region Based Methods (Based on similarity)

It is a very simple technique as compared to the other. Image is divided in different regions based on color, intensity or object. Image is first split and then adjacent and similar sub images are merged. There are three steps involved in this technique [94].

1. Region Growing
2. Region merging
3. Region splitting

Region based segmentation can be divided in to five parts.

1. Clustering : k means

Image split on to k groups. Every pixel corresponds to a cluster. Clustering depends upon texture, intensity or location. K values are selected with heuristic approach, manually or randomly [95]. This technique does not guarantee continuous area. This drawback is overcome by split and merges technique.

2. Split and Merge

It involves three steps splitting the image, initialize neighbor list and third is merging. Technically whole image is split until no splits are possible [96]. It has problem of over segmentation which is improved by normalized cuts.

3. Normalized Cuts

This method is based on graph theory. Optimal splitting is done with reduced number of regions. Vertex of the graph is pixel and branches of the graph signify its adjacent pixels. Weights of edges are given according to the texture, color, intensity, similarity or distance [96].

4. Region Growing

It is based on similarity of pixels. It starts with a pixel and end with until all the pixels are added with same similarity. It is very popular technique. It gives great result with less noisy image. But with high noisy image it could not differentiate the shading of real image [97].

5. Threshold Technique

This technique separates the object from background. It is a very common and easy technique. It is divided in to three groups local, global and adaptive. There are lots of threshold techniques like mean, p-tile, histogram dependent, edge maximization and visual technique [98].

4.3.2.3 Hybrid Techniques

Hybrid techniques are the combination of more than one segmentation techniques to obtain good results. A hybrid network is formed to improve the segmentation performance. This approach adds boundary based and region based technique to strengthen the technique and reduce the disadvantages [99].

4.4 OTHER TECHNIQUES

4.4.1 Partial Differential Equation Based Segmentation

Partial differential equations or model are used in image segmentation. Segmentation problem is converted in to partial differential equation with the help of active contour or snakes transform [100]. Common methods used for PDE are snakes, level set and Mumford shah method [101].

4.4.2 Watershed Method Based Segmentation

This method is region based and utilizes morphological process. Image is considered as a topographic landscape having valleys and ridges. Pixels gradient values define elevation values of landscape. Watershed transform break the image in catchment basins as shown in Figure 4.2. Each pixel is assigned in to a region or watershed [102].

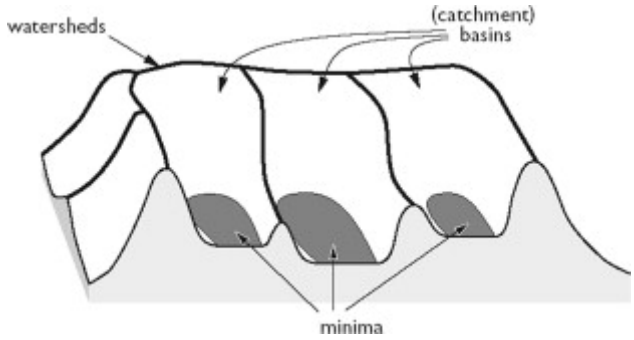


Fig. 4.2 watershed transform

4.5 BACKGROUND OF PROPOSED METHOD

Segmentation is not easy task as an image has different type, size, and textures in lesion. These lesions also have artifacts, hair, air bubble, wrong illuminations, irregularity and shadows. Since segmentation is early step of CAD methods, it is very essential to make it an area of research. As discussed above and in literature survey, thresholding is very basic and easiest technique of segmentation. Thresholding is used to convert color images in to binary images. The input of threshold segmentation is grey scale or color image and output is binary image. Background is considered as Black pixels (0) and foreground as white pixels. Thresholding algorithms are of three types, Global Thresholding, local Thresholding and adaptive Thresholding [103].

4.5.1 Global Thresholding

When intensity of background pixels and objects pixels are distinct then Global Thresholding is used. Here a single threshold value is used for whole image [104][105]. There are number of global Thresholding technique for segmentation. They are described as below.

4.5.1.1 Histogram Based Thresholding

This technique figures out thresholding value for the separation of two homogenous regions except the area between object and background [106][107]. If P1 and P2 be the grey values of peak in histogram then threshold value is given by

$$T= (P1+P2)/2$$

4.5.1.2 Iterative method based thresholding

This type of technique gives good result when histogram can not define valley points clearly. It has improved anti noise capacity [108].

4.5.1.3 Otsu's Method Based Thresholding

It is used to overcome the drawback of iterative method. In this method mean is calculated after every step. Optimal value of threshold is obtained with the help of histogram. Since this technique assumes histogram as bimodal, it could not be used with classes of different size and illumination [109].

4.5.1.4 Maximum Correlation Based Thresholding

Correlation is maximized between grey level image and threshold image. Two classes in threshold image are presented by above and below grey level values [110].

4.5.1.5 Multi Thresholding Method

In this method grey level image is segmented in to several distinct regions. This method has more than one threshold and determines one background with many objects. Generally this method is used for color and complex background [111].

4.5.1.6 Clustering based Thresholding

Clustering is unsupervised learning technique used for feature extraction. Fuzzy C means clustering has dataset clustered in to n groups [112]. It offers less iteration time and so it improves accuracy [113]. K means clustering is also an effective method for threshold selection. The algorithm is known as k means algorithm in which image is

divided in to k segments [114]. K means algorithm contains a simple heuristic approach based on iterative scheme.

4.5.2 Local Thresholding

Sometimes single threshold does not work due to the illumination and shadows of image. So image is divided in to sub partitions and then threshold is decided. In local thresholding , threshold value depends on grey level values and properties of neighbor pixels [115].

4.5.3 Adaptive Thresholding

If background illumination is not even then global thresholding cannot be taken in to the consideration. Here specific threshold values for specific local parts are used. This method takes color or grey scale image and gives binary image as an output. If threshold value is greater than pixel value it works as background value otherwise foreground value. To find the threshold value there are two approaches (i) the chow and kneko (ii) local thresholding [116].

4.6 PROPOSED APPROACH

Classifier performance depends upon dataset and segmentation of dataset images. In this work a novel and easy technique for the segmentation is used. The first requirement for the classification is to segment the images. In this work PH2 dataset is taken. This dataset already contains manually segmented lesion in form of binary maps. Segmented images are extracted using Binary Thresholding technique by using its respective binary lesion mapping. Figure 4.3 and 4.4 represents melanoma and non melanoma images with binary map of lesion region with finally segmented image.

4.6.1 Binary Thresholding Technique

This is simple form of thresholding . In this technique binary image is created by color image or grayscale image. Background object is separated from foreground object. This method gives each pixel as black pixel if threshold value is greater than

intensity value and gives white when vice versa [117] . Results show clearly that this method for segmentation works very well as compared to the other method of segmentations.

Fig. 4.3 Melanoma image, binary lesion map and segmented image

Fig. 4.4 Non-Melanoma image, binary lesion map and segmented image

4.7 SUMMARY

This chapter summarizes all segmentation technique used in automated skin cancer detection systems. The proposed method for segmented images is discussed. This technique is applied specially for melanoma detection but it can also be used for other aspects for good accuracy and precision.

CHAPTER 5

THESIS CONTRIBUTION TO FEATURE EXTRACTION METHODS

5.1 INTRODUCTION

This chapter describes image features and different technique applied to the feature extraction. This chapter has two sections. First section describes the proposed feature extraction with 3D CTF (color and texture feature) extraction. Second section describes the proposed feature extraction by 3D CTF with principal component analysis (PCA). Background of proposed feature extraction is also delivered. At last algorithms and results are also obtained for both proposed methodologies.

5.2 FEATURE EXTRACTION FOR SKIN CANCER DETECTION

Features are attributes which describe property of an image. Descriptor extraction is a significant step for CAD systems in skin cancer detection. Features of an image directly affect the classification process. To classify benign and melanoma or other different kind of cancers, feature extraction should be very accurate and precise. But still dermatologist cannot make sure which feature is most important and which not. So in Automatic diagnosing system feature extraction technique is used to measure different parameter related to the cancer detection. These parameters are used to distinguish normal skin and lesion.CAD system has advantage over dermatologist that the feature extraction helps in recognizing and quantifying important parameters for classification.

Research aim is also to prepare such features by different extraction methods for skin cancer detection. There are five main categories of extracted feature. 1) General features (Color, texture and shape). 2) Pixel level features (calculation of features at each pixel). 3) Local Features (features are calculated over sub image). 4) Global Features (features evaluated over whole image). 5) Domain –Specific features (features are calculated over a specified domain).

5.2.1 General Features (Shape, Texture and Color)

Benign and melanoma slightly differ in color and structure. That's why it is a challenging to separate melanoma to non-cancerous part. For an automated system for cancer detection, numbers of features are calculated to get the satisfactory classification.

5.2.1.1 Shape Descriptors

It is a vital descriptor in clinical diagnose. This type of feature is defined by these parameters,

Area

AREA is calculated by using number of pixels inside the border [118]. There is more accurate technique known as bit quads [119].

Border Length

It can be calculated by calculating boundary points on lesion mask. One can compare irregularity of border with the comparison of lesion size.

Irregularity

Irregularity in lesion can be calculated as, irregularity= (perimeter of lesion)^2/ Area of lesion.

Asymmetry

It is the percentage of non overlapping area of lesion while folding the border along largest diameter.

Circulatory Index

It is defined as CI= 4 Л.A/P^2

Where A= area of lesion and P= parameter of lesion.

Contour Ratio

It is a measure of roughness or bumpiness in the lesion. It is defined as C.R= length of contour hull of lesion/ P

Where P= parameter of lesion.

Defects

Lesion has rugged and irregular border. But benign border is smooth. These significant defects are used as feature [120].

5.2.1.2 Texture Features

Except shape and color features texture is also a very important feature to analysis irregularity, roughness or deformity in lesion. Human visual system is well for distinguishing textures but for diagnosis it is not an easy task. In local area of an image, a certain repeated pattern is known as texture feature [121]. Texture features can be divided in to three categories. 1) Statistical measures. 2) Wavelets. 3) Fractals.

5.2.1.3 Color Features

These are mostly used visual features. Skin lesion has very short color range so it is difficult to separate them from healthy skin. Melanoma can have some specific type of colors like blue-grey, red, black etc. which depends upon stage of cancer and its depth. They are usually defined as Moment's descriptor, Color layout descriptor, Color structure descriptor, Histogram descriptor, Scalable color Descriptor, and etc.

5.3 BACKGROUND OF PROPOSED FEATURE SELECTION METHODS

Feature extraction is a very important part before classification. If accurate and relevant features are selected then classification accuracy goes high. In chapter 3 we have discussed different type of feature extraction methods. In our proposed method, color as well as texture both descriptors are used to create a 3D approach based on CLCM (color level co-occurrence matrix) with PCA (principal component Analysis). CLCM is based on GLCM . In this section, color, texture features with GLCM and CLCM will be explained, so that it will create a good understanding for proposed work.

5.3.1 Color Features

Human eye can recognize colors so color feature plays an important role to classify the images. They are basic characteristics of an image and give detailed information about image.

5.3.1.1 Color Spaces

Manipulation of colors is done by color spaces. Color spaces are defined as the intensity values of image pixels. Colors are defined ion 3D space that is color space. There are mainly four models are used.

- HSV Color Model
- HMMD color Model
- RGB color model
- CIE lab color space

Among them RGB color model is used in our proposed method. RGB color space is an arrangement of three main colors Red (R), Green (G) and Blue (B). This is an important color model. Figure 5.1 clearly explains RGB color model.

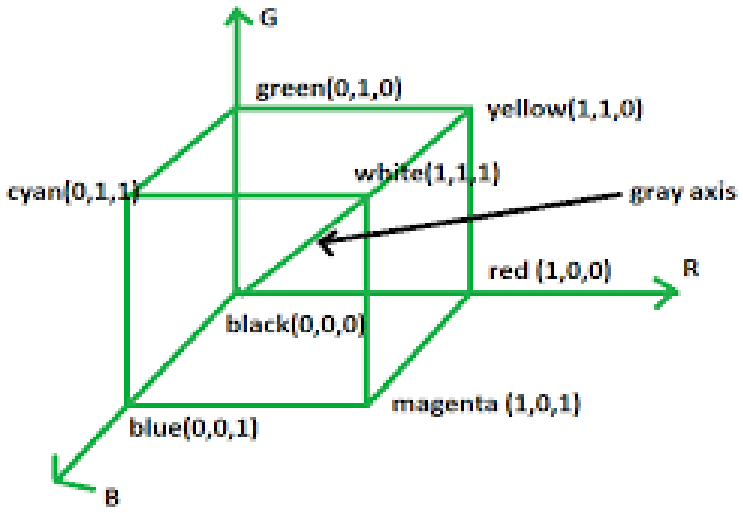


Fig. 5.1 RGB color model

5.3.1.2 Color Quantization

This technique is applied to lessen the quantity of colors for an image. This will lead to the less complexity in image retrieval process. Color histograms are produced after quantization. Color quantization is done by segmentation of color spaces.

5.3.1.3 Color Histogram

This graph is a presentation of colors of an image. In skin cancer images color histogram signifies the quantity of pixels in a range in image. It is mostly used in 3D

color model. Histogram is a method by which we can understand the color distribution in an image [122].

5.3.1.4 Color Moments

Color moments are an effective feature for image. To avoid quantization effects in histogram this feature is used. If Color distribution is done with probability distribution, then it is known as color moments [123]. There are three main low order moments known as mean, variance and skewness. They are defined as:

$$E = 1/N \sum_{j=1}^{N} Pij \quad (5.1)$$

$$\sigma = [1/N [\sum_{j=1}^{N} (Pij - Ei)^{1/2}] \quad (5.2)$$

$$S_i = [1/N [\sum_{j=1}^{N} (Pij - Ei)^{3}]^{1/3} \quad (5.3)$$

5.3.1.5 Color Coherence Vector

It is a refinement of histogram. Color histogram and color moments don't have spatial information, so coherence vectors are used to incorporate spatial information in histogram.

