



**T.C.
AKSARAY UNIVERSITY
GRADUATE SCHOOL OF NATURAL AND APPLIED SCIENCE**

**DEPARTMENT OF ELECTRICAL ELECTRONIC AND
COMPUTER ENGINEERING**

**CAD FOR CORNEAL DISEASES BASED ON
TOPOGRAPHICAL PARAMETERS TO IMPROVE THE
CLINICAL DECISION**

Ph.D. THESIS

**By
Samer Kais Jameel AL-SALIHI**

**SUPERVISOR
Prof. Dr. Sezgin AYDIN**

AKSARAY, 2021

PLAGIARISM PAGE

I hereby declare that all information in this thesis has been obtained and presented in accordance with academic rules and ethical conduct. I also declare that, as required by these rules and conduct, I have fully cited and referenced all material and results that are not original to this work; otherwise I accept all legal responsibility.



Samer Kais Jameel AL-SALIHI

ACKNOWLEDGEMENTS

First of all, I would like to express my deepest appreciation to my esteemed supervisor, Prof. Dr. Sezgin AYDIN, who gave me this great research opportunity. I am heartily thankful to him for his tireless guidance, extraordinary patience and constant encouragement during my academic journey. Without his persistent help, this thesis would not have been possible. I would also like to thank Dr. Nebras H. GHAEB for his technical support on my study and his invaluable advises. In particular, I would love to express my gratitude to my parents and my wife, for their love and support throughout my life, and my children, mother-in-law, sister, brothers, and friends, without their tremendous understanding and encouragement in the past few years, it would be impossible for me to complete my study. All of their love, support, and sacrifices over these past years gave me the strength and determination to make my dreams come true.

Samer Kais Jameel AL-SALIHI
AKSARAY, 2021

TABLE OF CONTENTS

ACKNOWLEDGEMENTS	i
TABLE OF CONTENTS	ii
ÖZET	iv
ABSTRACT	v
LIST OF FIGURES	vi
LIST OF TABLES	viii
ABBREVIATIONS	x
1. INTRODUCTION	1
1.1 Human Cornea Background	1
1.2 Challenges in CAD System.....	6
1.3 CAD System Evaluation	8
1.4 Corneal Image Databases	9
1.5 Thesis Motivation.....	10
1.6 Thesis Aims and Contributions.....	11
1.7 Method of Study.....	12
1.8 Thesis Outline	12
2. LITERATURE REVIEW	14
2.1 Review.....	15
2.1.1 Videokeratography.....	15
2.1.2 Artemis and videokeratography.....	20
2.1.3 ORA, pentacam, visante, and orbscan.....	20
2.1.4 Keratron corneal topographer 2000	21
2.1.5 Precision tomographic examination	21
2.1.6 Galilei analyzer system.....	21
2.1.7 Orbscan	21
2.1.8 ATLAS 9000	23
2.1.9 Optical coherence tomography	23
2.1.10 ArcScan	23
2.1.11 Data combined from scheimpflug and placido.....	24
2.1.12 Physician examination data	24
2.1.13 Eyesys system 2000.....	25
2.1.14 Data from interview	25
3. METHODOLOGY	32
3.1 Subbands Wavelet for Local Features Transform (SWFT)	32
3.1.1 SIFT background	33
3.1.2 Wavelet transforms.....	36
3.1.3 Support Vector Machine (SVM)	40
3.1.4 SWFT algorithm	44
3.1.5 Practical experiments.....	45
3.2 Multi-Subbands Wavelet Transform with SIFT Algorithm for Local Feature Extraction	46
3.2.1 Multi-scale wavelet.....	47
3.2.2 Practical experiments.....	47
3.3 Texture Feature Extraction and Time-Saving Based on Image Gradient and GLCM For Corneal Diseases Diagnosis.....	48
3.3.1 Gray level co-occurrence matrix.....	49
3.3.2 Image gradient	55
3.3.3 IG-GLCM algorithm.....	58

3.3.4 Practical experiment	59
3.4 Local Information Pattern Descriptor for Corneal Diseases Diagnosis (LIP). 59	
3.4.1 LIP algorithm.....	60
3.4.2 Practical experiments.....	66
4. RESULTS AND DISCUSSIONS	67
4.1 SWFT Algorithm.....	67
4.1.1 Results.....	67
4.1.2 Discussion.....	70
4.2 Multi-Subbands wavelet with SIFT algorithm for local feature extraction	71
4.2.1 Results	71
4.2.2 Discussion.....	76
4.3 IG-GLCM algorithm	77
4.3.1 Results	77
4.3.2 Discussion.....	81
4.4 LIP Algorithm	82
4.4.1 Results.....	82
4.4.2 Discussion.....	85
5. CONCLUSION AND FUTURE WORK	87
5.1 Conclusion.....	87
5.2 Future Work	88
REFERENCES	89

DOKTORA TEZİ

KORNEA HASTALIKLARINDA KLİNİK KARARI GELİŞTİRMEK İÇİN TOPOGRAFİK PARAMETRELERE DAYALI BİLGİSAYAR DESTEKLİ TANI

Samer Kais Jameel AL-SALIHI

Aksaray Üniversitesi
Fen Bilimleri Enstitüsü
Elektrik-Elektronik ve Bilgisayar Mühendisliği Anabilim Dalı

Danışman: Prof. Dr. Sezgin AYDIN

ÖZET

Bilgisayar Destekli tani, tıbbi görüntüde önemli bir konudur. Tıpta hekimlere tıbbi görüntülerin yorumlanmasında yardımcı olan sofistike bir prosedürdür. İnsan korneası, gözün önden şeffaf siperi. Görmeyi tetiklemek için ışığı retinaya yansıtır. Bu nedenle korneadaki herhangi bir kusur görme bozukluğuna neden olabilir. Bu eksiklik, oftalmologlar tarafından ölçülen ve değerlendirilen bir dizi topografik görüntü ile tahmin edilmektedir. Sonuç olarak, önemli bir öncelik, makine öğrenme algoritmaları kullanılarak kornea bütünlüğünü etkileyebilecek hastalıkların erken ve doğru teşhisidir. Bu nedenle, doğru teşhis, görüntüdeki yerel özelliklerin kullanılmasını gerektirir. Buna göre, bu zorlukların üstesinden gelmek ve cornel koşullarını teşhis etmeyi iyileştirmek için bu çalışmada önerilen yeni algoritmalar. İlk olarak, kornea görüntülerinden yerel özelliklerin çıkarılması için bir SWFT algoritması önerildi. Dalgacık dönüşümü, standart SIFT algoritmasında olduğu gibi Gauss Farkı (DoG) kullanmak yerine farklı ölçeklerde görüntüler üretmek için kullanılır. İkinci olarak, IG-GLCM algoritması, zaman alıcı bir kusur olarak bilinen GLCM algoritmasının dezavantajının üstesinden gelmeyi önerdi. IG-GLCM'de görüntü gradyanı farklı yönlerde ölçülür ve ardından GLCM'yi oluşturulan görüntülere uygular. Üçüncü olarak, SIFT'in dalgacık dönüşümünün çok ölçekli alt bantları ile kullanımını araştırır. Son olarak, Yerel Bilgi Modeli tanımlayıcısı adlı yeni algoritma, görüntüden bilgi kaybına neden olan yerel ikili model eksikliğinin üstesinden gelmeyi ve görüntü döndürme sorununu çözmeyi önerdi. LIP, hangi sözde kontrast Tabanlı Merkez (CBC) değerinin yanı sıra yerel paterni (LP) hesaplamak için kullanabilen komşuların ağırlıklarını tahmin etmek için alt görüntü merkez yoğunluğunu kullanmaya dayanır. Naive Bayes, KNN, karar ağacı ve SVM sınıflandırıcılar olarak kullanıldı. Önerilen model, farklı haritaların 4848 görüntüsünden oluşan toplanmış bir veri kümesi üzerinde eğitilmiş ve başarıyla test edilmiştir.

Anahtar Kelimeler: Bilgisayar destekli teşhis, Öznitelik çıkarma, Makine öğrenimi, Destek vektör makineleri, Yerel İkili Model, GLCM.

Mayıs 2021; 103 Sayfa

Ph.D. THESIS

**CAD FOR CORNEAL DISEASES BASED ON TOPOGRAPHICAL
PARAMETERS TO IMPROVE THE CLINICAL DECISION**

Samer Kais Jameel AL-SALIHI

**Aksaray University
Graduate School of Natural and Applied Sciences
Department of Electrical Electronic and Computer Engineering**

Supervisor: Prof. Dr. Sezgin AYDIN

ABSTRACT

Computer-Aided Diagnosis is an essential topic in the medical image. It is a sophisticated procedure in medicine that assists physicians in the interpretation of medical images. A Human cornea is the front see-through shield of the eye. It refracts light onto the retina to induce vision. Therefore, any defect in the cornea may lead to vision disturbance. This deficiency is estimated by sets of topographical images measured and assessed by ophthalmologists. Consequently, an important priority is the early and accurate diagnosis of diseases that may affect corneal integrity through the use of machine learning algorithms. Corneal images produced by a Pentacam device can be subjected to rotation or some distortion during acquisition; therefore, accurate diagnosis requires the use of local features in the image. Accordingly, new algorithms proposed in this work to overcome these challenges and improve corneal conditions diagnosing. Firstly, a SWFT algorithm suggested to extract the local features from the corneal images. Wavelet transform used to produce images with different scales instead of using the Difference of Gaussians (DoG) as in the standard SIFT algorithm. Secondly, IG-GLCM algorithm proposed to overcome the drawback of GLCM algorithm known as a time-consuming defect. In IG-GLCM the image gradient is measured in different directions then apply the GLCM to generated images. Thirdly, investigate the use of SIFT with multi-scale subbands of wavelet transform. Finally, new algorithm called Local Information Pattern descriptor suggested to overcome the lack of local binary patterns that loss of information from the image and solve image rotation issue. The LIP based on utilizing the sub-image center intensity for estimating neighbors' weights that can use to calculate what so-called contrast Based Centre (CBC) value, as well as local pattern (LP). The Naive Bayes, KNN, decision tree, and SVM employed as classifiers. The proposed model is trained and tested successfully on a collected dataset which comprises 4848 images of different maps.

Keywords: Computer-aided diagnosis, Feature extraction, Machine learning, Support vector machines, Local Binary Pattern, GLCM.

May, 2021; 103 Pages

LIST OF FIGURES

Figure 1.1. Eye cornea layers.....	2
Figure 1.2. Placido pattern.	3
Figure 1.3. A hand-held telescope.....	3
Figure 1.4. a.dry cornea. b. regular astigmatism c. irregular astigmatism d. Normal.	4
Figure 1.6. Pentacam output.	6
Figure 1.7. CAD stages.	7
Figure 1.8. Corneal topography containing the four maps.....	10
Figure 3.1. Scale space of an image in different octave used to calculate the Difference of Gaussians (DOG).	34
Figure 3.2. The orientations histogram of image region that used to determine its main orientation which is the highest bin (peak).....	35
Figure 3.3. The eight directions scale and orientation.	35
Figure 3.4. Sample of signals frequently.	36
Figure 3.5. Different sizes and shapes of wavelet.....	37
Figure 3.6. Scale and the frequency examples.....	38
Figure 3.7. Function of scale or frequency with time.	38
Figure 3.8. Wavelet Filter bank for one-level Image Decomposition.....	39
Figure 3.9. The support vector points samples from two classes.	40
Figure 3.10. The Margin and D-, D+ with samples from two classes	41
Figure 3.11. Transform nonlinear separable data into 2-Dimenssion.....	41
Figure 3.12. Transform 2-Dimenssion data into 3-Dimenssion.....	42
Figure 3.13. Decomposition image using first level wavelet transform.	44
Figure 3.14. Human Corneal topography from Pentacam device a) Sagittal map b) Corneal thickness map c) Elevation front map d) Elevation back map.	45
Figure 3.15. Human Corneal diseases examples a) astigmatism b) Thinness cornea c) like tongue d) Isolated land shape.	46
Figure 3.16. Image decomposition using DWT.	47
Figure 3.17. Different types of texture images a) Coarse b) Fine c) High-contrast d) Low-contrast e) Regular f) Directional g) Non-directional h) Rough i) Smooth g) Random.	49
Figure 3.18. 8x8 sub image example.	50
Figure 3.19. Present pares that 0 related with 0 in 45 ⁰ degree.	50
Figure 3.21. Generate 13 features in different angle degrees.	51
Figure 3.22. Sub image example to compute gradient.....	56
Figure 3.23. Image with horizontal ramp from A to B.	56
Figure 3.24. Image with vertical ramp from A to B.	57
Figure 3.25. Image with 450 ramps from A to B.....	57
Figure 3.26. Calculating the CBC value.	61
Figure 3.27. Structure of the LIP algorithm.....	61
Figure 3.28. A 3x3 sub-image example.	62
Figure 3.29. A CBC code in different angle rotation.....	63
Figure 3.30. Calculation of the LP from different sub-images.	65

Figure 3.31. Calculate the Local pattern from sub-image.....	65
Figure 3.32. Histogram illustration of local information pattern.....	66
Figure 4.1. Plotting the Compression of SIFT and SWFT performance with different strategies for a) Sagittal map b) Corneal Thickness map c) Elevation front map d) Elevation back map.	70
Figure 4.2. Results of precision in different strategies and subbands a) sagittal map b) Corneal Thickness map c) Elevation Front map d) Elevation Back map.	76
Figure 4.3. Chart for measurements of cost time for different methods.	80
Figure 4.4. Chart for measurements of cost time for proposed and different methods.....	81



LIST OF TABLES

Table 1.1. Terminology and derivations from a confusion matrix.....	9
Table 2.1. All research for corneal diagnosis arranged based on the device type.. ..	26
Table 4.1. Achievements of the algorithm on the sagittal map for diagnosis the corneal astigmatism using all strategies (%).	67
Table 4.2. Achievements of the algorithm on the corneal thickness map to diagnosis corneal-thinning disease using all strategies (%).	68
Table 4.3. Achievements of the algorithm on the corneal elevation front map for diagnosis the cornea-isolated-land disease using all strategies (%).	68
Table 4.4. Achievements of the algorithm on the corneal elevation back map to diagnosing the like tang diseases using all strategies (%).	68
Table 4.5. Accuracy of cornea disease diagnosis by applying the proposed algorithm on all corneal topography maps (%), and Loss cross-validation error.	68
Table 4.6. Accuracy of diagnosis comparing between the proposed algorithm and standard SIFT examed on different datasets and employing different classifiers (%).	69
Table 4.7. Cornea diagnosis in different subbands and SIFT using SVM classifier with 70%30% strategies using sagittal map (%).	71
Table 4.8. Cornea diagnosis in different subbands and SIFT using SVM classifier with 50%50% strategies using sagittal map (%).	72
Table 4.9. Cornea diagnosis in different subbands and SIFT using SVM classifier with 90%10% strategies using sagittal map (%).	72
Table 4.10. Cornea diagnosis in different subbands and SIFT using SVM classifier with 10%90% strategies using sagittal map (%).	72
Table 4.11. Cornea diagnosis in different subbands and SIFT using SVM classifier with 70% 30% strategies using corneal thickness map (%).	72
Table 4.12. Cornea diagnosis in different subbands and SIFT using SVM classifier with 50% 50% strategies using corneal thickness map (%).	73
Table 4.13. Cornea diagnosis in different subbands and SIFT using SVM classifier with 90%10% strategies using corneal thickness map (%).	73
Table 4.14. Cornea diagnosis results with different subbands and SIFT using SVM classifier with 10%90% strategies using corneal thickness map (%)... ..	73
Table 4.15. Cornea diagnosis in different subbands and SIFT using SVM classifier with 70%30% strategies using elevation front map (%).	73
Table 4.16. Cornea diagnosis in different subbands and SIFT using SVM classifier with 50%50% strategies using elevation front map (%).	74
Table 4.17. Cornea diagnosis in different subbands and SIFT using SVM classifier with 90%10% strategies using elevation front map (%).	74
Table 4.18. Cornea diagnosis in different subbands and SIFT using SVM classifier with 10%90% strategies using elevation front map (%).	74
Table 4.19. Cornea diagnosis in different subbands and SIFT using SVM classifier with 70%30% strategies using elevation back map (%).	74

