CHAPTER 2

LITERATURE SURVEY

2.1 Introduction

In the past few decades, malignant melanoma has been leading as the most common cancer in Australia, America and Europe [84]. If detected early, this type of cancer can be cured with a success rate of over 92% [85]. A biopsy is usually performed to determine if a tumour is malignant or benign. However as this laboratory medical procedure involves a high cost and morbidity, an equally fast and convenient screening technique is automatic early detection [250].

Researchers in the field of dermatology imaging believe that melanoma diagnosis can be computerized building on specific physical features and colour details that are characteristic of skin cancer types [87]. Major melanoma factors – both diagnostic and prognostic – lesion colour, 3D shape and size and vertical thickness.

There have been many attempts by researchers [88] at building an automated skin cancer detection system to improve the accuracy of diagnosis. It is important to study the path previously taken by these researchers to gain enough knowledge so as to try and achieve a reliable skin cancer detection system. The following literatures review these attempts.

2.2 Computer-aided diagnosis system

A mechanized detection procedure for skin cancer can bring down the false-positive or false-negative clinical diagnosis since it adds a quantitative observation to the regular human-eye observation. Early detection of skin lesion from cancer images is divided into four stages - pre-processing, segmentation, feature extraction and classification [83, 84, 85, 86, 87, 88, 89, 90].

The skill of the dermatologists is also critical to achieve accurate diagnostic performance considering dermoscopy images. Considering the varied type of melanoma, non-melanoma skin lesions and dependency on the skill level of dermatologist, accurate diagnosis of melanoma is still a problem. The use of computer aided diagnosis can be used to tackle this problem.
Availability of advance image processing techniques and decision making mechanisms to build computer aided diagnostic system can provide a wholistic solutions to aid early diagnosis of skin cancer melanoma. The computer aided diagnostic systems are also referred to as “Computerized dermoscopy” [251].

2.2.1 Image acquisition/ methods for screening skin lesions

Visual inspection is a common clinical diagnosis in melanoma detection which may however, involve some error [89]. There are different techniques which help dermatologists visualize morphological features that are not detectable by the naked eye. These include dermoscopy [90], solar scan [91], epiluminescence microscopy (ELM) [92], cross-polarization epiluminescence(XLM), and side transillumination (TLM) [93].

2.2.2 Pre-Processing

Any image considered for the purpose of cancer detection has to go through a pre-processing stage to mainly rid it of noise. It is mandatory to study and separate abnormalities in the background on the result [94]. And by noise, we mean parts of the image that are not required for detection purposes. Any redundant parts in the background will also be cut off, helping improve the image for the next process by retaining only the required information. Using a good pre-processing technique means better accuracy [95]. The pre-processing stage involves three processes, that of image enhancement, image restoration and hair removal.

2.2.2.1 Image Enhancement

Image Enhancement as the name suggests enhances the appearance of the image visually. This is a crucial step in providing an improved and transformed image to bring out more accurate results during further automated processing [96]. Image enhancement itself can be categorized into three:

2.2.2.1.1 Image Scaling

When a standard size of image is not available, image scaling technique does the needful. Skin cancer images are collected from different sources and may be of different sizes. The first
step hence would be to resize them into a resolution of a fixed width (in pixels). However they may vary in height [97].

2.2.2.1.2 Color Space Transformation

Detection systems use colour information as a vital component in demarcating one stage of skin cancer from another or to even differentiate between healthy and diseased. For the same reason scientists have worked on extracting the closest colour from images for further processing. Common colour representation models include RGB, HSV, HSI, CIELAB and CIE-XYZ. The RGB colour code is frequently used for processing images and represents the three primary spectral colours red, green and blue. But RGB colour space comes with limitations in high-level processing leading to the use of other colour space representations [98, 99]. HSV and HSI colour models perceive in a similar manner as that of the human eye when it comes to hue, saturation and intensity. They represent average spectral colour wavelength, amount of white in the colour and the brightness. Yet another colour model which is known for providing uniformity is CIE- LAB while CIEXYZcolour system is capable of producing every single colour with positive tristimulus values [100, 257].

Since images used in skin cancer detection systems are required to show high level intensity variations in colour for proper detection of lesion edges, it would be optimal to use LAB colour space commonly represented as ‘Lab’ since it encompasses the entire range of colours. ‘L’, here, stands for lightness or colour space’s brightness, ‘a’ is the axis along which red/green opponent colours are denoted while ‘b’ axis represents the yellow/blue opponent colours. This thesis applies Lab for image transformation from RGB using XYZ as an in-between colour space. The main image is converted to a greyscale image which provides the values for Lightness (from ‘0’ to ‘100’) [101, 256].