5.3.1.6 Color Correlograms

It is an image feature vector used for content based image retrieval. It is used for spatial color indexing, for large dataset its performance is far better than histogram or coherence vector.

5.3.1.7 MPEG7 Color Descriptor

It is a subset of above defined approaches. It covers different aspect of color and its application areas.

- Color layout descriptor
- Dominant color descriptor
- Color structure descriptor
- Scalable color descriptor

5.3.2 Texture Analysis

Texture is a very important characteristic for the classification of lesion. In broad way texture is spatial variation of pixel intensities. It is also defined as repetition of a assured pattern in local area of image [124]. Texture can very efficiently measure properties of image like smoothness, irregularity and bumpiness or roughness in lesion. Texture analysis is mainly used in classification, segmentation and synthesis. Textures give accurate information about spatial variation of intensities. Human eye can also detect texture changes in two images but for accurate analysis machine learning algorithm are far better than human perception. Julesz was the psychologist who told that, second order statistics plays very important role in differentiation between the textures of two images. Texture extraction and classification is critical as texture shows periodicity of several fundamental patterns. Scientists are trying to extract features based on texture features for great accuracy for years. In chapter 3, numbers of feature extraction technique based on texture have been discussed. According to the literature, texture filtering methods broadly can be classified as:

- Features based on statistical modeling(1^{st} order , 2^{nd} order and upper order)
- Descriptor extraction based on spectral analysis (Gabor filter, wavelet transform etc.)

In this thesis second order statistical modeling for texture extraction is used (GLCM and CLCM). So it will be discussed in detail.

5.3.2.1 Texture analysis based on statistical approach

In Statistical based approach image is treated as 3D surface structure. Figure 5.2 shows 3D texture intensity surface presentation. 3D approaches give greater accuracy than 2D approach. Literature shows that 3D approach can be effectively used to segment and classify medical images [125]. Feature based on statistical approaches can be further divided as

- First order statistical evaluation
- Second order statistical evaluation
- Upper order statistical evaluation
- Autoregressive modeling

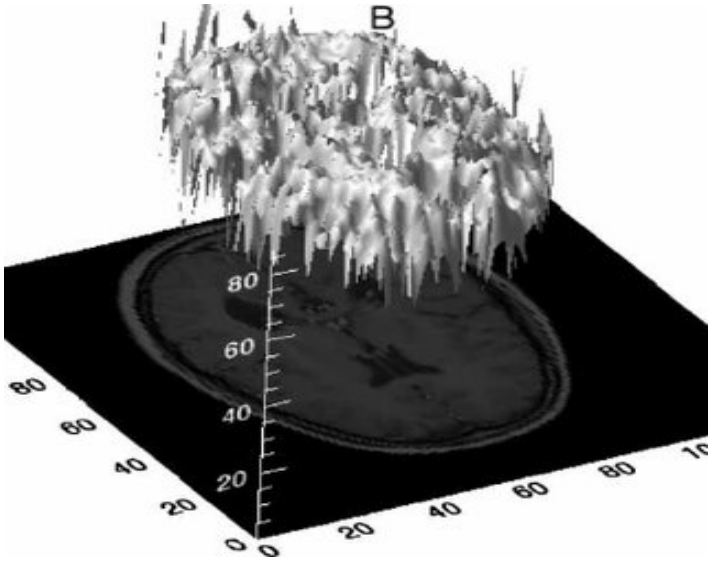


Fig. 5.2 3D representation of textured surface medical image

5.3.2.1.1 First Order Statistical Analysis

This approach deals with the occurrence of a particular grey level or pixel intensities. Correlation and co-occurrence between two pixels is not taken in to the consideration. Information of texture is filtered by image histogram intensities or pixel occurrence probability in first order statistics. If N_i is the quantity of pixels for intensity value i and N is the total quantity of pixels then probability of occurrence of pixel or histogram intensities is defined as:

$$P_i=N_i/N$$

In general there are seven features calculated to describe the histogram distribution and feature extraction. They are Coarseness, Skewness, Mean, Variance; Kurtosis, Energy, and Entropy.

5.3.2.1.2 Second Order Statistical Analysis

This approach deals with details about relationship between pixels, pixel dependencies on spatial variation and periodicity. In second order statistics GLCM (grey level co-occurrence matrix) is an extremely influential tool for feature extraction. GLCM is also known as Grey Tone Spatial Dependency Matrix. Texture feature extraction based on GLCM is well known and well established method. GLCM deals with spatial arrangement of pixels of an image. The frequency of pixels with intensities i and j having spatial distance d between them is known as spatial relationship in different angular direction [126]. To represent GLCM there are three parameters are calculated [127].

- The orientation of the measurement values
- Displacement values of measurement
- Quantization level of image

GLCM features calculate the frequency of pixels with specific value and specific spatial distance [82].the element in the matrix P (i, j/d, θ) has statistical probabilities between grey levels i and j with displacement d and angle θ. These probabilities are of second order. These are known as co-occurrence probability matrix or grey-tone spatial dependence matrices (GTSDM). Texture feature is calculated with these conditional joint probabilities by two parameters spatial distance (d) and angle (θ) for spatial window of interest. The probability of co-occurrence between two pixels (i, j) can be given as:

$$P(i, j) = \frac{P(i,j)}{\sum_{i,j=1}^{N} P(i,j)} \quad 5.5$$

P (i, j) = number of occurrences of grey level in defined window with (d, θ) pair.

N = C*R (where C = No of columns and R is No. of rows) = quantized number of grey levels

$\sum_{i,j=1}^{N} p(i,j)$ = total number of pairs in specified window.

Standard deviation and Mean can be calculated as:

$$n_x = \sum_i \sum_j i.p(i,j) \quad 5.6$$

$$n_y = \sum_i \sum_j j.p(i,j) \quad 5.7$$

$$\sigma_x = \sum_i \sum_j \sqrt{(i - n\ for\ row).p(i,j)} \quad 5.8$$

$$\sigma_y = \sum_i \sum_j \sqrt{(i - n\ for\ column).p(i,j)} \quad 5.9$$

From these equations probability can be calculated.

$P_{X+Y}(K) = \sum_i^N \sum_j^N P(i,j)$ where k = 2, 3--------2N and i+j= k 5.10

$P_{X-Y}(K) = \sum_i^N \sum_j^N P(i,j)$ where k = 0, 1---------- N-1 and i-j = k 5.11

Many statistics can be calculated from GLCM but there are 16 features that are calculated mostly [82] [128]. To set necessary parameters like “d”, “θ”, number of pixels and window size, research has been performed. For example high N value givers high complexity so high cost in evaluation of GLCM and its statistics [127]. Normalized GLCM should be dense for the accuracy of the calculation of joint probability. Graphically GLCM can be demonstrated from Figure 5.3&5.4. image contains dimension of 4*4 .total number of grey levels is 8 so GLCM of dimension

8*8 is used for the formation of matrix. In GLCM cell row number presents the intensity of first pixel and column presents intensity of second pixel in the pair. GLCM chamber shows frequency of the two adjacent pixels related to that chamber in the image. In figure 5.3 Image has only one pairs of pixels (1, 1) so the related coordinate for GLCM for row "1" and column "1" has a value 1. There are two spaces of the pair having grey level values 1 and 2, so the chamber in row "1" and column "2" has value 2. The same connection goes with every element of GLCM matrix and the pixel pairs of the image.

If pixel position is at '0' degree angle and neighbor distance is '1' then the position of pixel is (0, 1) or they will be in similar row but nearby column.

For heterogeneous texture structure different orientation and offsets are required for the calculation of GLCM. These offset pairs are shown in the Figure 5.4. Figure 5.4 (a) demonstrates the pixel pair intensity with different angles (0^0, 45^0, 90^0, 135^0 and 180^0). If d=1 then for 0^0: [0, d] for 45^0: [-d, d] for 90^0: [-d, 0] for 135^0: [-d,-d]. In figure 5.4 (b) illustration of calculation of GLCM for 0^0 and 45^0 is given.

Haralick proposed 14 GLCM parameters or descriptor for the calculation of GLCM matrix [82] [129]. The 14 Haralick features calculated from GLCM are defined as:

- Sum Average
- ASM
- Energy
- Contrast:
- Variance
- IDM
- Entropy
- Difference Variance
- Information measures of Correlation
- Maximal Correlation Coefficient
- Difference Entropy
- Sum Variance
- Correlation
- Sum Entropy

These 14 features have strong correlation between them. Among them only 4 are popularly used. In this thesis these 4 features are taken. So they are defined as:

- **Contrast**

Contrast is a parameter which makes image visible by calculating difference of brightness of one object with the other object in other kind of image. It can be calculated by difference in color and brightness of objects [130]. Human eye is more prone to contrast than luminance. Contrast gives spatial frequency of an image. To increase the definition of an image contrast should be high. Contrast ration is known as highest contrast. Contrast can also be defined as:

(Luminance difference / Average luminance). Contrast for GLCM features can be given as

$$\text{Contrast} = \sum_{i,j} |i-j|^2 P(i,j) \qquad 5.12$$

Harlik contrast can be defined as:

$$\text{Contrast}_{\text{harlick}} = \sum_{n=0}^{N-1} n^2 \left[\left[\sum_{i=1}^{N} \sum_{j=1}^{N} P(i,j)\right]\right] \text{ and } |i-j| = n \qquad 5.13$$

Where N = Number of gray levels in the digital image

$i = i^{th}$ element pixel intensity in matrix p

$j = j^{th}$ element pixel intensity in matrix p

$(i, j) = (i, j)^{th}$ access in normalized GLCM (in i row and j column of GLCM matrix).

They can be calculated on MATLAB [131].

- **Correlation**

It measures the correlation of pixel from its neighborhood pixel. It depicts grey tone variations in image. Pictorial information for 2D and 3D image are obtained from this statistical parameter and filters [132].

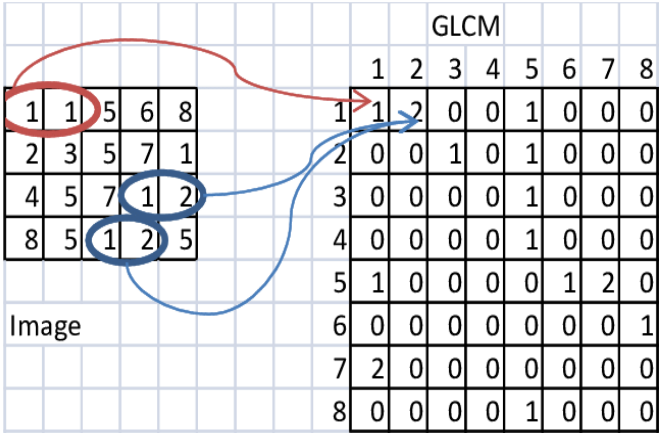
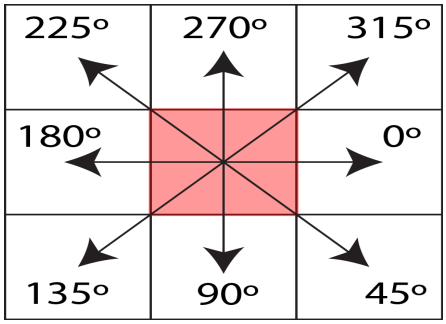
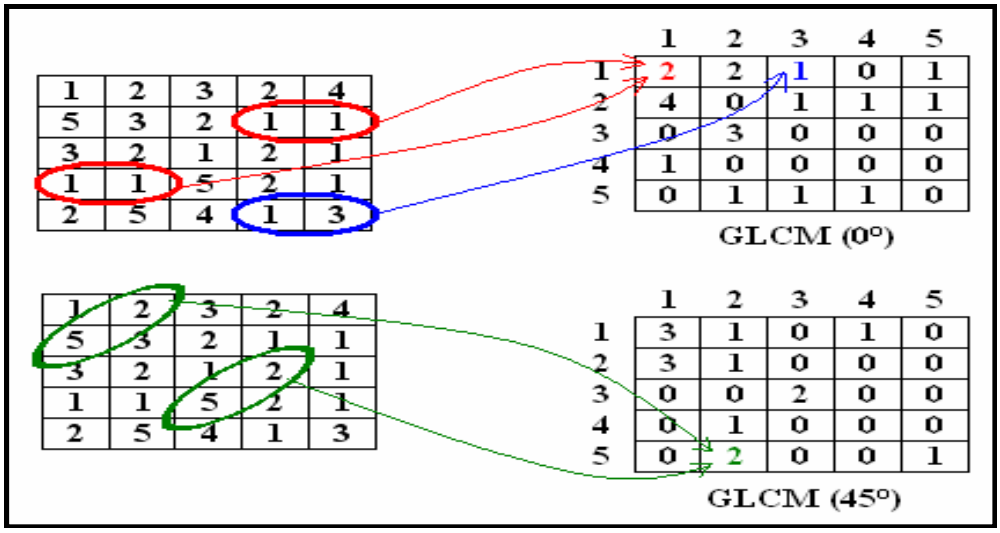


Fig. 5.3 GLCM showing frequency of occurrence of two neighbor pixels



(a)



(b)

(a) Adjacent pixel d=1 and angle= 0^0,45^0,90^0,135^0 and 180^0 (b) GLCM showing frequency of occurrence of two neighbor Pixels with 0^0 and 45^0

Fig. 5.4 GLCM presented by different direction 0^0, 45^0, 90^0, 135^0 and 180^0

It categorizes how good the projected values appropriate from an estimated model. GLCM correlation can be defined as:

$$\text{Correlation} = \sum_{i,j} \frac{(i-\mu i)(j-\mu j)P(i,j)}{\sigma_i \sigma_j} \qquad 5.14$$

Harlik correlation is defined as :

$$\text{Correlation}_{\text{harlick}} = (\Sigma_i \Sigma_j (i,j)\, P(i,j) - n_x n_y)/\sigma_x\, \sigma_y \qquad 5.15$$

Where x, y = pixel location of the image

nx = Mean of Px

ny= Mean of Py

σx = Standard deviation of Px

σy = Standard deviation of Py

- **Energy**

Energy is very important feature to define texture analysis. It is also known as angular second momentum (ASM) or uniformity. It is addition of the square of the elements in GLCM matrix. More homogenous image has more value of energy. If energy of an image is 1 then it is known as constant image [133].

