UNIVERSITI PUTRA MALAYSIA

DETECTION OF CORNEAL ARCUS USING RUBBER SHEET AND MACHINE LEARNING METHODS

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DETECTION OF CORNEAL ARCUS USING RUBBER SHEET AND MACHINE LEARNING METHODS

By

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Thesis Submitted to the School of Graduate Studies, Universiti Putra Malaysia, in Fulfilment of the Requirements for the Degree of Doctor of Philosophy

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Chair : Associate Professor Abd Rahman Ramli, PhD
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Corneal Arcus (CA) is a sediment accumulation that occurs by the production of lipid (i.e. cholesterol) in the ocular eye. It is associated with hyperlipidemia caused by abnormal lipids present in the blood vessels. It occurs around the cornea with 0.3 - 1 mm wide in the iris-sclera region. The appearance of it looks like a yellowish-white ring around the cornea. This condition often occurs among older people, but in the case with young people, it is risky which associated to heart problems or stroke. In a health examination, usually an ophthalmologist or doctor who finds the patient has a CA sign, will ask them to do further treatment such as blood test. This is to ensure cholesterol (lipid) in their blood is normal or not. This procedure requires a small amount of blood taken from the blood vessels in the patient's arms. It is slightly painful, requires cost and time, besides the patient should fast for 12 hours before the test can be done.

The current work for CA's classification only focusing in the entire area of iris segmentation. This research is focusing on better ROI for iris segmentation by reducing the unwanted area, in order to maximize the useful region contain the CA presence. The segmentation iris is transformed to rectangular shape using the Rubber Sheet method. In this research, two categories of eye's images which are the normal, and the abnormal (i.e. CA) are used. The normal eye, dataset are taken from the eye database (i.e. UBIRIS, CASIA, and IITD). Meanwhile, the CA's eye images were acquired from the medical website and the reports (e.g. journals). For the abnormal eye, the images has been examined and confirmed by a doctor who checks the images for verified that the images are the cases of CA.

The framework consists of three stages of implementation such as pre-processing, features extraction and classification. First stage (pre-processing stage) consists of segmentation and normalization of the region of interest (ROI). The second stage (i.e. feature extraction stage) extracts the features based on ROI using the grey-level co-occurrence matrix (GLCM). The last stage is the classification, where it is used to

identify the presence or absence of the CA. To ensure the obtained classification results are robust and stable the cross validation (CV) technique is used. The random dataset are selected by CV in the classification process (i.e. training, testing and validation). The benchmark of the classification algorithm for CA is needed to analyze the optimal output of the algorithm. The classification algorithms such as the Lavenberg-Marquardt (LM), Bayesian regularization (BR), scaled conjugate gradient (SCG) and one model of bag-of-features (BoF) are used in this research. The elements extracted from the confusion matrix parameters (i.e. accuracy, specificity, sensitivity, AUC, precision and f-score) are used in benchmarking the optimal performance of classification algorithms. Among the three neural network classifier used, BR is the best classifier. The accuracy output can be tune up to 97.2%, sensitivity 96.56%, and specificity 97.45%. On the other hand, the BoF model produced better precision of 98.04%, sensitivity 96.23%, and specificity of 100%. Based on this result, the neural network's platform for CA classification is successfully developed using the proposed framework. The result had been improved with the classification of the CA images from another benchmarking. The system can classify between CA and normal eye with good significant results.