Table 4.20. Cornea diagnosis in different subbands and SIFT using SVM classifier with 50%50% strategies using elevation back map (%).	75
Table 4.21. Cornea diagnosis in different subbands and SIFT using SVM classifier with 90%10% strategies using elevation back map (%).	75
Table 4.22. Cornea diagnosis in different subbands and SIFT using SVM classifier with 10%90% strategies using elevation back map (%).	75
Table 4.23. Comparison of the performance of applying different techniques with distance 1 and angle 0^0	78
Table 4.24. Comparison of the performance of applying different techniques with distance 1 and angle 45^0	78
Table 4.25. Comparison of the performance of applying different techniques with distance 1 and angle 90^0	79
Table 4.26. Comparison of the performance of applying different techniques with distance 1 and angle 135^0	79
Table 4.27. Comparison of the performance of applying different techniques with gradients in x, & y axis with distance 1 and angle 0^0	79
Table 4.28. Comparison of the performance of applying different techniques with gradients in x, & y axis with distance 1 and angle 45^0	79
Table 4.29. Comparison of the performance of applying different techniques with gradients in x, & y axis with distance 1 and angle 90^0	80
Table 4.30. Comparison of the performance of applying different techniques with gradients in x, & y axis with distance 1 and angle 135^0	80
Table 4.31. performance of different subbands wavelet with IG-GLCM algorithm.	80
Table 4.32. Achievements comparison of the LIP and LBP to corneal diagnosis by applying all strategies on the sagittal map (%).	83
Table 4.33. Achievements comparison of the LIP and LBP to corneal diagnosis by applying all strategies on the Corneal thickness map (%).	83
Table 4.34. Achievements comparison of the LIP and LBP to corneal diagnosis by applying all strategies on the Elevation front map (%).	83
Table 4.35. Achievements comparison of the LIP and LBP to corneal diagnosis by applying all strategies on the Elevation back map (%).	83
Table 4.36. Accuracy of cornea disease diagnosis apply proposed algorithm on all corneal topography maps (%).	84
Table 4.37. Accuracy of diagnosis of the proposed and standard SIFT (%).	84

ABBREVIATIONS

ANN	Artificial Neural Network
ASM	Angular Second Moment Feature
CAD	Computer Aided Diagnosis
CBC	Contrast Based Centre
CBR	Case-Based Reasoning
CFP	Columns Filtering Phase
CNN	Convolutional Neural Network
CT	Computed Tomography
CWT	Continuous Wavelet Transforms
DLT	Deep Learning Techniques
DOG	Difference of Gaussians
DT	Decision Tree
DWT	Discrete Wavelet Transform
ESI	Ectasia Status Index
FN	False Negative
FP	False Positive
GLCM	Gray Level Co-occurrence Matrix
GLOH	Gradient Location Gradient Graph
HCBC	Histogram of CBC
HLIP	Local Information and Patterns
IDM	Inverse Difference Moment
LBP	Local Binary Pattern
LIP	Local Information Pattern
LR	Logistic Regression
LSVM	Linear Support Vector Machines
MAE	Mean Absolute Error
ML	Machine Learning
MLP	Multi-Layer Perceptron
MLT	Machine Learning Techniques
MRI	Magnetic Resonance Imaging
MSE	Mean Square Error
NB	Näive Bayes
OCT	Optical Coherence Tomography
OPD	Optical Path Difference
PCA	Principal Component Analysis
PET	Positron Emission Tomography
RBF	Radial Basis Function
REF	Instrument Autorefraction
RFP	Rows Filtering Phase
RMSE	Rate Mean Square Error
ROC	Receiver Operating Characteristic
SIFT	Scale-Invariant Feature Transform
SVM	support vector machine
SWFT	Subbands Wavelet for Local Features Transform
TN	True Negative
TP	True Positive
VHF	Very High-Frequency
WF	Wave Front

1. INTRODUCTION

Currently, computer-aided diagnosis (CAD) is closely related to the area of medical imaging (Doi, 2007), which is a sophisticated procedure in medicine that assists physicians by using computer algorithms to aid the image interpretation process. Machine learning algorithms have become one of the most prevalent disease diagnostic methods (Kononenko, 2001). Such algorithms used to diagnose human eye diseases, one of the most sensitive, aggressive, and dangerous eye diseases is corneal diseases. The cornea is the front part of the eye which controls visual focus, carries more than two-third of the visual power and protects the eye from external foreign elements with its clear and smooth structure (Yang et al., 2018).

1.1 Human Cornea Background

The cornea is a smooth, clear structure at the front of the eye. It protects the eye from external substances and helps to control visual focus (Ludwig and Sevensma, 2018; Yang et al., 2018). Affecting factors for cornea damage are allergies, keratitis, dry eye, injury, and corneal dystrophies (Singh et al., 2017; Wan et al., 2017; Seitz et al., 2017). Corneal diseases are a serious condition that can cause clouding, distortion and eventually blindness. There are many types of corneal disease such as keratoconus, Fuchs' endothelial dystrophy, hereditary corneal dystrophies, corneal infection, and bullous keratopathy (Yamaguchi et al., 2017).

The cornea consists of five layers: epithelium, Bowman's layer, stroma, Descemet's membrane, and endothelium (Figure 1.1A) (Ludwig et al., 2018). The layer that absorbs oxygen to equip the other layers is called the epithelium, it is a soft layer, which prepares the nutrients it absorbs from tears to the rest of the layers, it is an external shell responsible for protecting the cornea from external impurities as illustrated in (Figure 1.1A light blue). The Bowman's layer is the second layer made up of collagen. This layer impedes the vision when injured or damaged (dark blue, Figure 1.1 A). The third layer is thicker than the other, which is composed of water with a little collagen, this layer called stroma, as shown in (gray, Figure 1.1 A). Next comes called Descemet's membrane layer, is a strong layer of collagen responsible for protecting the cornea from inflammation, in case of injury, this layer is renewed

through the deeper endothelial cells (orange, Figure 1.1 A) (Yang et al., 2018.). This layer responsible for the removal of excess fluid from the stroma, which leaks from the inside of the eye, as without the work of this layer swells the stroma, because of the lack of regeneration of endothelial cells in case of damage, leading to blindness (pink, Figure 1.1 A) (Ludwig et al., 2018).

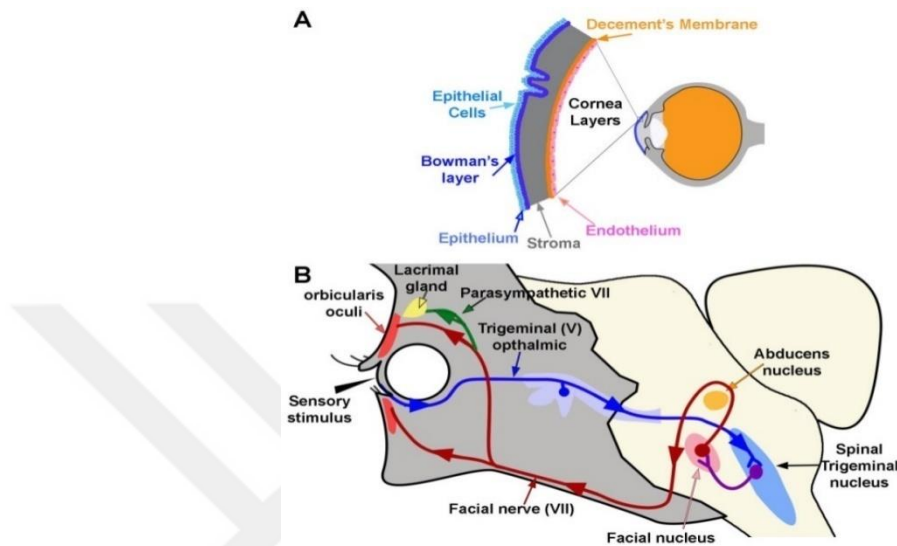


Figure 1.1. Eye cornea layers.

From the growing importance of the discovery of diseases that may affect the human cornea before aggravating the disease, it is an urgent need to build a reliable and accurate model of the surface of the cornea and especially its shape (Schwiegerling and Greivenkamp, 1989) because of its impact on the refraction of the eye, the analysis of topographical data is very important for ophthalmologists (Artal et al., 2002).

Corneal deformity leads to visual error, so models can help to detect the corneal diseases. On the other hand, the models could be used to monitor and evaluate the cornea after surgery (Maeda et al., 1995). Such these models can be composed and obtained for assessing structure and function of the cornea through corneal examination devices which are represented as cornea imaging techniques, such as Videokeratography, Orbscan, GALILEI, Optical coherence tomography (OCT), and ArcScan, that provides quicker and more accurate diagnosis and management of corneal diseases (Brody et al., 1994).

In the past, the topography of the cornea was only described as the frontal surface of the cornea. At present, the devices have an ability to distinguish corneal surfaces and build a complete map of the cornea with three dimensions that represent the shape of the cornea (Ambrósio and Belin, 2010).

The hardware development revolution began in the early 1980s and was characterized by the development of algorithms and methods for obtaining images from the Placido, a technique for assessing the shape of the cornea, where a reflection of the pattern of light is evaluated for a set of rings as seen in Figure 1.2, which represent the corneal shape (Klyce, 1984; Wilson et al., 2001). The posterior corneal surface cannot be characterized using Placido disc technology.

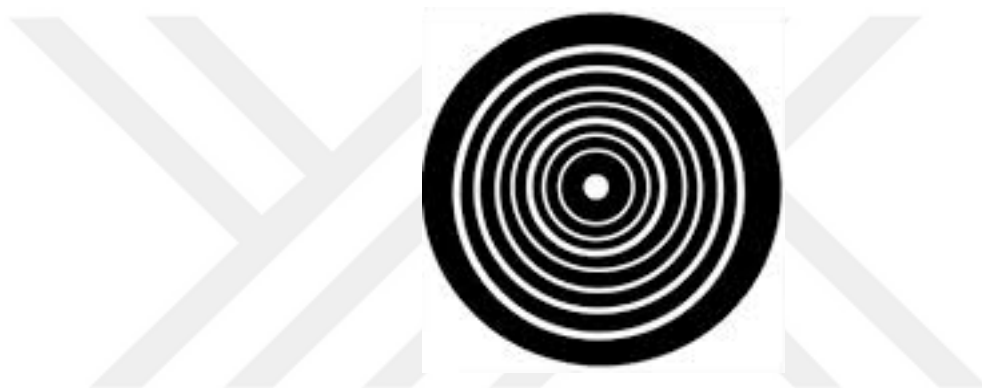


Figure 1.2. Placido pattern.

A hand-held corneal telescope (keratoscopes) is also used, where concentric rings are used with a lattice to evaluate the cornea as in Figure 1.3.



Figure 1.3. A hand-held telescope.

A second method has improved corneal tomography, known as scanning slit technique, using camcorders to record a reflection of a beam of light to form a map of the front and back of the cornea (Hashemi et al., 2010).

Finally, there is a technique capable of correcting the irregular shape of the cornea and making a three-dimensional map of the cornea with higher accuracy. It uses a rotating camera and depicts a set of sections of the cornea from different angles this technique known as Scheimpflug imaging, which used in this work (Oliveira et al., 2011).

Each of these devices has a specific way of the reading cornea and producing images as shown below.

a) Interpretation Placido Disc Images

As mentioned earlier, the Placido consists of concentric rings, these rings called mires. The corneal curvature can be deduced by examining the mires, as the sharp curvature of the cornea is coincided by very close mires to each other. On the other hand, the flat areas are represented as spaced mires. In addition, the good shape of the mires means that the cornea is smooth and regular (Ambrósio and Belin, 2010). Mires are distorted and irregular if the cornea suffered a disease, dry cornea, or suffering regular astigmatism, irregular astigmatism as shown in Figures 1.4 a, b, and c sequentially. In an undistorted cornea state (Normal), the mires should be equal to the surface of the cornea.

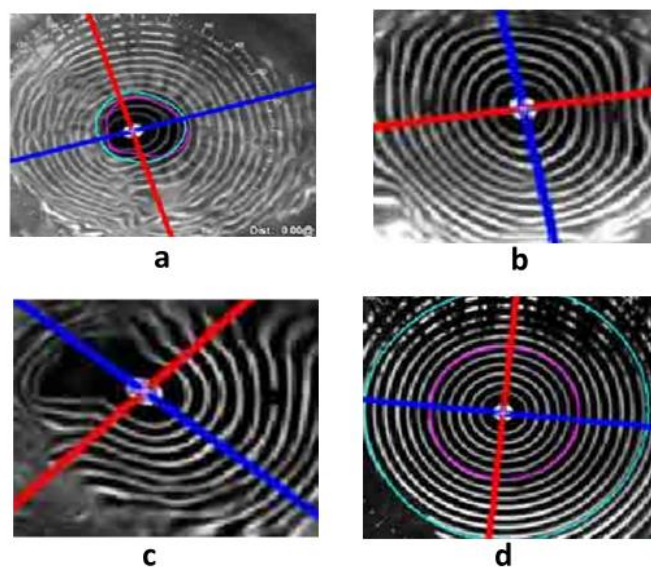


Figure 1.4. a. dry cornea b. regular astigmatism c. irregular astigmatism d. Normal

b) Interpretation of Atlas and NIDEK OPD-Scan

These types of devices usually use for screening purpose, it's given information of cornea elevation, tangential curvature, and axial curvature, it also produces maps, tangential provide the user a rich information of cornea curvature but it accompanied by some noise, as opposed to axial which appear less sensitivity to measure the cornea curvature. Both measurements are used in the NIDEK instrument autorefractometer (REF) and wave front (WF), to measure keratometry state. The Optical Path Difference (OPD) and the Internal OPD maps are produced, see Figure 1.5. (Friedman, 2013; Lopes et al., 2016).

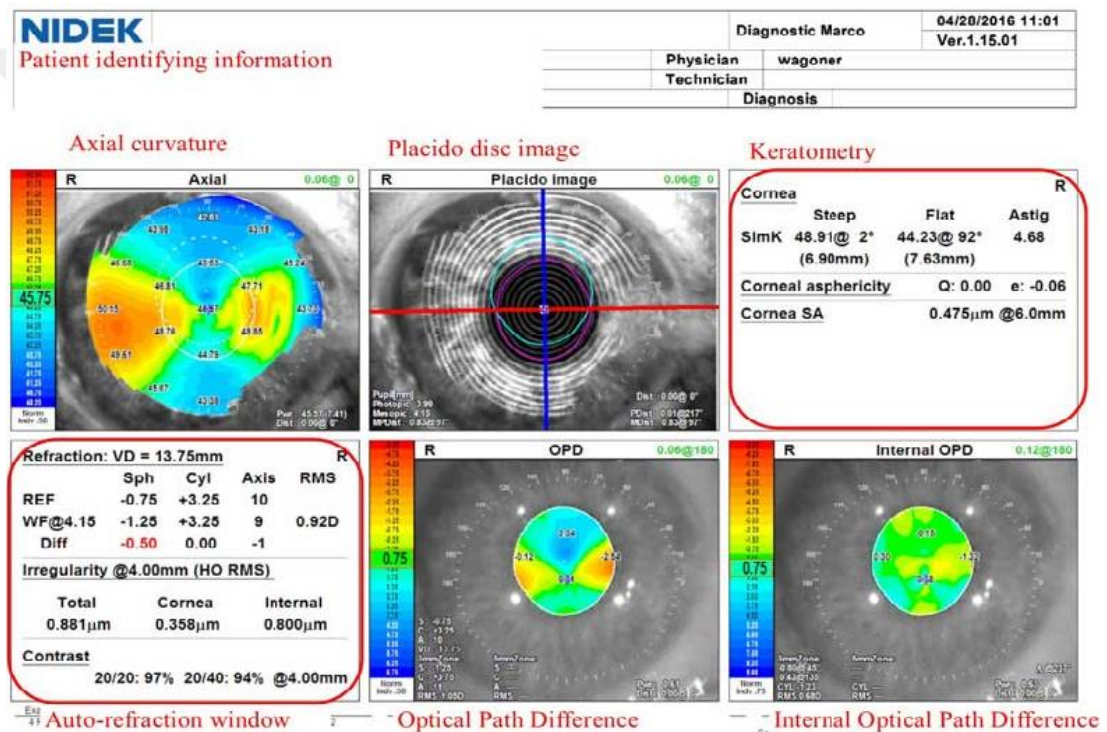


Figure 1.5. Optical Path Difference and the Internal OPD maps.

c) Interpretation of Pentacam

Four maps are produced using the Scheimpflug technique viewing the cornea, as shown in Figure 1.6. Front chamber, iris, and lens, as well as a comprehensive report containing information about the cornea is presented for the cornea and its curvature. It also provides a three-dimensional representation of the corneal shape, the corneal density also evaluated. A summary of the keratometry, pachymetry, and other numeric measurements is also reported. The shape of the cornea is displayed by elevation maps

through comparing it to a computer-generated best-fit sphere for both Posterior and anterior float (Sinjab, 2018; Quisling et al., 2006).