GLCM energy can be written as:

$$\text{Energy} = \sum_{i,j} P(i,j)^2 \qquad 5.16$$

Harlik Energy feature is defined as : Harlik Energy = $(ASM)^{1/2}$ 5.17

- **Homogeneity**

It tells us the closeness of elements to its diagonal elements in image. It is also known as Inverse Difference Moment (IDM). It is used to calculate similar parameters in number of images. Homogeneity signifies resemblance in datasets. Homogeneity has maximum value if all the elements in an image are same [134].

GLCM homogeneity can be calculated as:

$$\text{Homogeneity} = \sum_{i,j} \frac{P(i,j)}{1+|i-j|} \qquad 5.18$$

Harlick homogeneity can be defined as:

$\text{Homogenity}_{\text{harlick}} = \Sigma_i \Sigma_j \, 1/[1+(i-j)^2]P(i,j)$ 5.19

5.3.2.1.3 Color Level Co-occurrence Matrix (CLCM)

Color and texture descriptor both applied simultaneously with GLCM gives great results [135]. GLCM can be modified for the feature extraction with texture as well as color. Color and texture features in one feature are explained in next section. So GLCM as a modification is applied directly on color images. This modified form of GLCM with color textures is defined as Color level co-occurrence matrix (CLCM) . In color image representation RGB model work as three planes or dimensions (one for R, one for G and one for B). So color image representation with texture in CLCM also known as 3D representation of image. So for every one value of GLCM equation there will be three equations. Four GLCM equations are converted in to 13 matrices for CLCM [136]. Figure 5.5 clearly explains the principle of CLCM.

Here three cubes or planes for R, G and B is created with distance d=1 and angle $\theta = 0^0, 45^0, 90^0$ and 135^0. From these planes 13 directions are created and then 13

probability matrices or equations are derived. These 13 color texture feature is worked as single feature for the classification of melanoma with 3D CLCM method. It has been experimentally proved that CLCM has 90% success than traditional GLCM [136].

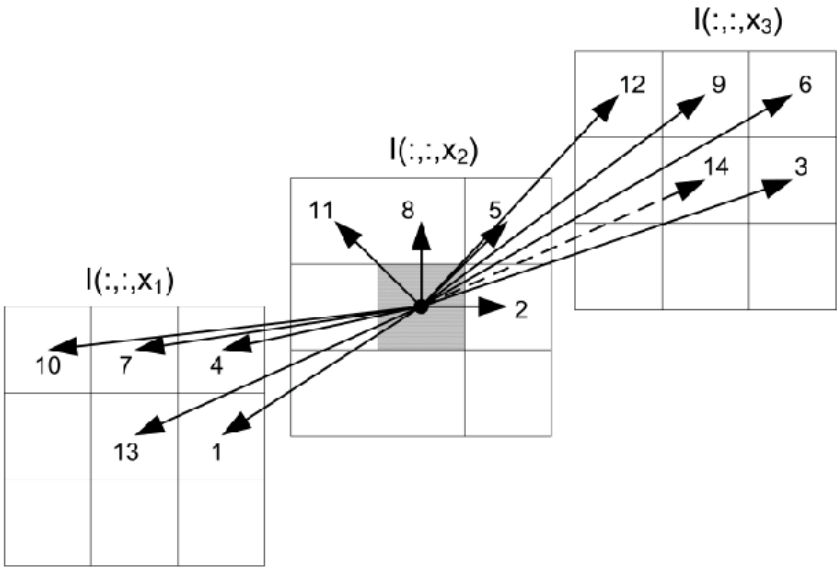


Fig. 5.5 Principle of CLCM for 13 directions with color components x_1, x_2 and x_3

5.3.3 Color Texture Feature Extraction (CTF)

Color feature has gained reputation for classification purpose. Texture feature also has increasing amount of work on pattern recognition and classification. Both color and texture if used separately can give good results [137]. Visual textures can be known as colored textures. They can have same structure with different color and different structure with same colors. So texture should include color features for better classification. Colors can be the feature set for visual texture [138]. Characteristic colors depend upon image and images of same texture can characterize dissimilar distinctive colors. This happens because colors are noisy. So organization of color with texture is essential for great results in classification. There is a lot of work done on color with texture feature extraction. All research proved that color information can play a significant role with texture in the field of classification or recognition. It increases the performance of classifier. When both color and texture are used altogether, it is known as CTF (color texture feature extraction). Color and texture are made in to one feature. These are 3D features. It improves classification accuracy but also complexity as number of features is more. So feature selection should be done

very carefully to optimize the results. In this technique features are extracted directly from color images. Experiments show that CTF gives better result than grayscale counterparts [139].Another work reports that use of color in grayscale texture analysis can provide better performance [140]. A work also reports that color with texture features can improve classification and recognition techniques. In chapter 3 we have also discussed in detail some important methods of CTF extraction like, Co-Occurrence [133], Gabor filters [141], Auto-Covariance [142] and Wavelets [143]. The fusion of color with texture descriptor is done by three levels.

- Extraction of features
- Measurement of similarity
- Classification

5.3.3.1 Feature Vector

Color-texture descriptors are link in to a one descriptor. This technique needs descriptor values in a proper scale.

5.3.3.2 Similarity Measure

A different similarity measure is used for both feature vectors. A single classifier is used for the classification of both features. The results of similarity measurement are scaled and combine for the final result [144].

5.3.3.3 Classifier Levels

In this technique color and texture descriptors are applied as complementary to each other. So after combining these two, they will work on weakness and strength both. In this level incorrect scaling is always present. This problem can be minimized by adding representations on classifier level. A separate classifier is used for both features. The classifiers will use irreconcilable similarity measures to reduce scaling now [145].

5.3.4 Principal Component Analysis

Classification of melanoma images heavily depends upon feature extraction.

Variables or feature in this technique are derived to have the properties and definition of image as discussed above. If one has too many features or variable, it will increase complexity and make accuracy less. This model can have a problem of over fitting. So we have to take all variables but focus few of them or rather we can say that we have to reduce the feature space that we are working on. With the reduction of the dimensions of feature space, over fitting will have less chance to occur. To reduce the feature space is known as Dimensionality Reduction. There are two popular techniques to reduce dimensions. They are known as:

- **Feature Elimination**

In this technique features are actually eliminated to reduce feature space. It is simple and maintains interpretability of variables. But it has a huge disadvantage of loosing information about dropped features.

- **Feature Extraction**

In this technique most important features are kept and drop least important ones. PCA is a technique for feature extraction. PCA combines input variables in a manner; we can drop least important features and still contain most valuable parts of all variables. After applying PCA all new features are independent [146]. PCA is a powerful tool to analyze data. It identifies patterns in data and expresses data in a way to find similarities and differences in them. In high dimension, patterns are very hard to find, PCA is used for graphical presentation [147]. After finding the patterns in data compression can be applied for the dimensionality reduction [148]. Generally PCA is used when variables cannot be identified but there is a need to reduce them. Moreover variables after PCA will be independent. Generally, Steps involved in PCA calculation are described as:

- **Step 1** Data Collection

First of all we have to collect data either in 2Dimension or 3Dimension.

- **Step 2** Subtraction of Mean

Each data dimension is subtracted by its mean for perfect working of PCA.

- **Step 3** covariance matrix calculation

Covariance matrix will be calculated

- **Step 4** Eigenvalues and Eigenvectors calculation from covariance matrix

They are calculated to tell useful information about data.

- **Step 5** Formation of feature vector by choosing components

This is the section where data compression or dimensionality reduction is actually done. It is done by arranging eigenvector values from highest to lowest. Eigen vector with highest Eigen value is principal component. Lower value of Eigen vectors can be discarded according to the need. Now feature vector is formed with all the selected values of Eigen vectors in to the columns [148].

$$\text{Feature Vector} = \{\text{Eigen1, Eigen2----------Eigen}_n\}$$

5.4 PROPOSED METHOD FOR FEATURE EXTRACTION AND SELECTION

Feature detection and selection is very significant step in classification of melanomas. If relevant features are extracted and selected, it will improve the classification accuracy. So feature extraction and selection is a procedure to get relevant features and leave redundant features from big feature data. Feature extraction is a process of vital importance for detection of melanoma in CAD diagnostic systems. Over the last decade a numerous methods to extract various features have been proposed and experiments were done in various color models as well. Although each classifier has its own characteristics and significance but its performance majorly depends upon the uniqueness of the features extracted.

A new approach is proposed in this thesis to extract two features i.e. color and texture, as single feature which is multi-direction 3D (CTF) color texture feature. The lesion part is processed in multiple small windows to evaluate the CTF matrix. This data is further scaled by using gray level spatial dependence matrix as per image intensities. This research work will be explained in two sections.

5.4.1 Model 1

Color feature provides better results in comparison to texture feature although they provide best results when both are used to classify melanoma [50]. A number of methods are proposed by authors to discretely extract the above two mentioned features. In this section a new methodology is proposed to extract the two features

color and texture as single feature known as CLCM. A functional block diagram of the proposed system is provided in the Figure 5.6.

14 statistical feature co-occurrence matrixes for texture classification was defined by Harlick [128]. Due to strong co-relation between these statistical features only 4 out 14 are popularly used. CLCM matrix is based upon GLCM and equations defining it are given in previous section.

$$\text{Contrast} = \sum_{i,j} (i-j)^2 P(i,j)$$

$$\text{Correlation} = \sum_{i,j} \frac{(i-\mu i)(j-\mu j)P(i,j)}{\sigma_i \sigma_j}$$

$$\text{Energy} = \sum_{i,j} P(i,j)^2$$

$$\text{Homogeneity} = \sum_{i,j} \frac{P(i,j)}{1+(i-j)}$$

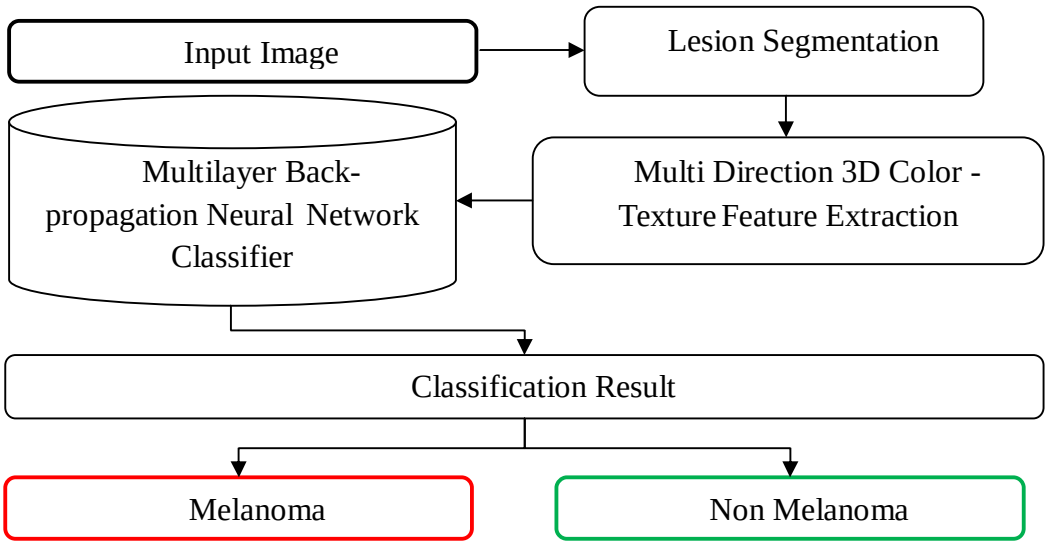


Fig. 5.6 Functional block diagram of proposed system

These equations computes how many times a pixel with grey level value is correlated to adjacent pixels by value j and is based on distance d (between pixel of interest and adjacent pixel) and angular spatial relationship theta (Θ= 0, 90, 45 and 135) of an image. Color component of all three planes (R, G, B) are also added while calculating texture feature GLCM; hence the matrix is called CLCM and as both features are calculated in integrity as single feature to form 3D CTF. These three values create a

3D representation of the pixel. The concept of distance (d=1) and angle (Ɵ= 0, 90, 45 and 135) between adjacent pixel in single plane is shown in Figure 5.7.

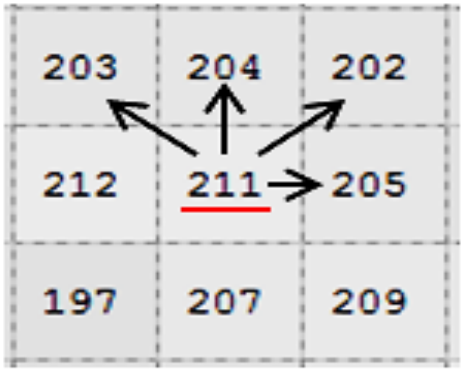


Fig. 5.7: Adjacent pixels (D = 1 and Ɵ = 0, 90, 45 and 135)

The interest pixel having intensity 211 is underlined in red color and at distance, d = 1 four pixels are indicated with arrows. The pixel with intensity 205represents angle 0, pixel with intensity 202 represents angle 45, pixel with intensity 204 represents angle 90 and finally pixel with intensity 203 represents angle 135.Results are calculated with d = 1 and Ɵ= 0, 90, 45 and 135. Although in this paper results shown and discussed are evaluated using distance and angle parameters as d = 1 and Ɵ = 0. Because they outperforms the results in comparison to parameters d = 1 and Ɵ=90, 45 and 135.

A model of 12x4 color-texture feature matrixes for a 30x30 frame of lesion part is presented in Table 5.1. In the table all 4 GLCM features namely contrast, correlation, energy and homogeneity are computed respectively as per equation 1 to 4using factors Ɵ = 0 and d = 1. Initial 3 values shows d = 0 because as the features are computed between interested pixels of different planes.

