



A Graph Theory Approach Towards Melanoma Detection

By

Asmaa Mohamed Mohamed Ahmed Elwer

A Thesis Submitted to the
Faculty of Engineering at Cairo University
in Partial Fulfillment of the
Requirements for the Degree of
MASTER OF SCIENCE
in
Biomedical Engineering and Systems

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Title of Thesis:

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Melanoma, dermoscopy, graph theory, local efficiency, graph Fourier transform (GFT).

Summary:

Melanoma is the most fatal type of skin cancer. Detection of melanoma from dermoscopic images in an early stage is critical for improving survival rates. Previous studies show that the detection performance depends significantly on the skin lesion image representations and features. In this work, we propose a melanoma detection approach that combines graph-theoretic representations with conventional dermoscopic image features to enhance the detection performance. A superpixel graph is constructed by generating superpixels for the dermoscopic images. An edge of such a graph connects two adjacent superpixels. Features are extracted from different graph models in the vertex domain at both local and global scales and in the spectral domain using the graph Fourier transform (GFT). Other features based on color, geometry, and texture are extracted from the original images. Datasets from the international skin imaging collaboration (ISIC) archive is fed to the system which achieved an AUC of 99.91%, an accuracy of 97.4%, a specificity of 95.16% and a sensitivity of 100%.

Disclaimer

I hereby declare that this thesis is my own original work and that no part of it has been submitted for a degree qualification at any other university or institute.

I further declare that I have appropriately acknowledged all sources used and have cited them in the references section.

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Date:

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Dedication

This thesis is dedicated to my family who never stop supporting me and whose words of encouragement were pushing me to get the best out of myself. Thank you for never left my side.

Acknowledgments

I take great pleasure in expressing my profound sense of gratitude to my supervisors, **Prof. Mohamed E. Rasmy**, **Prof. Mahmoud H. Annaby** and **Assistant Prof. Muhammad A. Rushdi**, for their continuous support, motivation and great insights. It would not have been possible to complete this work without their guidance, encouragement, patience, suggestions and generosity.

A very special gratitude is reserved for my parents and my brothers, **Eng. Abdalla** and **Eng. Eslam**. I admit that any success in my life would not have been achieved without their love, care, continuous encouragement, and support.

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Nomenclature

| | |
|--------|---|
| ABCDE | Melanoma parameters Like Asymmetry, Border, Color, Diameter and Evolving. |
| ACC | Accuracy |
| ACS | American Cancer Society |
| ASUWO | Adaptive Semi-Unsupervised Weighted Oversampling |
| BSL | Benign Skin Lesion |
| CIELAB | LAB Color Space |
| CPL | Characteristics Path Length |
| DWT | Discrete Wavelet Transform |
| GFT | Graph Fourier transform |
| GLCM | Gray Level Co-occurrence Matrix |
| HSV | Hue Saturation Value Color |
| ISBI | International Symposium on Biomedical Imaging |
| ISIC | International Skin Imaging Collaboration |
| KNN | K-Nearest Neighbors |
| LBP | Local Binary Pattern |
| MLP | Multi-Layer Perceptron |
| NMSC | Non-Melanoma Skin Cancer |
| RGB | Red green blue |

Abstract

Melanoma is one the most fatal and aggressive forms of skin cancers that threatens humans life. The incidence rate of melanoma has been raised over the past decades. There are about 232.000 new cases of melanoma and from 2 to 3 millions of non-melanoma cases worldwide diagnosed annually. The continual rise of cancer results in high treatment expenses and the decrease of the survival rates. The detection and curing of melanoma skin cancer and consequently giving the survival priority over the death rate is certainly relevant to the detection of the skin cancer at the beginning of its development. However much work has been done to enhance detecting the skin cancers at an early stage, it is yet a challenging task. Using the computerized systems for the automatic detection of melanoma can enhance the detection rate by 5-30% compared against the manual visualization of dermatologists via naked-eye. Because the manual inspection usually include many flaws, the presence of another decision that is more accurate is highly spotlighted. In addition, it assists the dermatologists since it saves time and effort and reduces the work and responsibilities conducted by physicians.

The objective of this thesis is to propose a framework for melanoma detection that is capable of making a binary classification of the skin lesions into melanoma and benign skin lesions (BSL). Any automatic diagnostic system of skin cancer consists of different phases: preprocessing, segmentation, features extraction, features selection, and classification. In this dissertation, we focus on the feature extraction step. A superpixel graph is constructed for each dermoscopic image where each superpixel in considered as a node (vertex) in the graph instead of considering the original pixels of the image which saves time and memory. An edge of such a superpixel graph is a link that connects every two neighboring superpixels. The edge weight is computed from a function that depends on the distance between the feature descriptors of connected superpixels via this edge. A graph signal values can be defined by assigning to each graph node the output of some single-valued function of the associated superpixel descriptor. Features are extracted from weighted and unweighted graph models in the vertex domain at both local and global scales and in the spectral domain using the graph Fourier transform (GFT). Global structural features extracted from the superpixel graph include characteristic path length (CPL), global efficiency (GE), global clustering coefficient (GCC), density and assortativity. Local structural graph features include local efficiency (LE), local clustering coefficient (LCC), nodal strength, eccentricity and nodal betweenness centrality (NBS). Other features based on color, geometry, and texture are measured globally from the skin lesion images. Several conventional and ensemble classifiers have been trained and tested on different combinations from those features using two datasets of dermoscopic images from the International Symposium on Biomedical Imaging (ISBI) 2017 challenge and the international skin imaging collaboration (ISIC) archive. The classifiers used in this work are Support vector machine (SVM) with different kernel functions, K-nearest neighbors (KNN), Multi-layer perceptron (MLP), and Random forest (RF). The performance of the proposed system is assessed using the 10-fold cross validation achieving an AUC of 99.91%, an accuracy of 97.4%, a specificity of 95.16% and a sensitivity of 100% using the RF classifier.