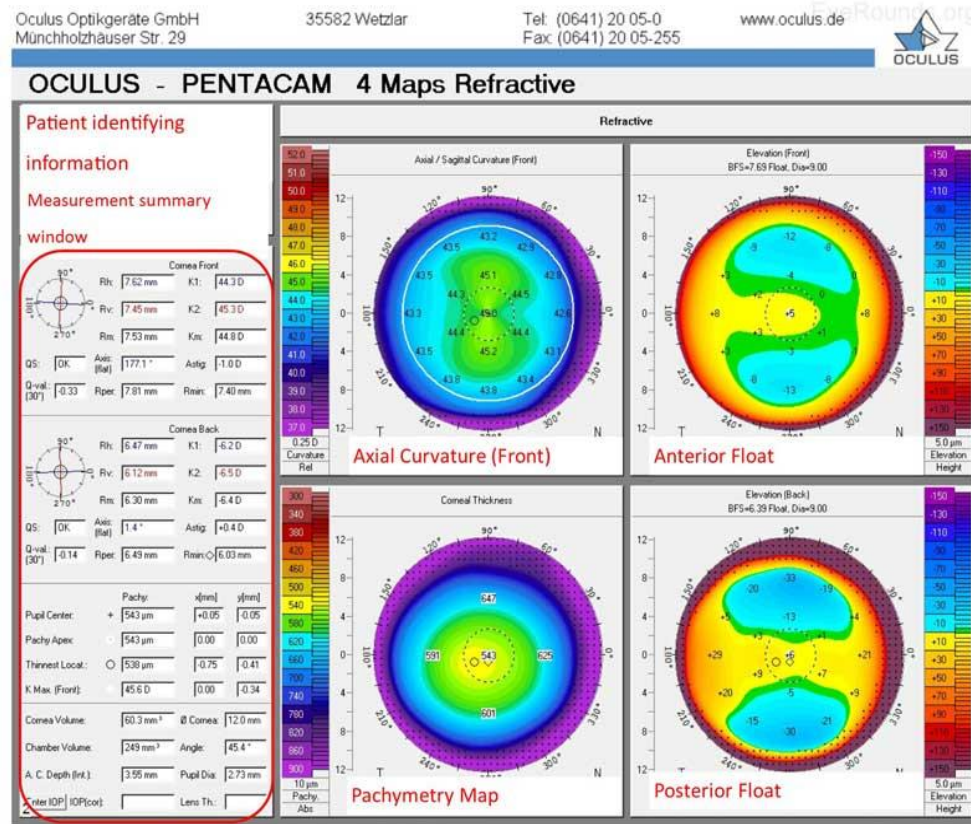


Figure 1.6. Pentacam output.

1.2 Challenges in CAD System

Processing the medical images using computer aided diagnosis (CAD) is an essential topic in the medical image (Doi, 2007). CAD is a sophisticated procedure in medicine that assists physicians in the interpretation of medical images; a procedure that use computer algorithms to aid the image interpretation process. Image feature analysis and data classification radiologic imaging have increasing importance in patient care. Today, the mainstream modalities, which are widely used in hospitals and medical centers, include radiography, fluoroscopy, computed tomography (CT), ultrasound, magnetic resonance imaging (MRI), positron emission tomography (PET), and corneal topography (Pereira, 2016).

The large set of images produced by screening Pentacam tests constitute a huge workload for the Ophthalmologists that need to interpret cornea images in order to

study the state of the patient's cornea. Thus, the computerized analysis will have a great impact in terms of easing the workload and assisting in the detection or diagnosis of corneal diseases.

There are many cases where the cornea including normal and abnormal, in addition to the types of diseases under the heading of cornea abnormality, i.e. the diagnostic system faces obstacles in the extraction of the precise characteristics that lead to a perfect diagnosis (Wirawan et al., 2012).

In general, CAD system includes a number of stages, as in Figure 1.7, such as preprocessing, segmentation, extraction the features and select the appropriate, and diagnosis. Each of these events affects negatively or positively on the step that follows. Corneal images/maps can be processed to remove noise, as well as segment the important part of the map, and thus diagnose the condition of the cornea (Li and Nishikawa, 2015; Masala, 2006).

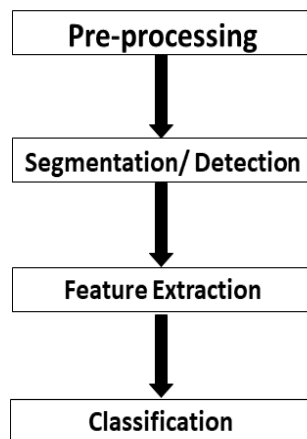


Figure 1.7. CAD stages.

Images taken from the scanning process may contain noise and impurities due to internal or external effects, so pre-processing is very important in a system, which may play a very important role in image analysis. There are many pre-processor methods such as noise removal, blur and focus corrections, region processing and filters, and illumination corrections (Krig, 2016; Vidal and Amigo, 2012).

The process of separation of images is one of the important stages in the CAD system and diagnosis planning (Sharma and Aggarwal, 2010). At this stage an area of interest

is separated in order to focus efforts on those areas, the segmentation process helps to determine the shape of the medical images (Piorkowski et al., 2017).

Extracting features from medical images is the most important step in the CAD system. Some types of features and characteristics are vague and invisible to ophthalmologists, such as texture, color features, and etc. These features are the key of the classification process, as the workbooks use these features as a raw material for classification process in order to separate the dataset into classes. Extracting poor features is insufficient for accurate diagnosis, analyzing the medical image for deep features and comprehensive characteristics may lead to a more accurate and efficient diagnosis. In addition, the choice stage of suitable features which called feature selection has the greatest influence on the classification results and thus on the process of diagnosis (Udomhunsakul and Wongsita, 2004).

1.3 CAD System Evaluation

There are various measures used to assess the performance of the diagnostic and detection, thus assess the performance of the CAD system such as accuracy, recall, precession, sensitivity, and specificity (Zhu et al., 2010; Anooj, 2012). Firstly, since seeking to enlarge the value of true positives and lessen the number of false positives, adopting the following computations, the proportion of cases that are genuinely positive and algorithm test also result in positive (recall), the proportion of the overall relevant results correctly classified by the system (precision), and the proportion of true results (positives and negatives) among all cases examined (accuracy) (Saito and Rehmsmeier, 2015) which calculated from Equations (1.1), (1.2), and (1.3) respectively. Secondly, paying attention to examines true negative rates, by measuring the following: the proportion of genuinely negative cases and the algorithm test also results negative (specificity), and the receiver operating characteristic (ROC) curve, which is commonly used in the literature that can define false detection rates (1–precision) (Agarwal and Roth, 2002; Fawcett, 2006), as denoted in Equation (1.4), and (1.5) respectively.

$$Sensitivity(recall) = \frac{True\ positive(TP)}{True\ positive(TP) + False\ Negative(FN)} \quad (1.1)$$

$$\text{precision} = \frac{\text{True positive}(TP)}{\text{True positive}(TP) + \text{False positive}(FP)} \quad (1.2)$$

$$\text{Accuracy} = \frac{(TP + TN)}{(TP + FP + TN + FN)} \quad (1.3)$$

$$\text{Specificity} = \frac{\text{True Negative}(TN)}{\text{True Negative}(TN) + \text{False positive}(FP)} \quad (1.4)$$

$$1 - \text{Precision} = \frac{\text{False positive}(FP)}{\text{False positive}(FP) + \text{True positive}(TP)} \quad (1.5)$$

where, TP is the result obtained by CAD system identifying corneal with diseases are compatible with the standard diagnostic. FN is the negative case that the model predicted incorrectly. (see Table 1). The value of the measurements is ranged between 0 and 1.

Table1.1. Terminology and derivations from a confusion matrix.

		Standard	
		Positive (cornea demonstrate normal)	Negative (cornea demonstrate abnormal)
CAD	Positive	TP	FP
	Negative	FN	TN

1.4 Corneal Image Databases

The dataset is consisting of images obtained by scanning the cornea called corneal topography which is used by ophthalmologists for the examination of the eye in clinics. Each patient's eye data are stored separately, which contains four corneal maps and a set of parameters. This information has an important role in the diagnostic process. The dataset collected using a device called a Pentacam, which is based on imaging Scheimpflug. The camera scans the eye from several angles in a circular path to provides information about the anterior and posterior segments of the cornea in the shape of maps as well as provides a fast screening report. The Oculus Pentacam can be updated and upgraded to suit the needs of the user (Hashemi and Mehravaran, 2010). The dataset comprises 4348 images of different maps such as sagittal, corneal thickness, elevation front, and elevation back maps, collected and labeled scientifically

with the help of ophthalmologists. Each image has a resolution 351 x 461 x 3. Example of the four maps shown in Figure 1.8.

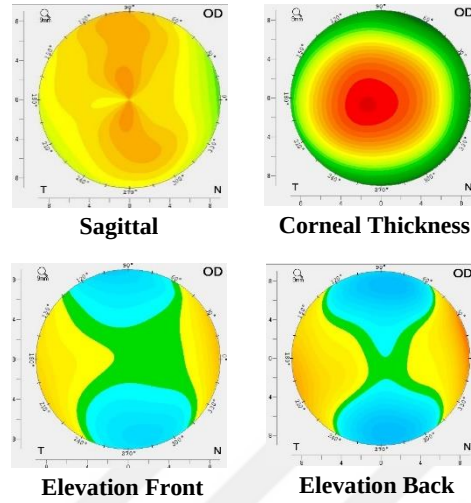


Figure 1.8. Corneal topography containing the four maps.

1.5 Thesis Motivation

Corneal diseases are a serious condition that can cause clouding, distortion and eventually blindness. There are many types of corneal disease such as keratoconus, Fuchs' endothelial dystrophy, hereditary corneal dystrophies, corneal infection, and bullous keratopathy (Yamaguchi et al., 2017).

Since the cause of most corneal diseases is still not certain, prevention against the complications of the disease and blind remains a challenge. However, there is a chance of complete recovery if an efficient diagnosis is made at an early stage. In other words, early detection of the diseases can play a key role in reducing blindness rates.

In recent decades, a great development has been made in the scanning tools of the cornea, which has helped to increase the accuracy of the diagnosis, but some obstacles are still a stumbling block in the way of accurate diagnoses such as noise accompanying the scan, distortions that appear in pictures, and other factors that negatively affect the purity of images.

Through the literature the guide for the cornea topographical parameters and the maps/images mostly discussed by different studies that could computerize and suggested a solution to improve the clinical decision (Sinjab, 2012).

These information and studies gave justification and motivation to create and design Computer-aided detection/diagnosis (CAD) systems, which use advanced image analysis techniques to detect abnormalities of the cornea. labeling the dataset images to the normal and abnormal is the first step towards detecting diseases with the help of ophthalmologists.

1.6 Thesis Aims and Contributions

To reduce the incidence of blindness due to certain corneal diseases, and prevent the aggravation of the disease and the occurrence of complications, it is necessary to build a CAD system relies on machine learning algorithms to analyze images and using data produced by the scanning in order to help perfect diagnosis needed by the ophthalmologists to make a decision. The objective of this thesis is to supply a screening algorithm design to aid in detecting corneal diseases, by providing and improve materials that are considered essential to develop a Computer-Aided detection system. In order to satisfy the mentioned aims, it can be stated the major contributions as follows:

1. Design a CAD systems able to determining the borderline for a topographical parameter that will be affecting the final clinical decision.
2. Investigate and propose multi-resolution feature extraction based on wavelet and Scale-Invariant Feature Transform (SIFT).
3. Classifiers are investigating and discuss such as support vector machine (SVM), Decision tree, k-nearest neighborhood, and Naïve Bayes.
4. Proposing a SWFT algorithm that employs the power of wavelet transform to improve the performance of the SIFT.
5. Composing an algorithm (IG-GLCM) to improve diagnosis accuracy and overcome the problem of time-consuming.
6. Overcoming the lack of losing information (LIP) by proposed an algorithm reserve the image information when calculating the features.

7. Provided suitably, trainables, and adaptive system to help the ophthalmologists with the behavior procedure.
8. Evaluating the most popular algorithms that fit with such a case.

1.7 Method of Study

A quantitative method will be used in this study, it is a type of general classification of research methods that intended to develop and employ a mathematical model and focused on the derivation of a conclusion from existing data using proven statistical or general quantitative methods (Mundar et al., 2012). One of the tools that will be used to get the data is called Pentacam i.e. device that gives corneal topography to evaluate the anterior, posterior, and total corneal power and astigmatism (García-García et al., 2019), which acquires images during a 180° rotation around the optical axis (Lackner et al., 2005), in addition it gives a set of parameters that help the specialist to build a perfect spectacle of the situation of the cornea.

The collected data, is processed through classifying it into classes with the assistance of specialists in this field in order to be ready for the processing and use to overcome the challenge mentioned in Section 1.2. Diagnosis and prediction for the topographical parameters are conducted through the number of smart algorithms after taking the supervised decision from the ophthalmologist, as well as the normality, and abnormality map will be computed after reviewing topographical parameters to present a new clinical decision map after validating by the ophthalmologists. Last stage of the CAD system is the classification, where it is determined whether the cornea contains disease or not, and what is the disease specifically, and can also determine the stage of the disease. This stage is conducted using one or more of the traditional machine learning algorithms such as decision tree, support vector machine, KNN, decision tree, Naive Bayes (Antonie et al., 2001; Li et al., 2014).

1.8 Thesis Outline

The rest of the thesis is organized as follows:

- Chapter Two: Provides a literature survey about the CAD system that used to detect the corneal diseases, a survey includes the machine learning techniques that had used as tool for diagnosing the diseases that infect the cornea.

- Chapter Three: Methodology. Describes and justifies outlines of data analyzing, defining the selected method, and describe research design and proposed algorithms used to increase system performance.
- Chapter Four: Findings. Addresses the results from data analysis, and describe analyses that conducted, used tables and figures to illustrate and summarize all numeric information and discuss the relation between the findings and the theory.
- Chapter Five: Conclusion. Conclude the thesis, and direction of future research work.



2. LITERATURE REVIEW

Machine learning is one of the important classes of artificial intelligence (Rahimy, 2018), it is oriented by a group of mathematical models, algorithms, and statistics using the computer as an instrument for performing certain tasks faster and with high accuracy with no instructions to the system. Machine learning systems are offered with particular symbols and patterns known as training data, which, the prediction and decision-making process is performed utilizing mathematical models based on a pre-programmed action of a definite function (Koza, 1996; Bishop, 2006).

These methods were utilized in numerous medical applications and fields for diagnostic targets with various medical images, in which the mathematical optimization methods are utilized on the input image to extract the characteristics known as feature vector used by the system for prediction and decision-making (Friedman, 1998). Corneal illnesses diagnosis is among these applications.

The cornea is the front part of the eye controlling the visual focus, and the part protecting the eye from external foreign elements with a clear and smooth structure (Rehman et al., 2019; Yang et al., 2018). Corneal disease as a serious condition cause distortion, clouding, and eventually blindness. Numerous kinds of corneal diseases exist to diagnose corneal diseases and tests are carried out under the ophthalmologists' supervision through progressive tools like corneal topography. These tools are able to scan the eye and provide outputs easy to analyze by specialists to make the optimum decision of the cornea condition (Ambrósio et al., 2010).

In the medical image, processing the medical images through computer aid diagnosis (CAD) is an essential topic (Doi, 2007). CAD is a sophisticated process in medicine helping physicians to interpret the medical images “using computer algorithms to assist in the image interpretation process”. Data classification Radiologic imaging and image feature analysis are increasingly important in-patient care. Nowadays, mainstream modalities are extensively utilized in medical centers and hospitals (Pereira et al., 2016).

Presently, numerous types of research aimed at developing tools and programs to diagnose eye troubles and corneal diseases in general (Fujita et al., 2008). This survey

includes all types of corneal scanning tools for CAD methods and systems to obtain data such as clinical data, image-based data representing the inputs (data, parameters, or the images) for CAD systems dominant for cornea disease diagnosis. However, there is no method in previous surveys providing a great motivation to offer a survey covering all the researches using such tools and developed approaches for CAD in cornea researches. It is worth noting that the parameters are data generated by the corneal eye examination devices, although some devices are not estimating all parameters but most of them. such as keratometric, pachymetric, posterior elevation, Pachymetric, anterior segment, Anterior chamber, corneal thickness, and sagittal parameters.

These studies used complex and different medical devices for data obtaining, some of devices have specifications which are not available in another. Additionally, the companies continue for developing devices able to capture the cornea's data better and easier to be used by ophthalmologists. This survey is arranged in terms of the type of device used for obtaining the data. Moreover, indicating the types of techniques used for the diagnostic process for each research, which most of them belong to machine learning techniques (MLT), while the rest belong to deep learning techniques (DLT), which is an extension of the first.

2.1 Review

In this survey, previous research was assorted according to the device types used to obtain corneal data.

2.1.1 Videokeratography

Videokeratography is one of the dominant ways to capture the cornea data. The data were utilized by researchers in 1995 to find the cornea's abnormality (astigmatism, keratoconus-mild, keratoconus-advance, keratoconus-moderate, poskeratoplosty, postphotorefraction keratectomy) through using one of machine learning technique which is artificial neural network (MLT-ANN). The authors characterized the dataset into various types of cornea diseases for training their system. A 183 cases with eleven parameters for each case were used as an input to the system. For disease detection, the overall precision of the system performance is 80%. They concluded that

topographical maps would be cooperative for diagnosing corneal diseases (Maeda et al., 1995).

Researchers in 1997, utilized a data set as input to the proposed system, containing numerous corneal diseases like keratoconus and suspect keratoconus, contact lens-including warpage, astigmatism, pellucid marginal degradation, photorefractive keratectomy gathered from 300 cases. The system outputs were in 3 groups of keratoconus, suspect keratoconus, and others. The data were gathered from the topographic modeling system (TOMY) and inserted into the MLT-ANN system for processing as the system input consisting of two diverse networks. The first network detects the keratoconus and keratoconus suspect, however, the other is for the severity of a cone pattern. They concluded that by neural networks, the keratoconus can be distinguished from other diseases (Smolek and Klyce, 1997).

To discriminate between keratoconus, normal, and other alterations of the cornea for both eyes for each subject, a system was built through MLT-ANN with less than 10 hidden layers and with learning rate 0.1. The system performance yielded very good results with a global sensitivity of 94% for entire cases. The authors concluded that the accuracy rate of correct diagnosis can be increased by utilizing the topographical parameters for both eyes (Accardo and Pensiero, 2002). An investigation was performed in 2003, to diagnose the human cornea using polynomial coefficients as input to the classifiers with the classification rate reaching 91%. This study concludes the effectiveness of the system in the clinics (Twa et al., 2003).

A group of authors, developed an MLT-ANN, in 2005. Using the coefficients of the Zernike various types of corneal categories were classified (normal, with-the-rule astigmatism, against-the-rule astigmatism, keratoconus, and post-laser-assisted in situ keratomileusis), with 15 neurons as input to the network and 5 cornea shapes as production. The system worked effectively with the accuracy of 94% for all the cases. The results of this study indicated that Zernike coefficients are a key parameter and could be used to estimate corneal shape, particularly through MLT-ANN even in the limited dataset cases (Carvalho, 2005).

In 2005, a dataset was provided including 132 normal cases, and 112 cases suffering from keratoconus employed as row data to create a system using machine learning

technique-decision tree classifiers (MLT-DT) for predicting the keratoconus cornea diseases. In this system the data were captured from 7th-order Zernike polynomial with a classification accuracy of 92%. Hence, it was concluded that using the decision tree to analyze the Zernike coefficients is a perfect quantitative technique for distinguishing keratoconus disease (Twa et al., 2005).

In late 2008, a study was performed using an artificial neural network (MLT-ANN) to detect typical cornea shape. In this study, a first 15 standard Zernike coefficients were utilized as input to the system, for which the data were acquired from the Eyesys System 2000 Videokeratograph device with 80 patients taken as a dataset of the system. The overall cases' accuracy was 94%. The authors deduced that despite using a relatively slight dataset, according to the results, Zernike coefficients could be used as reliable inputs for a system using neural networks for diagnosing some corneal diseases (Carvalho and Barbosa, 2008).

In 2012, a set of parameters were used directly from the pentagram device and 3 additional parameters determined from the maps extracted from the same tool to classify the cornea disease cases. In these cases, the dataset contained 125 eyes separated into 47 cases with keratoconus, 43 suspects to keratoconus, and 47 normal corneas. The authors used 4 classifiers of MLT-DT, radial basis function (MLT-RBF), Multi-Layer Perceptron (MLT-MLP), and support vector machine (MLT-SVM). By classifying the accuracy of 84% as the highest accuracy among all classifiers, the system performance was measured. In this study, it was concluded that the performance of the system could be improved by extracting more properties from the images (Toutounchian et al., 2012).

Zernike coefficients were used to train a system including 4 methods (k-nearest neighbor algorithm, linear discriminant analysis, neural network method, and Mahalanobis distance method), which are algorithms of machine learning techniques. To analyze the data, 212 cases were taken as a case study including normal cases, keratoconus, and keratoconus suspect with the dataset separated into two parts of testing and training and the average classification accuracy of 79%. They found that exploiting the data from Zernike coefficients could result in enhanced disease diagnoses (Saika et al., 2013).

In 2014, in a Master research, 151 images were employed in various cases and the investigators concentrated on distinguishing between the keratoconus and astigmatism diseases using the shape of the sagittal map. Therefore, an image processing technique (erode, dilate, open, close, and thick) was used to extract the shape and to identify between these two diseases. The results were calculated in terms of the confusion matrix and the accuracy of 74% for all the data. It was concluded that morphological operation was effective in diagnosing some cornea disease (Ali and Singh, 2014). In 2014, an approach was proposed by some authors to find cornea diseases, where the ability was observed to distinguish between astigmatism and keratoconus via various kinds of machine learning algorithms. It was found that MLT-ANN had the best performance (Valdés-Mas et al., 2014).

The data from 860 eyes were used as the input to a system using MLT-SVM to find cornea diseases such as forme fruste, Keratoconus, astigmatic, after refractive surgery, and normal eyes. As the feature vectors, 25 parameters were used, while achieving the accuracy of 88% for the system for all categories. They concluded that utilizing multi parameters as SVM input is optimal to increase the system performance rather than the single parameter (Hidalgo et al., 2016).

Through the spotlight on ectatic corneal diseases, and importunity is provided for search about its diagnosis methods. Therefore, some machine learning algorithms such as MLT-ANN, MLT-SVM, regression analysis, and decision tree algorithms were used by some researchers in 2016, to diagnose the disease. The data were collected from a group of patients, and 23 cases were found with ectasia after LASIK and from 266 stable post-LASIK cases with over one year of follow up. The results contained the sensitivity of 100% through the regression algorithm, and they concluded that this investigation approach still requires validation (Lopes et al., 2016).

Using an image processing technique, the features were extracted from the cornea maps, where the features for each map are extracted to exploit for decision making regarding the normal cornea condition or not. In this research, to find the corneal disease an MLT-SVM was used as a classifier. The dataset included 40 cases, 22 were female and the remaining were male. For all cases, the classification rate was 90%. It was observed that the cornea suffering from keratoconus disease involved a standard deviation of the top half for the cornea circle compared to the normal case, however, it

was higher in the bottom half (Ali et al., 2017).

Combining the cornea thickness and elevation, some parameters were represented to classify the keratoconus and normal corneas by MLT-SVM as a classifier. By the system performance of 97% sensitivity, the authors concluded that the currently suggested approach was reliable (Gao et al., 2017).

In 2018, a class of deep learning technique DLT-VGG-16 network was used to predict the corneal abnormality and normality using 732 submap (sagittal map, the elevation back map, the elevation front map, and the corneal thickness map) as input to the deep learning network trained individually and the results were obtained as 88.8%, 98.9%, 94.8%, and 94.5% respectively (Salih and Hussein, 2018).

In the same year, a group of authors worked on the detection of the keratoconus eyes dataset and recognition from the normal cornea. They utilized a collection of images (maps) including 145 normal cornea cases and 312 keratoconus cases. Using an MLT-SVM and multilayer perceptron algorithms as a classification tool, the features were extracted from the input images followed by inserting the parameters to the classifiers. The results indicated the system performance accuracy of 94% for all the data and they concluded that using such approach the system can be developed to reach a greater classification rate (Issarti et al., 2018).

As a case study, a model was created using one of the machine learning technique called forest algorithm and other AI models for diagnosing the diseases. Hence, within three groups (LASIK, ectasia susceptibility, and clinical keratoconus cases), the random forest performance was higher among all the models. The authors found that the ectasia risk needed to be assessed through perfect tools like the mentioned model (Lopes et al., 2018).

In 2019, using the SyntEyes model, two researchers utilized 145 cornea cases with and without keratoconus disease to create 3000 cases half with keratoconus disease and the remainder as the healthy cornea. The generated images were inserted as input to the deep learning technique-Convolutional neural network (DLT-CNN) system. They proposed the system termed Kerato Detect and the result mentioned in this paper was 99.33%. The ability for using as an integrated part of the diagnostic process is an

advantage of the proposed algorithm (Lavric and Valentin, 2019).

Using a feedforward MLT-ANN, 4 groups of corneal diseases were used as a dataset for classifying, and 851 cases with various states were used for training the system. They found the suspect keratoconus with an accuracy of 96.56%, 89.00% for Belin/Ambrosio Deviation, and 79% for Topographical Keratoconus Classification. Within this study, it was concluded that the proposed system can contribute to the early detection of keratoconus (Issarti et al., 2019).

2.1.2 Artemis and videokeratography

In a study, the patients' eyes were scanned using Pentacam and Ultrasound biomicroscopy (Artemis), and the parameters were examined through machine learning technique-stepwise linear discriminant analysis (MLT-SLD) to distinguish between keratoconus and normal cornea. The data of the system were gathered from three resources as data from Artemis, individual data extracted from pentagram, and the combination of both datasets. The result indicated that Artemis, Pentacam, and combined model contained the sensitivity of 100%, 97.3%, and 97.3% respectively. They concluded that using the model for early and subclinical keratoconus would ultimately require evaluating the combined approach effectiveness (Silverman et al., 2017).

2.1.3 ORA, pentacam, visante, and orbscan.

To detect astigmatism conditions, 96 measurements were taken from various patients, and the parameters were acquired by various types of tools. For classification, three different approaches were used as ANN with 8 hidden neurons, MLT-ANN with 10 hidden neurons, and decision tree algorithms. The system was evaluated using various measurements such as Mean Square Error (MSE), Rate Mean Square Error (RMES), and mean Absolute Error (MAE). The results indicated that most optimal results are found by the system with 8 hidden neurons. In this paper, summarized that the keratometry and the position of the ring are most astigmatism-related features (Valdés-Mas et al., 2014).

2.1.4 Keratron corneal topographer 2000

To detect the keratoconus cornea, a group used data for Zernike coefficients, which included 82 normal cases and 99 keratoconus cases. The MLT-DT classifier was utilized as a classification instrument. Comparing the result of this system with another model, 95% accuracy was obtained for this model for entire cases and it was concluded that using the Zernike parameters is effective to detect the keratoconus through machine learning algorithms (Twa et al., 2000).

2.1.5 Precision tomographic examination

In 2017, researchers used MLT-ANN (a mono-objective Genetic Algorithm), and a high-level accuracy was obtained to detect the keratoconus disease. The data were extracted from the Pentacam, and the classification rate of over 90% was obtained (Bevilacqua et al., 2017).

2.1.6 Galilei analyzer system

Using GALILEI Analyzer System for 55 parameters captured that involved 372 cases classified into normal, forme fruste, and keratoconus cases. To distinguish the different types of groups, machine learning algorithms were used (i.e. MLT-DT) in terms of three cornea diseases mentioned above. Using the parameters, very optimal system performance was very obtained, therefore, this study concluded that employing machine learning could lead to a perfect performance in diagnosing the corneal disease (Smadja et al., 2013).

2.1.7 Orbscan

In 2006, a team managed research to find the keratoconus and suspect keratoconus condition of the cornea, 165 cases were made with a slit-scanning corneal topographer. The anterior and posterior parameters of the corneal surface and corneal thickness were inserted in machine learning technique-logistic regression analysis (MLT-LR). Providing the sensitivity of 96%, it was concluded that the Orbscan information is effective to detect and diagnose the cornea disorders (Bessho et al., 2006). Marsolo's team conducted research using different kinds of classifiers, Zernike and pseudo-Zernike polynomials were employed as an input parameter to a system, i.e. C4.5 MLT-

DT, MLT-ANN networks, machine learning-technique Naïve Bayes algorithm (MLT-NB), and Voting Feature Intervals, to diagnosis the various type of diseases (postoperative myopic LASIK, keratoconus, and normal). Spatial transformations were utilized to compare with the results of Zernike and pseudo-Zernike polynomials. According to the results of this study, which indicated that better feature representation is provided by the Zernike polynomials than the pseudo-Zernike, moreover, the decision tree classifier obtained the highest classifier accuracy. concluded of this study is, increasing the fidelity of the surface model, classification performance was not improved and variations to their strategy may contribute to further enhance this classification exercise (Marsolo et al., 2007).

A back-propagation MLT-ANN used by a team as an essential instrument for distinguishing between the keratoconus and normal cornea, the authors used 98 cases, and 25 tests to assess the network performance, 19 were normal, and 6 presented keratoconus. The network found sensitivity and specificity of 83% and 100%, respectively (Souza et al., 2008).

To test three various machine learning technique classifiers (SVM, multi-layer perceptron, and radial basis function neural network) Souza's group had obtained parameters from 318 cases that were used for training and testing the performance of the classifiers that 11 parameters captured from each case. The accuracy, sensitivity, and specificity calculated for every classifier with very close results. The authors propose to use all the mentioned classifiers as the tools for detecting the keratoconus disease (Souza et al., 2010).

In 2011, researchers adopted a dataset with 344 cases as input to MLT-SVM and MLT-ANN systems to extract a set of parameters, the data were classified into various groups for training the system to diagnose the cornea condition (normal, keratoconus, astigmatism, forme fruste keratoconus, photorefractive keratectomy, and keratoconus suspect) and both the classifiers acted perfectly. Ultimately, they summarized that MLT-ANN and MLT-SVM are brilliant tools for improving the keratoconus detection procedure (Souza, 2011).

2.1.8 ATLAS 9000

An ATLAS 9000 has employed by researchers as a medium to find the cornea diseases, a MLT-SVM method was used with 12 parameters for each case of study as a feature vector to the system. All the cases were collected through ATLAS 9000 to train the system, 239 cases were classified as non-normal cases with 80 cases as the normal cases. By the discrimination percentage of 90%, the system worked efficiently. This study indicates that passing the parameters extracted from the corneal topography as a feature vector to the SVM classifier is effective in predicting some corneal diseases (keratoconus, hyperopic laser vision correction, suspect keratoconus, myopia, orthokeratology, and pellucid marginal degeneration) (Bagherinia et al., 2008).

2.1.9 Optical coherence tomography

A group of researchers utilized SS-1000 CASIA 1.1.1 Optical coherence tomography (OCT) imaging systems for acquiring 3156 cases with Ectasia Status Index (ESI), and they created 420 corneal parameters. Contributing the machine learning technique, they created a system for detecting the corneal keratoconus. The principal component analysis was used to reduce the dimensionality of data, as well as used the manifold learning for selecting two Eigen-parameters. Hence, using CLUTO software, it was altered to the MLT-k-mean clustering technique for classifying the data into 4 predefined types of the eye with the same cornea characteristic to detect the keratoconus condition. They found the use of the parameters from the cornea profiles as essential in the detection of the keratoconus status by clustering techniques and indicated that such a system is useful in clinics for improving the keratoconus diagnosis (Yousefi et al., 2018).

2.1.10 ArcScan

All the data were extracted by Silverman and his group, from a machine with a very high-frequency (VHF) digital ultrasound system, the images (maps) acquisition from 130 normal and 74 keratoconic subjects. The features were captured from the images producing 161 features vector for each arbitrary image and were used as input to the MLT-ANN for classifying into normal or keratoconus cornea. The result indicated that a very good system performance, wherever, the sensitivity was 94% for all cases.

According to the results of this paper, it was confirmed that epithelial remodeling is an independent factor to distinguish between the normal and keratoconus cornea (Silverman et al., 2014). Three years later, a team, used the same machine to gain data for diagnoses cornea diseases, data from Sirius, another physical tests have complied with 143 healthy eyes, and 321 keratoconus eyes to be used in logistic regression analysis. There was a significant difference between the normal and keratoconus cornea, as well as between the keratoconus group, and the parameters were boosted for diagnosing rate to be 97% for all the cases. This study concluded that analyzing the cornea as a solid is important for keratoconus detection (Cavas-Martínez et al., 2017).

2.1.11 Data combined from scheimpflug and placido

In the study of Arbelaez's team, a collection of data derived from both Placido and Scheimpflug is used as a vector of features to MLT-SVM to analyze and classify into various corneal diseases, and the gathered dataset included 1259 normal cases, 877 cases with keratoconus, and 426 cases with subclinical keratoconus. The data of posterior and anterior corneal surface, corneal thickness and iris are extracted from Scheimpflug, however, anterior surface data from both Scheimpflug and Placido images are merged utilizing a proprietary technique. The system was tested with and without posterior corneal surface, and the excellent performance was obtained in both cases with an accuracy of 93% and 95% respectively. It was concluded that the thickness and the posterior parameters are essential instruments for predicting the corneal keratinous, and preventing an eye surgery with early corneal ectasia disease (Arbelaez et al., 2012).

2.1.12 Physician examination data

In 2014, researchers placed MLT-SVM and MLT-ANN as instruments to detect the hyperopia, myopia, and astigmatism. The data obtained from clinics including the information regarding SPH and CYL of patients showed the accuracy of 92% for the system performance for disease detection and 97% for MLT-ANN and MLT-SVM respectively. The authors concluded that the MLT-SVM using Kernel function is more appropriate than MLT-ANN to deal with such cases, as a result of using feature space for classification rather than input space (Noaman et al., 2014).

2.1.13 Eyesys system 2000

A group of researchers used a chosen objective parameter and MLT-ANN to classify the cornea into normal or keratoconus disease. The two techniques were utilized as monocular (data of only one eye) and binocular (data from both eyes). It was indicated that using the parameters from both eyes does not improve the ability of the MLT-ANN. The classification accuracy was 92%. Ultimately, the authors concluded that the monocular and binocular are indifferently used for keratoconus detection (Perissutti et al., 1998). MLT-DT classifier have used, 208 cases were classified into 8 classes (normal, cataract, astigmatism, radial keratotomy, myopic keratomileusis, photorefractive keratectomy, penetrating keratoplasty, and keratoconus) while combining 2 indices, and the sensitivity and specificity of 88.5% and 94.9% were respectively obtained by the system. It was concluded that a decision tree combining 2 indices from the EyeSys system is an effective tool to detect the keratoconus disease (Chastang, 2000).

2.1.14 Data from interview

In 2014, a team worked with a system to diagnose the cornea diseases, they created the knowledge base of the system served from an interview with experts. An MLT-NB classifier was used as a classification method while using Case-Based Reasoning (CBR) for reasoning as well. The accuracy of the system efficiency was 82%. This study concluded that the MLT-NB classifier is a powerful tool effectively in the expert system to diagnose corneal diseases (Kurniawan et al., 2014).

In the following Tables, a complete survey of all researches mentioned in this paper is represented, associated with corneal disease diagnosis studies using machine- learning algorithms. Table 2.1 comprises a set of attributes. Which provides the re- searcher with information about each research, including the kind of data that was used, the diseases that were diagnosed, in addition to the machine/deep learning algorithms that were exploited for diagnosing corneal diseases, and the device's brand that used to obtain data. This gives the researcher the ease and flexibility to find the information he is looking for.

Table 2.1. All research for diagnosis arranged based on the device type.

Devices	Reference	Type of data	Normality	Kerato	Sus.kerato	Astigmat	Relloid	Mayopia	AdvanceKera	mild-Kera	Postphot	Postkera	contact lens-	forme fruste	ectasia	pellucid	Orthokeratolo	Algorithms
Videokeratography	(Maeda et al., 1995)	P				*			*	*	*	*						ANN
	(Smolek and Klyce, 1997)	P		*	*	*	*				*		*					ANN
	(Accardo and Pensiero, 2002)	P		*														ANN
	(Twa M.D., et al., 2003)	Z																DT
	(Twa et al., 2005)	Z		*														DT
	(Carvalho, 2005)	Z		*		*												ANN
	(Carvalho and Barbosa, 2008)	Z		*	*	*												ANN
	(Toutounchia et al., 2012)	P		*	*													DT SVM MLP RBF
	(Saika et al., 2013)	Z		*	*													KMN
	(Vald_es-Mas et al., 2014)	P		*		*												M.L
	(Ali and Singh, 2014)	I		*		*												morphologic operation
	(Hidalgo et al., 2016)	P		*		*								*				SVM
	(Lopes et al., 2016)	P													*			SVM, NN, DT, regression analysis
	(Ali et al., 2017)	I	*															SVM
	(Gao et al., 2015)	P		*														SVM
	(Issarti et al., 2018)	I		*														SVM

Table 2.1. (Continued) All research for diagnosis arranged based on the device type.

Devices	Reference	Type of data	Normality	Kerato	Sus.kerato	Astigmat	Relloid	Mayopia	AdvanceKera	mild-Kera	Postphot	Postkera	contact lens-	forme fruste	ectasia	pellucid	Orthokeratol	Algorithms
Videokeratography	(Salih and Hussein, 2018.)	I	*															VGG-16
	(Lopes et al., 2018)	P		*											*			random forest
	(Lavric and Valentin, 2019)	I		*														CNN
	(Issarti et al., 2019)	P		*	*	*												ANN
Artemis	(Silverman et al., 2017)	P		*														linear discriminant
ORA, Pentacam, Visante and Orbscan.	(Valdes-Mas et al., 2014)	P				*												NN, DT
keratron corneal topographer 2000	(Twa et al., 2000)	Z		*														DT
Precision tomographic examination	(Bevilacqua et al., 2017)	P		*														ANN
GALILEI Analyzer System	(Smadja et al., 2013)	P		*										*				M.L
OCT	(Cavas-Martnez et al., 2017)	P		*														LR
	(Yousef et al., 2018)	P		*											*			Clustering

Table 2.1. (Continued) All research for diagnosis arranged based on the device type.

Devices	Reference	Type of data	Normality	Kerato	Sus.kerato	Astigmat	Reliuid	Mayopia	AdvanceKera	mild	Postphot	Postkera	contact lens-	forme fruste	ectasia	pellucid	Orthokeratolo	Algorithms
(Bessho et al., 2006)	Orbscan	p		*	*													LR
(Lopes et al., 2016)	Videokeratography	P													*			
(Cavas-Martnez et al., 2014)	(OCT)	p		*														
(Marsolo et al., 2007)	Orbscan	Z		*				*										NB
(Kurniawan et al., 2014)	Data from Interview	p	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	
(Salih and Hussein, 2018)	Videokeratography	I	*															VGG-16
(Lopes et al., 2018)	Videokeratography	P		*											*			random forest
(Ali and Singh, 2014)	Videokeratography	I		*		*												morphology operation
(Lavric and Valentin, 2019)	Videokeratography	I		*														CNN
(Saika et al., 2013)	Videokeratography	Z		*	*													KNN
(Silverman et al., 2017)	Artemis and Videokeratography	P		*														Linear discriminant

Table 2.1. (Continued) All research for diagnosis arranged based on the device type.

Devices	Reference	Type of data	Normality	Kerato	Sus.kerato	Astigmat	Reluid	Mayopia	Advance	mild-Kera	Postphot	Postkera	contact	forme fruste	ectasia	pellucid	Orthokeratolog	Algorithms
Orbiscan	(Bessho et al., 2006)	P		*	*													logistic regression
	(Marsolo et al., 2007)	Z		*				*										DT, NB
	(Souza et al., 2008)	P		*														ANN
	(Souza et al., 2010)	P		*														SVM, NN
	(Souza, 2011)	P		*	*	*					*		*					SVM, ANN
ATLAS 9000	(Bagherinia et al., 2008)	P		*	*			*								*	*	SVM
ArcScan	(Silverman et al., 2014)	I		*														ANN
Data combined Scheimpflug Placido	(Arbelaez et al., 2012)	P		*														SVM
Physician examination data	(Perissutti et al., 2000)	P		*														ANN
Physician examination data	(Noaman et al., 2014)	P				*		*										SVM, ANN
EyeSys. system 200	(Chastang et al., 2000)	P		*		*					*		*					DT
Interview Data	(Kurniawan et al., 2014)	P	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	NB

P: Parameter, Z: Zernike, I: Image.

To facilitate the searching process for investigators to obtain the desired information readily and accurately, in Table 2.2, the papers present in this survey have been classified based on the algorithms that were used for the diagnosis of corneal diseases.

Table 2.2. All research for corneal diagnosis arranged based on the methods type.

Algorithm	References	Devices	Type of	Normality	Kerato	Sus.kerato	Astigmatism	Reluid	Mayopia	Advance	mild-Kera	Postphotoreflexion	Postkera	contact	forme	ectasia	pellucid	orthokerat
ANN	(Maeda et al., 1995)	Videokeratography	P				*			*	*	*	*					
	(Smolek and Klyce, 1997)	Videokeratography	P		*	*	*	*				*		*				
	(Perissutti et al., 1998)	Physician-exam	P		*													
	(Souza et al., 2008)	Orbscan	P		*													
	(Perissutti et al., 1998)	Videokeratography	P		*													
	(Carvalho, 2005)	Videokeratography	Z		*		*											
	(Carvalho and Barbosa, 2008)	Videokeratography	Z		*	*	*											
	(Souza et al., 2008)	Orbscan	P		*													
	(Souza et al., 2010)	Orbscan	P		*													
	(Souza et al., 2011)	Orbscan	p		*	*	*					*			*			
	(Vald_es-Mas et al., 2014)	Videokeratography	P		*		*											
	(Vald_es-Mas et al., 2014)	ORA, Pentacam, Visante and Orbscan.	P				*											
	(Bevilacqua V. et al., 2017)	ArcScan	I		*													
	(Perissutti et al., 1998)	Physician examination data					*		*									
	(Lopes, et al., 2016)	Videokeratography	P													*		
	(Bevilacqua et al., 2017)	Precisio tomograph exam	p		*													
	(Issarti et al., 2019)	Orbscan	P		*	*	*											
	(Toutounchian et al., 2012)	Videokeratography	P		*	*												

Table 2.2. (continued) All for corneal diagnosis arranged based on the methods type.

Algorithm	References	Devices	Type of data	Normality	Kerato	Sus.kerato	Astigmatism	Reluid	Mayopia	Advance	mild	Postphot	Postkera	contact	forme fruste	ectasia	pellucid	orthokeratol
SVM	(Bagherinia et al., 2008)	ATLAS 9000	P		*	*			*								*	*
	(Souza et al., 2010)	Orbscan	P		*													
SVM and DT	(Souza et al., 2011)	Orbscan	p		*	*	*					*			*			
	(Toutounchian et al., 2012)	Videokeratography	P		*	*												
	(Arbelaez et al., 2012)	(OCT)	P		*													
	(Bessho et al., 2006)	(OCT)					*		*									
	(Hidalgo et al., 2016)	Videokeratography	P		*		*								*			
	(Lopes et al., 2016)	Videokeratography	P													*		
	Ali et al., 2017	Videokerat	I	*														
	(Gao et al., 2017)	Videokeratography	P		*													
	(Toutounchian et al., 2012)	Videokeratography	P		*	*												
	(Vald_es-Mas et al., 2014)	ORA, Pentacam, Orbscan.	P				*											
	(Twa, et al., 2000)	topographer 2000	Z		*													
DT	(Twa et al., 2003)	Videokeratography	Z															
	(Twa et al., 2005)	Videokeratography	Z		*													
	(Chastang et al., 2000)	EyeSys 2000	P		*		*					*		*				
	(Marsolo 2007)	Orbscan	Z		*				*									
	(Smadja, et al., 2013)	GALILEI Analyzer	P		*										*			
	(Vald_es-Mas et al., 2014)	Videokeratography	P		*		*											
	(Lopes et al., 2016)	Videokeratography	P													*		

P: Parameter, Z: Zernike, I: Image

3. METHODOLOGY

3.1 Subbands Wavelet for Local Features Transform (SWFT)

The efficiency of the diagnostic performance may be negatively affected by poor medical images that may be produced such as the noise from the device itself, or the movements of the patient during the time of capturing the image causing a slightly rotating of the image, diverse distances of the sensor, or a different point of view (Sinjab, 2018). Therefore, corneal diseases diagnostic requires to extract local features that are not much affected by such factors, for instance, the features applied in plenty of real-world implementations (Verma and Raman, 2018), like object recognition (Arya et al., 2019; Kamdi et al., 2018), object tracking (Dai-Hong et al., 2019), and image retrieval (Cheng et al., 2019; Xie et al., 2018). Consequently, for feature extraction, we propose an improved algorithm for extracting the local features based on the SIFT algorithm (Lowe, 1991) called Subbands Wavelet for local Features Transform (SWFT). As known, SIFT works in two successive phases which are the detector, and the descriptor phases (Morel and Yu, 2011). This work focuses on developing the first phase by constructing various scales of the image via decomposition the image into different subbands using wavelets transform. In the literature, some researchers have improved the SIFT algorithm, which was introduced by Loewe (Lowe, 1999). In 2004, (Ke and Sukthankar, 2004) treated the normalized gradient sub-image by using the principal component analysis (PCA) technique. They showed that using such descriptors for image retrieval yields an increase in accuracy. Mikolajczyk and his team (Mikolajczyk et al., 2005) introduced a Gradient Location Gradient Graph (GLOH), used the SIFT algorithm to extract features from eight angle directions producing 272 histogram bins that were reduced using PCA. Based on the strength of the available detectors and descriptors in 2006 and earlier, Bay's team (Bay et al., 2006) presented a useful scale- and rotation-invariant method for many computer vision tasks that depend on the integral filter for image convolutions. J. Morel and G. Yu (Morel and Yu, 2009) suggested a strategy based on what was ignored by the SIFT algorithm, which simulated all image views that may occur by shifting latitude and longitude angles of the camera axis. They attempted to mathematically prove that their algorithm is fully affine invariant. A proposal has presented an approach to improve the representation of the local image descriptor by augmenting the histogram, which

led to high performance in matching real-world images after many levels of geometric and photometric transformations (Tang and Tang, 2012).

3.1.1 SIFT background

SIFT stands for a scale-invariant feature transform (Lowe, 1999), used to addresses the scale and rotation changing problem (Bauer et al., 2007). Moreover, it primarily used for recognizing objects (Potthast, 2018), the recognition system training with images of the object and try to recognize it from new images with different scenes, side of view, and scales. This algorithm been tried by the number of researchers and achieve amazing performance, and has considered as one of the best approaches for feature matching (Dong et al., 2019; Alhwarin, et al., 2010). SIFT was initially developed by Lowe in 2004, there have been many variants since that time. The approach of this transform is starting with creating a scale space of images uses the Gaussian function with increasing values of Sigma, as in (3.1). It creates a set of progressively blurred Gaussian images then takes the differences of each pair of images in the scale to get a difference of Gaussian pyramid (Abdel-Hakim and Farag, 2006), as expressed in Equation (3.2), which could be an exceptionally great approximation to the function DoG.

$$L(x, y, \sigma) = G(x, y, \sigma) * I(x, y) \quad (3.1)$$

$$DOG(x, y, \sigma) = L(x, y, k\sigma) - L(x, y, \sigma) \quad (3.2)$$

where, L could be a blurred image, G is the Gaussian blur operator, I is an image, and considered as "scale" parameter. The next step is to find local extrema in this scale space, which helps to remove the scale uncertainty and find key points or features reliably. Once found these key points, it is straightforward to calculate the vector by creating a histogram of gradient directions from the 16x16 neighbors around those key points, as appeared in Figure 3.1 which shows the scale space of images that apply a Gaussian, thereafter, computing the difference of Gaussian array via the difference between every pair of images in the stack.

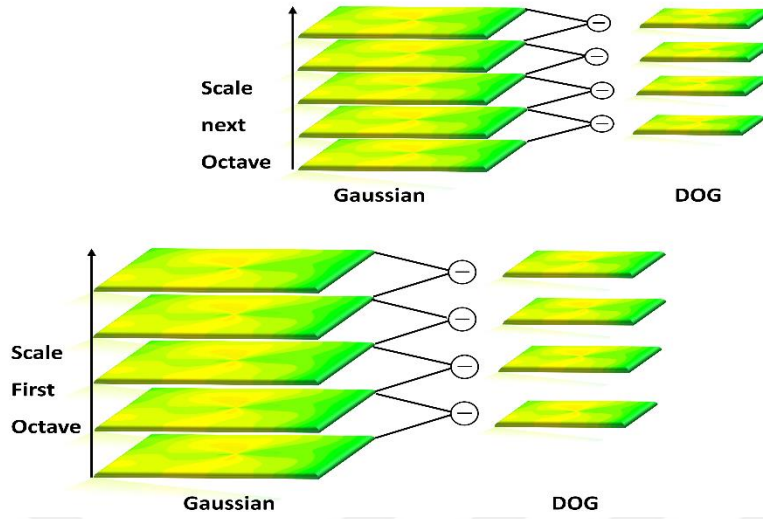


Figure 3.1. Scale space of an image in different octave used to calculate the Difference of Gaussians (DOG).

Ultimately, localizing the keypoints (minima or 1 maximum peak), that can localize more precisely within the image by fitting a quadratic surface to the values in the neighborhoods, as expressed in Equation (3.3), and finding the peak of that surface that gives a sub-pixel precision of the location of the peak (Brown and Lowe, 2002). The offset of extremum (use finite differences for derivatives) as expressed in (3.4).

$$D(x) = D + \frac{\partial D^T}{\partial x} x + \frac{1}{2} X^T \frac{\partial^2 D}{\partial X^2} x \quad (3.3)$$

$$\hat{X} = -\frac{\partial^2 D^{-1}}{\partial X^2} \frac{\partial D}{\partial D} \quad (3.4)$$

For selecting canonical orientation, the features are found around all key points then computes a histogram of the local gradient directions at the selected scale to disclose the peak (highest pin in the histogram), it is assigned to be the angle of that whole patch, useful to removes the rotational uncertainty or degree of freedom of these points, see Figure 3.2. at each pixel, A_{ij} , the image gradient magnitude, M_{ij} , and orientation, R_{ij} , are computed using pixel differences (Lowe, 1999) as in Equations (3.5) and (3.6).

$$M_{ij} = \sqrt{(A_{ij} - A_{i+1,j})^2 + (A_{ij} - A_{i,j+1})^2} \quad (3.5)$$

$$R_{ij} = \text{atan2}(A_{ij} - A_{i+1,j}, A_{i,j+1} - A_{ij}) \quad (3.6)$$

where, A_{ij} , and $A_{i+1,j}$ are two consecutive pixels in the x-direction, and A_{ij} , and $A_{i,j+1}$ are two consecutive pixels in the y-direction. Finally, each key point specifies the stable 2D coordinate location, scale, and orientation (X, Y, Scale, Orientation), which represent the key point features that have been extracted from the image where the length of the vectors corresponds to the scale and the angle of the vector, thereafter applying a threshold on the image gradients and sampled over 16x16 array of locations 1 in the scale space.

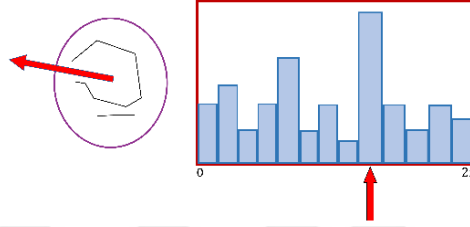


Figure 3.2. The orientations histogram of image region that used to determine its main orientation which is the highest bin (peak).

The feature vector is constructed by selecting the 16x16 array around the key point and compute the gradient directions of all those points and quantize them into eight different directions in a 4x4 array, producing 128 elements of a very rich features vector (Nowak et al., 2006), see Figure 3.3.

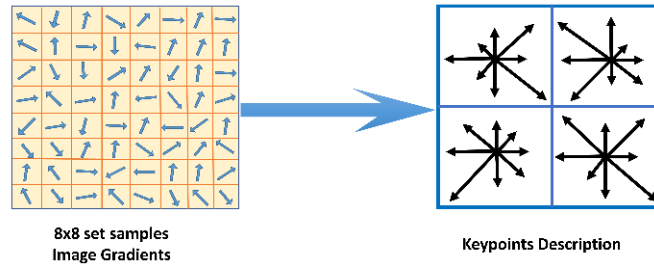


Figure 3.3. The eight directions scale and orientation.

3.1.2 Wavelet transforms

An image is a group of pixels whose values represent the intensities. These values carry information about the extent of illumination (energy) that exist in pixel. Because the image contains an object (s), changes in intensity occur due to the difference in the amount of illumination between the object and the background of the image which represents an edge. Edge information is important because it indicates a change in image content. Therefore, representing the image in the frequency domain by scanning a horizontal line from the image will contain different oscillations that change suddenly due to the shift of the scan from the smooth areas to the texture areas in the image or vice versa, as given in Figure 3.4. Hence, to analyze images precisely, we need to exploit wavelet transform techniques that have characteristics of localizing in time and frequency (Daubechies, 1990). Wavelet is a finite duration wave-like oscillation, that starts from zero, increases and decreases by the same amount and thus returns to zero. Therefore, it has zero mean, and has diverse forms and sizes (Subasi et al., 2019), see Figure 3.5, uses to decompose a given signal into parts that can be studied individually that could be a key quality of the wavelet analysis (Rhif et al., 2019).

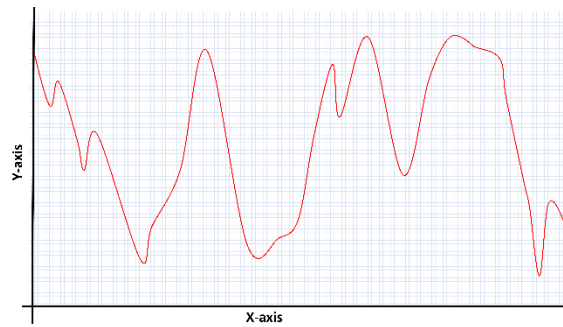


Figure 3.4. Sample of signals frequently.

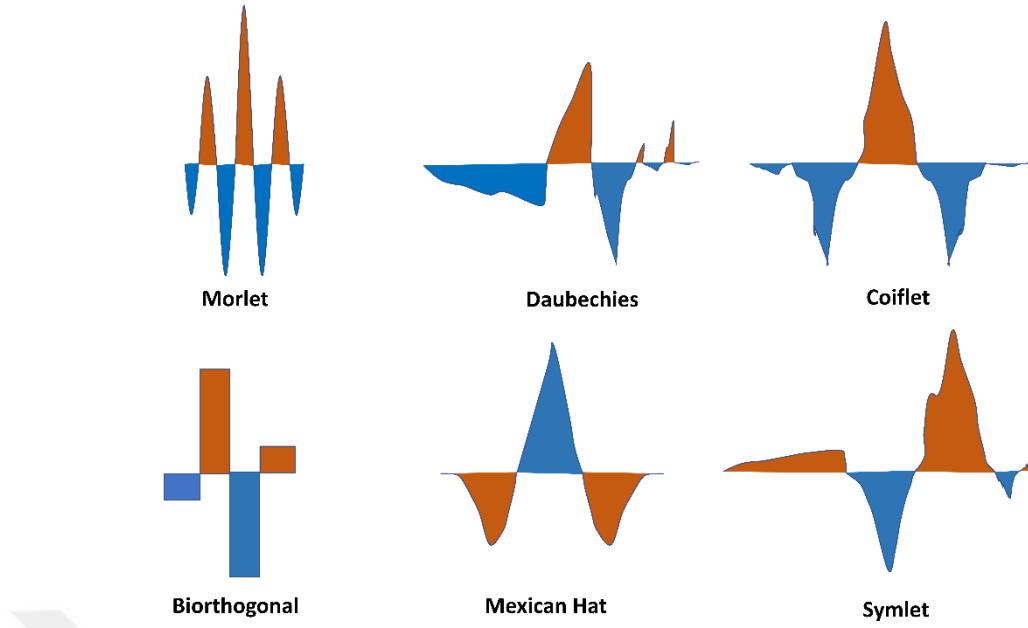


Figure 3.5. Different sizes and shapes of wavelet.

Set of coefficients are composed by level 1 applying the wavelet, which represents the components of signal analysis in different scales and translation, where scale refers to either increasing or decreasing wavelet pitch, as expressed in (3.7).

$$\Psi\left(\frac{t}{s}\right) \quad s > 0 \quad (3.7)$$

where s is a positive value represents the scaling factor, which can be controlled through stretching or shrinking the wavelet (Meng et al., 2019), where stretch it out (high scale) for the low frequency and shrink it (low scale) for high frequency. Figure 3.6 illustrates the inverse relationship between the frequency and scale, which is called the center frequency of the wavelets (Maity et al., 2019). Translation indicate to shifting the wavelet forward in time on the entire signal i.e. shifted and centered at K for acquiring the sought information (Bharath et al., 2018), as expressed in Equation (3.8).

$$Translation = \phi(t - k) \quad (3.8)$$

The transforms are contrasting with the way of translation and scaling such as discrete, and continuous wavelet transforms.

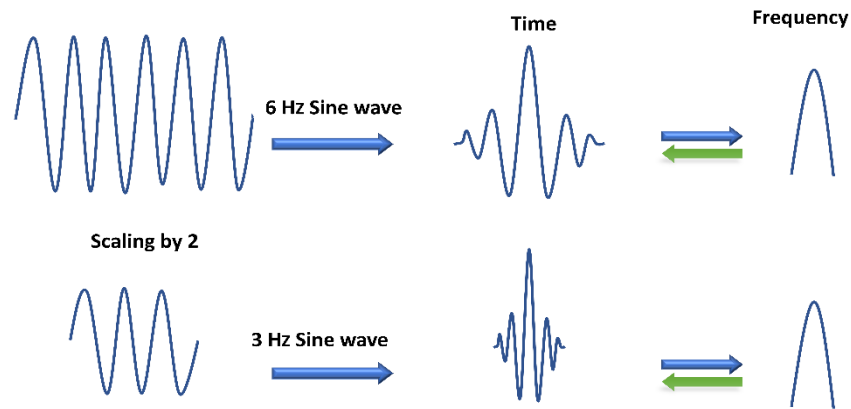


Figure 3.6. Scale and the frequency examples.

3.1.2.1 Continuous wavelet transforms

Continuous Wavelet Transforms (CWT) is a mathematical function that expresses the time-frequency analysis, where translation and scale factors are changing continuously (Koh et al., 2017), as illustrated in Figure 3.7. The idea is the wavelet constructs a less resolution in time within the condition of low frequencies whereas more resolution in high frequencies (Amiri et al., 2016). The wavelet moves along the signal and repeated over and over again with different scales to compose various coefficients (Starck et al., 2015).

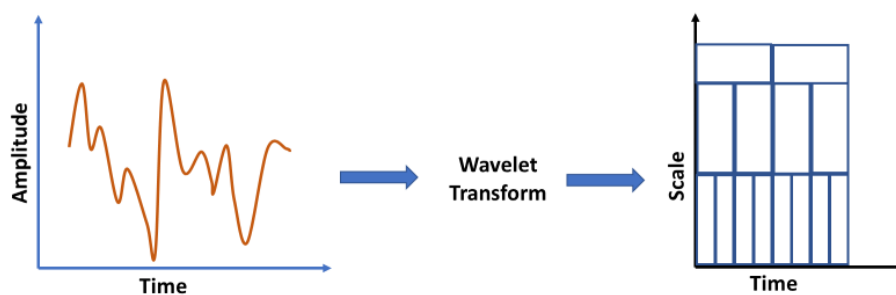


Figure 3.7. Function of scale or frequency with time.

3.1.2.2 Discrete wavelet transforms

Discrete Wavelet Transform (DWT) is a mathematic function that helps to represent images with a little number of coefficients that can be deal separately, which distinguishes it to be a suitable tool for image compression (Bhosale et al., 2018). It is established on multiresolution analysis, where the scale generated easily by increasing the value of the base scale which is represented by 2^j (Acharya et al., 2016), as calculated from Equation (3.9). The wavelet applies over the entire signal, mathematically, translation represented as an integer value.

$$2^j \quad (j = 1, 2, 3 \dots) \quad (3.9)$$

The DWT process is a multiresolution signal analysis. Conceptually, to applying 2D-DWT on a given image, first should pass through a low-pass filter and high-pass filter along on the columns that yield $h\varphi(-n)$ and $h\psi(-n)$ subbands which represent the Columns Filtering Phase (CFP), where n represent the columns of the given image. The bandwidth of the signal essentially gets halved in each of these subbands that the original signal is splitting up into two subbands, that causing getting redundant samples. Therefore, apply a subsampling by a factor of two where out of two consecutive samples pick up only one of them while discarding the other. For next-level, apply the same technique along the rows. Therefore, it split each subband again into two other subbands $h\varphi(-m)$ and $h\psi(-m)$ which represent the Rows Filtering Phase (RFP), where m represents the rows of the given image shown in Figure 3.8.

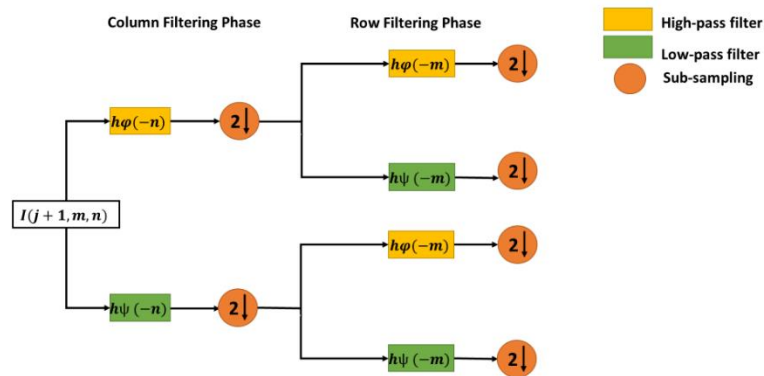


Figure 3.8. Wavelet Filter bank for one-level Image Decomposition.

Consequently, each of these subbands will contain half of the samples, so sub-sample by a factor of two will be getting four outputs $W\varphi(j)$, W_{ψ}^H , W_{ψ}^V and W_{ψ}^D , refer to horizontal extracted edges, where represents the low-pass and high-pass subbands in CFP and RFP phases respectively. The V superscript refers to vertical extracted edges that represent the high-pass and the low-pass subbands in the CFP and RFP phases respectively. whereas D superscript refers to diagonal extracted edges that represent the high-pass and the high-pass subbands in the CFP and RFP phases respectively (Kashyap and Sinha, 2012).

3.1.3 Support vector machine

Support Vector Machine (SVM) is an algorithm (Cortes et al., 1995) that draws a decision boundary near the extreme points in the dataset known as a hyperplane. where the features should be chosen to decide where to draw a good decision boundary (Suykens and Vandewalle, 1999). The line might draw over different locations and directions. Therefore, it could incorrectly classify classes since there is no optimal decision boundary. So, a data points help to margin pushes up against all points that are close to the opposing class known as support vectors (Dadi and Pillutla, 2016) See Figure 3.9.

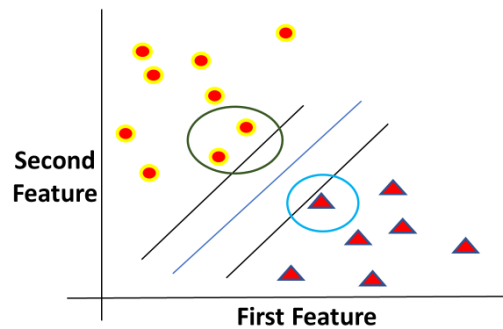


Figure 3.9. The support vector points samples from two classes.

The support vectors are the most important aspect in SVM, whereas training examples are ignorable, for instance, samples of first-class looks like second class or vice versa. Such issue required classifiers that looking for extremes points and set margins based on these support vectors. The shortest distance to the closest positive point called D^+ , shortest distance to the 1 closest negative point called D^- , and separating hyperplane that is the D^+ plus the D^- called Margin (Dadi and Pillutla, 2016). See Figure 3.10.

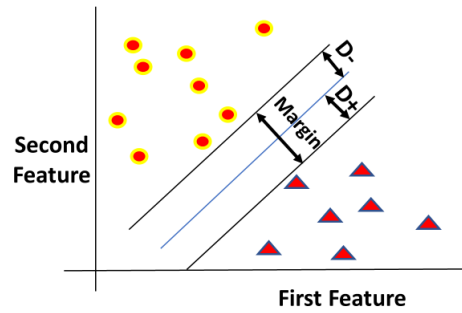


Figure 3.10. The Margin and D_- , D_+ with samples from two classes.

The line (decision boundary) that segregates the two classes is commonly referred to a hyperplane because SVM can be used in multi-dimensional data sets. The data points are referred to vectors as they have coordinates within the space of data (Mun et al., 2019), This type is known as linear support vector machines (LSVM) because the classes are linearly separable. On the other hand, the data might look impossible to separate two classes by using a single line. Consequently, to draw hyperplane easily, the data needs to transform into high dimensional space. For example, by using a simple polynomial function a parabola can be obtained from one-dimensional space (Fung and Mangasarian, 2005). See Figure 3.11.

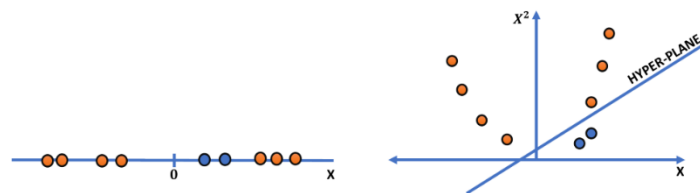


Figure 3.11. Transform nonlinear separable data into 2-Dimension.

The data set with two-dimensional space simply treat with the same method by using a function to transform data from two-dimensional to three-dimensional feature space. The only problem with transformation is a computationally expensive, see Figure 3.11. This issue defeated by using a kernel trick to reduce the computational costs (Bergman, 1970). Kernel trick is a function that takes vectors in the original space and returns the dot product of the vectors in the feature space as inputs. Finally, it returns a similarity

score between any two points, which can be considered as a metric of closeness (Lane et al., 2016; Achirul et al., 2018). There are many SVM Kernels, such as linear kernel which is a straight-line hyperplane as shown in Figure 3.12.

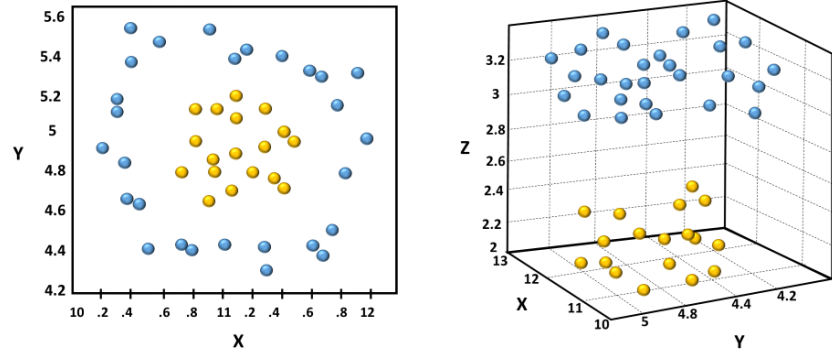


Figure 3.12. Transform 2-Dimension data into 3-Dimension.

Additional to linear kernel there are other kernels which are summarized below:

a) Radial Basis Function (RBF) Kernel: RBF helps to avoid the expense of additional features as well as it can build and plot very complex decision boundaries as a curve shape. The curve shape comes out when the RBF function moves away from the support-vector (center). It is providing an opportunity to draw hyperplane that aptly separate points (Khalaf et al., 2019). It can calculate by Equation (3.10).

$$K(X,Y) = \exp(-\gamma \|X - Y\|^2) \quad \gamma > 0 \quad (3.10)$$

where X and Y are vectors in the input space, and γ is the gamma parameter.

b) The Polynomial Kernel: Polynomial Kernel has the ability to reach the interaction characteristics derived from combining features that used to learn patterns. Worth noting that polynomial kernel with degree one is a linear kernel (Schölkopf et al., 2002). It can be applied by the mathematical function expressed in Equation (3.11).

$$K(X,Y) = (X \cdot Y + C)^\gamma \quad \gamma > 0 \quad (3.11)$$

where X and Y are input space vectors, γ is the gamma parameter, C is the penalty

parameter, and d is the polynomial degree.

c) Sigmoid Kernel and Pairwise Metrics: The sigmoid kernel is originated from the Neural Networks field which is called Multilayer Perceptron (MLP) kernel, that's why it is very popular and interesting when utilizing in SVM, which considers the same as two-layer perceptron neural network. It is also known as Hyperbolic Tangent (Liu et al., 2014). See Equation (3.12).

$$K(X, Y) = \tanh(\gamma X \cdot Y + C) \quad (3.12)$$

In addition to the kernel, there is also an important optimization parameter such as;

1. Penalty Parameter: It is usually symbolized with letter C . It is used to hegemony systematic outliers and to control errors, i.e. it informs the algorithm of the amount of attentiveness about misclassified points. Accordingly, the large value of the penalty parameter indicates to paying high attention to correctly classify the training set instead of leaving plenty of room for the test set (Kaestner, 2013).
2. Gamma parameter: It is a hyperparameter that should be set prior to train the model. As previously mentioned, that the RBF is getting weaker when move away from the center causing the curvature of boundaries. Gamma is the parameter that sets the desired amount of curvature and dissipation. Gamma is a parameter that determines the dissipation swift and the quantity required for the curvature. Accordingly, a larger Gamma drops the influence of individual center, and curvature. (Saito and Rehmsmeier, 2015). Gamma is one over the number of featured in dataset as in Equation (3.13).

$$\gamma(\text{gamma}) = 1/N \quad (3.13)$$

where N is the number of Features.

3.1.4 SWFT algorithm

The proposed Subbands Wavelet for Local Features Transform (SWFT) algorithm, which based on the standard SIFT algorithm, accepts the same inputs as the original algorithm. The essential function for the standard SIFT algorithms are to obtain the DoG images in which edges and blobs can be found. The image needs to be compared at different scales (image pyramid) to find key points by smoothing the image with a Gaussian filter. Our proposed algorithm uses wavelet transform subbands at different levels as a tool to create scale space of image to be used to extract the local features, as well as sets the contrast threshold parameter value to 0.002. The image is decomposed at level four using the 2D-DWT (Symlets) as a tool for multiresolution decomposition, which provides a robust analysis of the image based on the important aspects of scaling and shifting. Moreover, the DWT is skillful to overcome the perspective shifts caused by changing the camera angle, because it is the most perfect method that used for localized time and frequency to analyze the image. Thus, facilitate calculating the keypoints, which are mostly represented as the anomalies of a particular pixel intensity value against its neighbors' intensity values. Scale-space of an image is generated as follows, after decomposition the image at level one using DWT, the first scale obtained by reconstructing the image without the level one details (horizontal, vertical, and diagonal). Whereas, the next scale obtained by decomposition the image at level two then reconstructing the image without the details of levels one and two, and so on. Similar considerations hold for the other octaves, one level image decomposition is illustrated in Figure 3.13.

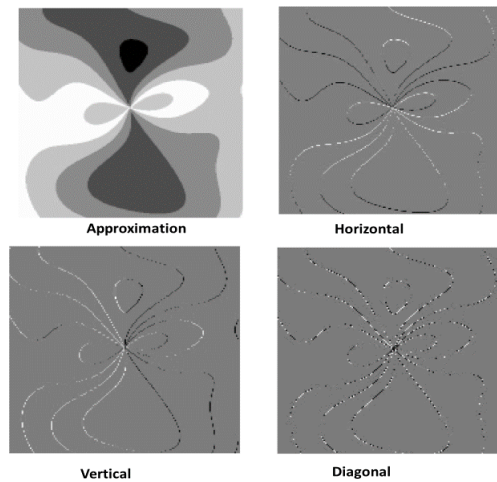


Figure 3.13. Decomposition image using first level wavelet transform.

3.1.5 Practical experiments

Corneal topography is used as data of the human cornea, consisting of four different maps, as shown in Figure 3.14.

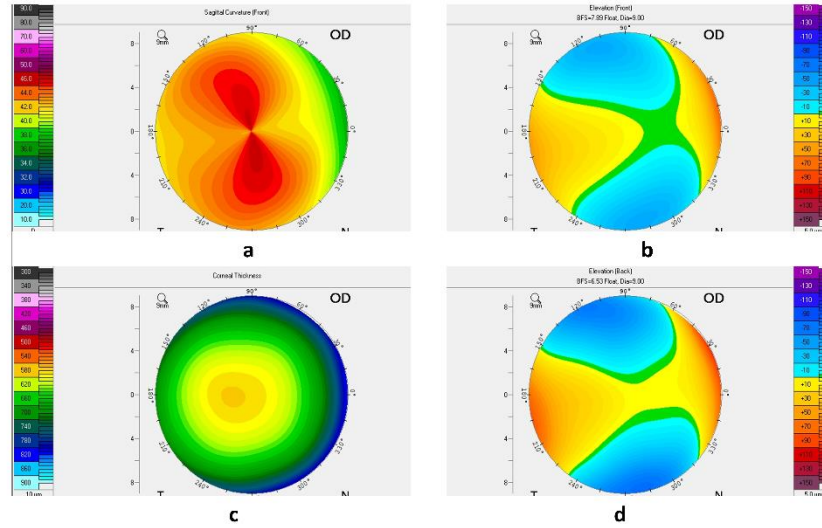


Figure 3.14. Human Corneal topography from Pentacam device a) Sagittal map b) Corneal thickness map c) Elevation front map d) Elevation back map.

The first map called the sagittal map provides information about the astigmatism disease of the cornea (see Figure 3.15 a). The second map, called the corneal thickness map, reads the extent of the corneal thinness in various places of the cornea and gives the coordinates of the pupil center (see Figure 3.15 b). The third and fourth maps are the elevation front and elevation back maps, which provide information about the front and the back-cornea surfaces condition (see Figure 3.15 a and b), thereby could be used to diagnosing different corneal diseases. Each map is analyzed separately to be separately to diagnoses the condition as normal or abnormal using the SVM algorithm with "linear" Kernel function, $C=100$, and Gamma. Accordingly, it can diagnose many morphological and clinical findings such as cornea within rule astigmatism and oblique astigmatism diseases from the first map, thin corneas disease from the second map, lastly, isolated land and like tang shape diseases from the third and fourth maps. Different maps provide an opportunity to examine the algorithm in a big range of data. Therefore, we perform four types of examinations for a more accurate and reliable diagnosis, discover the performance of the proposed method, and to achieve a perfect

comparison with the standard SIFT algorithm. The results are given in chapter 4 section 4.1.

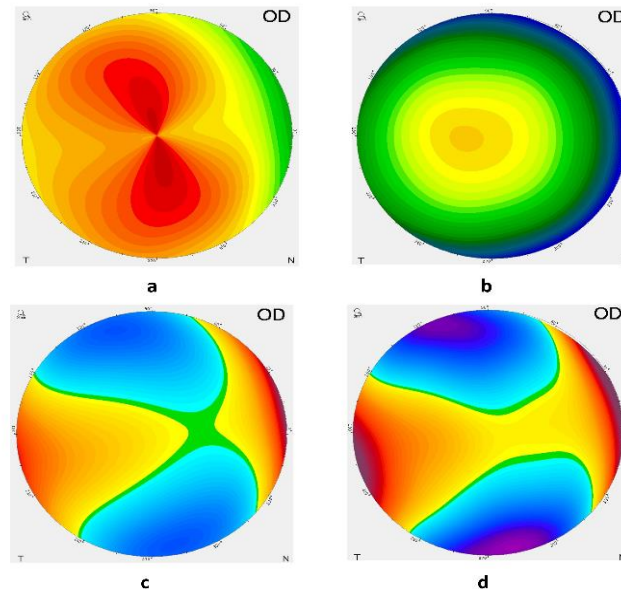


Figure 3.15. Human Corneal diseases examples a) astigmatism b) Thinness cornea c) like tongue d) Isolated land shape.

3.2 Multi-Subbands Wavelet Transform with SIFT Algorithm for Local Feature Extraction

One of the essential elements for any diagnosis system is feature extraction. The methods of extracting the feature from the medical images is important due to its effect on the accuracy of the diagnosis. Accordingly, we proposed to investigate the use of SIFT with multi-scale subbands of wavelet transform. The SIFT algorithm applied on each wavelet subbands individually, which is illustrate the combination of the features mapped from both the spatial domain and the signal processing features (Elshinawy, 2010). From the literature of corneal diseases diagnosis mentioned in chapter two of this thesis, there was no specific feature extraction technique had tack advantage of combining the wavelet subband advantages with the SIFT algorithm. These local features represented by this combination are getting more attention for diagnosing corneal image. Wavelet give an opportunity to deal with coefficients separately, where the least can map to spatial domain, which is consider the property of the wavelet transform (Mallat, 1989).

3.2.1 Multi-scale wavelet

One level of wavelet transforms (see section 3.1.2) using discrete wavelet transform and Haar filter has applied on the cornea images that derived from the four subbands (LL, LH, HL, HH) as shown in Figure 3.16. The proposed method treated each subbands individually directly by applying the SIFT to extract the features that represents the corneal image, to be used for diagnosing the diseases of the cornea.