2.2.2.1.3 Contrast Enhancement

Aside from image enhancement which improves colour, this step enhances contrast which again helps improve perception for further processing. Image borders can be sharpened and accuracy can be improved by emphasizing on the brightness difference between background and foreground. Enhancing contrast also improves the quality of an image [102]. Two techniques
that are widely practised for contrast enhancement are ‘Linear contrast enhancement’ and ‘Non-Linear contrast enhancement’ [103].

- **Linear contrast enhancement techniques:**

Linear contrast enhancement incorporates stretching techniques to transform the image to one of higher contrast. Grey-level values are stretched or remapped thereby spreading the histogram over a wide range [104]. Figure 2.1 depicts three classifications of the linear contrast Enhancement methods.

- **Non-Linear contrast enhancement techniques:**

In the field of medicine, this technique is commonly used [105] and methods under this process have to do with histogram equalizations and algorithms [103] as shown in figure 2.2. The most prominent limitation of the non-linear contrast enhancement technique is the lack of accurate brightness of an object, as multiple values of an output image are generated against each value of an input image [103].
Histogram Equalization (HE), Adaptive histogram equalization (AHE) and Unsharp Masking are the three popular non-linear methods applied in this stage of pre-processing since diagnosis of skin cancer depends on localised details rather than global ones [97]. Figure 2.3 below shows the result sample of all three techniques on skin cancer images. As can be seen, HE not only sharpens the image, but also brings down the surrounding detail [106].

![Figure 2.3. a) Adaptive Histogram Equalization b) Histogram Equalization c) Unsharp Masking. [106]](image)

### 2.2.2.2 Image Restoration

Various defects on an image can degrade it to a low quality one which cannot be used for disease detection. Hence, Image Restoration procedure is necessary to increase the quality of a degraded image by removing noise and blur among others [107]. Imperfections commonly found on an image can be caused due to a bad imaging system, bad focusing or even movement consequently resulting in an image which is blurry [107]. This process helps restore a bad image in more than one way. To apply the most appropriate algorithm for the purpose of de-noising, it is crucial to study the different noises that may be present as part of the image. Samples of four different noises simulated in Matlab are shown in figure 2.4. They are named Gaussian, Salt and Pepper, Poisson and Speckle [108].

![Figure 2.4. a) Gaussian b) Salt c) Poisson d) Speckle. [108]](image)
2.2.2.1 Restoration from noise

An efficient de-noising method can be defined as one that effectively reduces the noise on an image but do not have any effect on the edges [109]. With each noise requiring a different algorithm for its reduction, applying an appropriate de-noising algorithm for various types of noisy images is a bit complex task. Some of the de-noising methods that exist today come under two broader methods called Spatial Filtering and Transform Domain Filtering [110]. Spatial filtering includes Mean filters, Median filters, Wiener filter, Lee filter, Anisotropic diffusion filter and Total variation filter. All these filters work in the same manner in that it has a so-called neighbourhood. The grey value of each pixel is converted to that of a set of pixels that make up its neighbouring square, through an operation that has been pre-defined [111]. The following spatial filters are commonly used [108].

- **Mean filters:**
  - It works great for Gaussian noise and is also effective on salt and pepper noise. Although this filter reduces noise, it also blurs the image and reduces sharp edges.
  - Arithmetic mean filter: This is the simplest mean filter which works well on Gaussian noise. It spreads the noise uniformly.
  - Geometric mean filter: This filter is better than the one above as it is more efficient at preserving the details of an image better.
  - Harmonic mean filter: This can be applied on salt noise and sometimes even Gaussian noise, but salt and pepper de-noising will not be possible.
  - Contraharmonic mean filter: This works more effectively compare to arithmetic mean filter and is efficient at preserving the edges.

- **Adaptive filters:**

  When noise found is a constant-power additive noise (like speckle), adaptive filters work best.
  - Adaptive local noise reduction filter: It is used for random noises.
  - Adaptive median filter: As opposed to a traditional median filter, this is used for preserving information while smoothing out non-impulse noise.
• **Order statistics filters**
  - Median filter: It is more rigid to extreme values than a mean filter and hence works best for salt and pepper noise. Hence, the outlier can be removed while retaining the image sharpness.
  - Max and min filters: The darkest points of an image can be calculated using this filter.
  - Mid-point filter: Speckle noise or other randomly distributed noise can be suppressed using a mid-point filter.
  - Gaussian smoothing filter: It is best suit for smoothing an image and sharpening an image.

The de-noising method of Transform Domain Filtering uses an extended form of Fourier transform called wavelet transforms. These represent functions through means of wavelets. Wavelets themselves are mathematical functions which analyse data based on scale or resolution [112].

Median filter, Adaptive Median filter, Mean filter and Gaussian smoothing filter are the most common de-noise filters used in medical applications, especially in the analyses of skin cancer [113].

**2.2.2.2 Restoration from blur**

As seen above, a blur is a type of degradation of an image which occurs due to an imperfect image formation process. Bad focusing or motion during capture of the image by a camera can cause a blur. An image has to be de-blurred and restored to a good-quality image for any further processing. The Lucy- Richardson algorithm techniques, Inverse filter, Wiener filter deblurring technique and Neural network Approach are all de-blurring techniques of which the Wiener filter is one of the most powerful and common ones used in medical applications. This method has the added advantage of noise removal capabilities as well.

**2.2.2.3 Removing Thick Hairs**

Most of the restoration methods help smoothen thin blood vessels and remove skin lines, but the image may still show thick hair. The presence of thick hair in the automated analysis of
small skin lesions is a proven nuisance and will lead to misjudgement in the segmentation process [114]. Hair-free images can be generated using certain methods like mathematical morphology methods [115], curvilinear structure detection [118], an in painting based method approach [116], automated software called Dull-Razor [117] and Top Hat transform combined with a bi-cubic interpolation approach. With this process, the pre-processing step of skin cancer detection system comes to an end. The end-result is a pre-processed distinguishable image which is almost ready for the segmentation stage.

2.2.3 Segmentation

A major challenge for research and development in this field includes segmentation of skin cancer images. This process is essential in digital image processing as it is ultimately used for image description and classification. Various properties like shape, brightness, colour and/or texture are applied to assist in the segmentation of skin lesion. In the past few decades, many algorithms have been proposed for the detection of lesions in skin cancer images. Celebi et al. [119] categorized the segmentation methods into:

a. Histogram thresholding which separates the area of interest (ROI) and background using one or more threshold values [120, 253]
b. Region-based methods which incorporate the pixels into their similar regions using region-splitting and region-merging algorithms [121]
c. Edge-based methods in which the edges of lesions are determined using edge operators [122]
d. Active-contour methods in which the contours in the shape are made to evolve using curve evolution techniques [123, 254]
e. Morphological methods determine the seeds and employ watershed transform to identify contours of an object [124]
f. Colour-clustering methods employ unsupervised clustering algorithms to generate homogeneous areas by separating the colour space [125]
g. Soft-computing methods employ different soft-computing techniques to classify the pixels [126]
h. Model-based methods, in which the image is considered as a random field and the model is parameterized using optimisation methods [127]

In segmentation, sets of objects with similar characteristics are classified into different groups. This process called clustering has been widely applied in many areas such as image processing, machine learning, pattern recognition, data mining and statistics. Recently, clustering algorithms found crucial applications in medical imaging field [128].

In these algorithms, the number of clusters, initial centres of each cluster and selecting the proper parameters are the main issues. Many researchers dedicated time and effort to improve these techniques for application in skin cancer detection systems [129]. Schmid [130] presented a segmentation algorithm based on fuzzy c-means in which the histogram maxima are employed to determine the number of clusters. K-means, as in [129], is known to be a non-deterministic, unsupervised numerical and iterative method which has proven to provide good clustering results. It is famous for its fast running speed and simplicity. Another powerful and robust segmentation technique which is flexible under challenging conditions is the level set method which runs on both intrinsic and extrinsic factors such as intensity and curvature [131]. Many researchers have mentioned that since this method is flexible, it takes a long time to perform calculations thus putting it at a disadvantage in the medical field. They [132] have also indicated that this technique is likely to bring down the flexibility of complex segmentation tasks in medical applications. However there are some studies [133] that proposed that level-set method is not to be used merely for segmentation.

Many researchers have applied Active-contour methods as a successful method of segmentation. In [134], a new algorithm of multi-direction gradient vector flow (GVF) was proposed. They applied a diffusion filter with the new computation along with the adaptive threshold for noise removal. Afterward, the multi-direction GVF was employed for segmentation. In another research [135], the radial search algorithm was applied for borders detection. Abbas et al. [136] presented a segmentation algorithm based on the Active Contour model. They automatically set the initial value of threshold and employ the Courant-Friedreichs-Lewy as their function in an algorithm which controls the curves stability. The results demonstrated better performance than any other methods.
Some researchers have merged the different segmentation methods for even more improved results. For instance, Pagadala [137] proposed a segmentation algorithm by merging the achievements of three threshold-based algorithms which were employed independently on various channels of a skin cancer image. Ganster et al. [138] employed a fusion process and used the combination of three segmentation methods including dynamic and global thresholding, and also an algorithm which applies the 3D colour clustering idea [139]. The results showed an improved performance; while the segmentation results achieved by global thresholding were about 80%, the other two methods provided a poor segmentation performance.

Melli et al. [140] merged the supervised classification module with the component of unsupervised clustering to segment the lesion from skin. They applied different clustering algorithms of mean-shift, k-means, median-cut and fuzzy c-means and made comparisons to determine the best outcome. They assumed that the tumour was located in the centroid of the skin and considered the corners as the skin part. They used the corner pixels for classifier training and the resulted clusters were incorporated as a background provided the colours were considered as background in training. The results cluster the image into skin and lesion. They compared their achievements with the ground truth skin images determined by dermatologists in 117 images. They obtained better performance with mean-shift algorithm. Hance et al. [141] investigated six segmentation algorithms of median cut, spherical transform, fuzzy c-means, multi-resolution, adaptive thresholding, and split and merge. They compared the results achieved by these methods. Despite other colour segmentation algorithms they kept the number of segmentation to four [255]. Their results indicated better performance of adaptive thresholding and also median cut. Moreover, they merged these algorithms to evaluate the result. They could obtain further improvement in their investigation [254].

2.2.4 Feature Extraction
The process of feature extraction involves extraction of image parameters to characterize the dermatological features of melanoma and diagnosis based on these parameters. Medical experts rely on the features of melanoma. The method of diagnosis applied is important for feature selection. For instance, asymmetry and pigmented network are respectively the features in ABCD-rule and pattern analysis.

The features evaluation of melanoma diagnosis is visually very difficult because the content of information in dermatoscopic images is very complicated and requires experienced physicians for analysis. The diagnosis methods by non-dermatologists to determine melanoma lesions in the screening process are listed as ABCD rule [142], ABCD-E criteria [143] and Glasgow 7-point checklist [144].

The ABCD rule of dermoscopy consists of four criteria: Asymmetry, Border sharpness, Colour variegation and Differential structures. ABCDE has the added factor of E or Evolving. The 7-point checklist consists of seven criteria: Atypical pigment network, Blu whitish veil, Atypical vascular pattern, Irregular streaks, Irregular dots/globules, Irregular blotches and Regression structures. Pattern analysis consists of Global patterns and Local features [145].

According to [146], symmetry achieved the highest weight in the ABCD rule of dermoscopy. Stolz et al. [15] indicated that 96% of asymmetry in melanoma cases had score 2 (both axes represent asymmetry) while it was just about 24.2% in benign images. Many researches considered asymmetry according to the axis of symmetry in the tumour. In such studies, the axis of symmetry may be identified using Fourier transform [147], best-fit ellipse [148], diameter length [149] and principal axis [150]. Post that, both created areas by the axes are differentiated. In many studies, the roundness, compactness and thinness of lesion have been considered as appropriate properties of skin cancer images [149] and in [151], they have been considered as accurate geometry variables. In [152], the symmetry distance (SD) was introduced as another measure in images. Seidenari et al. [153] presented a method to estimate distribution in skin lesions. Their purpose was to determine the effectiveness of distribution parameters to identify melanoma from the normal ones. They found out about the non-homogeneity of lesion
region; they computed the mathematical parameters such as mean, variance, and Euclidean distance.

Manousaki et al. [151] proposed estimation of distribution irregularity using the fractal dimension in the surface of the lesion. Also, they computed the standard deviation to measure the sharpness of borders. Lee et al. [154], presented an algorithm to search a convex and curvature maxima’s locations in an image. In [155], the standard deviation and mean are calculated in six colour spaces. In another approach [156], the different statistical properties of standard deviation, energy, mean and entropy are computed as extracted features. The Neural Network has been trained using these features and the accuracy of 79% was achieved.

The significance of color features to classify skin lesions is put forth in [256, 257]. A K-means clustering algorithm is incorporated to extract the color features. The Congenital nevi, combined nevi, Reed/Spitz nevi, melanomas, dysplastic nevi, blue nevi, dermal nevi, seborrheic keratosis and dermatofibroma lesion images are considered for evaluation. Using a symbolic regression algorithm the skin lesion are classified into benign or malignant types.

In [258] the authors consider that each dermoscopic image represents a Markov model. The parameters estimated from the model are considered as the features of the skin lesion. Classification is performed to identify the globular, reticular and homogeneous patterns in the pigmented cell.

The Gray Level Cooccurrence Matrix (GLCM) as another popular method to extract the image features has been employed by different researchers in various applications [157]. Many other researches have been reported on feature extraction of skin cancer in literature [158].

### 2.2.5 Feature Selection

Feature selection is an important process and is performed prior to lesion classification. Its purpose is to reduce the computational cost of classification by decreasing the extracted feature descriptors in number. However this decrement is not trivial due to eliminating redundancy which may have a negative effect on discriminatory power. Feature selection process can be explained thus [159]. Firstly, the search procedure as subset generation is performed to
provide various subset candidates of features [160]. An evaluation criterion is considered to evaluate the subset candidates. This is compared and replaced with the estimated performance of the prior best subset in a case of preference. As illustrated in Figure 2.5, this process is repeated till the stopping criterion is met. In the final stage, validation and testifying the best selected subset are performed [161].

![Diagram of Feature Selection Process](image)

To develop the process of feature selection, various researches have been undertaken [162]. In 2009, a very useful review on feature descriptors was revealed by Maglogiannis and Doukas [54]. Walvick et al. [163] applied the Principal component analysis to achieve the optimal subset from the set of eleven features. Ro et al [164] employed sequential forward selection (SFS) to decrease the set of eighty seven features to five. In [165], a statistical feature selection algorithm optimized the vector of 34 features to five. In another study [166], the neural network along with node pruning was employed to cut down the number of features to optimize the solution. Ganster et al. [167, 168] optimized the number of features by applying statistical approaches. Such methods include Sequential Floating Backward Selection (SFBS), Leave One Out (LOO) and Sequential Floating Forward Selection (SFFS).
Particle Swarm Optimization (PSO) is extensively applied in feature selection problems to search for the optimal feature subset of a large database of possible candidates [169]. Binary Particle Swarm Optimization is another extension for PSO where particles are considered by a point in a binary multidimensional space. This type of PSO is also widely applied in feature selection [170]. In [166], authors represented an algorithm for feature subset selection by employing PSO along with the fuzzy evaluation function. In [170], a PSO algorithm was developed using artificial neural network for feature subset selection. Yashar et al. [171] proposed a Particle Swarm Optimization - Support Vector Machines (PSO-SVM) feature selection algorithm in their study in Sleep Apnea. They could effectively reduce the number of features and select the best subset for their purpose. PSO computationally is less expensive than other methods and can quickly perform convergence. Thus, PSO is used as an effective technique in many fields such as feature selection [172]. Several computerized dermoscopy systems to have been developed considering all or combinations of shape, texture, color features and incorporating varied decision support mechanisms [251].

2.2.6 Classification

The final step in computerized analysis of melanoma detection, to estimate if a lesion is malignant or benign, is Lesion classification. To carry out the classification task, existing systems utilize different classification methods with feature descriptors that were extracted in the previous stage. The efficiency of these methods appertains to both extracted descriptors and selected classifier [173]. There are different classifiers that currently exist namely Discriminant Analysis, Artificial Neural Network, K-Nearest Neighbourhood, Support Vector Machine (SVM), Decision Trees and Self-Advising SVM.

In Different researches [174], Discriminant analysis was applied as a classifier to make predefined classes from a set of observations. It works by the values of determined measurements which are called predictors. Artificial Neural Networks (ANN) is another tool that was employed in [175]. This approach connects the inputs and outputs for detecting the patterns
in data. It is usually employed in classification problems. In [176] another algorithm called k-nearest-neighbourhood (K-NN) was considered for distinguishing lesions as melanoma or benign. This classifier employs distance measure like Euclidean distance to evaluate the distribution of data and classify the objects according to their closeness to the training set. SVM displayed a powerful ability of solving problems of nonlinear classification in many applications (high dimension as well). Furthermore, SVMs prevented over-fitting by selecting a particular hyper-plane among many by separating the data in feature space [174]. SVM has been used as a popular technique in [54] for classifying skin cancer melanoma. In some other researches [174], Decision trees separated the data set into different groups according to its disparity and made the classification schema. Based on high-level intuitive features (HLIF) and SVM classifiers the diagnosis of melanomas and non-melanoma skin lesions is presented in [252]. In addition to the HLIF features, low-level features and their combinations are also considered. Dreiseitl et al. [177] compared the different classification techniques of artificial neural network, k-nearest neighbourhood, support vector machine, logistic regression and decision tree in skin cancer detection systems. The results obtained proved an effective performance of SVM, ANN and logistic regression [258].