Abstrak tesis yang dikemukakan kepada Senat Universiti Putra Malaysia sebagai memenuhi keperluan untuk ijazah Doktor Falsafah

PENGESANAN ARCUS KORNEA MENGGUNAKAN KAEDAH LEMBARAN GETAH DAN KAEDAH PEMBELAJARAN MESIN

Oleh

RIDZA AZRI RAMLEE

Mac 2019

Pengerusi : Profesor Madya Abd Rahman Ramli, PhD
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Corneal Arcus (CA) adalah pengumpulan sedimen yang terhasil daripada penghasilan lipid (iaitu kolesterol) di kawasan ocular mata. Ia dikaitkan dengan hiperlipidemia yang disebabkan oleh lipid yang tidak normal di dalam saluran darah. Ia berlaku di sekitar kornea dengan lebar 0.3 - 1 mm di rantau iris-sclera. Kemunculannya kelihatan seperti cincin kuning-putih di sekeliling kornea. Keadaan ini adalah kejadian biasa di kalangan orang tua, tetapi dalam kes orang muda, ia dikaitkan dengan masalah jantung atau strok. Dalam pemeriksaan kesihatan, apabila mendapati pesakit menunjukkan tanda-tanda CA, pakar mata atau doktor biasanya mencadangkan penilaian selanjutnya seperti ujian darah. Ini untuk memastikan paras kolesterol (lipid) dalam darah mereka adalah normal atau sebaliknya. Prosedur ini memerlukan sejumlah kecil darah yang diperoleh dari pembuluh darah di lengan pesakit. Ia sedikit menyakitkan, dan kompleks seperti pesakit harus berpuasa selama 12 jam sebelum ujian boleh dilakukan.

Amalan semasa untuk klasifikasi CA memberi tumpuan kepada keseluruhan kawasan segmentasi iris. Kajian ini akan memberi tumpuan kepada rantau yang lebih menarik (ROI) untuk segmentasi iris dengan mengurangkan kawasan yang tidak diingini, untuk memaksimumkan rantau yang berguna dengan kehadiran CA. Segmentasi iris diubah menjadi bentuk segi empat tepat menggunakan kaedah lembaran getah. Dua kategori imej mata, iaitu normal dan tidak normal (dengan CA), digunakan dalam kajian ini. Set data mata biasa diperoleh dari pangkalan data mata yang sedia ada (iaitu UBIRIS, CASIA, dan IITD) sementara itu, imej mata CA diperoleh dari laman web dan laporan perubatan (contohnya: Jurnal). Untuk kategori mata yang tidak normal, imej tersebut diperiksa dan disahkan oleh doktor bahawa imej itu adalah dari kes CA.

Rangka kerja ini terdiri daripada tiga peringkat pelaksanaan, iaitu pra-pemprosesan, pengekstrakan ciri, dan klasifikasi. Peringkat pertama (tahap pra-pemprosesan) terdiri daripada segmentasi dan pernormalan kawasan minat (ROI). Tahap kedua (iaitu tahap pengekstrakan ciri) mengekstrak ciri-ciri berdasarkan ROI menggunakan matriks co-

occurrence level kelabu (GLCM). Peringkat terakhir ialah klasifikasi, di mana ia digunakan untuk mengenal pasti kehadiran atau ketiadaan CA. Untuk memastikan keputusan klasifikasi yang diperolehi mantap dan stabil, teknik pengesahan silang (CV) digunakan. Set data rawak telah dipilih melalui CV semasa proses klasifikasi (iaitu latihan, ujian, dan pengesahan). Penanda aras algoritma pengklasan untuk CA diperlukan untuk menganalisis keluaran optimum algoritma pengelas. Algoritma pengklasifikasian seperti Levenberg-Marquardt (LM), penyesuaian Bayesian (BR), skala kecerunan konjugat (SCG) dan satu model ciri-ciri (BoF) digunakan dalam penyelidikan ini. Unsur-unsur yang diekstrak dari parameter matriks kekeliruan (iaitu ketepatan, kekhususan, kepekaan, AUC, ketepatan dan skor-f) digunakan dalam menanda aras prestasi optimum algoritma klasifikasi. Antara tiga pengeluar rangkaian neural, BR adalah pengelas terbaik. Ketepatan keluaran boleh mencapai sehingga 97.2%; kepekaan, 96.56%; dan kekhususan, 97.45%. Sebaliknya, model BoF menghasilkan ketepatan yang lebih baik sebanyak 98.04%; kepekaan, 96.23%; dengan kekhususan pada 100%. Berdasarkan keputusan ini, platform rangkaian neural untuk klasifikasi CA berjaya dibangunkan menggunakan rangka kerja seperti yang dicadangkan. Keputusan menunjukkan penambahbaikan berbanding dengan klasifikasi imej CA dari platform penandaarasan yang lain. Pada asasnya, sistem boleh membezakan antara CA dan mata normal dengan hasil yang sangat baik.

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I certify that a Thesis Examination Committee has met on 1 Mac 2019 to conduct the final examination of Ridza Azri bin Ramlee on his thesis entitled "Detection of Corneal Arcus Using Rubber Sheet and Machine Learning Methods" in accordance with the Universities and University Colleges Act 1971 and the Constitution of the Universiti Putra Malaysia [P.U.(A) 106] 15 March 1998. The Committee recommends that the student be awarded the Doctor of Philosopy.

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LIST OF ABBREVIATIONS

ASM	Angular Second Moment
AUC	Area Under Curve
BoF	Bag of Features
BoW	Bag of Words
BR	Bayesian Regularization
BRA	Big Ring Area
BFGS	Broyden-Fletcher-Goldfarb-Shanno Memory-Less Quasi-Newton Algorithm
CHD	Cardio Heart Diseases
CHT	Circular Hough Transform
CCD	Clear Corneal Diameter
CT	Computed Tomography
CAD	Computer-Aided Detection
CM	Confusion Matrix
CM	Confusion Matrix
CGL	Conjugate Gradient Algorithm With Line Search
CA	Corneal Arcus
CH	Corneal Hysteresis
CRF	Corneal Resistance Factor
CV	Cross-Validation
DLS	Damped Least-Squares
DLS	Damped Least-Squares
DIDO	Daugman Integra-Differential Operator
DR	Diabetic Retinopathy
DWT	Discrete Wavelet Transformed
DP	Dyslipidemia Patient

EEG	Electroencephalogram
ECOC	Error-Correcting Output Codes
FPR	False Positive-Rate
FN	False-Negative
FP	False-Positive
FREAK	Fast Retina Key-Point
FS	Feature Selection
FFNN	Feed-Forward Neural Network
GMM	Gaussian Mixture Model
GMM	Gaussian Mixture Model
GNA	Gauss–Newton Algorithm
GNA	Gauss–Newton Algorithm
GLPI	Gray Level Pixel Image
GLCM	Grey Level Co-Occurrence Matrix
HG	Hand Gesture
IT	Information Technology
CASIA	Institute Of Automation, Chinese Academy Of Sciences
IQR	Interquartile Range
KNN	K-Nearest Neighbor’s
KW	Kruskal-Wallis
KWT	Kruskal–Wallis Test
LM	Lavenberg-Marquardt
LMBP	Lavenberg-Marquardt back-propagation (LMBP)
LDL-C	Low-Density Lipoprotein- Cholesterol
LDL	Low-Density Lipoproteins
ML	Machine Learning
MRI	Magnetic Resonance Imaging

MSE	Mean Squared Error
NB	Naive Bayesian
NPV	Negative Predective Value
non-HDL-C	Non-High-Density Lipoprotein-Cholesterol
ND	Normal Distribution
OD	Original Data
PM	Performance Measurement
PPM	Performance Prediction Models
POI	Pixel Of Interest
PPV	Positive Predictive Value
PET	Positron Emission Tomography
PCA	Principal Component Analysis
P	Probability
RBF	Radial Basis Function
RAD	Rapid Application Development
RAMI	Recent Acute Myocardial Infarction
ROI	Region Of Interest
SIFT	Scale Invariance Feature Transforms
SCG	Scaled Conjugate Gradient
Se	Sensitivity
SRA	Small Ring Area
Sp	Specificity
SURF	Speeded Up Robust Features
SF	Statistical Feature
SF	Strongest Features
SVM	Support Vector Machine
SVM-RBF	Support Vector Machine With Radial Basis Function Kernel

UTeM	Technical University Of Melaka
TPR	True Positive Rate
TN	True-Negative
TP	True-Positive
VWI	Visual Word Index
VW	Visual-Words

CHAPTER 1

INTRODUCTION

1.1 Background

Conventionally, cholesterol in the bloodstream is measured through lipid profile testing. To perform this procedure, the patient's blood sample should be taken after the patient is made to fast for 9 – 12 hours. This blood sample is expected to have undergone some of the enzyme response to obtain the presence of cholesterol. The procedures of lipid profile are performed in a medical laboratory using lab instrumentation. Nevertheless, lipid profile has its difficulties because it requires a laboratory facility for testing and storage of the samples. Moreover, the procedure is time-consuming as it involves particular procedural steps for measuring cholesterol levels. Due to these complications in conventional lipid profile, alternative cholesterol detection methods have been sought by researchers involving either invasive or non-invasive techniques. The invasive method (Sarkar et al. 2012) exploits the dielectric properties in certain microwave frequencies to measure cholesterol in blood. Another cholesterol detection method utilises the infrared (IR) absorption properties in bloodstreams via the vein (Haq et al. 1991). Oncescu et al. (2014) proposed a system that measures blood cholesterol levels using a smart-phone application (Oncescu et al. 2014). The system requires blood droplets to be placed on test strips, of which filtering is also involved. The images of the resulting reaction of the blood with the enzymes are then stored in the phone's memory card. These images are then processed such that the HUE status is evaluated by referring to the amount of cholesterol in the blood. In contrast, the invasive methods require blood samples to be taken from the patient's body. This circumstance can impose discomfort on the patients, especially those with diabetes. Thus, non-invasive methods significantly reduce complexity and pain in measuring cholesterol levels, making it one of the viable alternatives for cholesterol detection. The method does not require penetration or piercing of the skin, hence eliminating pain and discomfort from the patients. Furthermore, non-invasive methods may even detect the presence of cholesterol using other mediums instead of blood samples. According to medical research, cholesterol detection can be ascertained from the presence of cholesterol that is deposited in the corneal region of the eye (Urbano 2001; Fernández et al. 2007; Panahi-Bazaz et al. 2014; Reddy et al. 2015). Corneal arcus (CA) occurs in the ocular section when there are abnormalities in the human metabolism. These abnormalities include cholesterol, lecithin, and other lipids in the blood that will deposit in the cornea (Macchiaiolo et al. 2014; Chang & Yuan 2016). Researchers have proposed a number of corneal arcus classification systems based on different extraction techniques and used a variety of algorithm classifiers (Rajendra et al. 2006; Acharya et al. 2007; Kumar & Gunasundari 2018; Kumar et al. 2016; Mahesh & Gunasundari 2016). Several gaps in CA classification have been identified. These pertain to three issues: segmentation and ROI; feature’s extraction; and classification, training, testing, and evaluation.

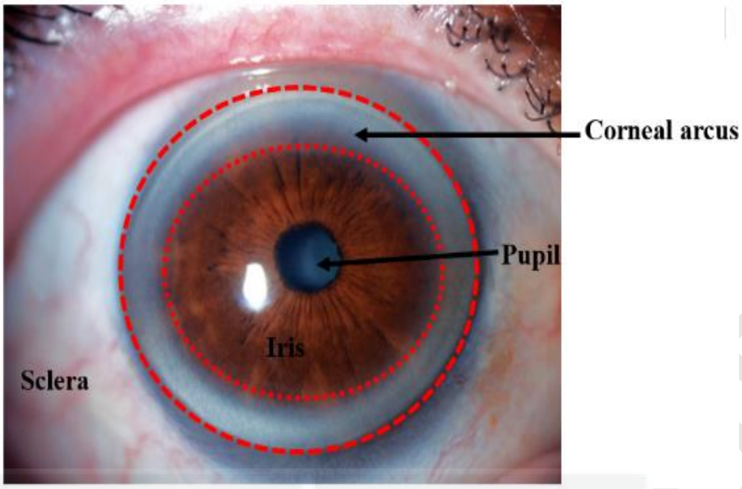

Figure 1.1: The CA condition in the patient's eye.

The cornea is the outermost layer of the eye that serves as a transparent front layer to the eyeball, which allows light to be focused into the centre of the retina. Corneal problems occur when the cornea is prevented from receiving or allowing light to enter the retina, a condition which causes partial vision impairment and may lead to total ocular impairment or blindness. Examples of eye diseases related to corneal problems are corneal arcus (CA), corneal haze (Acharya et al. 2007), corneal abrasion (Khurana 2007), corneal dystrophy (Bigar et al. 2001), pterygium (Abdani et al. 2016), glaucoma (Acharya et al. 2015), cataracts (Patwari 2011), and diabetic retinopathy (DR) (Akrama et al. 2013). Some of the aforementioned corneal problems was not only found to be associated with ocular health but may also be related to bodily health (Coady et al. 2014). There are situations where a systemic disease is initially undetected but subsequently discovered through eye examinations that revealed the existence of abnormalities in the eye (cornea) or its surrounding area. These abnormalities indicate symptoms of a systemic disease or complications with other organs (Bigar et al. 2001; Panahi-Bazaz et al. 2014; American Optometric Association [APA] 2015; Coady et al. 2014; Bronner 2015). Studies showed that a comprehensive eye examination can be used as a precursor to the detection of signs of more serious diseases (for example; acute diabetes, cancer and heart problems). Moreover, the detection of systemic diseases using eye examinations is inexpensive and reduces the cost of healthcare or rehabilitation, which would otherwise incur due to a delay in disease detection. There have been many studies on how classification is applied to medical images. Most studies on classification use a framework consisting of three elements; pre-processing, feature extraction, and classification. The differences between the studies are the image dataset, the segmentation, the technique of extracting and selecting features, and the classifier used in each study. The challenge when suggesting a framework is to produce the most accurate framework of classification for the findings using the proposed algorithm. Akram studied a micro-aneurysm image for early detection of diabetic retinopathy (Akrama et al. 2013). Researchers like Acharya et al. (2015), A.Rajan et al. (2014) have conducted studies on glaucomatous or glaucoma diseases. Acharya extracted features using PCA and made classification using support vector machine (SVM) (Acharya et al. 2015), while Rajan used a single level discrete wavelet transformed (DWT) for feature extraction and then classified the data using the k-nearest neighbors (KNN) classifier (A.Rajan et al. 2014). Iridology is a method used in complementary medicine. Iridology uses the eye as a medium for the diagnosis of diseases associated with the health of the human body. Hussein et al. used adaptive Neuro-fuzzy inference system (ANFIS) in their studies (Hussein et al. 2013). They proposed a system to classify the eye that has features referring to kidney problems and eyes that show the patient is free from kidney problems. Nor'aini et al. (2013) investigated the use of the eye as a diagnostic medium for the study of the pelvis and the vagina (Nor'aini et al. 2013). The division of both positions was based on the iridology eye chart. They proposed the use of a support vector machine with radial basis function kernel (SVM-RBF) for image classification.

1.2 Problem Statement

The CA segmentation region is indeed a challenging aspect of classification. Consequentially, improper segmentation can cause misclassification of normal eyes to be falsely diagnosed with CA thus significantly diminishing the accuracy of the classification. Commonly affected area for CA is in fact the lower iris, which borders the limbus on the eyes. According to Urbano, CA is identified as a yellowish-white ring around the cornea, separated from the limbus area with a clear zone of approximately 0.3 to 1 mm in width (Urbano 2001). It is usually perceived at the bottom of the iris and does not cover the entire iris and pupil. The most common method to define the CA area is by pupil segmentation and iris circle (Acharya et al. 2007; Kumar & Gunasundari 2018). However, considering the whole segmentation area into the CA region analysis does not necessarily benefit accuracy. This is because these areas also include sections that are unaffected by CA (i.e. pupil and part of the iris). In another work, CA segmentation is proposed using component fusion, union-find algorithm, and colour quantitative analysis (Chang & Yuan 2016). Nevertheless, the work only pertains to the segmentation process and does not include any classification method. A state-of-the-art segmentation of ROI for CA is crucial for this research to ensure efficient analysis on the characteristics of the CA region. In addition, this effectively reduces the areas that are inapplicable to the analysis, which will benefit image processing by reducing overall time consumption and optimizing algorithm processing.

Essentially, the focus of this research is to attain ROI that contains CA features by eliminating unwanted areas and maximizing useful areas. A proper segmentation is worthwhile and helpful for the following process in feature extraction. It can produce relevant texture features that can represent each image category. Binary classification is used in this research such that there are two categories of eye images (i.e. normal and CA). Feature extraction (FE) is another challenge that needs to be considered in this work. FE provides the input data to be processed by the classifier. One of the classic methods for FE is the statistical method (SM) that calculates operating statistics based on the pattern images. SM is the easiest method for texture extraction purposes as it has strong adaptability and robustness (Zhang et al. 2017). A first-order SM calculation was once used to gain texture features that was then fed into SVM for classification of CA (Mahesh & Gunasundari 2016). Another type of SM is the co-occurrence level grey matrix (GLCM) which is widely used in texture descriptions (Haralick et al. 1973). In the study of other types of images, GLCM is used as feature extractor. It is reported to have good contribution towards classification results. Some of these studies include face recognition (Eleyan & Demirel 2011), x-ray images (Zare et al. 2013), glaucoma (Karthikeyan & Rengarajan 2013), mammogram (Beura et al. 2015), brain image (Veeramuthu et al. 2015), liver (Nusantara et al. 2015), and MRI (Brynolfsson et al. 2017). Other feature extraction methods for CA are statistical value (Rajendra et al. 2006), extract cluster centroid and k-means algorithm (Acharya et al. 2007), grey level mean (GLM) (Kumar et al. 2016), first-order statistical and wavelet (Kumar & Gunasundari 2018), exact Legendre moment (ELM) and geometric moment (GM) (Nasution & Kusuma 2009).

The selection of feature extraction is another challenge especially when it involves large numbers of features. The best features must be acquired from the feature extraction to be fed into the classifier. This includes feature ranking and feature selection in order to obtain only good features for the classification. The feature ranking is used (Kumar & Gunasundari 2018) such that five numbers from each feature extraction are of first-order statistical (FOS) and wavelet feature extraction. Most of the work involving CA studies did not clearly state the methods executed for feature ranking and feature selection. Thus, this is one of the gaps that can be studied and discussed in more detail especially on the methods for texture features. After the features have been decided, the next process is the CA classification.

This process involves training, testing and validation using feature data as inputs. Establishing the best classifier for CA classification is also another challenge faced in this research. There are different types of classifiers that have been used by researchers in relation to CA studies such as neural network, fuzzy, adaptive neuro fuzzy inference system (ANFIS) (Rajendra et al. 2006), radial basis function network (RBF) (Acharya et al. 2007), and support vector machine (Kumar & Gunasundari 2018). In this research, three types of neural network were proposed (i.e., LM, BR, and SCG) with the addition of one of the bag-of-features (BoF) model, used in the classification process. The state-of-the-art classification techniques were experimentally evaluated within the context of CA studies.

1.3 Objectives

The main intent of this thesis is to identify an abnormal eye, specifically corneal arcus (CA), using image processing. The objectives of this study are listed below;

i. To develop the algorithm for segmentation of the iris and obtain the region of interest (ROI). The aim is to reduce unwanted areas and maximize the information for classification. The rubber sheet method is applied for transforming the circle segmentation into a rectangular shape and perform area truncation encompassing the CA region.

ii. To develop an algorithm for extracting features and accomplish feature selection with the image texture as input data to the classifier using GLCM in neural network and SURF features descriptor in the BoF model.

iii. To investigate the effectiveness of the classifiers for the CA images. Furthermore, comparisons were made based on the previous classifications used for benchmarking.

1.4 Scope

This research predominantly focuses on improving the classification of corneal arcus. Two categories of images are used in this research; the normal eye category images were acquired from publicly available datasets such as CASIA, UBIRIS and IITD; meanwhile, for the abnormal eye category, the images were collected from many sources i.e. medical and alternative medicine practitioners' websites, journals, reports and articles. The verification from an eye specialist are as described in Appendix E, which confirms that the abnormal images indeed fall into the CA category. The experiment was conducted using four classifiers which were BR, SCG, LM, and BoF model. Several benchmark works (Acharya et al. 2007; Rajendra et al. 2006; Mahesh & Gunasundari 2016; Kumar & Gunasundari 2018) were chosen to be compared with the experiment findings. Performance evaluation based on confusion matrix was used to gain necessary parameters such as accuracy, sensitivity, specificity, precision, and f-score. The AUC value was also presented based on the ROC. The experiment used neural network topology for the three classifiers (i.e. BR, SCG, and LM). The input of the neural network was the five statistical features calculated from GLCM matrix. The hidden layers (HL) were limited to ten with the output being the binary classifications, either normal or abnormal.

1.5 Thesis Layout

The following paragraph in this section comprises a summary of each chapter of this thesis.

Chapter 2 contains the literature review of the related processes around corneal arcus (CA) from a medical perspective and a discussion regarding of the classification of the CA classification system. The objective of the chapter is to locate the gaps in research and to answer research questions such as about the CA, the importance of this study, problem statement and how to solve it. Relevant literature related to classification performance is discussed alongside possible causes and effects.

Chapter 3 consists of a discussion the methodologies used for the entire work. An explanation is made of the process; from raw images, the localisation and segmentation the ROI, image extraction, selection features, and classifier process. For this process, an explanation has been made of the issue of narrowing on the grey level extraction feature using the grey level co-occurrence matrices (GLCM) and their statistical features. The technique for each of the stages is discussed in terms of establishing a mainstream for image processing technology.

Chapter 4 presents the results and the discussion. All techniques found in the literature are presented and implemented with example images obtained from each process. A detailed discussion is undertaken on the implementation of co-occurrence matrix statistical features from the images. The emphasis stage of ROI and selection of features proposes a novel implementation to demonstrate the meaning of successful CA classification.

Chapter 5 concludes the entire work, summarises the contribution to research and suggests future work in this field.

The Appendix F includes attachments such as the MATLAB script file, data image of the texture features, and eye images.

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Ridza Azri Ramlee, who is from Johor, is the eldest son of five siblings. He earned his bachelor's degree in UiTM Shah Alam in 2000, in electrical engineering (electronics industry). In 2006, he was awarded a master's degree in telecommunications engineering and information at the same university. He is a senior lecturer at the Technical University of Melaka since 2008 until now. Having industrial experience as an electrical and biomedical engineer at UKM Hospital from 2001 to 2006. He obtained the Professional Engineer with Practising Certificate (PEPC) status from the Board of Engineer (BEM). This due to the experience gained in industrial work in the Electronic field.

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Exhibition

Ridza Azri Ramlee, Abd Rahman Ramli (2017), Classification Corneal Arcus using Machine Learning, *National Innovation & Invention Competition through Exhibition 2017 (ICompEx2017), POLIMAS Jitra*, 21-23 March 2017, [won gold medal].

Ridza Azri Ramlee, Abd Rahman Ramli (2017), Classification Corneal Arcus for detection the Hyperlipidemia Presence, *International EUREKA Innovation Exhibition, Kulim Kedah. UniKL* 2017, 25 July 2017, [won silver medal].