Chapter 1 : Introduction

In skin health care, prognosis or diagnostic process is the action of characterizing and identifying a skin textural appearance or problem by picking up any noticeable marks, symptoms and the result of different inspection procedures. By the end of this process, the outcome concluded is called a diagnosis. Automatic skin cancer detection system is an analysis tool to handle a problem by answering some questions that aim to get a solution to the problem. This can provide an early detection of the cancer and thus treating it easily. In addition, it will assist the physicians since it saves lots of doctor's effort and time with higher diagnostic accuracy. It also helps the dermatologists to guide the patient to the right treatment procedure instead of performing excessive unwanted surgeries.

1.1. Motivation

Melanoma is considered as the most serious and aggressive kind of skin cancers that threatens human life. In spite of this fact, Studies demonstrated that it is the most curable type, relying on detecting it at an early stage. Early detection is more than 90% treatable and late is less than 50% [1]. Melanoma skin cancer results from the abnormal growth of melanocytes skin cells. During current decades, the incidence rate of melanoma skin cancer has been increased. According to the skin cancer foundation, there are about 232, 000 new cases of melanoma skin cancer and between 2 and 3 millions new cases of non-melanoma skin cancer (NMSC) diagnosed annually in the world wide [2] In 2010, the American cancer society statistics showed that the number of the new patients with the skin cancer are about 68, 130 in the United States of America (USA) with the death rate of 8, 700 patients while it was 8, 420 in 2009 [3]. In 2018, the society presented that around 91, 270 new melanoma cases will be diagnosed and 9, 320 patients are anticipated to die. Melanoma spreads globally in several countries particularly in the Western ones. Australia and New Zealand has the highest incidence rates of melanoma (more than double the rate in North America). The incidence is much higher than UK, US and Canada with the rate more than 10, 000 new cases and death rate of 1250 patients per year. Its proportion is 10% between all cancer types [4], [5]. The continual increase of the skin cancers globally [2], results in higher clinical cost and mortality rate become higher than the early diagnostic rate of melanoma.

Detecting the melanoma early at the beginning of its development is of great importance due to two main causes [6]- [7]: The first one is the simplicity of the detection and prognosis of skin cancer since it is localized on the skin. At all events melanoma has higher ability to metastasize and spread to other parts of the body than other skin cancer types [8], [9]. The second one is that the diagnosis of melanoma lesions is highly related to the lesion structure, texture and color. Detecting the melanoma at an early stage increases its probability of treatment with higher success rate. However, it is not very easy process to detect the melanoma in the beginning of its development even by experienced dermatologists [10], [11], [12].

Many researches and studies has been developed in the field of the diagnosis of skin cancer. They involve various detection techniques such as pattern analysis [13], the method

of Menzies [14], CASH algorithm [15] as well as the ABCD technique using dermoscopy [16], 7-point checklist [17] and many methodologies that depend on imaging technologies such as dermoscopy [18], which is further described and explained in Chapter 2. These different techniques are also further explained in Chapter 2. In spite of that, the usage of these methodologies does not always lead to satisfying and acceptable results. Since the interpretation of the dermoscopic images is highly depending on the physicians who make the diagnosis even if it is done by experienced dermatologists, it may lead to a wrong or indecisive diagnostic decision. For these reasons, Many Computer-Aided Diagnosis (CAD) systems for melanoma diagnosis have been emerged during the last two decades. Different researches have proved that the diagnostic systems have the ability to enhance the diagnostic rate of melanoma up to 5 – 30% compared with the visual inspection via the naked-eye manually [19], [20]. The detection process of melanoma is highly depending on the medical experience and the visual observation of clinicians. However now the dermatoscopy is utilized, the diagnostic accuracy is yet around 75 – 85% [21]. This percentage grabs attention to the importance for the presence of a second opinion or system to minimize the false detection rate. This system can make the detection process made automatically, assist clinicians to save effort and time and carry out fewer tasks and increase the accuracy of the melanoma detection. However, reducing the false detection rate is still challenging task and preoccupying because false positive rate trigger the alarm and require intervention by an expert pathologist for further inspection and analysis. The automatic systems are used as a stand-alone early warning alarm. Effective implementation of these automatic systems certainly minimizes the mortality rate with profits for both the patients and the healthcare system.

Several studies and researches have been implemented to develop automatic techniques in the area of melanoma detection. The latent advantages of these studies are remarkable and estimable. In addition to that, the problems accompanied count much, and the new contributions in this field get high appreciation. Since, more accurate and sensitive automatic detection techniques are extensively demanded, it will be highly trustful and reliable.

1.2. Study Aim

It is very difficult to inspect and diagnose the skin cancer manually via the naked eye since it is not sufficient to do the diagnosis meticulously [22], [23]. The automated computer detection systems are of great interest during the current decades. The purpose of those systems is to provide a second opinion to aid the dermatologists in the diagnostic process with less error, high accuracy and reliability of the results than that achieved manually by experts and dermatologists [24], [25], [26]. Identification and measurement of most effective features from the pigmented skin lesion is very significant and the most challenging task. Melanoma and benign skin lesions both have different features that characterize each class. We utilize these various features to perform the binary classification. Feature extraction extracts useful features or properties from original dataset of an image. These extracted features easily classify the classes of skin cancer.

The purpose of this master thesis is to study the influence of the superpixel graph theoretical features as well as the color, texture and geometric properties on both local and global scales on the differentiation between melanoma and non-melanoma skin lesions (NMSL) using dermoscopic skin images. Furthermore, a comparison between global and local extraction of color, texture and geometric features is also performed. This target has been accomplished via the following means: