TOWARDS AUTOMATION OF SKIN DISEASE DIAGNOSIS USING IMAGE CLASSIFICATION

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TOWARDS AUTOMATION OF SKIN

DISEASE DIAGNOSIS

USING IMAGE CLASSIFICATION

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DECLARATION

I, Damilola Ayokunle Okuboyejo, declare that the dissertation work entitled “Towards Automation of Skin Disease Diagnosis Using Image Classification” submitted in fulfilment of the requirements for the Magister Technologiae (MTECH) degree: Software Engineering is my own original work and that it has not previously been submitted to any other institution by another student. All resources used are indicated and acknowledged by means of a comprehensive list of references and source citation where appropriate.

D.A. Okuboyejo

____________________  ____________________

Date:
ACKNOWLEDGEMENTS

This work was possible as a result of God’s guidance and innumerable support received from my supervisors and supporting organisations.

Mum, many thanks for the priceless advice and financial support given throughout this study. Doctor Yemisi, I am sure words cannot repay your critical analysis on this work and language editing carried out to ensure the work comes out best. My brothers (Doctor Bj, Gbolahan, Fisayo and Femi), I owe you a lot for the prayers of strength and grace.

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ABSTRACT

The overarching aim of this study is to prototype a system that contributes towards effective segmentation and classification of medical images in order to reduce heavy dependence on medical experts for a diagnosis procedure of Pigmented Skin Lesion (PSL).

Given the great need and importance of localising the image area to be diagnosed, this study focuses on performing a pre-processing computation on a given PSL image and then segments the lesion area of the healthy surrounding skin. This is particularly important to avoid unnecessary computation of a non-lesion area of the image data.

The presence of artefacts such as hair shaft, thin blood vessel, ruler marking, and air bubble in medical images makes the diagnosis of skin-related medical images very difficult. This study uses a two-stage artefact detection termed Fast Image Restoration (FIR) via the Canny algorithm and the Line Segment Detection (LSD) operation to achieve an effective detection of artefacts. The Fast Marching Method (FMM) was applied at each stage for the removal of artefacts from a dermoscopic image in an unsupervised environment while ensuring that morphological features of the lesion areas of the image data are preserved. Statistical Analysis was performed to determine the accuracy of artefact recognition. The repair validation of the method used yields a Sensitivity of 98.27%, Specificity of 93.75% and Diagnostic Accuracy of 96.10%. These results indicate that the method used gives an acceptable level of accuracy.

In addition, the localisation of the actual lesion area is an important step towards the automation of a diagnostic system for discriminating between malignant and benign lesions. A combination of methods has been applied, including intensity equalisation, thresholding, morphological operation and GrabCut algorithm to segment the lesion area in a dermoscopic image. The results show that the approach used in
the study is effective in localising lesion pixels in a dermoscopic image. This would aid the selection of discriminating features for the classification of malignancy of a given dermoscopic image.

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<td>Auto Associative Network</td>
</tr>
<tr>
<td>AdaBoost</td>
<td>Adaptive Boost</td>
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<tr>
<td>ADAM</td>
<td>Automatic Detection and Analysis of Melanoma</td>
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<td>AHE</td>
<td>Adaptive Histogram Equalisation</td>
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<td>ANN</td>
<td>Artificial Neural Network</td>
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<td>ART</td>
<td>Adaptive Resonance Theory</td>
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<td>AS</td>
<td>Adaptive Snake</td>
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<td>Back Propagation Network</td>
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<td>Boundary Tracing Algorithm</td>
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<td>CAD</td>
<td>Computer-Aided Diagnosis</td>
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<tr>
<td>CASH</td>
<td>Colour, Architecture, Symmetry, and Homogeneity</td>
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<tr>
<td>CDF</td>
<td>Cumulative Distribution Function</td>
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<td>CIE</td>
<td>Commission Internationale de l'Eclairage</td>
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<td>CLAHE</td>
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<td>Diagnostic Accuracy</td>
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<td>Discriminant Analysis</td>
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<td>DALYs</td>
<td>Disability-Adjusted Life Years</td>
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<td>DBSCAN</td>
<td>Density-Based Spatial Clustering of Applications with Noise</td>
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<td>DOG</td>
<td>Derivative of Gaussian</td>
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<td>Full Form</td>
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<td>DSSA</td>
<td>Dermatology Society of South Africa</td>
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<td>ELM</td>
<td>Epiluminiscence Light Microscopy</td>
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<td>FBSM</td>
<td>Fuzzy-Based Split and Merge</td>
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<td>Feed Forward Network</td>
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<td>GLCM</td>
<td>Grey-Level Co-occurrence Matrix</td>
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<td>HSV</td>
<td>Hue Saturation Value</td>
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<td>ICA</td>
<td>Independent Component Analysis</td>
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<td>IHP</td>
<td>Independent Histogram Pursuit</td>
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<td>ImT</td>
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<td>IRMA</td>
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<td>ISODATA</td>
<td>Self-Organising Data Analysis Technique</td>
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<td>IT</td>
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<td>JPEG</td>
<td>Joint Picture Expert Group</td>
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<td>Description</td>
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<td>KNN</td>
<td>K-Nearest Neighbour</td>
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<td>KPP</td>
<td>K-means ++</td>
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<tr>
<td>LA</td>
<td>Lacunarity Analysis</td>
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<tr>
<td>LDmA</td>
<td>Linear Discriminant Analysis</td>
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<tr>
<td>LiR</td>
<td>Linear Regression</td>
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<tr>
<td>LM</td>
<td>Levenberg-Marquardt</td>
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<tr>
<td>LMT</td>
<td>Logistic Model Tree</td>
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<tr>
<td>LoG</td>
<td>Laplacian of Gaussian</td>
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<td>Leave-One-Out</td>
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<td>LoR</td>
<td>Logistic Regression</td>
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<td>MIUA</td>
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<td>MLP</td>
<td>MultiLayer Perceptron</td>
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<td>MRF</td>
<td>Markov Random Field</td>
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<td>Naïve Bayes</td>
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<td>PCA</td>
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<td>Probabilistic C-Means</td>
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<td>PDE</td>
<td>Partial Differential Equation</td>
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<td>PPHT</td>
<td>Progressive Probabilistic Hough Transform</td>
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<td>PSL</td>
<td>Pigmented Skin Lesion</td>
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<tr>
<td>Abbreviation</td>
<td>Description</td>
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<tr>
<td>RBF</td>
<td>Radial Basis Function</td>
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<td>RES BP</td>
<td>Resilient Back Propagation</td>
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<tr>
<td>RF</td>
<td>Random Forest</td>
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<td>RGB</td>
<td>Red-Green-Blue</td>
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<tr>
<td>ROI</td>
<td>Region of Interest</td>
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<td>RS</td>
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<td>RW</td>
<td>Random Walker</td>
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<td>Support Vector Machine</td>
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<td>TM</td>
<td>Thin Melanoma</td>
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<tr>
<td>VLR</td>
<td>Variable Learning Rate</td>
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<td>WHO</td>
<td>World Health Organization</td>
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<td>WN</td>
<td>Wavelet Network</td>
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<td>XLM</td>
<td>eXtreme Learning Machine</td>
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CHAPTER ONE: INTRODUCTION

1.1 Background

Medical imaging provides techniques and processes in creating images of the human body or samples (such as blood or sputum) for clinical purposes (medical procedures seeking to reveal, diagnose or examine disease), medical science (study of normal anatomy and physiology) or for knowledge discovery. Digital image processing involves the screening of a region for processing and saving this region to a location (possibly a file) for processing using operations such as fractal (see Figure 1-1) and texture analysis.

![Sample Fractal Structure](image)

**Figure 1-1** Sample Fractal Structure

A fractal is an object that technically displays self-similarity on all scales, such that even if the object does not exhibit exactly the same structure at all scales, it would have the same type of structures appearing on all scales (Mathworld, 2013). Fractal dimension is a ratio that provides a statistical index of complexity, comparing how details in a fractal pattern changes with the scale at which it is measured, such as given by the relationship between an object’s length (or area) and its diameter. In medical imaging, fractal analysis typically determines the fractal dimension of an image using techniques such as global box-counting, mean fractal dimension, and local
connected fractal dimension for binary threshold used during analysis of an image. Texture analysis, on the other hand, uses methods such as co-occurrence matrices calculus and evaluation of texture features (e.g. energy, entropy, contrast and correlation during image processing).

\[
Fractal \ Dimension = \frac{\log(\text{no of self similar pieces})}{\log(\text{magnification factor})} \tag{Eq 1-1}
\]

1.1.1 Human Skin

![Figure 1-2 Skin Anatomy](Healthfavo, 2014)

The skin’s surface is a detailed landscape with complex geometry and local optical properties. The skin is the largest organ in the human body and consists of three principal layers: the
epidermis (see section 1.1.1.1), the dermis (see section 1.1.1.2) and the subcutis (subcutaneous layer).

Skin features depend on many variables such as body location (e.g. forehead or cheek), subject parameters (e.g. age or gender), imaging parameters (e.g. lighting or camera), and also the direction from which it is viewed and illuminated. Bacterial and viral skin infections generally affect the skin by decolorising and distorting pigmented skin areas, further making automation of medical image analysis difficult (Tushabe, Mwebaze & Kiwanuka, 2011).

1.1.1 Epidermis

The epidermis is a layered scale-like tissue which serves as protection against external belligerences (such as extreme radiation, wounds and contaminations). The epidermis consists of four types of cells:

[a] Keratinocytes

[b] Melanocytes

[c] Langerhans cells

[d] Merkel cells

1.1.2 Dermis

The dermis is composed of collagen and elastic fibres. The dermis has two primary sub-layers:

[a] Papillary dermis (thin layer): Acts as a glue to hold the epidermis and the dermis.

[b] Reticular dermis (thick layer): Supplies energy and nutrition to the epidermis. It contains nerve endings, sweat glands, hair follicles, blood vessels and lymph vessels. In addition, it is responsible for healing and sense of touch.
1.1.1.3 Subcutaneous

The subcutaneous layer, which is sometimes referred to as subcutis or hypodermis, is responsible for supplying nutrients to the other two layers. The subcutis, being made of made of fat and connective tissue, also helps to cushion and insulate the body.

1.1.2 Medical Imaging of the Skin

The major aim of image analysis is to use image processing techniques to provide a machine interpretation of an image, typically in a format that could foster the decision-making process. In the past two decades, a strong impulse has been given to developing automated systems capable of assisting physicians in medical imaging tasks (Dobrescu et al., 2010). However, the presence of noise, masking structures, variability of biological shapes and tissues, and imaging system anisotropy make the automated analysis of medical images a very hard task (Dobrescu et al., 2010; Rubegni et al., 2002; Stanganelli et al., 2005).

One of the best approaches to overcome the aforementioned challenges in automating medical imaging diagnosis is to simplify the objective of the analysis and to exploit some kind of hypothetical information about the imaged structures. The information about the structures to be analysed can be anatomical knowledge about their typical appearance (such as shape and grey levels) and position; or it can be statistical knowledge of their properties (e.g. grey level of the tissues included in those structures). The images can then be classified using their morphological, colour, fractal, and texture properties.

Laws (1980), in his work, transformed digital images to identify regions of interest and provided an input data set for segmentation and features detection operation. The same author used operations such as thresholding, morphological analysis and texture detection to divide a
digital image into individual objects to perform a separate analysis of each region. The incidence of skin cancer is rapidly increasing throughout the world, and it is gradually becoming one of the predominant forms of cancer, especially in Caucasian population and among fair-skinned people (Ali & Deserno, 2012; Han, Colditz & Hunter, 2006; Sboner et al., 2001).

Skin cancer incidence is on the order of 10 to 12 in Europe, 18 to 20 in United States, and 30 to 40 in Australia per 100000 subjects (Schmid-Saugeon, Guillod & Thirana, 2003). Australian Institute of Health and Welfare & Australian Association of Cancer Registeries (2012), in their reports, detailed that more people have had skin cancer than all other cancers combined in the past three decades. Robinson (2005), in his study, reported that one out of five Americans develop skin cancer in the course of a lifetime. Forty to fifty per cent of Americans who live up to the age of 65 have a high risk of having either Basal Cell Carcinoma (BCC) or Squamous Cell Carcinoma (SCC) at least once (National Cancer Institute, 2013).

In 2013, 9480 people were predicted to die of Melanoma (American Cancer Society, 2013). It is important to note that most cases reported in the literature where among Caucasians, but some reports such as (Asuquo et al., 2012; Samalia & Rafindadi, 2006) state that black Africans and Asians account for 20% of the world’s melanoma. Though most reports of melanoma reflect an infection rate among Caucasians, the overall five-year melanoma survival rate for African-Americans and other people of colour is only 77% compared to 91% for Caucasians (Ahmedin et al., 2010). Melanoma, which is currently the third prevalent cancer in Australia, was reported to occur in 61.7 for every 100000 Australian men; and 40.0 for every 100000 women (Australian Institute of Health and Welfare & Australian Association of Cancer Registeries, 2012). In the same study, melanoma of the skin was judged to have accounted for 22800 Disability-Adjusted Life
Years (DALYs) in Australia. DALYs depict years of healthy life lost either through premature death or via living with illness/injury-bound disability.

Melanoma skin cancer disease is one of the rarest among many cancerous diseases, and it currently accounts for 79% of the deaths resulting from skin cancer (Ali & Deserno, 2012). The incidence of cutaneous melanoma in Caucasian patients has been reported to increase historically in most parts of the world over the decades (Iyatomi et al., 2006; Stanganelli et al., 2005). In Europe for instance, it has been reported that malignant melanoma incidence is steadily increasing by 5% year-on-year, and it is responsible for 91% of skin cancer deaths (Sboner et al., 2001). A fact sheet report compiled by Cancer Association of South Africa (2010) stated that South Africa has the second highest incidence of skin cancer in the world after Australia. Study conducted by Vorobiof (2013) has reflected that Superficial Spreading Melanoma is the most frequent type of melanoma incidence in South Africa.

Gruesome reports as highlighted above have led to many advances in computer-aided systems towards assisting dermatologists to administer the diagnosis of skin-related diseases. The development of automated diagnosis systems that are capable of performing some level of remote diagnosis of skin cancer diseases (such as melanoma and basal cell carcinoma) and equally assisting physicians in various imaging tasks have also gained tremendous attention in the bioinformatics and computer vision research (Dobrescu et al., 2010). The efforts towards automation of diagnosis procedures are geared mainly to improve the speed of diagnosis and to increase reproducibility of results. The automated diagnosis has also helped in reducing first-time diagnosis errors, which sometimes could be as much as 40% (Kantrowitz, 2009; Singh et al., 2007).
Over the years, it has been reported that automatic data analysis used for melanoma showed a higher diagnostic performance compared to a physician’s observation in terms of sensitivity (proportion of true positives), though lower in terms of specificity (proportion of true negatives) (Abbas, Celebi & García, 2011a; Ali & Deserno, 2012; Kittler, 2004; Zagrouba & Barhoumi, 2005). A common technique used for the foregoing automated data analysis is Dermoscopy or Epiluminiscence Light Microscopy (ELM), an in-vivo, non-invasive technique that in recent years has revealed a new dimension of the clinical morphological features of Pigmented Skin Lesion (PSL) using different light magnification systems with an oil immersion technique (Ali & Deserno, 2012).

Dermoscopy or its synonymous dermatoscopy provides dermatologists with a technique for in-vivo inspection of PSL, and it renders a higher accuracy for detecting suspicious cases than it is possible with popular practice of naked-eye inspection (Kittler, 2004). Dermoscopy aids in the diagnosis of several other skin tumours such as Angiomas, Basal Cell Carcinomas, Cylindromas, Seborrheic Keratosis, and Hematomas, just to mention a few. In relation to malignancy classification of melanocytic images, the ELM has been a great tool for dermatologists to distinguish between life-threatening (malignant) and benign melanocytic lesions.

Interestingly, while merit of medical imaging is getting popular, the World Health Organization (WHO) reported in one of its findings that three quarters of the entire world population is yet to have access to medical imaging, which is an essential technique in the new age of telemedicine such as in automation of skin disease diagnosis (World Health Organization, 2007). Hitherto, medical imaging has contributed immensely towards advancing medical procedures. One notable challenge, however, is that interpretation and analysis of medical imaging results are still heavily
dependent on medical experts (whose availability are low or non-existent) is a serious concern for developing and underserved regions (especially rural settings). An approach is needed to minimise this dependency and also to limit probable bias of medical personnel in the analysis of a medical image result, hence this particular study.

1.2 Problem Statement

Bias essentially influences the analysis made by medical practitioners, just as with any human search that begins with keywords chosen by the user. In the process of diagnosing a patient, medical doctors sometimes have an assumed diagnosis opinion. To validate their assumptions, further searches are then carried out. In cases where these assumptions are not validated, the medical practitioners might have missed other potential diagnoses. When a doctor begins searching by symptoms – while this may be accurate – the order or weight given to any of the symptoms would most likely give a bias towards a related diagnosis when, in fact, there may be a symptom that is not given any credit and thus not included in the search or considered in a timely fashion. Bias such as aforementioned can be very costly. Bickers et al. (2006) revealed that the health care cost for diseases such as melanoma averaged about $39.3 billion in 2004.

The heavy dependencies on medical experts for medical image diagnosis analyses are a serious challenge for regions (especially low- and medium-income countries) where an expert might not be readily available, inadequate, or may be non-responsive to an urgent medical need (such as dermatological-related requirements). Usage of a dermoscope for the diagnosis of PSL images has been reported to be characterised by several complexities and subjectiveness, thus associated with poor reproducibility and low accuracy, especially among inexperienced dermatologists. In most cases, even the accuracy of experts in the usage of dermoscope has been
reported to be in the range of 65%-84% (Argenziano et al., 1998; Argenziano, Soyer & Chimenti, 2003; Hintz-Madsen, 1998; Hintz-Madsen et al., 1996; Rosendahl et al., 2011; Rubegni et al., 2002). One report has it that a number of dermatologists perform a biopsy (appropriating a part of patient lesion to ascertain whether the skin lesion is benign or malignant) on patients only to discover later that just 10% of these procedures actually reveal a cancerous pathology (Zagrouba & Barhoumi, 2004). The foregoing problems suggest that a better and manageable solution is urgently needed with the view of minimising these dependencies and human bias, thus leading to the research question.

1.2.1 Research Questions

1.2.1.1 Primary Question

The primary research question is what system can be designed and prototyped towards enhancing automated diagnosis procedure of PSL in patients residing in remote or underserved areas be minimised, and thus leading to reduction in heavy dependencies on medical experts for diagnosis purposis?

1.2.1.2 Sub-Questions

The main research question could be favourably answered if emphasis is placed on areas below.

[i]. What algorithm design can be developed for effective segmentation and classification of pigmented skin lesion such as melanoma and naevi, thus minimising the potential bias made by medical experts?
[ii]. How can noises that are usually present in medical images detected and repaired while ensuring that quality and a time-effective diagnosis is achieved at a reasonable speed without losing the morphological feature of the image data?

[iii]. What technique(s) can be used for localisation of skin lesions from healthy surrounding skins for faster provision of segmentation and diagnosis results?

1.2.2 Research Focus

This research is motivated by the need for studies that can help provide ways or approaches that can be used by medical practitioners (such as dermatologists) and at the same time not heavily depend on opinions of dermatologists, which can often be subjective (Rubegni et al., 2002; Stanganelli et al., 2005). Over the decades, the research community has come to terms with a standard automation procedure for diagnosing a typical pigmented skin lesion. The automation process includes four main phases:

[i]. Image acquisition and pre-processing

[ii]. Segmentation of lesion from surrounding healthy skin

[iii]. Feature extraction

[iv]. Classification of the lesion

Given the great need and importance of localising the image area to be diagnosed, this study focuses on performing a pre-processing computation on a given PSL image and then segment the lesion area from healthy surrounding skins. This is particularly important to avoid unnecessary computation of a non-lesion area of the image data.
1.3 Research Aim and Objectives

1.3.1 Aim

The purpose of this study is to prototype a system that contributes towards effective segmentation and classification of medical image in order to reduce heavy dependencies on medical experts for diagnosis procedure of PSL (especially melanoma and naevi) in patients.

1.3.2 Objectives

[i]. To develop an algorithm for efficient standardisation and repair of hair-occluded skin lesions to avoid misdiagnosis caused by image noise.

[ii]. To design a system that can ease the localisation of a lesion area from the healthy surrounding skin for effective selection of discriminating image features.

[iii]. To improve the speed of diagnosing pigmented skin lesions using a well-defined system architecture based on ground truth knowledge of past diagnosis of PSL as a medical image library.

1.4 Relevant Works

During the last few years, telemedicine with remote image viewing and analysis has emerged as a highly valuable and versatile tool, particularly suited to places where local medical expertise is limited. Granot, Ivorra and Rubinsky (2008) worked on creating a medical imaging system consisting of physically separated components of medical imaging system in order to produce a robust and less expensive system that can be used by trained non-medical personnel. Adoption of a simple method of microphotography that could significantly increase opportunities and quality diagnostics while lowering costs and considerably increasing connectivity between most isolated laboratories and distant reference centres has been proposed by Aher and Kaore (2010).
Dobrescu et al. (2010) described a method of algorithm for automatic detection of malignancy of skin lesion, which is based on both local fractal features (local fractal dimension) and texture features derived from medium co-occurrence matrices (such as contrast, energy, and homogeneity). Tushabe et al. (2011) proposed an image-based diagnosis method where images of skin disorder were used to classify skin diseases into a broad category of either viral infected or bacterial infected.

Malignant melanoma currently accounts for a third of most frequent types of skin cancer and 79% of skin cancer deaths. The incidence of malignant melanoma in fair-skinned patients has increased histrionically in most parts of the world over the past few decades (Dobrescu et al., 2010; Rubegni et al., 2002; Stanganelli et al., 2005). In a bid to improve early detection, a number of diagnostic checklists and rules have been proposed such as 7-point checklists (Healsmith, Bourke & Graham-Brown, 1994) and ABCDE: Asymmetry, Border, Colour, Diameter, Evolution checklist (Fitzpatrick et al., 1998). These rules and checklists specify visual features associated with malignant lesion symptoms.

In their work, Stolz et al. (1994) developed a diagnosis scheme for dermoscopic images, accessing the Asymmetry (A), Border (B), Colour (C), and Diameter (D) of different image structures. This ABCD rule became the standard in dermoscopy for staging PSL into benign, suspicious, or malignant moles (melanoma). However, dermoscopic diagnosis is often complex and subjective, thus associated with poor reproducibility and low accuracy especially among inexperienced dermatologists, as the accuracy of experts is 65%-84% (Argenziano et al., 2003; Lee, 2001; Stanganelli et al., 2005). Also, visual interpretations of these features by
dermatologists have so far proven to be a difficult task. In his study, Lee (2001) reported the detection rate based on clinical visual investigation to be about 65%.

Melanoma is highly curable if diagnosed early and treated properly, as survival rates vary between 15% and 65% from terminal to early stages respectively (Ali & Deserno, 2012). Depending on the practitioner’s experience, dermoscopy improves the diagnostic accuracy for melanoma detection up to 50% as compared with traditional visual inspection (Kittler, 2004). In the last decade, the usage of Dermoscopy or Epiluminiscence Light Microscopy (ELM) changed the dermatologist’s approach to suspicious PSL. However, the analysis made using ELM are extremely complex and subjective (Rubegni et al., 2002). To prevent the aforementioned challenge of quantitative interpretation, methods based on Computer-Aided Diagnosis (CAD) have been introduced towards automating diagnosis procedures (Barata et al., 2013; Jaleel, Salim & Aswin, 2013; Mittra & Parekh, 2011; Rubegni et al., 2002; Stanganelli et al., 2005).

Gilmore et al. (2009) used Lacunarity (a measure of transitional invariance of an object used in quantifying aspects of patterns that exhibit scale-dependent changes in structure) to provide a promising method for automated assessment of melanocytic naevi and melanoma. The fuzzy-based histogram analysis technique used by Stanley et al. (2003) provided a possibility for automated skin lesion discrimination in dermatological clinical images. Rubegni et al. (2002) developed an automated process using artificial neural network methods based on mathematical analysis of pigmented skin lesions to avoid the problem of qualitative interpretation made by the use of ELM by dermatologists. Kreutz et al. (2001) presented a combination of artificial neural network approach with texture analysis using digital image processing and a mixture of experts to attempt automation of skin cancer diagnosis. Ganster et al. (2001) developed a computerised
automated system for analysis of images obtained from ELM in order to enhance the early recognition of malignant melanoma. Sheha, Mabrouk and Sharawy (2012) used Grey-Level Co-occurrence Matrix (GLCM) and Multilayer Perceptron Classifier (MLP) for automatic detection of melanoma skin cancer using texture analysis. One core challenge, however, with many of previously mentioned approaches is their inability to integrate well with ubiquitous devices such as mobile telephony, now largely accessible to underserved areas.

A global mobile statistics report compiled by Mobithink (2014) highlighted that out of about 6835 million mobile cellular subscribers, the developing nations constitute 76.59% (5235 million). A similar trend was reported for active mobile broadband subscriptions, where developing nations account for 55.44% (1162 million out of available 2096 million).

1.5 Benefits

This study attempts to model a system that would help to improve remote patient diagnosis, screening and examination of skin problems at a reduced cost while reducing overdependencies on medical experts. The health hazard within rural communities and emerging urban cities can be reduced. It is also expected that the output of the study would result in a system that would increase the speed of skin disease diagnosis, given that the time lag that could be caused by heavy dependency on medical experts would be greatly reduced.

Acquiring images nowadays is easy. Most cellphones can capture good quality images. New generations of image-based diagnosis systems using digital technologies are increasingly being developed (Arani & Ghassemian, 2010; Baldi et al., 2009). So, it may be possible even with the use of mobile devices, which are increasingly available in low- and medium-income countries (Mobithink, 2014), to diagnose a skin disease once the mobile phone uploads the captured image
to a server (such as connected via a Virtual Private Network). By so doing, in no time the analysis would be done on the image and relevant diagnosis result would be automatically published back to the phone.

No doubt, the death tolls as a result of lack or unavailability of dermatologists in underserved areas could be largely reduced. It is believed that the study would in the near future open opportunities in developing better and low-cost effective solutions to mitigate dermatological challenges.

1.6 Research Ethics

[a]. Protection from Harm: The research team did not experience any harm whatsoever, be it physical, social, or emotional throughout this study.

[b]. Right to Privacy: In the course of the study, privacy was maintained by not disclosing identities of the subjects whose PSL images are being used for the study. Also, appropriate reference to relevant authors is made in the documentation of the study.

[c]. Confidentiality: All communications with the source of image data regarding the subjects whose PSL images were used have been treated with absolute confidentiality.

[d]. Sample Data: Appropriate reference is made in the entire documentation of the study to identify the sources of sample data used. The team has also ensured that misrepresentation of sample data is avoided.
1.7 Dissertation Outline

Following the objectives of this dissertation as outlined in section 1.3.2, Chapter 2 of this study focuses on the review of current efforts demonstrated in the literature in a bid to automate the diagnosis procedure of skin disease.

Chapter 3 discusses an algorithm-based pattern matching technique that can be used to identify as well as restore hair-occluded lesion image data. The chapter also prototypes a system component for testing the algorithm and then discusses the result from the usage of the prototype.

Chapter 4 focuses on algorithm design for segmenting lesion image from non-lesion areas of a healthy skin. A prototype system was created to test the algorithm, and results of the work were compared with notable research efforts in the literature.

Chapter 5 concludes the dissertation and makes appropriate recommendation for future work and areas that can be further improved upon.

1.8 Summary

Automatic diagnosis of skin cancer is feasible and achievable through the use of a well-defined segmentation and classification technique. While much success has been recorded in the current advances in automation of medical diagnosis, this study focuses on prototyping a system that uses optimised algorithms to aid pre-processing of lesion image data and extraction of lesion data from healthy surrounding skin. The optimised algorithms would help provide a cost-effective, easier and faster diagnosis for underserved areas.
CHAPTER TWO: LITERATURE REVIEW

2.1 Selection of Studies

This study uses five primary digital research libraries (PubMed, IEEE Xplore, ACM, ScienceDirect, and Google Scholar) to obtain relevant literature on diagnosis of melanocytic lesions. The keywords utilised in obtaining resources include automation skin diagnosis, skin lesion feature extraction, fully automatic skin tumour segmentation, automatic skin lesion segmentation and skin lesion segmentation. After selecting most relevant literature based on the scope of this study, a comparative revision was then carried out on the selected literature (see Figure 2-1).

2.2 Findings on the Reviewed Literature

2.2.1 Dermoscopic Algorithm Methods

The literature review generally shows that several dermoscopic algorithmic methods have been proposed to assist in the diagnosis of melanocytic lesions over the years. Prominent among these methods are Pattern Analysis (Pehamberger, Steiner & Wolff, 1987), ABCD Rule (Stolz et al., 1994), ELM 7-Point Checklists (Argenziano et al., 1998), Menzies Score (Menzies et al., 1996), seven Features for Melanoma (Dal Pozzo, Benelli & Roscehi, 1999) and Modified ABC-Point list of Dermoscopy (Blum, Rassner & Garbe, 2003). The quantitative pattern analysis proposed in Pehamberger et al. (1987) is based on a detailed qualitative assessment of numerous individual ELM criteria and typically requires a significant degree of formal training. The ABCD rule employs a semi-quantitative counting classification based on the evaluation of Asymmetry, Border irregularity, Colour variation and Different dermoscopic morphological structures of the lesion.
Abstracts vetted using following criteria:
[i]. Image segmentation
[ii]. Skin lesion diagnosis automation
[iii]. Cell carcinoma
[iv]. Image Registration
[v]. Patient
[vi]. Automated Diagnosis

112173 Abstracts from primary literature search
1107 Abstracts screened for relevance
350 Full Text publications screened for reference listing

218 publications excluded because:
[i]. Methodological procedures were not clearly stated
[ii]. Number of dataset used were not clearly defined
[iii]. Results not properly stated

[i]. Clinical Decision-Support System not automated
[ii]. Exclude studies with no clear systematic review

132 Full Text publications included

Figure 2-1 Literature search upshot
ELM 7-point checklist proposed in Argenziano et al. (1998) use three major criteria and four minor criteria, with each major criterion having a score of two points, whereas each minor criterion is awarded one point. A minimum total score of three is required for the diagnosis of melanoma.

A comparative analysis made in Annessi et al. (2007) on three of the algorithmic methods (Pattern Analysis, ABCD rule and 7-Point Checklists) using 198 equivocal melanocytic lesions revealed that Pattern Analysis was the most sensitive (85.4%) and specific (79.4%) in identifying Thin Melanoma (TM), followed by ABCD rule. Over the years, dermatologists have been using the ABCD rule (a technique built on Pattern Analysis) as standard for classifying pigmented skin lesion (PSL) as benign, suspicious or life-threatening (malignant) primarily because of its simplicity, yet efficient approach (Blum et al., 2003; Day & Barbour, 2000; Gilmore et al., 2009). Typically, a lesion is said to be malignant according to the ABCD rule if its Region of Interest (ROI) is not symmetrical, (if it has an irregular border structure), varies in colour and with different dermoscopic structures (e.g. diameter greater than 6mm), with some exceptions such as thin melanoma.

2.2.2 Diagnosis of Melanocytic Lesions

While there has been a measure of success in the usage of a dermoscope by dermatologists inspired by aforementioned algorithms (Kittler, 2004; Lee, 2001), the subjective analysis made by dermatologists has been of major concern (Rubegni et al., 2002; Stanganelli et al., 2005). Diagnosis of PSL using a dermoscope has been reported to be characterised with several complexities and subjectiveness, thus associated with poor reproducibility and low accuracy, especially among inexperienced dermatologists. The accuracy of experts is bid to be in the range
of 65%-84% (Argenziano et al., 1998; Argenziano et al., 2003; Hintz-Madsen, 1998; Hintz-Madsen et al., 1996; Rosendahl et al., 2011; Rubegni et al., 2002). It has also been reported that many dermatologists perform a biopsy (appropriating a part of patient lesion to ascertain whether the skin lesion is benign or malignant) on patients only to discover later that just 10% of these procedures actually reveal a cancerous pathology (Zagrouba & Barhoumi, 2004).

There exists thus a number of research interests towards development of methods based on Computer-Aided Diagnosis (CAD) that can be employed to prevent aforementioned problems (Mitra & Parekh, 2011; Rubegni et al., 2002; Stanganelli et al., 2005). The need for CAD systems is also required to make a diagnosis faster and reproducible. To this end, a number of CAD-based medical imaging diagnostic techniques have been proposed in the literature to automate the diagnosis process. Typically, a CAD-based medical diagnostic system would have a form of accepting an image to be diagnosed as input, either in Red-Green-Blue (RGB) or other formats such as grey or YCbCr. Some method of pre-processing is then carried out on the image in order to remove artefacts that might make classification difficult. Rather than examining the whole image, segmentation of Region of Interest (ROI) is usually performed to localise a point of interest. Once the region of interest has been determined, morphological and possible chromatic features can then be obtained as parameters to enhance effective diagnosis. A number of researchers generate quantitative parameters using some dermoscopic algorithmic methods as rules. These parameters, sometimes called features or attributes, are then analysed to describe the malignancy of a particular PSL. Commonly used statistical analysis for grading the performance of the varying medical imaging diagnostic techniques are highlighted in Figure 2-2,
and these metrics are used in this study. The automation process was previously discussed in section 1.2.2 and includes four main phases, which are as follows:

[a]. Image acquisition and pre-processing

[b]. Segmentation of lesion from surrounding healthy skin

[c]. Feature extraction, which deals with generation of parameters and sometimes reduction of parameters

[d]. Classification of the lesion, either as malignant or benign using extracted features

\[ \text{True Positivity (TP)}\]: correctly identified subject against a particular criteria in a given set of subjects

\[ \text{False Positivity (FP)}\]: incorrectly identified subject against a particular criteria in a given set of subjects

\[ \text{True Negativity (TN)}\]: correctly rejected subject against a particular criteria in a given set of subjects

\[ \text{False Negativity (FN)}\]: incorrectly rejected subject against a particular criteria in a given set of subjects

\[ \text{Sensitivity (Sn)}\]: statistical measurement of the percentage of proportion of true positive

\[ Sn = \frac{TP}{TP+FN} \times 100\% \]

\[ \text{Specificity (Sp)}\]: statistical measurement of the percentage of proportion of true negative

\[ Sp = \frac{TN}{TN+FP} \times 100\% \]

\[ \text{Likelihood Ratio Positive: } LR+ = \frac{Sn}{1-Sp} \]

\[ \text{Likelihood Ratio Negative: } LR- = \frac{1-Sn}{Sp} \]

\[ \text{Diagnostic Accuracy: } DA = \frac{TP+TN}{TP+TN+FP+FN} \]

Figure 2-2 Accuracy Assessment
2.2.2.1 Image Acquisition and Pre-processing

Image acquisition is an important step that can contribute towards effective understanding of varying principal clinical morphology features of skin-related cancerous disease such as melanoma (Esmaeili et al., 2008). Imaging technique is the general term used to refer to the act of obtaining and screening lesion images. Several imaging techniques such as Photography, Sentinel Lymph Node Biopsy (SLNB), Magnetic Resonance Imaging, Ultrasound, Molecular Profiling, Tomography and Dermoscopy are currently being used and experimented by medical practitioners alike. Notable imaging techniques recorded in the literature towards application of a computer vision in a diagnostic system have been summarised in Table 2-1. Arguably, due to slow adoption of advances in other diagnostic technologies by many dermatologists, the trend noticed in the literature is a consistent increase of the usage of dermoscopy (dermoscopy).

A majority of data sets discussed in the literature were acquired primarily using a dermoscope, either directly by the authors or from a dermatology institute such as clinics, hospitals and universities. Given that one of the main reasons for automation is to be able to reproduce the same results for a given similar set of conditions, most authors use already diagnosed images that have been histopathologically or clinically confirmed by one or more dermatologists as being of a particular melanocytic type (such as Clark nevus, Blue nevus, melanoma) or non-melanocytic type (such as basal cell carcinoma, Hematoma). In order to ensure that a good discriminating result is obtained via an automation process, most authors use varying sets of melanocytic images. Except in few cases did the researcher see melanocytic and non-melanocytic lesion images being examined in a single study, primarily because of the great results reported by
dermatologists in the usage of a dermoscope to trivially differentiate melanocytic lesions from non-melanocytic ones (Iyatomi et al., 2010).

A number of diagnosis accuracy results recorded in the literature have been reported to be highly dependent on the volume of images used (Ali & Deserno, 2012; Blum et al., 2004; Iyatomi et al., 2010; Iyatomi et al., 2008a). This arguably might be because of unpredictable morphological features exhibited by medical images. Another major factor that strongly influences the success of most diagnosis automation work carried out in the literature was the need for standardisation of images used for pre-processing (Day & Barbour, 2000). With each author determining what is best for standardisation, varying results have been recorded in the literature to a noticeable degree, hence making reproducibility of the research work very difficult. Furthermore, as reported in Rahman, Bhattacharya and Desai (2008), images collected from separate data sets are often captured by different devices under varying conditions, thus making both the retrieval and the classification tasks very challenging.

In Dobrescu et al. (2010), each image used was converted to 256 grey levels image of the same size as a form of pre-processing of the image in Hue Saturation Value (HSV) colour space. The study in Rubegni et al. (2002) reported the usage of calibrated camera to ensure the image obtained falls between 4mm to 4cm in size. In Zagrouba and Barhoumi (2004), each image used was coded on 24 bits bitmap format of size 150 × 150 × 3 pixels and a resolution of 0.0264cm × 0.0264cm per pixel. In Hashim, Osman and Khairudin (2009), after having ensured that images were captured with a resolution of 786 × 512, the researcher further resized each of the image to 500 × 500 pixel areas before performing noise filtering to improve the segmentation result. The study in Gilmore et al. (2009) first cropped each of the images used to a rectangle or square
shape such that the boundary of the lesion was adjacent to all four edges of the image, and each image was then compressed to a size where the shortest axis was 120 pixels wide. In Iyatomi et al. (2010), each image was standardised as 24-bit Joint Picture Expert Group (JPEG) with a resolution of $1136 \times 852$ pixels.

### Table 2-1 Comparative Imaging Techniques

<table>
<thead>
<tr>
<th>Imaging Techniques</th>
<th>Merits</th>
<th>Shortfalls</th>
</tr>
</thead>
<tbody>
<tr>
<td>Digital Photography</td>
<td>◆ Ease of use</td>
<td>◆ Decrease in sensitivity caused by reliance on monitoring for the decision whether to excise a lesion</td>
</tr>
<tr>
<td>(Dancey, Mahon &amp; Rayatt, 2008; Marghoob et al., 2003; Menzies, 2006; Psaty &amp; Halpern, 2009)</td>
<td>◆ Reproducibility</td>
<td>◆ Results largely depend on usage experience</td>
</tr>
<tr>
<td>Dermoscopy (Braun et al., 2009; Dancey et al., 2008; Marghoob et al., 2003; Menzies, 2006; Psaty &amp; Halpern, 2009)</td>
<td>◆ Image Quality</td>
<td>◆ Difficult to discriminate between malignant and benign lesions</td>
</tr>
<tr>
<td>Optical Coherence Tomography (Dancey et al., 2008; Marghoob et al., 2003; Psaty &amp; Halpern, 2009)</td>
<td>◆ Non-invasive</td>
<td>◆ Requires formal training</td>
</tr>
<tr>
<td>Reflectance-mode Confocal Microscopy (Marghoob et al., 2003; Menzies, 2006; Psaty &amp; Halpern, 2009)</td>
<td>◆ Suitable for melanocytic lesions</td>
<td>◆ Requires formal training</td>
</tr>
<tr>
<td></td>
<td>◆ Preserves natural tissue architecture</td>
<td>◆ Requires formal training</td>
</tr>
<tr>
<td></td>
<td>◆ Evaluation of recurrent malignant tumours</td>
<td>◆ Requires formal training</td>
</tr>
</tbody>
</table>

The use of these imaging techniques, such as digital photography and dermoscopy, has been widely studied for their merits and shortfalls in the diagnosis of melanoma. Digital photography offers ease of use, reproducibility, and improved diagnosis sensitivity of melanoma, while dermoscopy is non-invasive and its dermoscopic colours and structures tend to correlate well with histopathology findings, enhancing diagnosis accuracy. In contrast, optical coherence tomography and confocal microscopy are non-invasive and suitable for melanocytic lesions, preserving natural tissue architecture and evaluating recurrent malignant tumours, but require formal training.
For archiving, each image used in Blum et al. (2003) was saved in JPEG format having a resolution of $765 \times 576$ pixels. It would indeed be interesting to see how calibration-based image acquisition assists in image standardisation in future research.

One of the major hindrances to a successful diagnosis in medical imaging is the presence of artefacts (noise), such as air bubble, hair shafts and dermoscopic-gel (Abbas et al., 2013; Abbas, García & Rashid, 2010; Hintz-Madsen et al., 1996; Huang et al., 2013; Kiani & Sharafat, 2011; Zhou et al., 2008a). A number of ways such as popular DullRazor hair removal (Lee et al., 1997) have been proposed in the literature to overcome these challenges. In (Zagrouba & Barhoumi, 2004, 2005), three pre-processing techniques were applied to remove small structures and artefacts. In the study, the researcher first applied median filtering according to (Hintz-Madsen et al., 1996) for minimising the influence of small structures (such as thin hair) and isolated islands of pixels (such as small air bubbles). DullRazor (Lee et al., 1997) was then applied on the previous result to remove thick hairs. Karhunen-Loève Transform (a principal component analysis which is used in projecting three colour components on the eígen-vectors of their co-variance matrix) was finally employed to smoothen the edges of each image. In (Abbas, Celebi & García, 2012; Abbas et al., 2011b; Abbas et al., 2010), three different techniques were used in reducing notable

| Magnetic Resonance Imaging (Dancey et al., 2008; Marghoob et al., 2003; Psaty & Halpern, 2009) | ≠ Produces high-resolution image when used with specialised surface coil | ≠ Few dermatological applications ≠ Difficult to discriminate between malignant and benign lesions |
artefacts, after having transformed each image from RGB to International Commission Internationale de l'Eclairage (CIE) L*a*b* colour space.

Table 2-2 Pre-processing Techniques

<table>
<thead>
<tr>
<th>Publications</th>
<th>Year</th>
<th>Lesion Type</th>
<th>Techniques</th>
<th>Artefact Removal &amp; Post-processing Algorithm</th>
</tr>
</thead>
<tbody>
<tr>
<td>(Kiani &amp; Sharafat, 2011)</td>
<td>2011</td>
<td>unspecified</td>
<td>Prewitt Filter, Thresholding</td>
<td>Linear Interpolation</td>
</tr>
<tr>
<td>(Xie et al., 2009)</td>
<td>2009</td>
<td>melanocytic</td>
<td>Morphology closed-based Top Hat, Thresholding</td>
<td>Region growing, PDE-based inpainting</td>
</tr>
<tr>
<td>(Huang et al., 2013)</td>
<td>2013</td>
<td>unspecified</td>
<td>Curvilinear matched filter</td>
<td>Region growing, LDmA b</td>
</tr>
<tr>
<td>(Zhou et al., 2008a)</td>
<td>2008</td>
<td>unspecified</td>
<td>Curvilinear matched filter</td>
<td>Exemplar-based inpainting</td>
</tr>
<tr>
<td>(Sultana et al., 2012)</td>
<td>2012</td>
<td>melanocytic</td>
<td>CLAHE, Morphology closed-based Top Hat, Thresholding</td>
<td>Nagao Filter, Bi-cubic Interpolation</td>
</tr>
<tr>
<td>(Afonso &amp; Silveira, 2012)</td>
<td>2012</td>
<td>unspecified</td>
<td>Percolation Algorithm</td>
<td>-</td>
</tr>
<tr>
<td>(Fiorese, Peserico &amp; Silletti, 2011)</td>
<td>2011</td>
<td>melanocytic</td>
<td>Morphology closed-based Top Hat, Decision tree filter (density, sphericity &amp; convex hull sphericity)</td>
<td>PDE-based inpainting</td>
</tr>
</tbody>
</table>
The study then used a homomorphic filtering technique to reduce specular reflection by normalising the brightness across the image while increasing the contrasts. An adaptive and recursive weighted median filter was then used in the study to reduce the impact of air bubble and dermoscopic-gel. Finally, a hair-repairing algorithm (consisting of line detection, line replacement by exemplar-based image inpainting and black frame removal algorithm) was developed in the same study and then applied to remove hair pixel noise.
The main challenge with most of the noise reduction pre-processing techniques aforementioned is that they arguably require sophisticated processing software and sometimes create new artefacts (Gilmore et al., 2009; Iyatomi et al., 2010). Lacunarity algorithm (a measure of transitional invariance of an object that computes aspects of patterns that exhibit scale-dependent changes in structure) was proposed by Gilmore et al. (2009) as a way of obviating some of the challenges. The same authors reported that the algorithm is insensitive to the presence of artefacts such as hair shafts. Their work recorded a comparable sensitivity (percentage of true positives) result to the ones obtained in the literature, however, a lower specificity (percentage of true negatives) compared to other notable approaches such as in (Abbas et al., 2012; Iyatomi et al., 2010; Zagrouba & Barhoumi, 2005).

Table 2-2 summarises the major techniques used in the literature for performing pre-processing tasks as an important step for effective location of skin lesion area. It is evident that future research would likely engage more mixture of techniques for image cleansing in order to achieve better lesion localisation. Researchers can also take advantage of new dermoscopy types [such as vascular-based or CASH (colour, architecture, symmetry, and homogeneity) based Dermatoscopy] to improve lesion image quality towards having a much better diagnostic result (Braun et al., 2009).

Considering that variation in illumination can greatly affect image features, it is also important that more effort should be made towards corrective illumination measures (Glaister et al., 2013; Glaister, Wong & Clausi, 2012). Future research might also validate the usage of mobile communication devices now capable of acquiring high-resolution images, and in some cases
these mobile devices could be combined with other imaging techniques to simplify image acquisition tasks (Doukas et al., 2012; Ramlakhan & Shang, 2011; Wadhawan et al., 2011).

2.2.2.2 Image Segmentation

Segmentation is one of the most difficult tasks in medical imaging, most especially because of irregular structures characterising lesion images, low contrasts surrounding the skin, fuzzy borders and existence of artefacts (Abbas et al., 2012; Cudek, Grzymala-Busse & Hippe, 2010; Dobrescu et al., 2010; Zagrouba & Barhoumi, 2004). Even tumour areas manually extracted by dermatologists have been discovered not to be consistent (Barhoumi, Dhahbi & Zagrouba, 2007; Guillod et al., 2002; Silletti et al., 2009; Zhou et al., 2009a). Being able to segment a lesion’s region of interest from healthy surrounding skin is a major step in a successful diagnostic process of melanocytic lesions.

Notable lesion localisation approaches and algorithms have been summarised in Table 2-3. The study in Iyatomi et al. (2006) led to the development of an algorithm, which is referred to as dermatologists-like tumour area extraction algorithm to discriminate the actual tumour area from surrounding skin.
<table>
<thead>
<tr>
<th>Methods</th>
<th>Description</th>
<th>Source</th>
<th>Mean Statistics</th>
</tr>
</thead>
<tbody>
<tr>
<td>≠ Edge-based (AS, RS, GVF, LoG, Canny, BTA)</td>
<td>Uses information about edges of lesion image coupled with other post-processing techniques to estimate lesion boundary</td>
<td>(Abbas et al., 2012; Chiem, Al-Jumaily &amp; Khushaba, 2007; Chung &amp; Sapiro, 2000; Denton, Duller &amp; Fish, 1995; Madhankumar &amp; Kumar, 2012; Mendonça et al., 2007; Parolin, Herzer &amp; Jung, 2010; Pires &amp; Barcelos, 2007; Silveira et al., 2009; Taouil &amp; Romdhane, 2006; Yasmin, Sathik &amp; Beevi; Zhou et al., 2010b)</td>
<td>Er=0.11 – 16.00; ( S_n=90.89%-95.47% ); ( S_p=93.65%-91.33% )</td>
</tr>
<tr>
<td>≠ Region-based, Contours (FBSM, LS, JSEG, RW)</td>
<td>A seed-based approach that considers grey levels from neighbouring pixels resulting in grouping of regions according to common image properties</td>
<td>(Barhoumi et al., 2007; Cavalcanti &amp; Scharcanski, 2013; Cavalcanti et al., 2011; Celebi, 2011)</td>
<td>Er=9.16 – 22.00; ( S_n=83.39%-93.67% ); ( S_p=93.83%-97.45% )</td>
</tr>
<tr>
<td>Clustering (DBSCAN, FCM, HCM, PCM, KPP, ART)</td>
<td>Map pixels into varying feature spaces upon which they are subjected to a grouping algorithm</td>
<td>Er=0.058 – 0.34;</td>
<td></td>
</tr>
<tr>
<td>---</td>
<td>---</td>
<td>---</td>
<td></td>
</tr>
<tr>
<td>Aslandogan &amp; Bergstresser, 2005b; Chung &amp; Sapiro, 2000; Ivanovici &amp; Stoica, 2012; Mendonça et al., 2007; Nourmohamadi &amp; Pourghassem, 2012; Silveira &amp; Marques, 2008; Silveira et al., 2009; Situ et al., 2007; Wighton et al., 2009; Wong, Scharcanski &amp; Fieguth, 2011; Zagrouba &amp; Barhoumi, 2004, 2005)</td>
<td>(Celebi, Aslandogan &amp; Bergstresser, 2005a; Devi, Suresh &amp; Shunmuganathan,</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Method</td>
<td>Description</td>
<td>Example Results</td>
<td></td>
</tr>
<tr>
<td>--------</td>
<td>-------------</td>
<td>-----------------</td>
<td></td>
</tr>
<tr>
<td><strong>Exemplar-based</strong></td>
<td>Utilises global colour model to retrieve annotated examples which are most similar to a given query image and then generate pixel labels via probabilistic voting rule</td>
<td>Er=13.70 – 26.76;</td>
<td></td>
</tr>
<tr>
<td><strong>Neural Network, Machine Learning (RBF, BPN, XLM, MRF, WN, MLP, Bayesian)</strong></td>
<td>Uses expert systems to process small areas of an image for classification. Areas of the image are then categorised based on classification recognised by the network</td>
<td>$S_n=94.34%; S_p=99.84%$</td>
<td></td>
</tr>
</tbody>
</table>
Thresholding (Otsu, Kittler, Kapur, AT, IT, ImT, SRBDK)

A non-linear operation that produces a binary image by assigning two levels to pixels below or above a specified threshold value. It is currently the most widely used technique for discriminating intensity images. It could be based on histogram shape, clustering, entropy, spatial or local lesion properties.

2012; Zhou et al., 2009b

(Abbas et al., 2012; Capdehourat et al., 2011; Cavalcanti & Scharcanski, 2013; Cavalcanti, Yari & Scharcanski, 2010; Celebi et al., 2010; Cudek et al., 2010; Dalal et al., 2011; Ebrahimi & Pourghasem, 2010; Ganster et al., 2001; Humayun, Malik & Kamel, 2011; Madhankumar & Kumar, 2012; Mendonça et al., 2007; Mete et al., 2011; Norton et al., 2010; Rahman et al., 2008; Rahman, Desai

Er=0.25 – 19.00; $S_n$=84.5%-100%; $S_p$=54%-99.09%
<table>
<thead>
<tr>
<th>Morphology &amp; Statistical based (normalized cut, PCA, median cut, ICA, grab cut, IHP)</th>
<th>Uses morphological features to estimate discontinuity in lesion images</th>
<th>Er=0.17</th>
</tr>
</thead>
<tbody>
<tr>
<td>Curve fitting, Dynamic Programming</td>
<td>Aid effective extraction of edge pixels, such as by fitting an elastic to an initial boundary, and then shrink or expand it to approximate</td>
<td>Er=0.052; $S_n=94.64%$; $S_p=98.14%$</td>
</tr>
<tr>
<td>#Evolutional Strategy</td>
<td>A random-based search technique that can seek global optimum and extract local optimum automatically. It is mostly used in combination with other methods such as region growing</td>
<td>(Situ et al., 2007)</td>
</tr>
</tbody>
</table>

| PCA: Principal Component Analysis | FCM: Fuzzy C-Means | BTA: Boundary Tracing Algorithm |
| ICA: Independent Component Analysis | HCM: Hierarchical C-Means | AT: Adaptive Thresholding |
| IHP: Independent Histogram Pursuit | PCM: Probabilistic C-Means | IT: Iterative Thresholding |
| AS: Adaptive Snake | KPP: K-means ++ | ImT: Intermeans Thresholding |
| RS: Robust Snake | ART: Adaptive Resonance Theory | |
| LoG: Laplacian of Gaussian | FBSM: Fuzzy-Based Split and Merge | |
| GVF: Gradient Vector Flow | LS: Level Set | RW: Random Walker |
| MLP: Multilayer Perceptron | JSEG: J-Image Segmentation | SRBDK: Spatial Relations Based Knowledge |
| $S_n$: Sensitivity | RBF: Radial Basis Function | DBSCAN: Density-Based Spatial Clustering |
| $S_p$: Specificity | | |
Rubegni et al. (2002) in their study utilised Laplacian filter to localise the lesion area, and in the same study, zero-crossing algorithm helped the authors to perform automatic outline of the lesion border. The combination of statistical clustering of the lesion colour space and hierarchical region-growing algorithm were used in Kreutz et al. (2001) as a segmentation technique. In Zagrouba and Barhoumi (2004), segmentation was performed using a combination of bimodal histogram based on fuzzy set region growing. Three segmentation algorithms (global thresholding, dynamic thresholding and a 3-D colour clustering concept), together with fusion strategy, were used in Ganster et al. (2001) to obtain binary segmentation of the lesion.

Abbas et al. (2012) proposed a new segmentation method based on Skin Dynamic Programming (SDP) using CIE L*a*b* colour space. Their work reported a notable result such as overcoming limitation of thresholding, region-growing, clustering and level set-based segmentation methods highlighted in the literature. The method also compared favourably with the existing methods in the literature, primarily due to usage of CIE L*a*b* colour space. The sensitivity of their study was reported to be 96.64%, with specificity of 98.14% and 5.23% error probability. The major challenge, however, as mentioned by the same authors was the inability
of their proposed method to detect accurate outline of lesion in scenarios where areas belonging to the lesion are divided into multiple tumours.

While most of the segmentation techniques discussed above yielded considerably promising results, the main problem with most of the approaches is that the computer-extracted regions sometimes were often smaller than the dermatologist-drawn ones (segmentation ground truth). Consequently, this makes some areas surrounding the tumour (which are an important feature in the diagnosis) to be excluded from subsequent analysis (Gilmore et al., 2009; Iyatomi et al., 2010). Rahman et al. (2006) also argued the need to convert colour images to intensity images for effective lesion localisation. It is equally important to state here that although most research results recorded in the literature favoured the usage of HSV colour space in segmenting lesion boundary arguably due to its inherent ability to separate luma (image intensity) from chroma (colour information), CIE L*a*b* colour space is however judged in the literature to have produced a more convincing result (Kaur & Kranthi, 2012; Zhou et al., 2008b).

There are indications from the literature that many existing segmentation systems have high sensitivity rates towards effective diagnosis; they however experience high computing time (Iyatomi et al., 2006; Zagrouba & Barhoumi, 2005). The usage of more than one algorithm for segmentation is one of the major causes of the non-realistic computing time as highlighted in Zagrouba and Barhoumi (2005). It has also been noted that large amounts of the past works have focused significantly on developing algorithms based on colour information in non-uniform colour spaces (disregarding the role of textural information), thus sometimes yielding unsatisfactory segmentation results (Abbas et al., 2012). Another major issue of concern is that most segmentation methods in the literature were unable to define the clear and precise
criterion to accurately separate pigmented lesion from the surrounding healthy skin (Zagrouba & Barhoumi, 2005).

While future research most likely would continue to use a mixture of algorithms due to increasing the success rate of such approaches, more effort should be made towards optimising these algorithms to reduce their computing time. Future studies can also attempt to improve on advances in the usage of machine learning systems (e.g. Extreme Learning Machine, Radial Basis Function Network) towards effective lesion segmentation as exemplified in Vennila et al. (2012).

### 2.2.2.3 Feature Extraction

An important step in the diagnosis of lesion as reported in the literature is feature extraction. Skin features depend on many variables such as body location (e.g. forehead or cheek), subject parameters (e.g. age or gender), imaging parameters (such as lighting or camera), and direction from which the lesion image is viewed and illuminated. Bacterial and viral skin infections generally affect the skin by decolorising and distorting pigmented skin areas, further making automation of medical image analysis difficult (Tushabe et al., 2011). One of the best approaches to overcoming the aforementioned challenges in automating medical imaging diagnosis is to simplify the objective of the analysis and exploit some kinds of hypothetical information about the image structures. The information about the structures to be analysed can be anatomical knowledge about their typical appearance (e.g. shape, grey levels and position) or statistical knowledge of their properties (such as grey level of the tissues included in those structures). The images can then be classified using their morphological properties: colour, fractal and texture. However, while it is desirable to determine features to represent these structures directly, extracting these features is often challenging primarily due to a vast variety of dermoscopic
images and the highly subjective definitions of these features (Gilmore et al., 2009; Iyatomi et al., 2008a; Iyatomi et al., 2006).

A fractal is an object that technically displays self-similarity on all scales, such that even if the object does not exhibit exactly the same structure at all scales, it would have the same type of structures appearing on all scales (Mathworld, 2013). In medical imaging, the usage of fractal analysis typically helps to determine the fractal dimension of an image using techniques such as mean fractal dimension and local connected fractal dimension. Fractal dimension specifies a ratio that provides a statistical index of complexity of comparing how details in a fractal pattern changes with the scale at which it is measured. Texture analysis involves the usage of approaches such as co-occurrence matrices calculus for the evaluation of texture features (e.g. energy, entropy and contrast) during image analysis and processing.

![Discriminating Features](image)

**Figure 2-3 Discriminating Features**
Statistics analysis in Figure 2-3 indicates that Colour-based and Geometric-based parameters are the two most widely used discriminating features either individually or in combination with other features.

The study reported in Dobrescu et al. (2010) used both local fractal and texture features resulting from medium co-occurrence matrices (such as homogeneity, energy, and contrast) to automate the detection of malignancy in a skin lesion. Their study reported excellent results though the processing time was a concern and inaccuracy in image retrieval was also recorded.

In Zagrouba and Barhoumi (2005), 14 features (based on colour and geometric properties) were used to produce numerical features which designate clinical symptoms of malignancy before using Sequential Floating Forward Selection (SFFS) and Sequential Floating Backward Selection (SFBS) to allow for the selection of a reasonably reduced number of five useful features. This permits the reduction of lesion’s vector dimension and the computing time without significant loss of information. Their work recorded above 95% of good classifications on the training set and above 82% of good classifications on the test set. A similar technique was used in Ganster et al. (2001), where 122 features containing shape and radiometric features as well as local and global parameters were first calculated to describe the malignancy of the lesion, after which 21 significant features were selected from this set by the application of statistical feature subset selection methods of SFFS, SFBS and Leave-One-Out (LOO).

In Iyatomi et al. (2010), the authors’ study attempt to quantify features from each image using the ABCD rule and thus came up with 428 features as colour (140), symmetry (80), border (32) and texture (176) properties. Statistical F-test was then applied on each of the feature to determine a set of optimal features that can serve as a discriminant. At first, 33 image features
were obtained (yielding 98.54% sensitivity and 97.27% specificity), and the process continues till only one image feature $k_{180}$ (skewness of bright region with intensity less than 180 in the tumour along its major axis) was used, which yielded 94.34% sensitivity and 76.36% specificity result. The ADAM system utilised in Stanganelli et al. (2005) used a combination of image boundary shape, texture and colour distribution as features to discriminate between melanocytic lesion types.

The study in Rubegni et al. (2002) used 13 features to sufficiently discriminate melanomas and naevi. The features were of four main categories, namely, geometries (minimum diameter), colours (mean values of red inside the lesion, deciles of red inside the lesion, quartiles of blue inside the lesion, mean values of green inside the lesion, and mean skin-lesion gradient), texture (mean contrast of lesion and contrast fractality evaluated by co-occurrence matrices) and islands of colour, i.e. colour clusters inside the lesion, considering the lesion’s peripheral dark regions, transition area, transition region imbalance, background area, background region imbalance and circularity (difference between lesion and circle of equal area). In the same study, the combination of varying features was reported to provide good classification accuracy with sensitivity of 99% and specificity of 72.5% without using training data set as part of the test, while the usage of the training data set as part of testing data yielded 94.3% sensitivity and 93.8% specificity. A novel approach was proposed in Zhou et al. (2011) by first extracting 3-D based differential forms of the lesion image, after which the statistical moments of enhanced principal curvatures of lesion image were computed in order to describe its geometrical texture patterns. The authors then fed these features to an ensemble classifier to generate an optimal mean sensitivity and specificity of 89.24% and 87.62% respectively.
In Mittra and Parekh (2011), normalised symmetrical Grey Level Co-occurrence Matrices (GLCM) were used to automate the detection of skin diseases using texture features. GLCM defines the probability of a particular grey level occurring in the neighbourhood of another grey level at a specified distance along a particular direction, such as probability of grey level $i$ occurring in the neighbourhood of another grey level $j$ at a distance $d$ in direction $\theta$; $G = \Pr(i, j | d, \theta)$ (Mittra & Parekh, 2011).

This current study reveals that the major concern in feature extraction is that quantification of these features are complicated and often require time-consuming computation due to different values of the varying features used (Blum et al., 2003; Iyatomi et al., 2010). The major rule of thumb adhered to in the literature has been to use a feature selector in determining the best feature candidates that can successfully discriminate between lesion classes, thus further reducing the number of features used. The reduction usually yields a faster classification computation time. Future research would most likely look into improving the mechanism used by current feature selectors (such as Genetic Algorithm, Principal Component Analysis, Plus-I-Take-Away-r, SFFS, SFBS and LOO) towards ensuring more optimal results.

### 2.2.2.4 Image Classification

Image classification involves using selected features of an image to classify pixels in a digital image into one of several classes depending on knowledge domain such as in medical imaging and geographical information systems. It also involves training a model using a data set and then testing the model using a data set, which is disjoint from the training set. Several classification algorithms have been used in the literature, including Support Vector Machine (SVM), Random Forest, Naïve Bayes (NB), Boosting, Multiple-Instance Learning, Fuzzy C-Means (FCM), K-Nearest
Neighbour (KNN), Multilayer Perceptron (MLP), Thresholding, Discriminant Analysis (DmA) and C4.5 Decision Trees.

There are two main classification methods, which are supervised classification and unsupervised classification. Supervised classification involves the identification of samples of available information classes (as it relates to an image for a given knowledge domain), and then applying an image analysis tool to generate a statistical characterisation (such as mean and covariance) of the reflectance for each information class (Bhatnagar & Singh, 2012). Upon completing the characterisation, each image can then be classified by examining the reflectance for each pixel and deciding on the best matching signatures. For cases of overlapping signatures, a decision criterion such as maximum likelihood classification or parallelepiped classification can be used to assign pixels to the highest probable class. Unsupervised classification examines a large number of unknown pixels and divides them into a number of classes based on natural groupings present in the image values using techniques such as clustering (Bhatnagar & Singh, 2012). The standard employed here is that values within a given class should be close together in measurement space (such as exhibiting similar grey levels); however, data in different classes should be comparatively separated (Lillesand, Keifer & Chipman, 2004).

In image classification, ground truth (actual condition) of the image and diagnostic accuracy assessment are very important in ensuring a good classification result. In this current study, most classification methods used in the literature for automating skin diagnosis were seen to be supervised training.
In the domain of machine learning, depending on the nature of the problem, a linear or non-linear classification technique might be used. Image problems having spherical, connected or regular shapes are commonly solved using linear classifiers, unlike the non-linear classifiers.

In medical imaging, the literature has recorded usage of both linear and non-linear classifiers in discriminating between varying lesions or image class, such as distinguishing between varying melanocytic lesions. The researcher discovered from his study (see Table 2-4) that most classifications were achieved using several supervised machine learning algorithms given their capability to learn from existing patterns within a set of lesion image data.

Skin infections classification was achieved in Tushabe et al. (2011) using a combination of expert systems of Naïve Bayes (NB), two-layer Multilayer Perceptron (MLP) neural network, a 2-norm Support Vector Machine (SVM) and K-Nearest Neighbour classifier (KNN). In the same study, KNN was reported to have an accuracy result of 100%. Studies in (Mittra & Parekh, 2011; Tomatis et al., 2005; Zagrouba & Barhoumi, 2005) used MLP to distinguish between varying skin infections, with accuracy ranging from 77.7% to 96.67%. The researcher’s study indicates that Mixture of Expert (MOE) gating network classifier consisting of a set of function approximators is gaining much traction. A well-implemented gating network such as the ones used in (Kreutz et al., 2001; Rahman et al., 2008) has been seen to have produced a promising result compared to just using a single classifier.
<table>
<thead>
<tr>
<th>Methods</th>
<th>Classifier</th>
<th>References</th>
<th>$S_n$</th>
<th>$S_p$</th>
<th>DA</th>
<th>*LR+</th>
<th>*LR-</th>
</tr>
</thead>
<tbody>
<tr>
<td>Artificial Neural Network (ANN)</td>
<td>Back Propagation Network (BPN)</td>
<td>(Chiem et al., 2007; Dalal et al., 2011; Iyatomi et al., 2008a; Jaleel et al., 2013; Lau &amp; Al-Jumaily, 2009; Taouil &amp; Romdhane, 2006; Zagrouba &amp; Barhoumi, 2005)</td>
<td>75%–100%</td>
<td>86.0%–100%</td>
<td>88.0%–100%</td>
<td>12.5</td>
<td>0.13</td>
</tr>
<tr>
<td>Auto Associative Network (AAN)</td>
<td></td>
<td>(Lau &amp; Al-Jumaily, 2009)</td>
<td>×</td>
<td>×</td>
<td>×</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Feed Forward Network (FFN)</td>
<td></td>
<td>(Maglogiannis, Pavlopoulos &amp; Koutsouris, 2005)</td>
<td>79%–100%</td>
<td>90%–100%</td>
<td>×</td>
<td>17.9</td>
<td>0.11</td>
</tr>
<tr>
<td>Multilayer Perceptron (MLP)</td>
<td></td>
<td>(Barhoumi et al., 2007; Mittra &amp; Parekh, 2011; Sheha et al., 2012; Tomatis et al., 2005; Zagrouba &amp; Barhoumi, 2004, 2005)</td>
<td>70.5%–100%</td>
<td>75.6%–100%</td>
<td>76%–100%</td>
<td>6.99</td>
<td>0.17</td>
</tr>
<tr>
<td>Single Layer Perceptron (SLP)</td>
<td></td>
<td>(Rubegni et al., 2002)</td>
<td>94.3%–99%</td>
<td>72.5%–93.8%</td>
<td>94%</td>
<td>5.74</td>
<td>0.04</td>
</tr>
<tr>
<td>Classifier</td>
<td>Method</td>
<td>Authors</td>
<td>Accuracy Range</td>
<td>Execution Time</td>
<td>Standard Deviation</td>
<td></td>
<td></td>
</tr>
<tr>
<td>--------------------------------</td>
<td>-------------------------------</td>
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<td>----------------</td>
<td>----------------</td>
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<td></td>
<td></td>
</tr>
<tr>
<td><strong>Bayesian Classifier</strong></td>
<td>Naive Bayes</td>
<td>(Parolin et al., 2010; Tushabe et al., 2011)</td>
<td>72.2% - 82.55%</td>
<td>×</td>
<td>×</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Hidden Naive Bayes (HNB)</strong></td>
<td></td>
<td>(Garnavi, Aldeen &amp; Bailey, 2010, 2012)</td>
<td>81.37% - 86.27%</td>
<td>×</td>
<td>×</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Statistical</strong></td>
<td>Discriminant Analysis (DmA)</td>
<td>(Maglogiannis et al., 2005; Zhou et al., 2011)</td>
<td>86%-93% - 90%-100%</td>
<td>×</td>
<td>×</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>K-Nearest Neighbour (KNN)</strong></td>
<td>K-Nearest Neighbour (KNN)</td>
<td>(Barata et al., 2013; Ganster et al., 2001; Nie, 2011; Rahman et al., 2008; Ramlakhan &amp; Shang, 2011; Tushabe et al., 2011)</td>
<td>60.7%-100% - 44%-92% - 75%-100%</td>
<td>2.51</td>
<td>0.29</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Hierarchical KNN</strong></td>
<td></td>
<td>(Ballerini et al., 2012)</td>
<td>74.3%</td>
<td>×</td>
<td>×</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Decision Trees (DT)</strong></td>
<td>C4.5 DT</td>
<td>(Capdehourat et al., 2011)</td>
<td></td>
<td>×</td>
<td>×</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Logistic Model Tree (LMT)</strong></td>
<td></td>
<td>(Garnavi et al., 2010, 2012)</td>
<td>80.39%-86.27%</td>
<td>×</td>
<td>×</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Random Forest (RF)</strong></td>
<td></td>
<td>(Garnavi et al., 2010, 2012)</td>
<td>80.39%-93.21%</td>
<td>17.89</td>
<td>0.06</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Adaptive Boosting</strong></td>
<td></td>
<td>(Capdehourat et al., 2011)</td>
<td></td>
<td>×</td>
<td>×</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Method</td>
<td>Model Description</td>
<td>Accuracy (%)</td>
<td>Precision (%)</td>
<td>F1-Score (%)</td>
<td>AUC</td>
<td></td>
<td></td>
</tr>
<tr>
<td>------------------------</td>
<td>--------------------------------------------------------</td>
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<td></td>
<td></td>
</tr>
<tr>
<td><strong>Regression Analysis</strong></td>
<td>Logistic Regression (LoR)</td>
<td>80%-92.6%</td>
<td>76%-87.2%</td>
<td>82.3%-87.2%</td>
<td>4.69</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Linear Regression (LiR)</td>
<td>81.1%-100%</td>
<td>83.9%-95.9%</td>
<td>×</td>
<td>8.97</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Lacunarity</strong></td>
<td>Lacunarity Analysis (LA)</td>
<td>91%-92%</td>
<td>61%-81%</td>
<td>×</td>
<td>3.16</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Support Vector</strong></td>
<td>Support Vector Machine (SVM)</td>
<td>77.12%-82.50%</td>
<td>92.5%-91.7%</td>
<td>×</td>
<td>10.64</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Machine (SVM)</strong></td>
<td></td>
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<tr>
<td><strong>Markov Random</strong></td>
<td>Gaussian Maximum Likelihood (GML)</td>
<td>×</td>
<td>×</td>
<td>×</td>
<td>5.47</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Field (MRF)</strong></td>
<td></td>
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<td></td>
</tr>
<tr>
<td><strong>Mixture of Expert</strong></td>
<td>Combination of varying Machine Learning Algorithms such as C4.5 DT, GML and AdaBoost</td>
<td>71.3%-90%</td>
<td>77%-93.5%</td>
<td>83.75%-90%</td>
<td>5.47</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Systems</strong></td>
<td></td>
<td></td>
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<td></td>
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</tbody>
</table>
In attempting to screen for malignant skin tumour, the study in Iyatomi et al. (2008a) used an Artificial Neural Network (ANN) consisting of several training algorithms based on simple back-propagation algorithm, back-propagation with Variable Learning Rate (VLR), Resilient BackPropagation (RES BP), Scaled Conjugate Gradient (SCG) and Levenberg-Marquardt (LM). In their study, Iyatomi et al. (2008a) judged the input tumour as malignant if the output of the ANN exceeded a set diagnostic threshold, and their results reported 85.9% sensitivity and 86.0% specificity.

A shift from machine learning were seen in (Cudek et al., 2010; Madhankumar & Kumar, 2012) towards classification of skin lesion by using the ABCD rule to compute a Total Dermatoscopy Score (TDS) = 1.3 * Asymmetry + 0.1 * Border + 0.5 * Colour + 0.5 * Diameter of Structure. The study claimed a reduction in diagnostic error rate compared to other approaches in the literature. TDS that is greater or equals to 4.76 is considered as a malignant tumour. TDS between 4.76 and 5.45 is considered suspicious, while TDS less than 4.76 is screened as benign.

While notable results might have been recorded in the literature by various classification methods and structures, there still exists some level of difficulties in lesion classifications, such
as great unbalance between image classes, visual similarities between some classes, multiplicities of some classes, difficulty in defining discriminating visual features and need for retraining classification model (Gilmore et al., 2009; Qiu, Xu & Tian, 2006). It is also important to state here that with the exception of rule-based classification, discrimination results largely depend on the volume of images used for training a classifier, numbers of training image set present in the testing image set, and the set of features selected for discriminating melanocytic lesions. There is therefore a need for the research community to have more image libraries easily accessible by researchers in order to provide for better comparable and reproducible results.

2.3 Summary

The CAD-based medical image technique has largely contributed towards making diagnosis of pigmented skin lesion easier. Most of the literature was found to have preferred HSV colour space over RGB primarily because of its inherent ability to separate luma (image intensity) from chroma (colour information) and conveniences in converting between RGB and HSV.

From the literature, the HSV and CIE L*a*b* colour space recorded higher diagnostic results compared to RGB. While good results have been documented, more efforts should, however, be undertaken towards standardising test images being used in order to provide reproducibility of research works. In addition, given that most results recorded in the literature were highly dependent on numbers of images used, efforts need to be made to have a large image library of varying skin lesion, with categories based on lesion types. Such a library should be made accessible to researchers for use to ensure proper benchmarking of research results such as the current efforts by Image Retrieval in Medical Applications (IRMA) as reported in Ali and Deserno (2012).
Traction gained in the usage of machine learning to make reproducibility of diagnosis possible is on the increase as illustrated in this chapter. It should however be noted that the choice of a particular technique over another comes with both its merits and pitfalls. So far, the results from literature suggest that efforts should be made to have systems that can help researchers detect the best method to be used considering the characteristics or perhaps the class of a given image data set. This would promote better reproducibility of research results and equally offer improved performance. Automated diagnosis systems bring a win-win situation to the field of medical imaging for medical practitioners as well as patients. Expert personnel can easily use such a system to have an objective second diagnosis opinion. In addition, the automated diagnostic system can be very helpful for underserved areas where availability of medical practitioners is low or non-existent.
CHAPTER THREE: LESION IMAGE RESTORATION

3.1 Background

In the course of examining skin-related medical images, the presence of artefacts such as hair shaft, thin blood vessel, ruler marking and air bubbles make diagnosis very difficult (Abbas et al., 2010; Mittra & Parekh, 2011; Zhou et al., 2008a). Image acquisition conditions and variations in Pigmented Skin Lesion (PSL) has also made the process of diagnostic image processing a daunting task.

It is very important to mitigate these challenges while still ensuring that quality and a time-effective diagnosis can be achieved at a reasonable speed. The literature has recorded a number of approaches to solve the above challenge. A popular approach is DullRazor hair removal (Lee et al., 1997), which uses a Top-Hat greyscale morphological closing operation to smoothen out low intensity data of thick dark hairs. One major challenge, though, in this approach is the inability to effectively detect fine and thick dark hairs in the shade (Fiorese et al., 2011; Huang et al., 2013). In reference to (Lee et al., 1997; Sultana et al., 2012), the study in Fiorese et al. (2011) also implored the usage of Top-Hat operator but then applied Partial Differential Equation (PDE)-based inpainting to replace detected dark hairs with estimated underlying occluded skin. The study in Abbas et al. (2013) detected and segmented rough hairs using Matched Filtering with First Derivative Order of Gaussian (MF-DOG) and morphological edge-based threshold technique respectively before repairing the artefacts with fast marching methods. Curvilinear Structure analysis and exemplar-based inpainting were used in Zhou et al. (2008a) to detect artefact and repair artefacts respectively. The challenge in most of the current effort is the limitation in detecting and repairing thin hair structures while preserving the morphological feature of the
image data. In addition, high computational resources required by most of these techniques are also a challenge.

This chapter discusses an approach using a bilateral filter and a two-stage artefact detection via Canny (Canny, 1986) and Line Segment Detection (LSD) (Gioi et al., 2012) operation with fast marching inpainting technique. This is to autotomise hair-occluded artefacts from a dermoscopic image in an unsupervised environment while ensuring morphological features of the lesion areas of the image data are preserved. The rest of the chapter is organised as follows: Section 3.2 illustrates the methods vis-à-vis data source, algorithms and techniques used in achieving the objectives. Section 3.3 describes notable results achieved and analyses the performance of the approach used based on sensitivity, specificity and a measure of accuracy of the results obtained as it compares with the approaches proposed in the literature. This chapter is drawn to conclusion in section 3.4.

3.2 Materials and Methods

3.2.1 Data Sets

Dermoscopic images of PSL were selected from a database of known diagnostic results provided by the Dermatology Society of South Africa (DSSA). Permission was also granted by corresponding authors of (Zhou et al., 2008a) to use their images for evaluation of results of the technique used in this study.

All images are originally in Red-Green-Blue (RGB) colour space. The data sets consist of a total of 299 images that are classified in Table 3-1. The size of each image as obtained from the DSSA ranges from 43 kilobytes to 309 kilobytes, all of which have a dimension of 640 × 480 pixels; horizontal resolution of 20 dpi (dots per inch); vertical resolution of 15 dpi; and 24-bit depth.
Images obtained from (Zhou et al., 2008a) have a dimension of 399 × 300 pixels; horizontal resolution of 96 dpi; vertical resolution of 96 dpi; and 24-bit depth.

3.2.2 Algorithm

**Table 3-1 Image Data Set**

<table>
<thead>
<tr>
<th>Lesion Type</th>
<th>No of Images</th>
</tr>
</thead>
<tbody>
<tr>
<td>Superficial Spreading Melanoma</td>
<td>104</td>
</tr>
<tr>
<td>Spitzoid Naevi</td>
<td>15</td>
</tr>
<tr>
<td>Junctional Naevi</td>
<td>15</td>
</tr>
<tr>
<td>Dermal Naevi</td>
<td>18</td>
</tr>
<tr>
<td>Congenital Naevi</td>
<td>20</td>
</tr>
<tr>
<td>Compound Naevi</td>
<td>27</td>
</tr>
<tr>
<td>Blue Naevi</td>
<td>29</td>
</tr>
<tr>
<td>Atypical Naevi</td>
<td>65</td>
</tr>
<tr>
<td>Acral Lentiginous Melanoma</td>
<td>1</td>
</tr>
<tr>
<td>Others</td>
<td>5</td>
</tr>
</tbody>
</table>

**Step 1**: Input dermoscopic image in RGB colour space

**Step 2**: Bilateral filtering of image in CIE*Lab space (Tomasi & Manduchi, 1998)

**Step 3**: First-level hair shaft and ruler marking detection using Canny operator (Canny, 1986) with Gaussian filtering and Progressive Probabilistic Hough Transform (Matas, Galambos & Kittler, 2000) on result of step 2
**Step 4:** Apply Fast Marching inpainting Method (FMM) (Talea, 2004) on resulting image in **step 3**

**Step 5:** Dilate result of **step 3** with kernel $k_{2x2}$ in CIE*Lab to remove noise

**Step 6:** Perform second-level hair shaft and ruler marking using a Line segmentation operator

**Step 7:** Reapplied fast marching inpainting

**Step 8:** Dilate again with kernel $k_{2x2}$ in CIE*Lab to remove noise

### 3.2.3 Image Standardisation

In order to avoid device dependency requirement of RGB colour space, all images were converted to a much suitable Commission Internationale de l'Eclairage (CIE) L*a*b colour space for each morphological operation. In agreement with the study in Kaur and Kranthi (2012), the researcher discovered that the CIE L*a*b colour space produced a better result compared to its counterparts (CIE L*u*v and CIE X*Y*Z) and the popular YCbCr colour space. After each morphological operation, the resultant image was then converted back to RGB for human visualisation.

### 3.2.4 Filtering Techniques

Because of variation in adjacent pixels of a typical image, images by default are not smooth upon capture and often contain undesired pixels for a given computer vision objective. In dermoscopic images, hair shaft, air bubbles and thin blood vessels are considered as potential artefacts. To be able to effectively identify these artefacts without overlaps into actual lesion areas or surrounding healthy skin, the lesion image data is required to go through some sort of smoothening in order to make adjacent pixels look similar. Common filters (blurring techniques) typically used for smoothening includes Bayesian filter, Gaussian blur, Median filter, Wavelets,
Diffusion and Bilateral Filter. In this chapter, Gaussian and Bilateral filters were used as a form of pre-processing for edge and artefacts recognition respectively.

3.2.4.1 Gaussian Filter

Gaussian filter has been used to compute a weighted mean of pixels while being independent of image resolution and spatial location.

\[
Gaussian \ Function \ G(x, y) = \frac{1}{2\pi\sigma_x\sigma_y} e^{-\left[\frac{(x-\mu_x)^2}{2\sigma_x^2} + \frac{(y-\mu_y)^2}{2\sigma_y^2}\right]} \quad Eq \ 3-1
\]

\[x \in (-\infty, \infty)\]
\[y \in (-\infty, \infty)\]

\(\mu_x\) is the mean value about \(x\)

\(\mu_y\) is the mean value about \(y\)

\(\sigma_x\) is the standard deviation about \(x\)

\(\sigma_y\) is the standard deviation about \(y\)

Assuming a bivariate normal distribution with equal standard deviation, \(\sigma = \sigma_x = \sigma_y\)

\[
Gaussian \ Function \ G(x, y) = \frac{1}{2\pi\sigma^2} e^{-\frac{(x-\mu_x)^2+(y-\mu_y)^2}{2\sigma^2}} \quad Eq \ 3-2
\]

the filter can then be computed as:

\[
Gaussian \ Filter \ G(\delta)_i = \sum_{j \in S} G_\sigma(||i-j||)\delta_j \quad Eq \ 3-3
\]

\(||i-j||\) is the intensity differences

\(\delta_i = \text{pixel value of image } \delta \text{ at } i_{x,y}\)

\(\delta_j = \text{pixel value of image } \delta \text{ at } j_{x,y}\)
One major challenge that was noticed with the use of Gaussian blur is that edge preservation, which is required in the detection of hair shaft, was an issue (see Figures 3-1, 3-3 and 3-4). It was observed in the study that after smoothening an image, both Median filter and Gaussian filter did little to preserve artefacts edges for recognition purposes.

![Figure 3-1 Original](image1) ![Figure 3-2 Bilateral](image2) ![Figure 3-3 Gaussian](image3) ![Figure 3-4 Median](image4)

The problem above is due to averaging of edges caused by the filters. Anisotropic Diffusion (Sapiro & Ringach, 1996) and Bilateral Filter (Tomasi & Manduchi, 1998) have been proposed in the literature to address the edge blurring challenge while ensuring averaging within smooth region. In this study, Bilateral filtering was applied due to its non-iterative nature and to ensure smoothening does not stop at thin lines, unlike Diffusion.

### 3.2.4.2 Bilateral Filter

Bilateral filter combines greyscales or colours, based on geometric closeness and photometric similarities while favouring near values to distant values in both domain and range space. Bilateral filtering is particularly different from traditional filtering because computations performed by other filters in the domain space are performed in the range space of the bilateral filter. Traditional low-pass filters perform domain filtering and enforce closeness (neighbourhood in the domain) by weighting pixel values with coefficients that fall off with distance (Tomasi &
Manduchi, 1998). In contrast, a bilateral filter computes range filtering in addition to domain filtering. Range filtering average image pixel values with weights that dwindle with dissimilarity (far away in the range). When smoothening an image, preservation of edges can be achieved by combining range filtering with domain filtering (see Figures 3-1 and 3-2).

The implementation of domain filtering used by the researcher is according to Gaussian (see Eq 3-3).

\[
\text{Gray Images: } B(\delta)_{ig} = \beta^{-1} \sum_{j \in S} G_{\sigma_r}(||i_g - j_g||) G_{\sigma_s}(||i_g - j_g||) \delta_{ij} \\
\text{Colored Images: } B(\delta)_{ic} = \beta^{-1} \sum_{j \in S} G_{\sigma_r}(||i_c - j_c||) G_{\sigma_s}(||i_c - j_c||) \delta_{ij} \\
\]

\[\beta^{-1} \text{ is the normalization factor} \]
\[||i_g - j_g|| \text{ is the intensity changes} \]
\[||i_c - j_c|| \text{ is the color difference in either RGB or CIE*Lab} \]
\[\delta_{ij} \text{ and } \delta_{ic} \text{ represents scalar and 3D vector quantity respectively} \]

\[\sum_{j \in S} \text{ is the sum over all pixels } j_g \]
\[\sum_{j \in S} \text{ is the sum over all pixels } j_c \]
\[\sigma_s \text{ is the window size} \]

### 3.2.5 Artefacts Recognition

Among several approaches proposed in the literature towards effective detection of artefacts, the edge detection has proven to be a good technique (Abbas et al., 2013; Fiorese et al., 2011; Lee et al., 1997). Edge detection is simply a mathematical method that aids the identification of pixel areas in a given digital image where image intensity discontinuity occurs. In the quest to
achieve the objective for effective detection of pixels categorised as noise, the researcher utilised two different operators: Canny (Canny, 1986) and Line Segment Detection (LSD) (Gioi et al., 2012).

A Canny operator was used to ensure no response is given to non-edge and a single response given to a detected edge. Section 3.2.5.1 detailed the algorithm of a Canny operator used for the implementation.

### 3.2.5.1 Canny Algorithm Implementation

**Step 1:** Gaussian noise filtering of image (as discussed in Eq 3 – 3) with kernel $k_{3x3}$

**Step 2:** Apply convolution mask in 2-D

$$M_x = \begin{bmatrix} -1 & 0 & +1 \\ -2 & 0 & +2 \\ -1 & 0 & +2 \end{bmatrix}$$ representing convolution in x-direction \hspace{1cm} \text{Eq 3-6}

$$M_y = \begin{bmatrix} +1 & +2 & +1 \\ 0 & 0 & 0 \\ -1 & -2 & -1 \end{bmatrix}$$ representing convolution in y-direction \hspace{1cm} \text{Eq 3-7}

**Step 3:** Compute gradient vector and edge direction

weight $M_w = |M_x| + |M_y|$ \hspace{1cm} \text{Eq 3-8}

edge direction $\varphi = \tan^{-1}\left(\frac{|M_x|}{|M_y|}\right)$ \hspace{1cm} \text{Eq 3-9}

- $if\ (0^\circ \leq \varphi \leq 22.5^\circ) \ || \ (157.5^\circ \leq \varphi \leq 180^\circ)$ then $\varphi = 0^\circ$
- $else\ if\ (22.5^\circ < \varphi \leq 67.5^\circ)$ then $\varphi = 45^\circ$
- $else\ if\ (67.5^\circ \leq \varphi \leq 112.5^\circ)$ then $\varphi = 90^\circ$
- $else\ if\ (112.5^\circ \leq \varphi \leq 157.5^\circ)$ then $\varphi = 135^\circ$

**Step 4:** Estimate edge using non-maximum suppression to produce valid edges while suppressing pixels judged not to be edges by reinitialising their values to zero. Non-maximum suppression aid edge tracing in a given direction, leading to creation of thin line in resulting image to
represent suspected edges.

**Step 5:** Use hysteresis threshold to eliminate edge contour breaks resulting from pixel data that fluctuates below and above set threshold

\[
\text{let } D \text{ represent edges} \\
P \text{ represent any valid pixel} \\
P_G \text{ represent pixel gradient been considered} \\
L_1 \text{ represent lower threshold} \\
L_2 \text{ represent upper threshold}
\]

such that

\[
\text{if } (P_G > L_2) \text{ then } P_G \in D \\
\text{else if } (P_G < L_1) \text{ then } P_G \in D \\
\text{else if } (L_1 < P_G < L_2) \text{ && } P_G \rightarrow (P > L_2) \text{ then } P_G \in D
\]

### 3.2.5.2 Progressive Probabilistic Hough Transform

Progressive Probabilistic Hough Transform (PPHT) has been applied in this study to estimate hair shafts and ruler marking based on the result of canny edge (see Figures 3-5, 3-6, 3-7, 3-8 and 3-9). PPHT performs line segmentation by using the difference in the fraction of votes needed to effectively detect lines with different numbers of supporting points resulting from operators such as Sobel and Canny (Canny, 1986).

One particular advantage of PPHT is that the fraction of voting need not be indicated using presumptive knowledge.
3.2.5.3 Fast Marching Inpainting

Inpainting involves using textures and colours identical to a defined boundary of an identified gap to fill different regions in the identified gap demarcated by contour lines. An optimised version of Fast Marching Methods (FMM) proposed in Talea (2004) was applied as highlighted in the following illustration and pseudo code:

Let $\delta$ represent an image having gradient $\mathbf{g}$,

such that

$\delta_i = \text{pixel value of image } \delta \text{ at } i_{xy}$

$\delta_j = \text{pixel value of image } \delta \text{ at } j_{xy}$

$\mathbf{g}_i = \text{gradient resultant from } \delta_i$

$\mathbf{g}_j = \text{gradient resultant from } \delta_j$
if \( D \) represent First Order Derivative Approximation (FDA),

such that

\[
D_i = FDA \ of \ \delta_i \\
D_j = FDA \ of \ \delta_j
\]

then, it follows that

\[
D_i = \delta_j + g_j(i - j)
\]

Eq 3-10

let \( N_{\epsilon_i} \) = neighborhood pixel of size \( z \) of the known image around \( i \)

if \( R \) represent region to be inpainted

\[ B \] represent boundary of the region

\( R_i \) represent initial position in the region

\( \xi_i \) represent inpaint point \( i \)

\( \beta_{i,j} \) = weighted function to propagate sharp image details into inpainted arena

\[
\xi_i = \frac{\sum_{j \in N_{\epsilon_i}} \beta_{i,j} D_i}{\sum_{j \in N_{\epsilon_i}} \beta_{i,j}}
\]

Eq 3-11

While (\( B \) still contains valid points)

\[ \rightarrow \quad i = \text{pixel } \not\in \text{ nearest to } R_i \]

\[ \rightarrow \quad \text{perform interpolation on } i \text{ using Eq 3-8} \]

\[ \rightarrow \quad \text{advance } B \text{ into } R \]

Applying the implementation of FMM on Figure 3-5 using Figure 3-8 resulted in Figure 3-10 (without the arrows). While the combination of bilateral filtering, canny operation, and PPHT
using well-defined hysteresis threshold achieved a level of success, a thorough detection of the noise was however not performed (see sample arrows drawn in Figure 3-10). This challenge was addressed by performing a second-level artefact recognition using a Line segmentation operator.

3.2.5.4 Line Segment Detector

The Line Segment Detection (LSD) has gained traction in computing vision applications such as in robot navigation (Kahn, Kitchen & Rieseman, 1990) and crack detection (Mahadevan & Cassasent, 2001). Efforts have been made in the literature towards effective recognition of well-localised line segments while reducing false positives (Akinlar & Topal, 2011; Beveridge, Graves & Lesher, 1996; Burns, Hanson & Rieseman, 1986; Desolneux, Moisan & Morel, 2000; Etemadi, 1992). Contours on images are basically regions in a given image where grey level discontinuity occurs such as from light to dark or vice versa. In this dissertation, the researcher followed the recommendations from Gioi et al. (2012), considering the objectives of the study. The approach proposed in Gioi et al. (2012) is based on (Beveridge et al., 1996; Burns et al., 1986) and Desolneux’s line validation method (Desolneux et al., 2000) using Helmholtz principle (Desolneux, Moisan & Morel, 2008).
The LSD technique was applied on results produced by FMM (see Figure 3-10) and generated edge points for remaining hair shafts as highlighted in Figure 3-11.

Figure 3-12 is a mask of Figure 3-11, and this is later used by FMM to perform a second-level inpainting which resulted in Figure 3-13.

While the result of Figure 3-13 looks promising in the repair of detected noise artefacts from Figure 3-5, some artefacts as pointed out by the arrows were still noticeable. Morphological dilation was performed on Figure 3-13 to remove salient salty noise, and this resulted in the output in Figure 3-14.

### 3.2.6 Morphology Dilation Operation

In relation to mathematical morphology, dilation provides a maximising operation technique for causing bright regions within an image to grow, thus leading to the removal of salient noise. It works by convolving an image $\delta$ with a structuring element (kernel) $\kappa$ of any shape or size.

$$\delta \oplus \kappa = \bigcup (\kappa + \iota; \iota \in \delta)$$

*Eq 3-12*
3.3 Results and Discussions

The method used by the researcher has been applied on a total of 299 images as described in Table 3-1 of section 3.2.1. A total of 294 of the images are melanocytic lesion bound, and five are non-melanocytic. Out of the 294 melanocytic images, 105 images were histopathologically certified as melanoma, and the remaining 189 images as being benign nevus.

Implementation of each step in the highlighted algorithm of section 3.2.2 was computed on a virtual machine running Ubuntu 12.0.4.3 LTS, with a base memory of 3096MB and two processors. The machine has VT-X/AMD-V hardware virtualisation capability with nested paging. The average speed of execution of the complete algorithm is 380ms.

In order to ensure that hair shaft, including fine hairs and other related artefacts are well recognised, the first part of the approach is centred on smoothening each image while retaining the edges of artefacts to be repaired. The study indicates that the best filtering technique for the objective in this study is bilateral filter (see Figures 3-1, 3-2, 3-3, and 3-4). The second part of the researcher’s approach is focused on the identification of artefacts in a given lesion using a two-stage detection process of a Canny operator with PPHT and Line Segment Detector in that order. Remarkable results were achieved in this study due to the usage of both Canny and LSD, rather than using either of them in isolation. It is also important to state that applying a Canny operator with PPHT before LSD produced a better result than the reverse. For each of the two-stage process of artefact detection, FMM is applied to repair the recognised artefacts with average region neighbourhood pixels as highlighted in section 3.2.5.3.
Statistical Analysis method as given below was used to determine the accuracy of artefact recognition and repair validation of the researcher’s method in terms of Sensitivity \((S_n)\), Specificity \((S_p)\), and Diagnostic Accuracy \((DA)\).

\[
S_n = \frac{\mu_{TP}}{\mu_{TP} + \mu_{FN}} \quad \text{Eq 3-13}
\]

\[
S_p = \frac{\mu_{TN}}{\mu_{TN} + \mu_{FP}} \quad \text{Eq 3-14}
\]

\[
DA = \frac{\mu_{TP} + \mu_{TN}}{\mu_{TP} + \mu_{TN} + \mu_{FP} + \mu_{FN}} \quad \text{Eq 3-15}
\]

\(\mu_{TP}\) represents mean value of true positives (correctly detected)

\(\mu_{FP}\) represents mean value of false positives (incorrectly detected)

\(\mu_{TN}\) represents mean value of true negatives (correctly rejected)

\(\mu_{FN}\) represents mean value of false negatives (incorrectly rejected)

The proposed approach reports a true positive rate (Sensitivity) of 98.27% and a true negative rate (Specificity) of 93.75%. Diagnostic Accuracy achieved is recorded at a high level of 96.10%. Figures 3-15, 3-16, 3-17 and 3-18, as well as Figures 3-19, 3-20, 3-21 and 3-22 highlight a comparable output of the researcher’s approach with that of DullRazor (Lee et al., 1997) and Zhou et al. (Zhou et al., 2008a). This would invariably assist dermatologists and medical practitioners alike to discriminate between melanocytic lesions. Over and above that, localisation of lesion areas from surrounding healthy skin can easily be achieved for effective classification of lesions by automated diagnosis systems. Figures ranging from 3-23 to 3-58 highlight the chapter’s results.
3.4 Summary

In this chapter, a fast and effective approach towards repairing hair-occluded and other artefacts in dermoscopic images was proposed. The artefacts recognition involves a two-stage process of using a Canny and LSD operator. Experimental results indicate that the proposed approach is dependable, robust and can effectively repair lesions occluded with hair shafts and air bubbles. Dermatologists can easily use this approach as a form of pre-processing of dermoscopic images before lesion segmentation and classification. The main output of this chapter is in proceedings of MIUA 2014 (Okuboyejo, Olugbara & Odunaike, 2014).
Figure 3-23 Original Image

Figure 3-24 Result of FMM after applying Canny and PPHT

Figure 3-25 Result of FMM after applying LSD

Figure 3-26 Original Image

Figure 3-27 Result of FMM after applying Canny and PPHT

Figure 3-28 Result of FMM after applying LSD

Figure 3-29 Original Image

Figure 3-30 Result of FMM after applying Canny and PPHT

Figure 3-31 Result of FMM after applying LSD
Figure 3-32 Original Image
Figure 3-33 Result of FMM after applying Canny and PPHT
Figure 3-34 Result of FMM after applying LSD

Figure 3-35 Original Image
Figure 3-36 Result of FMM after applying Canny and PPHT
Figure 3-37 Result of FMM after applying LSD

Figure 3-38 Original Image
Figure 3-39 Result of FMM after applying Canny and PPHT
Figure 3-40 Result of FMM after applying LSD
Figure 3-50 Original Image  
Figure 3-51 Result of FMM after applying Canny and PPHT  
Figure 3-52 Result of FMM after applying LSD

Figure 3-53 Original Image  
Figure 3-54 Result of FMM after applying Canny and PPHT  
Figure 3-55 Result of FMM after applying LSD

Figure 3-56 Original Image  
Figure 3-57 Result of FMM after applying Canny and PPHT  
Figure 3-58 Result of FMM after applying LSD
CHAPTER FOUR: SEGMENTATION OF LESION IMAGE

4.1 Background

Since 1663 when the first observation of vessels in respect to nail matrix was examined with a microscope by Kohlhaus (Gereli, 2006), the field of dermatology has since advanced through the advent of first Binocular Dermatoscope in 1916 by Zeiss (Gereli, 2006). The introduction of pattern analysis by Pehamberger et al. (1987) has inspired the acclaimed ABCD rule: Asymmetry, Border, Colour, Diameter, which was proposed by Stolz et al. (1994). The ABCD rule has now become the standard that is widely used by most dermatologists for screening malignancy of melanocytic lesions.

The use of a dermoscope, which is sometimes called a dermatoscope by dermatologists, has recorded great success (Kittler, 2004). The heavy dependencies on medical practitioners such as dermatologists for diagnosing medical images is however a major concern for underserved areas where such experts might not be readily available or non-responsive for urgent medical needs (Okuboyejo, Olugbara & Odunaike, 2013a). Even for areas where dermatologists are available, their diagnosis interpretation of results obtained from image acquisition devices such as a dermoscope has been characterised with subjectivity and sometimes poor reproducibility (Rosendahl et al., 2011; Rubegni et al., 2002). For the past two decades, medical image analysis has seen the application of image processing techniques for providing machine interpretation of medical images for fostering a better objective decision.

Computer-Aided Diagnostic (CAD) systems have greatly contributed positively at each stage of medical image analysis to ensure faster and reproducible diagnosis (Mitra & Parekh, 2011;...
Okuboyejo et al., 2013a; Stanganelli et al., 2005). In relation to skin disease diagnosis, the automated ordered steps involved typically include:

- Image formation and pre-processing
- Segmentation of lesion area
- Extraction and selection of discriminating features
- Classification of the lesion based on selected morphological features

In this chapter, a Fast Image Segmentation (FIS) method based on Contrast-Limited Adaptive Histogram Equalisation (CLAHE) (Zuiderveld, 1994) and Thresholding capable of segmenting a lesion area from surrounding healthy skin is proposed. The rest of the chapter is tersely structured as follows: Section 4.2 discusses relevant works and the importance of the study. Section 4.3 highlights the techniques used in this study, and the chapter is concluded in section 4.4. The work reported in this chapter has been published by Springer in a book chapter (Okuboyejo, Olugbara & Odunaike, 2013b).

4.2 Relevant works

The recognition of lesion areas within a dermoscopic image data has been characterised with several difficulties, mainly because of the lopsided structure that is exhibited by many of the available medical images (Abbas et al., 2012; Dobrescu et al., 2010). In addition, the smooth transition between the lesion areas and surrounding healthy skin makes it hard to effectively segment a lesion area from surrounding skin (Abbas et al., 2012; Ganster et al., 2001). Thresholding is one of the major techniques that are widely used for segmenting a lesion image based on colour differences between the lesion area and surrounding skin. A particular threshold value is selected based on histogram data of a medical image. This threshold value can then be
used to express the greyscale lesion image in a two homogenous mode (black and white). The white pixels of the binary image provide the necessary information for performing the segmentation task. One great merit of thresholding is that the method is computationally inexpensive and thus requires less computation time compared to other segmentation techniques such as region growing.

A number of thresholding approaches have been proposed in the literature for localising lesion areas. A three-stage segmentation technique including segmentation initialisation, processing and refinement was proposed by (Cavalcanti & Scharcanski, 2013). In the same paper, Otsu’s (Otsu, 1979) intensity thresholding methods were used for the initialisation task for obtaining a preliminary segmentation before later applying colour space projection technique proposed by Tsumura (Tsumura et al., 2003) to maximise the separability of the lesion pixels from the non-lesion counterpart. The skin tumour segmentation using dynamic programming was introduced by Abbas (Abbas et al., 2012) by combining a thresholding method with edge-based dynamic programming in Commission Internationale de l’Eclairage (CIE) L*a*b colour space.

Considering the difficulty in the detection of accurate threshold, Rahman (Rahman et al., 2008) used an iterative threshold clustering to segment lesion image data. A similar iterative technique using an Iterative Self-Organising Data Analysis Technique (ISODATA) algorithm was exemplified by Schaefer et al. (Schaefer et al., 2009a) for determining optimal threshold value that can be used for effective segmentation. Supot (Supot, 2009) used fuzzy c-means clustering to determine an acceptable threshold for lesion segmentation. The type-2 fuzzy-based thresholding was used by Yuksel (Yuksel & Borlu, 2009) to ensure lesion localisation is not affected by the fuzziness that is usually encountered at the border between lesion area and
surrounding skin. In a bid to achieve an optimal segmentation result, Ganster (Ganster et al., 2001) employed both thresholding and 3-D colour clustering. The fusion of thresholding methods using Sarsa reinforcement algorithm assisted the study conducted by Ebrahimi (Ebrahimi & Pourghassem, 2010) to detect the precise threshold value for localising the lesion part of dermoscopic images. A similar fusion technique was used by Celebi (Celebi et al., 2010) where a set of different thresholding algorithms were ensembled. A Tetra level segmentation of different lesions was performed by Humayun et al. (2011) to test the effectiveness of multi-level thresholding.

While considerable good results have been achieved in the literature using various thresholding-based segmentation techniques, the variation in image intensity at hand in lesion images sometimes makes these approaches to produce non-optimal segmentation results. In addition, the outcome of thresholding could be unfavourably affected by the shadow areas within the image data. These shadow areas due to their dark properties might be confused as being part of the lesion data. In this chapter, a Fast Image Segmentation (FIS) procedure using a mixture of methods involving the application of CLAHE, thresholding technique and GrabCut (Rother, Kolmogorov & Blake, 2004) is proposed.

4.3 Materials and methods

4.3.1 Data Set

A selected subset of dermoscopic images from the database provided by the Dermatology Society of South Africa (DSSA) is used. In total, 294 images comprising of 105 melanoma (Superficial Spreading melanoma and Acral Lentiginous melanoma) and 189 benign lesion images
were used in this study. Each image is of dimension 640 × 480 pixels and 24-bit depth. For more information on the data set, see section 3.2.1.

4.3.2 System Design

![System Model](image)

**Figure 4-1** System Model

4.3.3 Initialisation Phase

In the initialisation phase, the RGB colour space input is subjected to some pre-processing (see section 4.3.3.1) to remove unwanted artefacts (see Table 4-1). The system then generates the grey level of the pre-processed image. CLAHE (Zuiderveld, 1994) algorithm is then used to normalise the intensity of the grey image. It is important to state here that pre-processing is particularly important before normalising the intensity of the image histogram to avoid noise being part of the equalised pixels.
4.3.3.1 Pre-processing

The artefacts such as hair shafts and ruler marking make segmentation of a lesion very difficult. These artefacts are generally regarded as noise. In this study, artefacts were removed by first detecting line segments representing hair pixels and ruler markings. The recognised noise is then replaced with the neighbourhood pixels having the closet match to the lesion pixel under consideration (see Table 4-1). The pre-processing technique used is based on the concept discussed in Chapter 3 (see section 3.2.2).

Table 4-1 Image Cleansing

<table>
<thead>
<tr>
<th>Source Image</th>
<th>Image After Pre-processing</th>
</tr>
</thead>
<tbody>
<tr>
<td><img src="image1.png" alt="Image 1" /></td>
<td><img src="image2.png" alt="Image 2" /></td>
</tr>
<tr>
<td><img src="image3.png" alt="Image 3" /></td>
<td><img src="image4.png" alt="Image 4" /></td>
</tr>
</tbody>
</table>

4.3.3.2 Intensity Normalisation

Many lesion images tend to have some pixels that are confined to some specific range of intensity values rather than having pixels from all regions of the image. The Histogram
Equalisation (HE) algorithm could easily be used to improve the contrast of an image by stretching the intensity of the image histogram.

The HE algorithm computes the histogram of a given image and uses the information to transform all pixels of the image. This approach usually performs well if the distribution of the pixel values is identical across the image. However, an unfavourable effect of this approach is that regions within the image that have significant darker or lighter pixels with respect to other pixels within the image would not be satisfactorily enhanced. The Adaptive Histogram Equalisation (AHE) algorithm proposed by Ketcham, Lowe and Weber (1974) addresses this challenge by using a transformation function derived from the neighbourhood pixels to transform each pixel of the image.

A major challenge with the use of traditional AHE is that the method sometimes over-amplifies noise in the region having a relatively small intensity range. This study uses Contrast-Limited Adaptive Histogram Equalisation (CLAHE)(Zuiderveld, 1994) in order to limit the noise amplification. The procedure used by CLAHE algorithm involves partitioning of a given greyscale image into contextual regions and then equalising the histogram of each region. The CLAHE applies a contrast-limiting technique to each neighbourhood grid point within a particular region from which a transformation is derived. Noise amplification is reduced by a clipping image histogram at a predefined value just before computing the Cumulative Distribution Function (CDF) for each grid point.

Let $\delta_i$ represents image to be histogram equalised using CLAHE

$\kappa$ represents total number of image pixels
\( \kappa \) represents the number of occurrences of greyscale level \( \sigma \) within the image

\( \Gamma \) represents total number of greyscale levels within the image (typically 256)

\( P_{\delta_i} \) represents the probability of grey level \( \sigma \) appearing in the image \( \delta_i \)

\[
P_{\delta_i}(\sigma) = \frac{\kappa_\sigma}{\kappa}
\]

Eq 4-1

Let \( CDF_{\delta_i} \) represents the Cumulative Distribution Function of \( \delta_i \)

\[
CDF_{\delta_i}(\sigma) = \int_0^\sigma P_{\delta_i}(\sigma)
\]

Eq 4-2

The Histogram Equalisation (HE) of above \( CDF \) can be computed as:

\[
HE_{CDF} = \sim \left[ \left( \frac{CDF_{\delta_i} - CDF_{min}}{CDF_{max} - CDF_{min}} \right) \times (\Gamma - 1) \right]
\]

Eq 4-3

### 4.3.3.3 CLAHE Algorithm

[i]. Use a window size of eight with a clip-limit of one

[ii]. Define grid points (separated by window size) on the image, beginning from Point (0,0)

[iii]. For each grid point in a given region:

(a) define area = window size

(b) centre area at grid point

(c) compute histogram for region around grid point

(d) clip the histogram above the clip-limit to define a new histogram

(e) define \( CDF \) using new histogram

[iv]. For each pixel:

(a) find the four closest neighbouring grid points surrounding the pixel

(b) use the pixel intensity value to find the mapping of the pixel at the four grid points based on their \( CDF \)

(c) interpolate among the \( CDF \) values to get the intensity mapping at the current pixel location

(d) map the intensity to the intensity range values
(e) insert the intensity in the output image

Table 4-2 compares the effect of equalisation between CLAHE and HE technique to demonstrate the effectiveness of the contrast-limiting technique.

**Table 4-2 Intensity Normalisation**

<table>
<thead>
<tr>
<th>Source Image</th>
<th>Equalisation using HE</th>
<th>Equalisation using CLAHE</th>
</tr>
</thead>
<tbody>
<tr>
<td><img src="image1.png" alt="Image" /></td>
<td><img src="histogram1.png" alt="Histogram" /></td>
<td><img src="histogram2.png" alt="Histogram" /></td>
</tr>
<tr>
<td><img src="image2.png" alt="Image" /></td>
<td><img src="histogram3.png" alt="Histogram" /></td>
<td><img src="histogram4.png" alt="Histogram" /></td>
</tr>
</tbody>
</table>

### 4.3.4 First-Level Segmentation

To avoid data loss, the normalised image is first converted from greyscale to RGB before converting to CIE Lab*a*b colour space. The image is then filtered on a disk size of $3 \times 3$ to smooth the image. To avoid data loss, the system converts the filtered image from CIE Lab*a*b colour space to grey. In addition, a good morphological operation result was achieved by operating on the grey level of an image. Thresholding was performed on the resultant image to produce a
binary mask. The mask was then eroded with a $3 \times 3$ matrix kernel. The system then opened and closed the eroded image with a $9 \times 9$ matrix kernel. Kernel sizes $3 \times 3$ and $9 \times 9$ were chosen for the erosion for the morphological processes due to the positive results recorded in our procedures after several attempts with other sizes. Median filtering was then applied to produce a segmentation mask which was eventually used to automatically crop out the image lesion area from the original source image.

4.3.4.1 Thresholding and Morphological Operation

The estimation of the foreground pixel colours could sometimes be difficult for cases where a smooth transition exists between lesion areas and the surrounding skin. As a first-level segmentation, a mixture of morphological operation with thresholding was applied. This step is particularly important before application of a separation algorithm such as GrabCut as a second-level segmentation for accurate localisation of lesion areas. A Median filtering with kernel size of three was used to smooth the image in order to ensure that a better segmentation output is achieved. A threshold method was then applied on the filtered image to generate a binary image. The resulting silhouette image was eroded with a kernel size of three; later the image was opened with a kernel size of nine and closed with a kernel size of nine. An iterative median blurring was again carried out on the image using a disk size of three to produce a mask. This mask was then used to segment the lesion area from non-lesion ones.

4.3.5 Second-Level Segmentation

GrabCut Algorithm (see section 4.3.6) was used as a form of second segmentation process. The effect of the first level is very crucial for the success of the second-level segmentation.
GrabCut can sometimes perform poorly in instances where a smooth transition exists between foreground and background pixels. The first-level segmentation approach using a mixture of threshold and morphological operation assisted in estimated probable foreground. As shown in the column “Thresholding and Morphology” of Table 4-3, there are white pixels around the segmented image after undergoing first-level segmentation. These white pixels are very helpful in ensuring GrabCut performs accurate second-level segmentation to localise the lesion area from surrounding healthy skin.

4.3.6 GrabCut Segmentation

This study employed the GrabCut (Rother et al., 2004) algorithm to perform a second-level segmentation. GrabCut is a segmentation method that is based on the Graph cut (Boykov & Jolly, 2001) technique. The GrabCut algorithm combines graph cut implementation with statistical modelling to achieve a favourable 2-D segmentation. It uses an Orchard-Bouman (Orchard & Bouman, 1991) colour clustering algorithm to model foreground and background pixels as a Gaussian Mixture Model (GMM). The detailed information regarding the implementation of GrabCut was carried out by Rother (Rother et al., 2004).

4.3.6.1 GrabCut Algorithm Overview

[i]. (a) select a rectangle to create initial tri-map of the lesion area

(b) pixels outside the rectangle would be judged as known background pixels, whereas pixels inside the rectangle are classified as unknown

[ii]. classify all unknown pixels as probable foreground

[iii]. using the probable foreground pixel data, apply an Orchard-Bouman colour clustering algorithm to model initial foreground and initial background as a Gaussian Mixture Models (GMMs)
(iv). (a) assign each pixel in the initial foreground to the most likely Gaussian component in the foreground GMM
(b) assign each pixel in the initial background to the most likely Gaussian component in the background GMM

(v). discard GMMs in step [iii] and learn new GMMs from pixels in step [iv]

[vi]. (a) compute a graph and use graph cut to find new initial foreground and new initial background class
(b) model the new initial foreground and background as GMMs

[vii]. repeat steps [iv] to step [vi] until the classification converges

4.4 Results and Summary

Ensemble of segmentation techniques on a total of 294 dermoscopic images have been used. A detailed description of the images used appears in section 3.2.1. The pre-processing of the image is particularly important before either of the segmentation levels previously discussed is performed. The pre-processing used in this study ensured hair shafts and ruler markings are removed to avoid the segmentation process picking up noise pixels as valid lesion pixels. While there are many variations of AHE, the application of CLAHE was particularly effective for the objective of this study of reducing the contrast amplification of noise during histogram equalisation.

It might appear that the sole usage of a GrabCut algorithm would have been effective in the segmentation of lesion areas from surrounding skin. In this study, it was discovered that it performs poorly in instances where a smooth transition exists between foreground and background pixels. The first-level segmentation approach of the researcher using a combination of threshold and morphological operation assisted in estimated probable foreground. The actual lesion areas were then easily localised from the resultant image using a GrabCut algorithm. The
resultant effect of major techniques applied in this study to a given dermoscopic image were highlighted in Table 4-3. The researcher was then able to achieve an average speed of 5188ms on a heavily loaded virtual machine running Ubuntu 12.0.4.3 LTS, with a base memory of 3096MB and two processors (Intel Core i5, 2400 MHz with cache size 3072KB).

In this study, a mixture of methods including thresholding and GrabCut colour clustering to accurately localise lesion areas from surrounding healthy skin have been applied. This is essential for effective selection of discriminating features, which, in turn, could be used for classifying melanocytic lesions as either malignant or benign.

**Table 4-3 Lesion Segmentation**

<table>
<thead>
<tr>
<th>Source Image</th>
<th>Pre-processed Image</th>
<th>Image after using CLAHE</th>
<th>Thresholding and Morphology</th>
<th>Image after using GrabCut</th>
</tr>
</thead>
<tbody>
<tr>
<td><img src="image1.png" alt="Image 1" /></td>
<td><img src="image2.png" alt="Image 2" /></td>
<td><img src="image3.png" alt="Image 3" /></td>
<td><img src="image4.png" alt="Image 4" /></td>
<td><img src="image5.png" alt="Image 5" /></td>
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<tr>
<td><img src="image6.png" alt="Image 6" /></td>
<td><img src="image7.png" alt="Image 7" /></td>
<td><img src="image8.png" alt="Image 8" /></td>
<td><img src="image9.png" alt="Image 9" /></td>
<td><img src="image10.png" alt="Image 10" /></td>
</tr>
</tbody>
</table>
CHAPTER FIVE: RECOMMENDATION & DEDUCTION

5.1 Conclusion

Imaging Technique and Computer-Aided Systems have contributed immensely towards achieving a good automated diagnosis of skin-related cancers. The automation process typically involves acquisition and pre-processing of image lesion data, segmentation of the lesion data from surrounding healthy skin, extraction and selection discriminating features, and classification of lesion data.

The literature has recorded tremendous efforts and techniques for performing pre-processing and segmentation of actual lesion data from non-lesion counterparts. The success of the majority of the diagnosis automation has been seen in the literature to be largely dependent on the number of images used and the level of standardisation of the images. The trend observed in the literature is that each author tends to determine what is best for standardising image data set, thus making reproducibility of the research work tedious. The literature has also documented an increase in the usage of a mixture of algorithms due to the existence of artefacts and irregular structures that characterise a typical lesion image data. While the usage of ensemble algorithms has been seen to produce an increased success rate, this approach has led to high computing time. To alleviate this challenge, this study has described a prototype system involving optimised algorithms for effective pre-processing computation and localisation of lesion data. The study also boasts to have contributed towards the reduction of heavy dependency on medical experts for diagnosis procedures (whose availability in underserved areas might be very low or non-existent) using the researcher’s fast and effective algorithms (see sections of the algorithms).
Chapter 3 of this study discussed an approach using Bilateral Filter and Two-Stage artefact recognition via Canny Operation and Line Segment detection. In the same chapter, Fast Marching Method was employed to autotomise detected hair-occluding artefacts from a given dermoscopic image in an unsupervised environment. The system design proposed in Chapter 4 exemplifies a novel approach termed Fast Image Segmentation (FIS) method based on Contrast-Limited Adaptive Histogram Equalisation (CLAHE) and thresholding. The FIS method demonstrated an effective way of localising a lesion area from surrounding healthy skin.

The prototype system discussed in this study has been tested in order to perform an examination of pigmented skin lesion image data at an increased speed. As a result of the componentisation of the researcher’s system, the system can easily be integrated with ubiquitous devices for the acquisition and segmentation task processes. While this study aimed at reducing overdependencies on medical experts for automatic diagnosis procedures, it should be noted that the system can equally be used by medical experts for objective second diagnosis opinions.

5.2 Original Contribution

In Chapter 3, an algorithm (see 3.2.2) that provides a fast and effective approach for repairing hair-occluded and other artefacts in a dermoscopic images was proposed. The algorithm essentially leverages on Bilateral Filter, Line Segmentation Detection and Fast Marching Methods. The algorithm was used to model and prototype a segmentation system in Chapter 4 (see 4.3.2) as a three-phased process of initialisation, first-level segmentation and second-level segmentation.
The usage of a Bilateral filter (see 3.2.4.2) for the preservation of edges during image intensity normalisation by combining range filtering with domain filtering was demonstrated. This study also discussed the usage of ensemble detection operators comprising a Canny operator, Progressive Probabilistic Hough Transform and Line Segmentation Detection to produce an effective way of recognising artefacts such as ruler marking and hair pixels in a lesion image (see 3.2.5).

5.3 Recommendation for Future Work

The ultimate goal of automating diagnosis procedures in relation to skin cancer is primarily to discriminate between different lesion classes. Considering the diversities in the parameters associated with skin features, there exists a great need for optimal extraction and selection of discriminating features that could foster effective classification of skin lesion images. In the near future, the researcher aims to evaluate current feature extraction and selection techniques and propose an improvement. This would effectively enable the development of an unsupervised classifier that can be used to increase the speed of classification of lesion images using the image morphological properties.
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