To evaluate the CTF matrix for complete lesion part all interested pixels are selected with a 30x30 neighborhood block sequentially from Dermoscopic image until all the pixels of lesion part are processed and CTF matrix is also recursively appended for the same. The block selection is done on the basis of spatial map reference of lesion part and CTF is evaluated from selected block if it contains 95% or above pixels from lesion part only. So in this way generally a single Dermoscopic image is divided in to approximately 150 to 200 blocks of lesion parts. For example if an image have 200

blocks in lesion part then CTF matrix dimensions will have (200 x 12) 2400 columns and 4 rows of data. This is quite huge, non-uniform and computationally complex feature matrix. It does not seem practically efficient to store and use this large dataset for each image directly with classifier. Dimension of features extracted in this manner is non-uniform because lesion part division of each image has different number of blocks. So to make it computationally efficient and uniform this large matrix is scaled down from 4x2400 to 8x8 matrix by calculating how often a pixel with particular intensity value i occurs horizontally adjacent to pixel j or in short calculating GLCM again for CTF matrix. Now lesion part of each Dermoscopic image can be represented by this set of 8x8 matrixes irrespective to the numbers of 30x30 blocks. This 8x8 matrix is converted into 1x64 vector representation before using in classifier.

Table 5.1: 12x4 CTF matrix for 30x30 blocks

Features	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
D, Ɵ	**0, 0**	**0, 0**	**0, 0**	**1, 0**	**1, 0**	**1, 0**	**1, 0**	**1, 0**	**1, 0**	**1, 0**	**1, 0**	**1, 0**
Planes	**RG0**	**RB0**	**BG0**	**RR**	**BB**	**GG**	**RG**	**RB**	**GR**	**GB**	**BR**	**BG**
Contrast	1.2675	2.8308	0.5400	0.2142	0.2225	0.2050	1.4058	2.9133	1.3950	0.6125	2.91	0.6233
Correlation	0.5018	0.4024	0.7300	0.8974	0.8988	0.9097	0.5160	0.4102	0.5152	0.7082	0.4098	0.7172
Energy	0.3982	0.3600	0.3417	0.3484	0.5075	0.3694	0.3242	0.3487	0.3346	0.3407	0.3414	0.3302
Homogeneity	0.8152	0.6305	0.6383	0.7088	0.6513	0.7164	0.6121	0.4769	0.6457	0.5159	0.5124	0.5255

5.4.2 Model 2

In this section major emphasis is given on the improved computational complexity and dimensionality reduction for 3D color texture feature (CTF) extraction, using principal component analysis (PCA).Several machine learning classification algorithms for detection of melanoma are also evaluated to model and obtain the best performance classifier. Two features two features i.e., color and texture are extracted

as single feature using Multi Direction 3D color texture feature extraction technique. This technique produce better classification results in comparison to using only color or texture feature or both extracted separately and used in combination. But it involves high computational complexity cost in trade of increased classification accuracy [149], [17].

To reduce computational complexity; PCA dimensionality reduction technique is applied and to enhance the classifier accuracy, different types and variants of machine learning classification algorithm are evaluated. In Figure 5.8 block diagram of the planned is presented. After segmentation, features are detected and extracted from the output images by using a kernel of 30x30. Complete segmented image is processed sequentially by these kernels. If the kernel has at least 95% pixels from lesion region then only the CTF features are extracted from it otherwise it is skipped.

For texture classification Harlick et al. defined 14 statistical feature co-occurrence matrices [128]. These statistical features have strong co-relation between them. So, only 4 out of 14 are popularly used. Equations defining these 4 features are as follows [129], [136].

$$\text{Contrast} = \sum_{i,j} |i-j|^2 p(i,j)$$

$$\text{Correlation} = \sum_{i,j} \frac{(i-\mu i)(j-\mu j)p(i,j)}{\sigma_i \sigma_j}$$

$$\text{Energy} = \sum_{i,j} p(i,j)^2$$

$$\text{Homogeneity} = \sum_{i,j} \frac{p(i,j)}{1+|i-j|}$$

To compute the Colour level co-occurrence matrix (CLCM) for CTF extraction the parameters used are as follows:

d, distance = 0 and 1

Θ, angle = 0

By using specific values of d and Θ, a feature matrix of 12x4 is obtained from each kernel. 12 signifies the combination of planes (R-Red, G-Green and B-Blue) with variation in values of d and Θ. Planes having d = 0 and Θ = 0 are RG0, RB0 and BG0 whereas planes having d = 1 and Θ = 0 are RR, BB, GG, RG, RB, GR, BR and BG. 4 relates to statistical features namely Contrast, Correlation, Energy & Homogeneity.

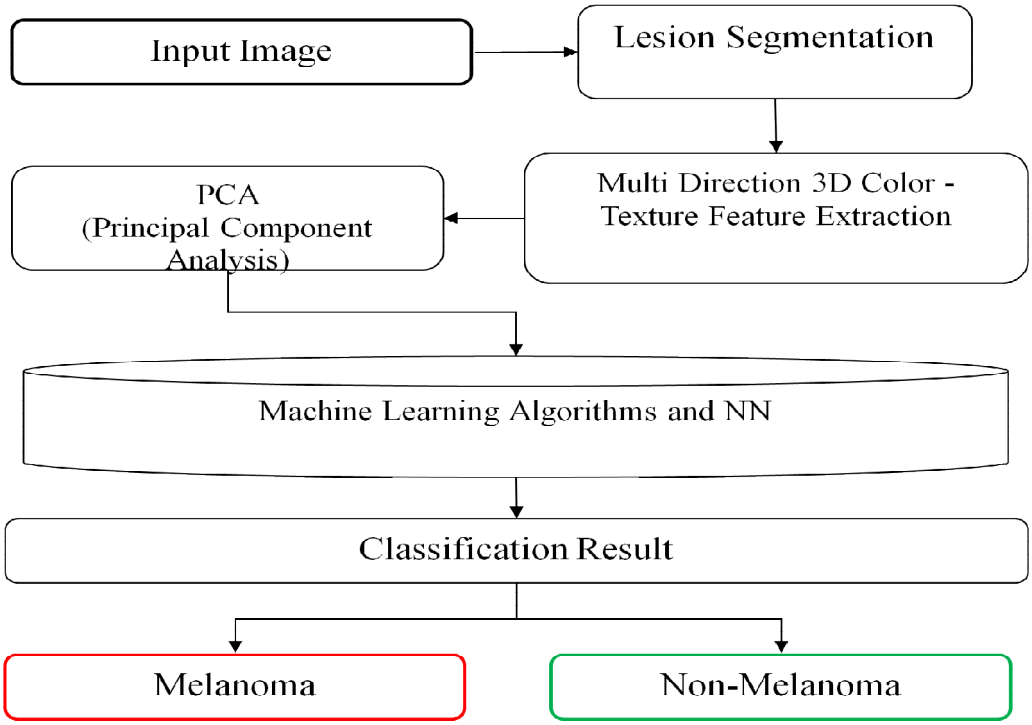


Fig. 5.8 Basic block diagram of planned structure

In this manner each Dermoscopic image produces approximately 150 to 200 blocks of 30x30 kernels with 95% legion region pixels. Suppose if an image has maximum 200 blocks where each block has 12x4 set of CTF then for complete image CTF matrix would be 2400x4 which is quite huge. To scale down the feature set this matrix of 2400x4 is again processed using GLCM which in turn provides a feature set of 8x8. This is further converted to a single row matrix of 1x64 irrespective to number of 30x30 blocks and which means now for every single image we can have a feature set of 1x64 instead of 2400x4. While selecting window size there is a trade-off between accuracy and computational complexity. Smaller window size will lead to increased computational complexity whereas the larger window size will lower the accuracy as well as resolution if the feature being extracted [149].

Figure 5.9 represents parallel coordinate plot for full 64 feature set of all 200 Dermoscopic images whereas Fig. 5.10 represents only 24 attributes selected after dimensionality reduction. On x-axis each row number is for the features and y-axis for its typical numerical values. Parallel coordinate plots are the best way to compare and analyze relationship between multiple variables. After complexity reduction by PCA, relationship between these features simplifies and the number of attributes downsized significantly by more than 66%. PCA helps to decrease the dimensionality of the data

samples variation by using orthogonal transformation presented in the dataset is maintained up to maximum possible extent [146], [147].

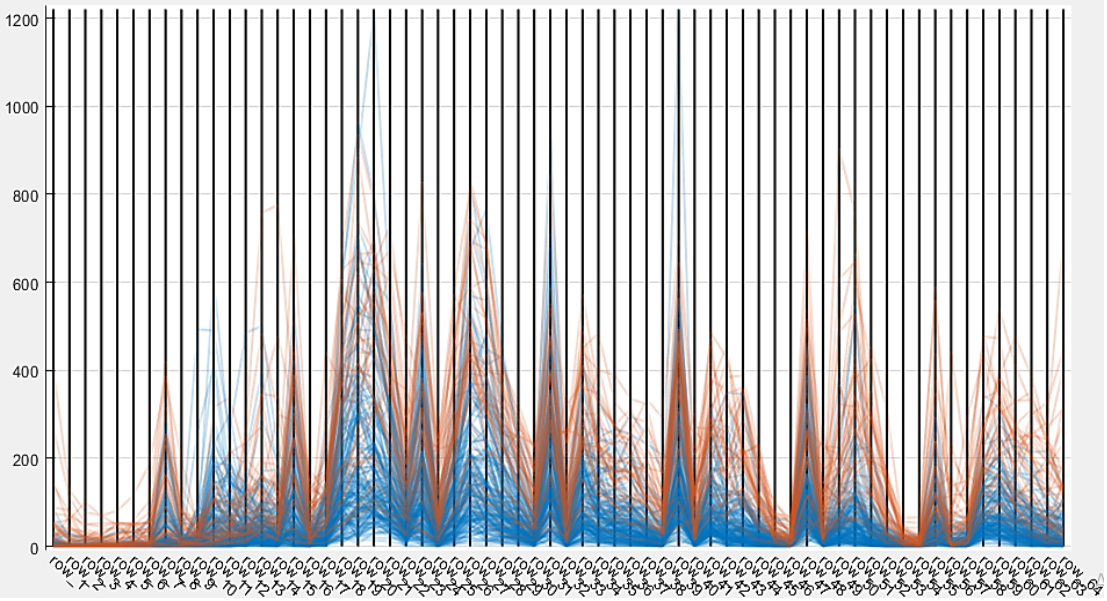


Fig. 5.9 Parallel Coordinate Plot showing all 64 features attributes from 200 Dermoscopic images

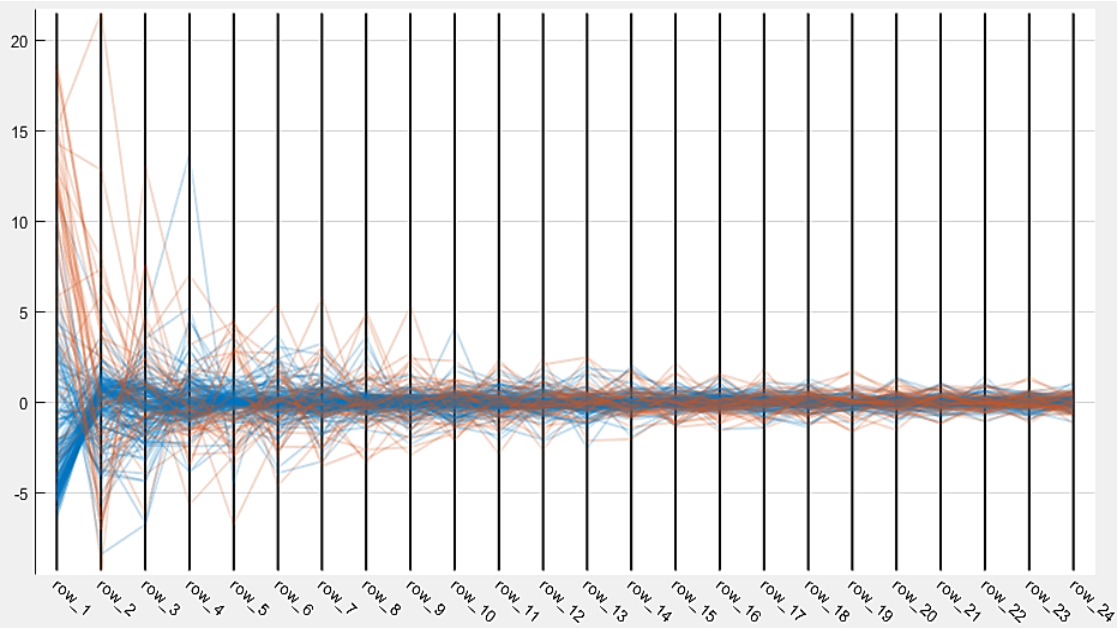


Fig. 5.10: Parallel Coordinate Plot showing all 24 features attributes from 200 Dermoscopic images after PCA

5.5 SUMMARY

This chapter delivers full detail for all feature detection and extraction approaches for various feature used to classify benign from malignant lesion. Two automated feature

extraction methods are proposed for relevant features for improving the classifier capability. 3D CTF extraction without PCA and with PCA both are milestone for the other datasets to work on as well as other application of feature optimization and selection.

The feature sets extracted in the previous part will be given to the different classifier to trace their role in differentiating benign from melanoma. This will help the appropriate features to attain their weight according to the performance related to the classification of melanoma.

CHAPTER 6

THESIS CONTRIBUTION TO CLASSIFICATION TECHNIQUES

6.1 INTRODUCTION

This section presents the contribution of classification methods for computer aided diagnose of skin cancer. The objective of the research in this chapter is to develop a more efficient technique for classification of melanoma.

This chapter is divided in two main sections. In first section classification is done on 200 images from PH2 dataset after extraction of features (3D CTF). This technique involve artificial neural network (ANN) with back propagation technique and results are compared from other work. In second section classification is done on same dataset with extracted features by CLCM and PCA. These reduced features are applied on numerous machine learning techniques like ANN with back propagation. Results are again compared with current work done on skin cancer detection.

Classification step of the lesion from cancerous and non cancerous is important and final step in computer aided diagnosis. Classification has a very major role in pattern recognition as well as vision analysis and artificial intelligence. Supervised classification has two steps, training or learning and testing. In stage of training, classifier is learned or trained with dataset giving features as input. When machine is trained or algorithm is done then it is given for the testing with reserved features means training is done with different images or feature vectors. In this way classifier performance is evaluated. In this work Artificial neural network (ANN) is used as classifier with different machine algorithm. So ANN will be discussed in detail.

6.2 ARTIFICIAL NEURAL NETWORK (ANN)

The first neural network was developed on 1973 depending upon the ability of brain to understand [150]. These networks are basically complex and parallel processing networks like human brain. Since development of artificial neural network is based on biological neurons, they are very much needed to be discussed in this work.

6.2.1 Biological neurons

There is very close relationship between biological neurons and artificial neurons. Basically artificial neurons have same computational capability as biological neurons. So some features of biological neural network are presented to understand the working of artificial neural network.

A biological neuron has three components: Axon, soma (cell body) and dendrites. A biological neuron is presented in Figure 6.1.

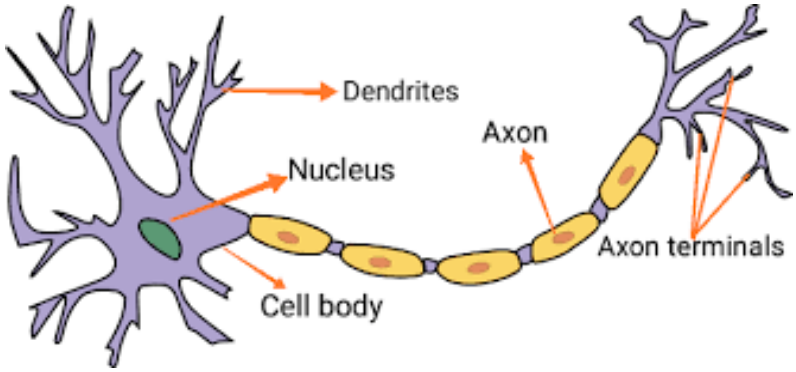


Fig. 6.1 Biological Neuron

- **Dendrites**

Dendrites receive signal from other neurons. It works as input in ANN. Signals is transmitted in electrical pulses after chemical process. Chemical process modifies signals by frequency scaling as weights done in ANN.

- **Cell Body**

Soma sums the incoming signals. When it gets sufficient input it fires the signal through axon to the next cell. Transmitted signal is considered as binary as soma fires and does not fire at particular instant of time. Soma adds all incoming signals at a specific point of time.

- **Axon**

The transmission of signal from one neuron to other is done by axon. They are very much like highly developed dendrites. They send signal to synapse (terminals). They are thin, long and fiber type structure.

6.2.2 Architecture of ANN

Neural network means arrangement of layers. Arrangement of neuron in to layers and their interconnection is known as net architecture. In many neural networks, layers are either fully connected or partially connected. Neural networks are classified as single layer neuron and multilayered neuron.

- **Single layer perceptron**

It has one layer of connected weights. Input units are connected to output but not connected to the other output units. For single layer net a weight of one output unit does not affect the weight of other output unit. It is the simple form of neural network. It is also known as Feed forward single layer neural network. These layers are shown in Figure 6.2.

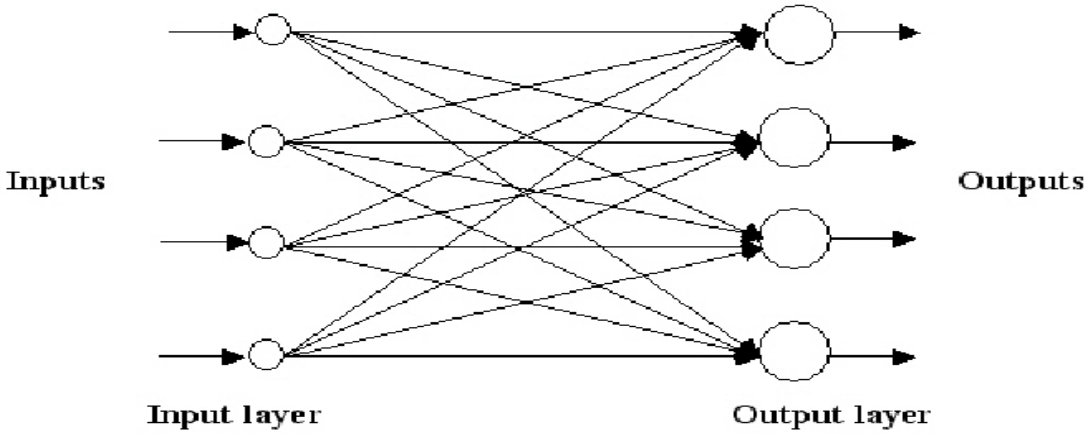


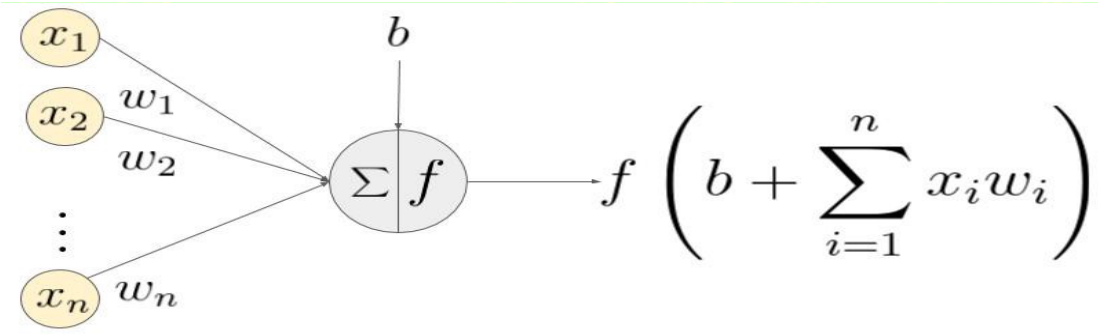
Fig. 6.2 Single Layer ANN

- **Multilayer perceptron (Feed forward multi-layer neural network)**

It has single or more than one buried layers between input layer and output layer. Typically there are three layers first is input, second is buried or hidden layer and third is output layer. Multilayer net solves more complicated and complex problems. There was a disadvantage in early neural networks as they are not able to solve linear problems. So multilayered perceptron model is developed by scientist [151]. These neural networks are able to learn from their interconnections and also apply their learning in testing phase [152].

6.2.3 Simple Neural Network Operation

Operation done by a neuron can be explained with the help of Figure 6.3. As it is shown in the figure, there is 'm' number of inputs x_1, x_2, x_3-------x_n. Weights with the specified inputs are w_1, w_2, w_3,----w_n. Weights are variable which are multiplied with the input and then summed up. After summation of weights and input values they are given to the activation function. Activation functions are also known as transfer functions. These activation functions convert total value in form of 0 or 1. If this value is zero then neurons does not fire means does not transmit signal but if it is 1 then it fires at the same instance of time [153]. Weights (w_1, w_2, w_3, ----w_n)control the signal between two neurons. They are defined as learnable parameters for machine learning model. Weights decide the influence of input over output. Bias (b) is just like weights but it has always value 1. If bias is increased then net value of input is also increased. It is just like constant in linear functions. They shift the activation function by adding '1' to the input. Activation function (f) defines output of a neural network according to the input. Their purpose is to introduce non linearity in to the output. It decides whether a neuron should be activated or not by adding weights and bias with it. There are number of activation functions like Binary Step Function, Sigmoid Function Linear Function, Tanh Function, Exponential Function, ReLU Function and Leaky ReLU Function.



An example of a neuron showing the input (x_1 - x_n), their corresponding weights (w_1 - w_n), a bias (b) and the activation function f applied to the weighted sum of the inputs.

Figure 6.3 A Simple Neuron Model

6.2.4 Model Architecture

Model structure means quantity of neurons in input layer, hidden layers and output layer. Number of hidden layers and algorithm used also play a very important role to

enhance training accuracy [154].there are no clear cut rule for the quantity of buried layers as well as quantity of neurons in input as well as in output layer. It depends upon the problem. According to the problem these numbers are given. Best network selected with a trial and error method. High numbers of input variables make the size larger and so learning time increases and learning quality decreases [155].

In chapter 3 it is discussed that ANN works well in skin cancer detection system. It has great capacity to work with complex problems with different parameters [155].there are number of neural networks in the literature. But mostly used neural networks are Radial Basis Function Network, Multilayered perceptron, convolution Neural Network and Recurrent Neural Network (RNN) and modular neural network (MNN). This work takes help from scale conjugate gradient algorithm with back propagation technique for classification. It will be discussed in detail in next section.

6.3 BACK GROUND OF PROPOSED WORK

6.3.1 Multilayer perceptron (FFNN)

A feed forward multilayer perceptron (MLP) is a system that adds up with further perceptron, connected in several layers, to solve complex problems. Each perceptron in each layers are interconnected and they send signal to their next one perceptron. These are hidden layers which ultimately go to output. For each signal perceptron uses different weights. If there is only one hidden layer then the network is known as non-deep or shallow neural network. But if it has more than three hidden layers then it is also known as deep learning network. This type of network is very much capable to solve nonlinear and complex problems. In these networks non linear active functions like sigmoid, ReLU, leaky ReLU and softmax etc are used to give output between 1 and 0 or -1 and 1. This permits for probability-based predictions or classification of objects into several labels. A multilayered perceptron model is shown in Figure 6.4.

In a supervised classification system like skin cancer detection, every input feature vector is connected with a tag or label or ground truth, giving its class. Labels are set with the data as a class. The network output provides a score of class, or forecast, for every input. To calculate the evaluation of the classifier, the function for calculation

of loss is defined. The loss goes more if the estimated class does not signify to the correct class, otherwise that will be little. At Some time the issue of over fitting and under fitting happens while training the model. In this situation, model works great on learning data but not well on testing sample data. For the training of the model, an optimal method is mandatory so it is done by application of an optimizer and loss function. This technique calculates the values as the group of weights (W). These weights are used to reduce the loss function. The common solution is to assign random weights and adjust them with lower loss.

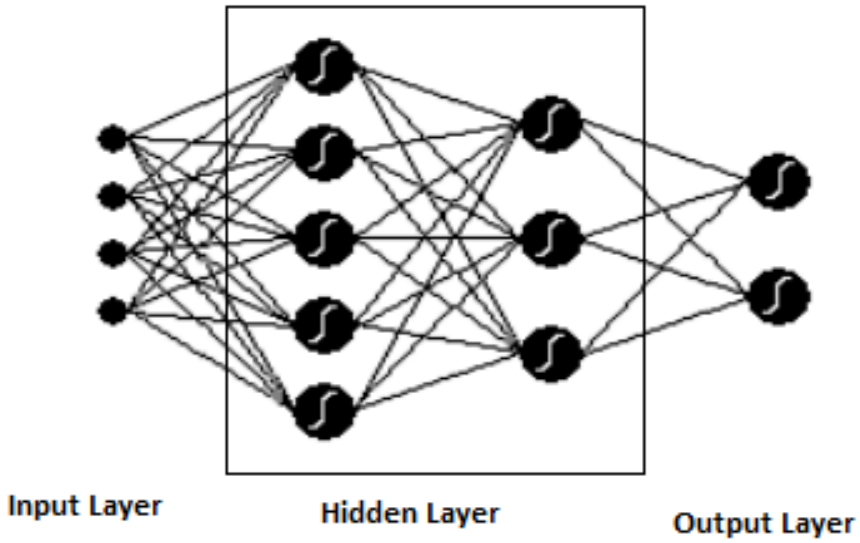


Fig. 6.4 Multilayered Perceptron Network

6.3.2 Training of model

Three steps are involved in training of a multilayered perceptron.

- **Forward Pass**

In this step input is passed to the model multiplied by weights and bias is added at each layer and output is calculated with the help of activation function.

- **Loss Calculate**

Output obtained from above is predicted output but we have real output or expected output means label data. These output have difference then lose is calculated with the help of different loss functions.

- **Backward Pass**

After calculating loss back propagation is done by updating the weights with different gradient. This is very important stage in learning or training of models. Weights are

adjusted by the flow of gradient algorithm in that direction. These neural networks are capable for generalization. They can classify the unknown image with other known image having same distinguishing feature. Moreover neural networks are fault tolerant. It means neural network because it keeps on working till its fraction of neurons fail in calculation.

6.3.3 Learning Algorithm for Multilayer Perceptron Networks

The learning or training rule for this network is defined as back propagation or widespread delta rule. These algorithms are improved with the time. Back propagation algorithm was introduced by Hinton, Williams and Rumelhart in 1980 [156]. The back propagation rule continually evaluates a cost function for every input data and propagates the error back from later layer to the earlier one [157]. The back propagation network has four stages:

1. Initialize the weight.
2. Calculation of output with feed forward algorithm.
3. Calculation of errors for the model
4. Updating of biases and weights.

The weights of a specific node are updated with respect to the error in every unit where nodes are connected. From Figure 6.5 a neuron getting n inputs, each input X_i (where i= "1" to "n") is multiplied it with a weight W_i for the updating of weight. Then W_iX_i product is calculated and their sum of all products goes to the activation of the neuron as input. Now the desired activation function or its value is feed to a transfer function to get the output of neural network.. The weights of the propagating signals going from neuron i through a neuron j is defined as W_{ij}.

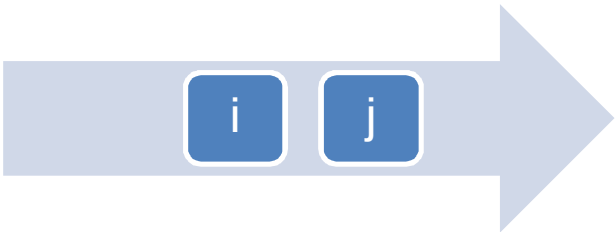


Figure 6.5 Direction of signal flow

Let E_G = Error function for pattern G

T_{Gj} = Desired output on node j for pattern G

O_{Gj} = Evaluated output on node j for pattern G

W_{ij} = Weights going from node i through node j

Since $E_G \propto (T_{Gj} - O_{Gj})$

$$\text{So } E_G = 1/2\sum(T_{Gj} - O_{Gj})^2 \quad \text{---------- 6.1}$$

The Transfer function of every unit "j" for pattern G is defined as

$$ACT_{Gj} = \sum W_{ij}O_{Gi} \text{ ---------- 6.2}$$

The output of every unit "j' is determined by

$$O_{Gj} = F_j (ACT_{gj}) \text{ ----------6.3}$$

Where nonlinear transfer function is F_j

We assume f_j to be the sigmoid function

$$F (ACT) = 1/ (1 + e^{act}) \text{ ----------6.4}$$

Where σ is a constant of positive value that signifies the area of the function.

Steepest descent technique is used in delta rule that updates weights.

Error E_G = elevation of a point on this surface.

So each weight is proportional to the change in weight directed by the delta rule, with a negative proportionality constant. Change in the weight according to the delta rule is proportional to the negative of derivative of error w.r.t the weights.

$$\text{So } \Delta_G W_i \propto -\partial E_G/\partial W_{ij} \text{ ----------6.5}$$

Algorithm used in neural network depends on trial and error estimation [158]. There are number of algorithm present for training FFNN [151]. Some important learning algorithms are discussed as follows.

6.3.3.1 LM (Levenberg–Marquardt) Algorithm

Levenberg–Marquardt is first published by Kenneth levenberg and then researched by Donald Marquardt. It is also known as damped least square method (DLS). LMA or LM incorporates Gauss-Newton algorithm and method of gradient descent. LMA is stronger than GNA. They are used to solve non linear problems. This method is an approximation to Newton method. Minimization function by this algorithm is sum of the squares of linear function. LMA is widely used in ANN applications but it is memory consuming method [26], [159].

6.3.3.2 BFG Algorithm (Broyden–Fletcher–Goldfarb–Shanno Algorithm)

It is an iterative technique for non linear optimization**.** It is also called as quasi-Newton method. In this technique, Hessian matrix is changed by Taylor series at every reiteration of algorithm. This is also a memory consuming approach [160].

6.3.3.3 Resilient Back Propagation (RP)

If sigmoid functions are applied for each action on hidden layers only then problem of squashing arises. The resilient propagation solves this problem. It increase the converge speed by only one sign of derivative. It does not use error function derivative for weight updates. It reduces the learning steps [161].

6.3.3.4 Gradient Descent Algorithm

It is a first order algorithm based on iterations to find local minimum of a differential function. To find local minima by this technique steps are taken that are proportional to the negative of gradient. This is known as gradient descent. Desired weights are given by the back propagation technique. GDA is standard back propagation algorithm. Its aim is to converge network as early as possible. It is a batch steepest descent training algorithm. It is the most straightforward technique for back propagation. One iteration of GDA is defined as:

$$W_{k+1} = W_k - a_k G_k \text{----------6.6}$$

Where W_k is weight and bias vector and G_k is gradient of error. a_k is learning rate. k = number of iterations. Equation 6.6 is repeated until network achieves convergence. In this technique weights are updated proportion to the negative derivative of error rate.
Stability of algorithms depends upon selection of learning rate. Choosing right learning rate leads to the faster convergence and stability. When learning rate is small training time is longer and computational cost is increased. On the other hand if learning rate is high it leads oscillation on the error surface. Local minimum will not be found out due to the jumps [162].

In gradient descent technique learning rate are constant throughout the training process and it leads to the slow convergence. To overcome this GDMB (Gradient

Descent with Momentum Back propagation), GDAM (Gradient Descent with Adaptive Learning Rate Back propagation), and GDXB (Gradient Descent with Momentum and Adaptive Learning Rate Back propagation) are used. These heuristic techniques give more success in results.GDA has adaptive learning rate. Initially output and error is calculated in first step. Later weights are updated in each epoch according to the learning rate. If there is no error then weights are shifted for next step otherwise weights are again updated. In GDA high learning rates are required to avoid oscillations. GDM has momentum as variable. These variables use past weights as well as current error. Combination of GDA and GDM is known as GDX.

6.3.3.5 Conjugate Gradient Algorithms (CGAs)

CGA are very much efficient than the GDA. They have lowest convergence time and low memory requirement [163]. The CGA works by searching in steepest direction which is the negative of gradients [164]. The calculations of learning rates are different. Fletcher-Reeves (FR) update is used by Conjugate Gradient Back propagation and Polak-Ribiére (PR) update is used by Conjugate Gradient Backpropagation [165]. PR performs better than FR [166]. Search directions are reset at regular interval in CGA. This is a balanced technique. It does not allow evaluation of second derivatives and converge a second order function. Scaled Conjugate Gradient Back propagation (SCG) is last algorithm in CGA [168]. In this thesis SCG back propagation is used for the classification. So it will be discussed in detail.

6.3.3.6 Scaled Conjugate Gradient Backpropagation (SCG)

SCG is established by Moller [167]. It was developed to overcome the time consumed in line search. LM (Levenberg-Marquardt model) is interpolated with CG (conjugate gradient) in this technique. This technique differs from other CGA because it has different line search technique for non linear function to make computation decreased in single epoch [164].

SCG is based on conjugate directions but it does not do a line search at every iteration. A search is done in conjugate direction which leads to the fastest convergence while in other CGA back propagation algorithms, weights are adjusted in

the steepest descent direction. That's why SCG gives faster convergence than other CGA techniques. In this process network is trained until total input weight, activation function and weights all are ones with a suitable derivative function. Back propagation method is applied to calculate derivate of output w.r.t weights and bias. A model of SCG-BPNN is presented in Figure 6.6.

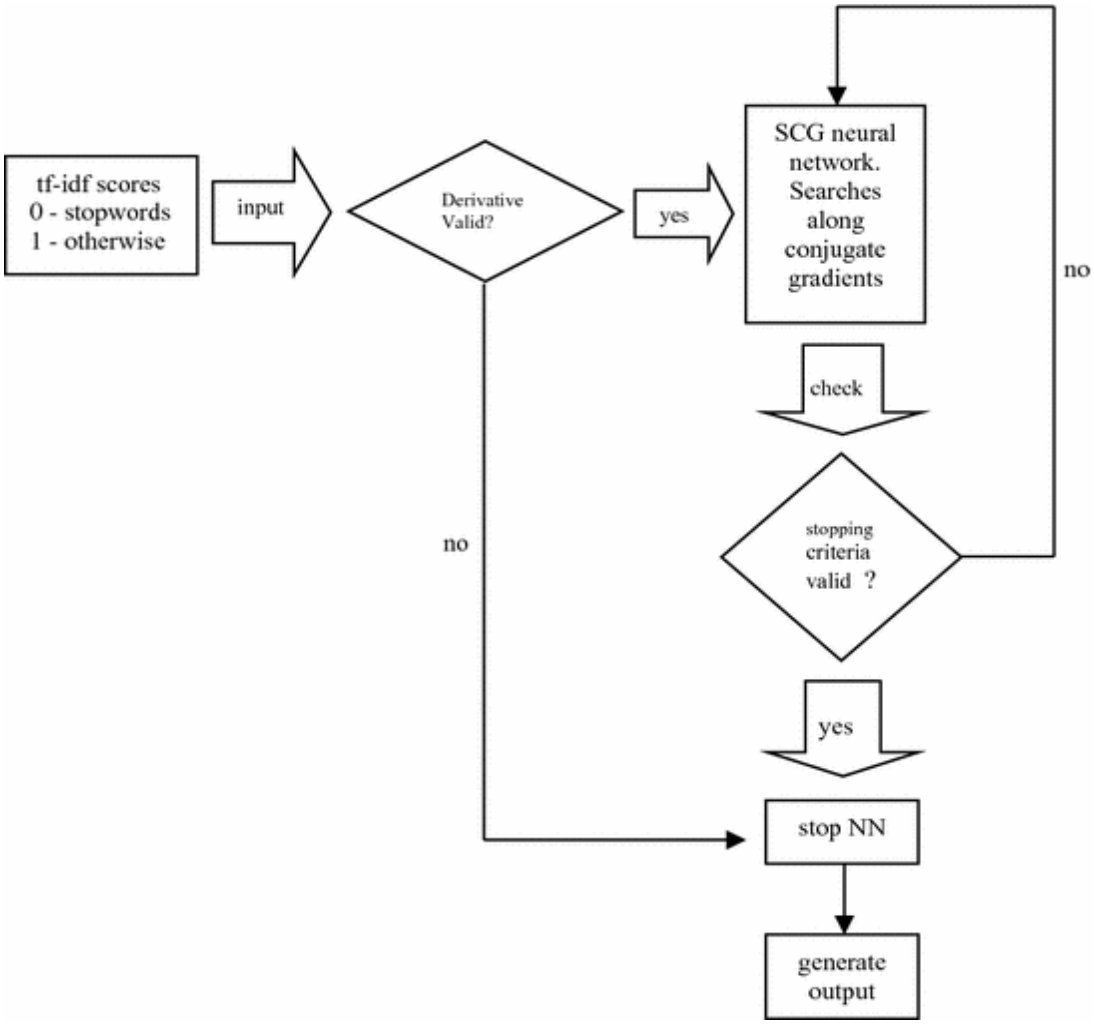


Fig. 6.6 General block diagram of SCG-BPNN

6.3.3.6.1 Mathematical model of SCG-BPNN

Let in a feed forward network is given having W a weight vector and N is the number of weights and bias [27], [167]. It is well known that error function E (W) in a given point (W+Y) can be expressed by Taylor expansion and given as:

$$E(W+Y) = E(W) + E^{|}(W)\,T(Y) + 1/2\; Y\; T\; E^{||}(W) \text{ ----------6.7}$$

So the approximation value to error in adjacent point Y

$$Eapr(Y) = E(W) + E^{|}(W)\,T(Y) + 1/2\; Y\; T\; E^{||}(W)\; Y \text{ ----------6.8}$$

To calculate critical points at minima for Eapr(Y) is given by the solution of equation 6.9.

$$Eapr(Y) = E^{\|}(W)\ Y + E^{|}(W) = 0 \text{ ----------6.9}$$

IF Y_1 is starting point and P_1, P_2 ---------P_N are conjugate system. So critical point Y^* can be calculated as :

$$Y^* - Y_1 = \sum_{i=1}^{N} ai\ Pi \text{----------6.10}$$

Where a_i€ R, where R is Euclidian space

Now equation 6.10 can be multiplied by $P_j^T E^N(W)$ and $E^{|}(W)$ can be replaced by – $E^N(W)\ Y^*$

$$So\ a_i = [P_j^T\{ E^{|}(W) - E^{\|}(W)\ Y_1\}] / (j\ P_j^T\ E^{\|}(W)\ P_j) \text{----------6.11}$$

Using equation 6.10 and 6.11 Y^* which is a critical point can be calculated. Only if E^N (W) is positive then $Eq_W(Y)$ can be calculated as :

$$Eapr(Y) = Eapr(Y^*) + 1/2\ (Y - Y^*)\ TE^N(W)\ (Y- Y^*) \text{----------6.12}$$

IF Y is minimum then term $1/2\ (Y - Y^*)\ TE^N(W)\ (Y- Y^*) \geq 0$

After calculating starting and critical point, one intermediate point is calculated to complete the path.

So it can be calculated as:

$$Y_{k+1} = Y_k + a_k P_k \text{----------6.13}$$

After solving this equation we can get all minima for $Eq_W(Y)$. In this way adopting this process SCG-BBNN avoids line search technique that is highly time consumable.

6.4 K -FOLD CROSS VALIDATION

After training the model it is not sure that model will accurately work. So model is validated. There are different techniques for validation. Model is tested on some unseen data. Model validation avoid over fitting and under fitting of model. Cross validation is a technique to test the effectiveness of machine learning model. It is a statistical method to approximate the ability of machine. It is a re sampling process to estimate the model on limited dataset for the optimization. k- Cross fold is one of them. This is a great validation technique for limited dataset as original dataset has an ability to appear both in training and test data at every observation [169]. Figure 6.7 clearly shows k fold cross validation with different iterations. It can be understood by following steps.

Step 1 entire data is split in to k folds. Value of k generally goes from 5 to 10 depending upon size of dataset. Lower value of k will lead towards under fitting while larger value of k will lead to the over fittings.

Step 2 In second step model is fit with k-1 folds and then model is validated with remaining kth fold. Performance or error of the model is noted.

Step 3 this process is repeated until every k -fold serve as a testing data. Then average of all performance is taken. The matrix generated by these average values is performance matrix for model.

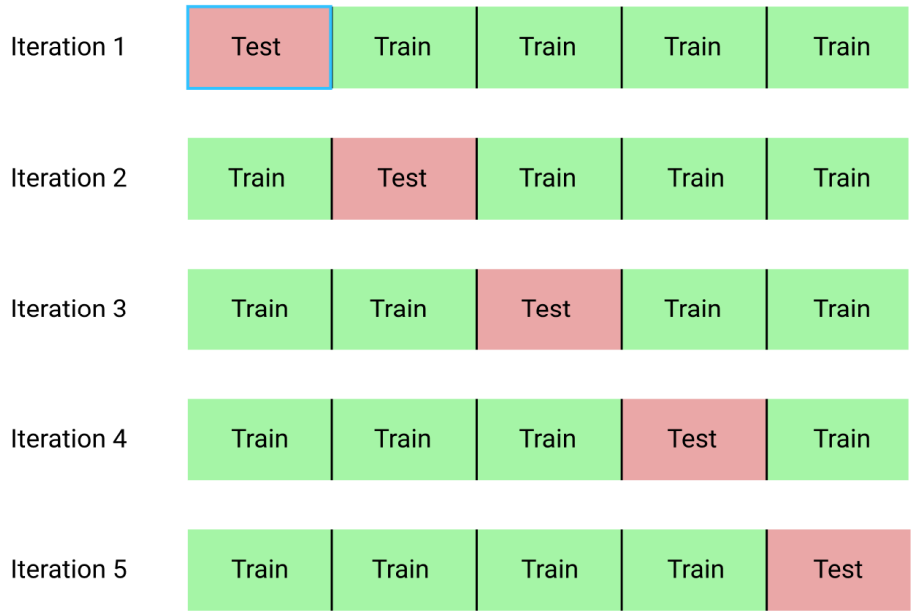


Fig 6.7 K fold cross validation

6.5 PROPOSED METHODOLOGY

Classification of skin cancer images is a final and important task. In this thesis proposed methodology for classification and validation is given in two sections.

6.5.1 Model 1

As per the PH^2 dataset it consists of a set of 200 Dermoscopic images. Out of 200 images 160 are non-melanoma and 40 are melanoma images. So a dimension of input dataset for neural network (NN) is 200 x 64. Target dataset is of 1x200 representing 0 for non-melanoma and 1 for melanoma images.

NN proposed for classification have 15 hidden layers. Data is divided randomly in to three subgroups: training (70%), testing (15%) and validation (15%). Scaled conjugate gradient back propagation method is used for training of the network. This method is based on the conjugate directions. It can train the network as long as network parameters are derivative. Functional block diagram is given as Figure 6.8.

The proposed algorithm is evaluated in MATLAB. Plot for best validation performance and all confusion matrixes are show in Figure 6.9 and 6.10 respectively. As we can analyze that test and validation curves varies in similar manner so there is no major problem in the network. The all confusion matrix represents the system performance in terms of accuracy, sensitivity and specificity. It also represents the true positive, true negative, false positive and false negative performances. By this matrix proposed system's results can be evaluated easily. In the field of machine learning confusion matrix is very simple to understand the results in statistical problems. It is also recognized as error vector matrix. Every matrix row signifies the occurrences in an expected class while every column signifies the occurrences in a true class.

6.5.2 Model 2

For classification of melanoma and non-melanoma images different supervised machine learning algorithms are executed in MATLAB 2020 tool. They are explained and categorized in following section. Each of the following mentioned classification algorithm is tested on dimensionally reduced 200x4 feature data set and to evaluate these models K-Cross Validation is used, where values of k = 5. Figure 6.11 represents the entire work as a flow diagram discussed later or before.

6.5.2.1 Decision Trees

They predict the response to the data and are also known by the name of regression trees or classification trees as well. In this paper only binary trees are evaluated, because only two categories are required to be detected which are melanoma and non-melanoma. In the beginning whole feature sets are considered as root. Each internal

node of the tree is relates to a feature characteristic and each leaf node relates to a class.

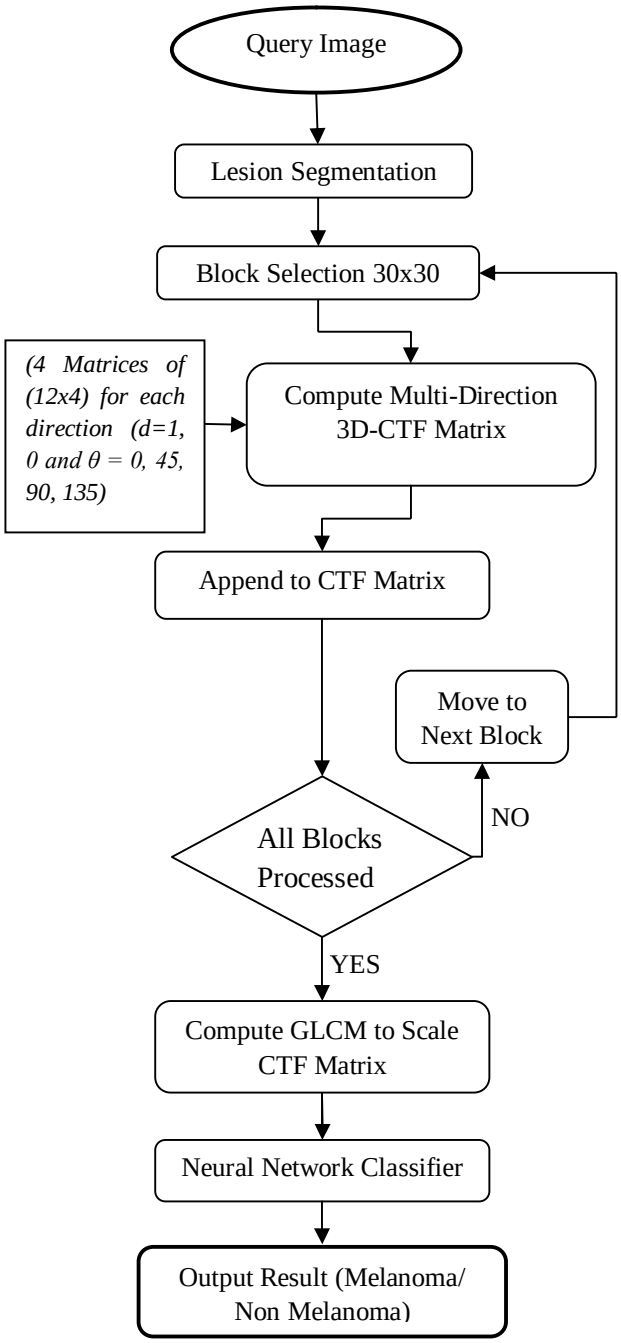


Fig. 6.8 Flow chart of the proposed Model 1

There are three popular split criteria: GDI (Gini's diversity index), Twoing rule and maximum deviance reduction. GDI is the measure of impurity of the node. In this paper GDI is used because in comparison to others it favors larger partitions and simpler to implement.

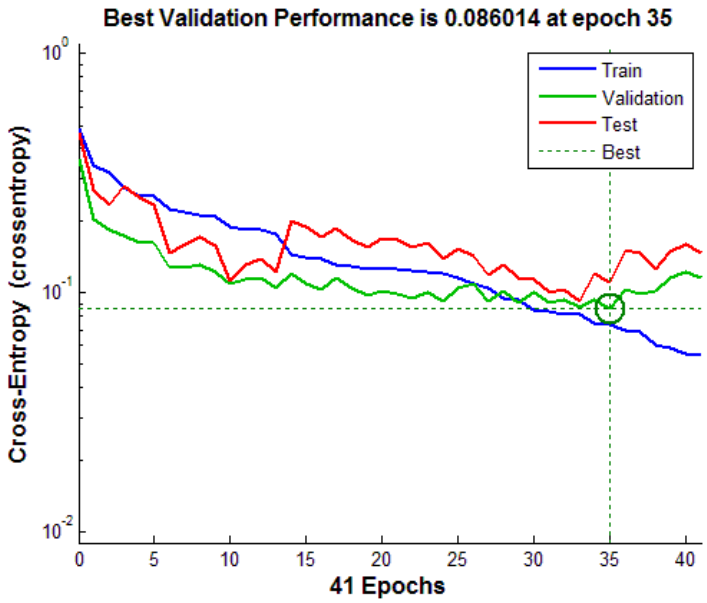


Fig. 6.9 Best validation performance plot of NN classifier.

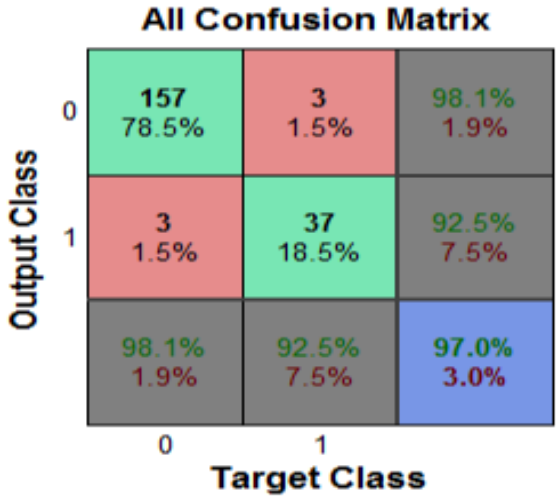


Fig. 6.10 All confusion matrix of NN classifier

It is calculated by subtracting the sum of the squared probabilities of each class from one and represented by Equation 6.14 [131], [170].

$$Gini = 1 - \sum_{i=1}^{C}(p_i)^2 \quad \text{----------6.14}$$

Where, p is the probability of each class C.

Classification is evaluated in three different variations of decision trees which are Fine Tree (maximum splits: 100), Medium Tree (maximum splits: 20) and Coarse Tress (maximum splits: 4). Surrogate decision splits is kept off as we don't have any missing values.

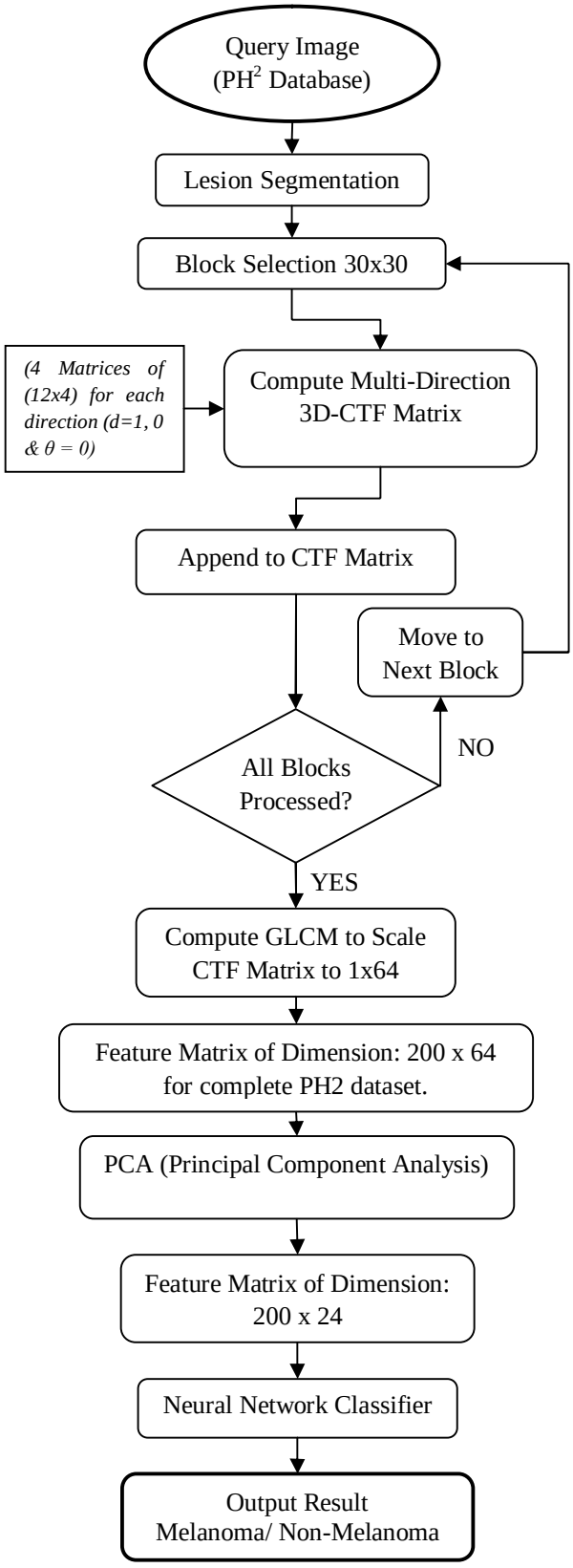


Fig. 6.11: Flow chart of proposed Model 2

6.5.2.2 Discriminant Analysis

This algorithm is quite fast, easy, accurate and good for wide dataset. Its working is based on Gaussian distributions. To build a training model it uses labeled training data. It classifies to minimize expected classification cost [131] [170]. In present paper both linear and quadratic models are evaluated for classification. It can be two dimensional or multi-dimensional and separating lines can be planes or hyper planes.

6.5.2.3 Ensembles

In ensemble five different type of classifier algorithms are used which are: Boosted Tree (uses Ada Boost with decision tree learners), Bagged Tree (uses Random forest bag, with Discriminant learners), Subspace Discriminant (with Discriminant learners), Subspace KNN (with KNN learners) and finally RUS Boosted Tree (with discriminant learners). Ensemble learners can provide results from weak learners to high quality ensemble models [131].

6.5.2.4 Logistic Regression

In this dependent variables are dichotomous. The goal is to drive the finest fitting model which best defines the association between independent and dependent variables. For logit transformation prediction of the probability for presence of the characteristic of interest is given using Equation 6.15, 6.16 and 6.17 [131].

$$logit(p) = b_0 + b_1x_1 + b_2x_2 + b_3x_3 + \cdots + b_kx_k \text{---------- 6.15}$$

Where p is the chance of occurrence of the characteristic of interest. The logit transformation can be computed as the logged odds.

$$odds = \frac{p}{1-p} = \frac{probabilityofprsenceofchracterstics}{probabilityofabsenceofchracterstics} \quad 6.16$$

$$logitp(p) = \ln\left(\frac{p}{1-p}\right) \quad 6.17$$

6.5.2.5 Nearest Neighbor

In low dimensions the nearest neighbor has good predictive accuracy. Six different variation of nearest neighbor is evaluated for classification 1. Fine KNN (Distance matric = Euclidean and Number of neighbor = 1) 2.Medium KNN (Distance matric =

Euclidean and Number of neighbor = 10) 3. Coarse KNN (Distance matric = Euclidean and Number of neighbor = 100) 4. Cosine KNN (Distance matric = Cosine and Number of neighbor = 10) 5. Cubic KNN (Distance matric = Minkowski and Number of neighbor = 10) and finally 6. Weighted KNN (Distance matric = Squared Inverse and Number of neighbor = 10) [131].

6.5.2.6 Support Vector Machines (SVM)

It works on finding the best hyper planes which that separates the data classes. Soft margin is used in this which fundamentally separates maximum data points not at all. In this paper SVM is optimized to differentiate only binary classes and multiple kernels are evaluated in the process [170].Six different variations of binary optimized SVM is used 1. Fine Gaussian SVM (Kernel Scale = 1.2, Kernel function: Gaussian,), 2. Linear SVM (Kernel function: Linear) 3. Medium Gaussian (Kernel Scale = 4.9,) 4. Quadratic SVM (Kernel function: Gaussian, Kernel function: Quadratic) 5.Cubic SVM (Kernel function: Cubic), and finally 6. Coarse Gaussian (Kernel Scale = 20, Kernel function: Gaussian,).

6.5.2.7 Multilayer Backpropagation Neural Networks

In comparison to all above defined classification algorithm it outperforms everyone and provides best results. Network architecture is represented in Figure 6.12 [171].

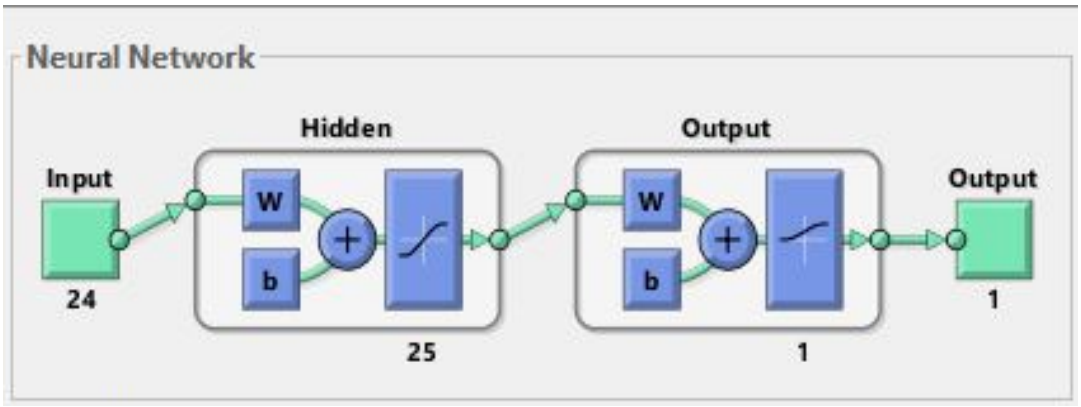


Fig. 6.12 Multilayers Neural Network Architecture

Network performance and confusion matrix are shown in Figure 6.13 and 6.14 respectively. CE is the cross entropy error. Lower values of CE are always better and network also tries to minimize it. Zero indicates no error. Error percentage represents the misclassified samples. 100 indicate maximum classification whereas 0 indicate no

misclassifications. Confusion matrix helps to evaluate output value in form of accuracy, specificity and sensitivity. It also classifications and misclassifications in terms of number of samples and percentage for all phases including training, testing, validation and all. In simplest term confusion matrix represents how much the model is confused while making predictions.

	Samples	CE	%E
Training:	140	6.10950e-0	0
Validation:	30	15.67669e-0	0
Testing:	30	15.31059e-0	10.00000e-0

Fig. 6.13 Network Performance

Fig. 6.14 Confusion Matrix

6.6 SUMMARY

This chapter represents the detail of classification phase in field of classification of skin cancer. A skilled scheme for classification is produced set up on bench mark SCG- BPNN. In parallel a number of machine learning techniques are applied and compared with SCG-BPNN technique. The proposed model shows great performance in the arena of skin laceration classification. The proposed algorithm is aimed for contributing to the computer aided diagnoses systems in melanoma detection.

CHAPTER 7

RESULT AND DISCUSSION

7.1 INTRODUCTION

This chapter provides all the results obtained by proposed methodology. A discussion is also provided in form of comparison of results with other research work. This is broadly divided in to two sections according to the algorithms applied.

7.1.1 Result Discussion on Model 1

Results are investigated on PH^2 dataset of 200 Dermoscopic images. 3D CTF matrix is extracted by combining both texture and color features from all of the 3 (R, G, B) color planes. Distance and angle parameters are taken as d = 1, Θ = 0. Proposed system is evaluated by accuracy, sensitivity and specificity in MATLAB using equations (5), (6) and (7) respectively. True Positive (T_P) provides the number of correctly classified melanoma images; False Positive (F_P) provides the number of incorrectly classified non-melanoma images as melanomas. True Negative (T_N) provides the number of correctly classified non melanoma images as non-melanomas. False Negative (F_N) provides the number of incorrectly classified non-melanoma images as melanomas. Recognition rate of the system is defines the accuracy. These can be explained with the equation 7.1, 7.2 and 7.3. Receiver Operating Characteristic (ROC) curve is graphical representation of True positive rate (TPR) versus False Positive Rate (FPR) which is shown in Figure. 7.1.

$$\text{Accuracy} = \frac{T_P+T_N}{T_P+F_N+T_N+F_P} \qquad 7.1$$

$$\text{Sensitivity (TPR)} = \frac{T_P}{T_P+F_N} \qquad 7.2$$

$$\text{Specificity (TNR)} = \frac{T_N}{T_N+F_P} \qquad 7.3$$

Results of the proposed system along the comparison with various novel works are given in Table 7.1. The best performance achieved in terms of accuracy is 97% although a comparative analysis in terms of accuracy, sensitivity and specificity with other novel work is also provided in Table 7.1.

Table 7.1 Comparative analysis of results

S. No.	Methods	Accuracy	Sensitivity	Specificity
1	A. R. Sadri [2]	91.82	92.61	91
2	G. Schaefer [6]	93.83	93.76	93.84
3	Z. Waheed [7]	96	97	84
4	L. Bi [12]	92	87.5	93.13
5	**Proposed Method**	**97**	**98.1**	**92.5**

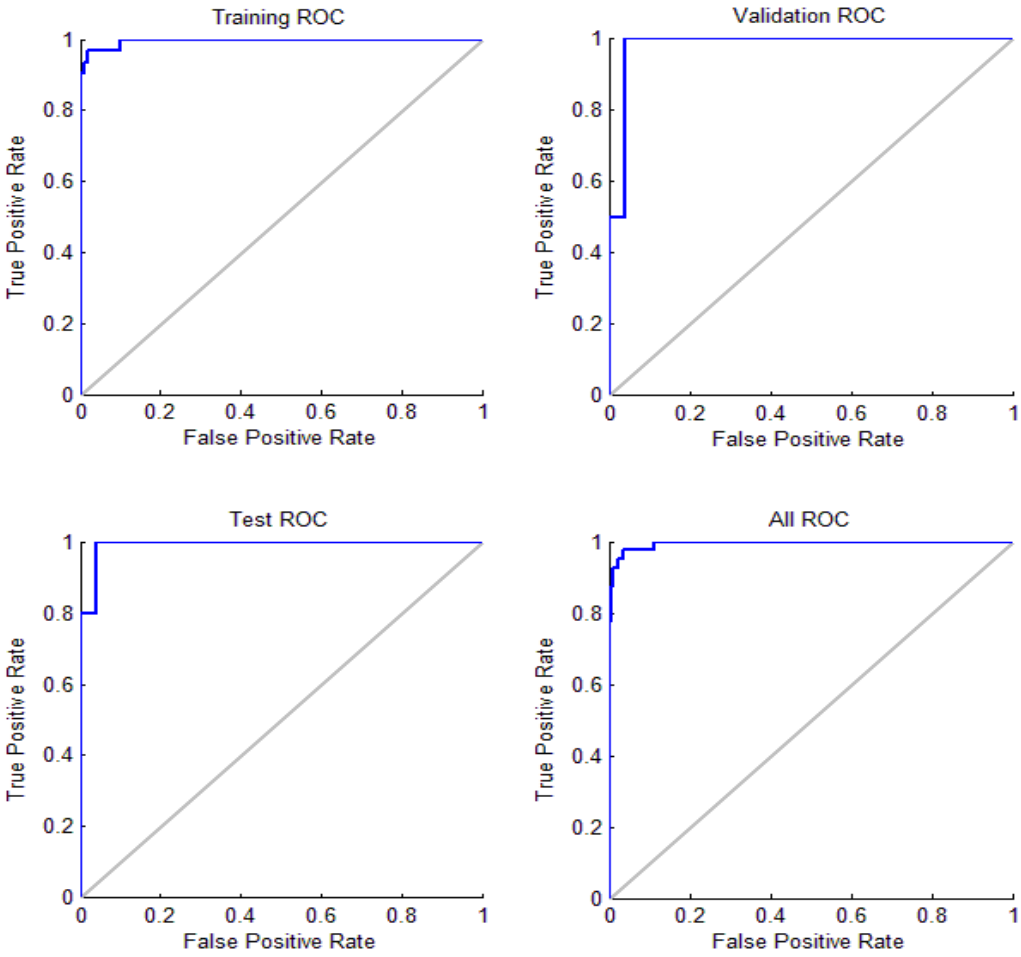


Fig. 7.1 Receiver operator characteristics (ROC)

7.1.2 Result Discussion on Model 2

Among all machine learning algorithm defined in this work, MLBPNN (multilayer back propagation neural network) outperforms all and can be analyzed easily from Table 7.2 .Results in term of accuracy, sensitivity and specificity are evaluated as per equation 7.1, 7.2 and 7.3 respectively.

Table 7.2 Results comparisons of proposed classification algorithms

S. No.	Model Name	Type	Accuracy %	Sensitivity %	Specificity %
1	Decision Tree	Coarse Tree	85.5	90.6	65.0
2		Fine Tree	81.5	88.1	55.0
3		Medium Tree	81.5	88.1	55.0
4	Discriminant	Linear	90.5	96.9	65.0
5		Quadratic	85.5	88.1	75.0
6	Ensemble	Bagged Trees	89.5	95.0	67.5
7		Boosted Trees	80.0	100.0	0.0
8		RUS Boosted Trees	85.5	88.1	75.0
9		Subspace Discriminant	88.0	98.8	45.0
10		Subspace KNN	89.0	96.3	60.0
11	Logistic Regression		85.5	89.4	70.0
12	Nearest Neighbour	Coarse KNN	80.0	100.0	0.0
13		Cosine KNN	80.5	100.0	2.5
14		Cubic KNN	80.0	100.0	0.0
15		Fine KNN	86.0	99.4	32.5
16		Medium KNN	80.0	100.0	0.0
17		Weighted KNN	80.0	100.0	0.0
18	SVM	Coarse Gaussian	81.0	100.0	5.0
19		Cubic	88.0	97.5	50.0
20		Fine Gaussian	50.0	100.0	0.0
21		Linear	89.5	100.0	47.5
22		Medium Gaussian	85.5	92.5	57.5
23		Quadratic	88.0	98.1	47.5
24	NN without PCA	NN-15	97.0	98.1	92.5
25	NN with PCA	NN-25	**98.5**	**99.4**	**95.0**

Table 7.3 represents the comparison of best result obtained from proposed classification algorithms with other novel works.

Table 7.3 Results comparisons of proposed work with other novel works

S. No.	Methods	Accuracy %	Sensitivity %	Specificity %
1	F. Warsi [2019]	97	98.1	92.5
2	C. Marin [2015]	-	76.56	87.58
3	A. R. Sadri [2017]	91.82	92.61	91
4	L. Bi [2016]	92	87.5	93.13
5	A. R. Lopez [2017]	81.33	78.66	-
6	T.Y. Satheesha [2017]	-	96	97
7	G. Schaefer [2013]	93.83	93.76	93.84
8	Z. Waheed [2017]	96	97	84
9	J. C. Kavitha [2013]	93.1	88.2	85.5
10	**Proposed Method**	**98.5**	**99.4**	**95**

7.2 SUMMARY

All results obtained from the proposed algorithm are fully explained in this chapter. Proposed method provides state of the art results in comparison to various novel methods.

CHAPTER 8

SUMMARY AND CONCLUSION

8.1 INTRODUCTION

This work has set algorithms for CAD system in the field of skin cancer detection. The algorithms in this thesis are related to the four steps of automatic lesion detection like segmentation, recommended feature extraction, dimensionality reduction and classification of melanoma from benign lesions. Many algorithms have been developed for skin cancer detection as well in wider range of image processing or computer vision. The summery and conclusion of this work are summarized below:

8.2 SUMMARY

A new technique is provided in this paper to compute color and texture features as single feature which is fairly distinctive and back propagation neural network classifier is used to detect melanoma and non-melanoma images.

Building upon the previous work and presenting a new feature extraction technique, in this work major emphasis is given on reducing the computational complexity of feature sets and evaluating the right classifier for best results which are also the important advantage of present work. All-important classification algorithms with their standard variations are evaluated to achieve the best results. Simplified feature extraction algorithm and use of well-known and established multilayer back propagation algorithm makes the proposed technique a good option for modelling the system for skin cancer detection.

8.3 CONCLUSION

This thesis starts with the background of skin cancer detection to give some foundation to computer diagnosis system for melanoma detection.

The contribution of thesis in segmentation is that an accurate segmentation from PH2 database has been completed known as binary lesion map. These maps are formed

from the digital images and segmented images in database. In this thesis sufficient literature about segmentation and its technique are discussed too.

The key reason of the thesis is to produce a novel method for feature extraction and selection for dermoscopic images. A novel technique CTF for feature extraction has been applied to extract the features. Features are generated based on statistical analysis of skin images. Features are well defined and methods of feature extraction are also presented in the literature. CTF extraction is also applied with dimensionality reduction based on PCA. The method is applied on PH2 dataset for skin lesion detections. The comparative analysis is also done with other algorithms in literature.
For classification phase two models are proposed. Ist model is trained and tested with SCG back propagation neural network with 15 layers. Ist model has reached an Sensitivity of 98.1%, Accuracy of 97%, and Specificity 92.5%. Second model is trained and validated by SCG-BPNN technique with k fold cross validation. In second model different machine learning like SVM, Logistic Regression, emsambles etc. are also applied and their performance are recorded. In second model ANN performs more accurate than other machine learning algorithms. Second model has reached an accuracy of 98.5%, sensitivity of 99.4% and specificity 95%.

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