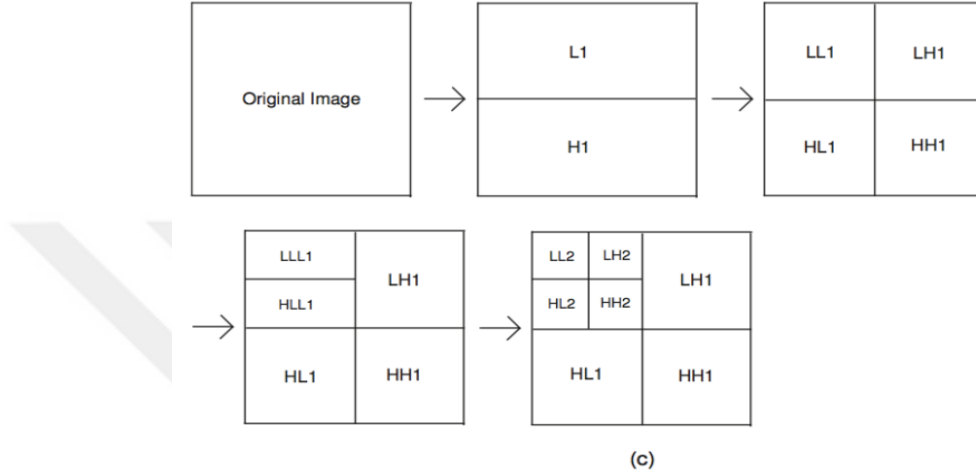


Figure 3.16. Image decomposition using DWT.

3.2.2 Practical experiments

Time frequency analysis applied on the corneal topography maps by using wavelet transform gives opportunity to analyze the input image with different stretching or shrinking signal in time through all images. The subbands that produced by analyzing the image are reconstructed separately by applying inverse wavelet transform on a specific subband and zeroing the rest, then treat by SIFT algorithm to extract the local features from those subbands. The proposed method applied on the collection of the corneal topographies with different maps (sagittal, corneal thickness, elevation front, elevation back). There are different numbers of data in the real world which might be faced by the CAD system, we used a different ratio of test and training set. Moreover, five different criteria have been used in the practical experiment to evaluate the proposed method efficiently and accurately. The results are given in section 4.2.

3.3 Texture Feature Extraction and Time-Saving Based on Image Gradient and GLCM For Corneal Diseases Diagnosis

In image processing, the term “texture” refers to complex visual patterns that resembles spatially organized entities with certain properties like color, size, shape, brightness, etc. It represents an image color, intensity, or region (Li et al., 2017; Huang et al., 2017). There are two types of textures: rough (or coarse) and homogenous. A texture is considered rough when the spatial arrangement of pixels is highly dramatic, due to many differences in pixel values. On the other hand, a texture is considered homogenous when the pixels in a given region have relatively similar values (Bhushan et al., 1997).

Image texture refers to a change in the value of a pixel over a certain region of the image. It is widely used to interpret visual images and understand land-cover characteristics. Nevertheless, it is currently being utilized in analyzing digital images for classification, segmentation, etc. (Ulyanov et al., 2017). Visually, texture can be characterized in several different manners: COARSE, where similar changes apply to pixel intensity over a specific region, and this pattern is replicated. FINE, where the texture elements known as “textile” are highly repeating themselves. HIGH-CONTRAST, where certain regions are highly bright while other regions are dim. LOW-CONTRAST, where there is low contrast between image background and foreground. REGULAR, where the regular pattern of a certain feature can be seen. DIRECTIONAL, where the texture elements are arranged unidirectionally, referred to directional texture. NON-DIRECTIONAL, where the texture elements are arranged non-directionally. ROUGH, where the image with many financial affairs varies in the value of brightness. SMOOTH, where gradual changes apply to the brightness value of the image. Finally, RANDOM, where rapid changes only apply to the brightness value of some regions of the image. Figures 3.17 a-g shows the texture type (Bhushan et al., 1997; Liu et al., 2019; Haralick et al., 1973).

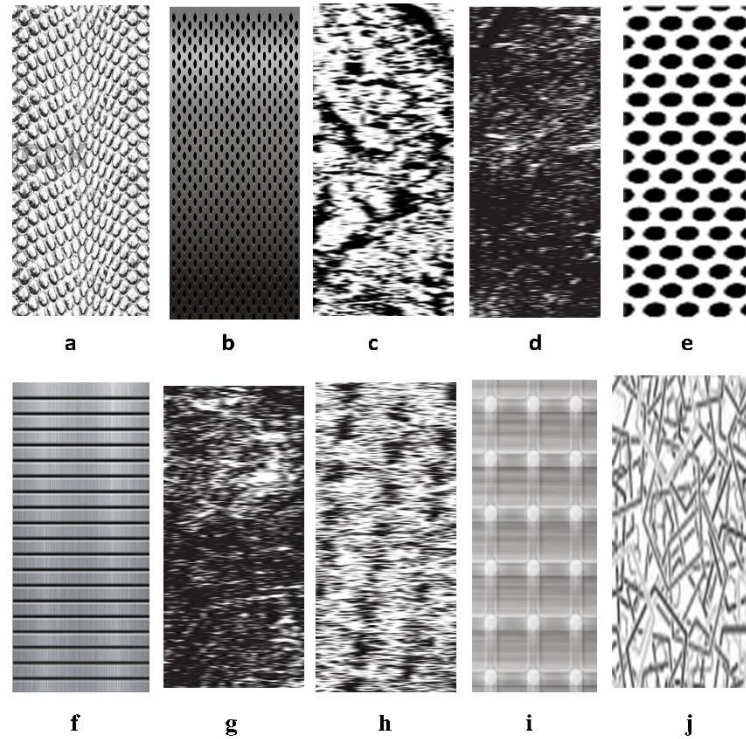


Figure 3.17. Different types of texture images a) Coarse b) Fine c) High-contrast d) Low-contrast e) Regular f) Directional g) Non-directional h) Rough i) Smooth g) Random.

3.3.1 Gray level co-occurrence matrix

Gray level co-occurrence matrix (GLCM) is synonymous to texture, a second-order statistical technique for texture analysis (Haralick and Shanmugam, 1973), representing the co-occurrence of intensity combinations in an image (Rafi et al., 2018). It also refers to the frequency of finding a pair of pixels in a specific direction of an image, or a co-occurrence distribution determining the distribution of pixels in an image. For the original image, GLCM (a square matrix) is computed for second-order texture measurements to determine the intensity of a given pixel. We should resample the image to more than 4 bits as it increases the number of bits, thereby making calculations tedious (Ye et al., 2017). We can compute the matrix in every direction. There are typically eight directions at any offset, where textures over 0° (nearest neighbor on the right-hand side) can be calculated. Moreover, the relationship between a certain pixel and diagonal pixels (45° , 90° , 135° , 180° , 225° , 270° , and 315°) can be found. Thus, each specific band is capable of computing eight GLCMs (Hu et al., 2008).

As its name would suggest, co-occurrence means the simultaneous occurrence of two objects and measure this simultaneity. In a certain image, 8*8 regions (Figure 3.18) can compute an operator known as “northeast” (45°) by utilizing various distances. That is, we can construct the matrix with the first neighbor symbolized by $d=1$, and $d=2$ with the second-pixel neighbor, etc. Thus, 1-pixel represents a certain pixel that requires to take an operator from a northeastern pixel.

0	1	2	3	3	2	1	0
1	0	1	2	3	1	0	1
2	1	0	1	0	0	1	2
3	1	0	0	1	2	2	3
2	1	0	0	1	1	2	3
3	1	1	0	0	1	2	3
2	2	1	0	0	1	2	3
2	2	1	0	1	2	3	3

Figure 3.18. 8x8 sub image example.

Here, a 1-pixel implies to the number of steps taken toward a certain location in a certain direction. The operators are direction-sensitive. The matrix needs to be constructed by exploring all possible grey values in the whole image. Here, the intensity value of the original matrix falls within the 0-3 range, certainly encoded in a 2-bit number. The elements represent the co-occurrence of a certain pair of pixels, e.g., (0, 0). In a given image, six pairs exist in which 0 is related to 0 in 45° -direction (Figure 3.19), by scan all image intensities with the same approach we can find the relation between pairs of intensities. Finally, the co-occurrence matrix is formed (Park et al., 2020).

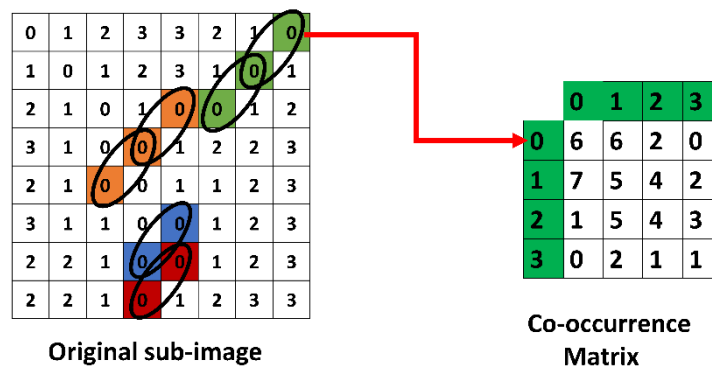


Figure 3.19. Present pares that 0 related with 0 in 45° degree.

To normalize the formed co-occurrence matrix, each element must be divided by the sum of all elements (Haralick and Shanmugam, 1973). From the generated matrix, many variation calculations for finding different features (Figure 3.20) and textures parameters represent second-order statistics.

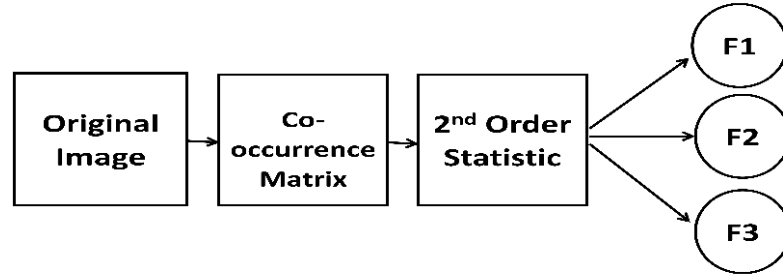


Figure 3.20. Number of second order statistics features.

Thirteen texture (Figure 3.21) can be calculated from an image in various degrees of directions, enabling systems to achieve high performance (Haralick and Shanmugam, 1973; Park et al., 2020).

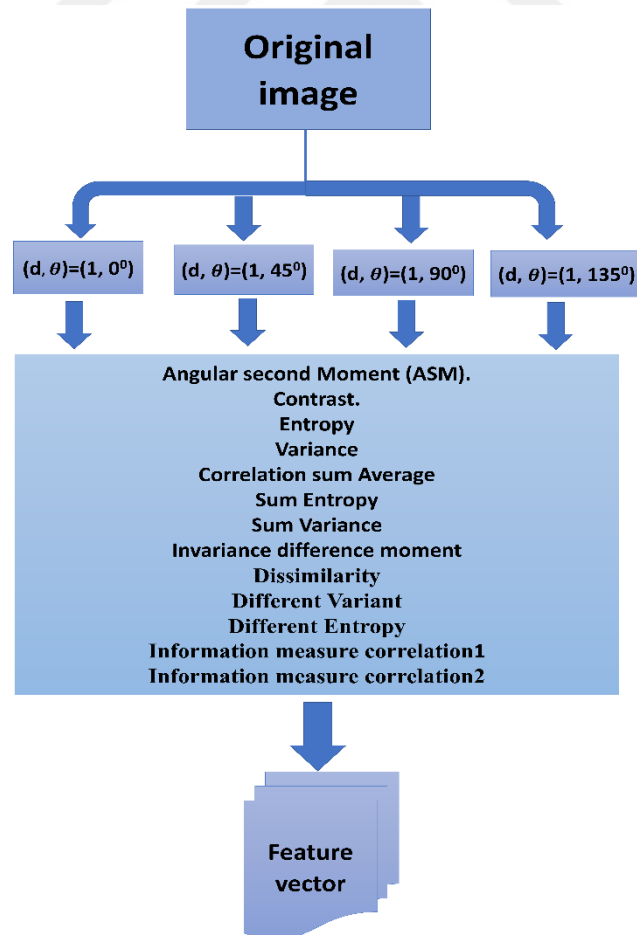


Figure 3.21. Generate 13 features in different angle degrees.

The all following Equations (Haralick and Shanmugam, 1973) of the measurements included $p(i, j)$ which is $(i, j)th$ of the GLCM matrix, N_g is the dimension matrix, and $p_x(i)$, $p_y(j)$ are the marginal probability, see Equation (3.14).

$$P_x(i) = \sum_{j=0}^{N_g-1} P(i, j), \quad P_y(j) = \sum_{i=0}^{N_g-1} P(i, j) \quad (3.14)$$

where $p(i, j)$ is $(i, j)th$ of the GLCM, N_g is the matrix dimension, and $p_x(i)$, $p_y(j)$ denote marginal probability.

1. Angular second moment feature (ASM)

The number of pairs of pixels that repeat themselves represents uniformity that determines ASM (Jimi et al., 2019). Which means, this measure can be used to extract the smoothness of images, as clarified in Eq. (3.15).

$$ASM = \sum_{i=0}^{N_g-1} \sum_{j=0}^{N_g-1} P(i, j)^2 \quad (3.15)$$

2. Entropy

Entropy refers to the complexity or disorder of a given image. The entropy of a homogenous area is less than that of a heterogeneous area. Simply put, entropy would be high if the image is not texturally uniform. Entropy is high in homogenous areas because pixels randomly change (Chandra et al., 2019). Accordingly, there is an inverse correlation between entropy and energy, as indicated by Eq. (3.16).

$$Entropy = \sum_{i=0}^{N_g-1} \sum_{j=0}^{N_g-1} P(i, j) \log (P(i, j)) \quad (3.16)$$

3. Contrast

Contrast determines the difference between the lowest and highest values of a contiguous set of pixels (Haralick and Shanmugam, 1973), as implied by Eq. (3.17).

$$Contrast = \sum_{i=0}^{N_g-1} n^2 \left\{ \sum_{j=0}^{N_g-1} \sum_{j=0}^{N_g-1} P(i,j)^2 \right\}, \text{ where } n = |i - j| \quad (3.17)$$

4. Homogeneity (Inverse Difference Moment (IDM))

As the name implies, it measures image homogeneity. Homogeneity is high in case of slight tone changes in intensity. Homogeneity is highly sensitive near the GLCM diagonal. It reaches its peak value for similar intensities. It is reduced as contrast increases, and energy is constant (Wang et al., 2019), as shown in Eq. (3.18).

$$IDM = \sum_{i=0}^{N_g-1} \sum_{j=0}^{N_g-1} \frac{1}{1+(i-j)^2} P(i,j) \quad (3.18)$$

5. Variance: sum of square

It is primarily associated with first-order statistics like SD. It is used to determine heterogeneity. Besides, it increases when pixel intensities are different from the mean (Eq. (3.19)) (Dharmalingam et al., 2019).

$$Sum \text{ of squares} = \sum_{i=0}^{N_g-1} \sum_{j=0}^{N_g-1} (i - \mu)^2 P(i,j) \quad (3.19)$$

6. Dissimilarity

As opposed to contrast, weights linearly increase. Homogenous areas are of less dissimilarity than heterogeneous areas (Park et al., 2020) (Eq. (3.20)).

$$Dissimilarity = \sum_i \sum_j |i - j| p_{ij} \quad (3.20)$$

7. Sum entropy

$$Sum \text{ Entropy} = - \sum_{i=0}^{2(N_g-1)} p_{x+y}(i) \log p_{x+y}(i) \quad (3.21)$$

8. Sum variance feature

$$Sum \text{ Variance} = \sum_{i=0}^{2(N_g-1)} (i - Sum \text{ Entropy})^2 p_{x+y}(i) \quad (3.22)$$

9. Correlation:

A measure of dependency of image intensity.

$$\text{Correlation} = - \sum_{i=0}^{N_g-1} \sum_{j=0}^{N_g-1} p(i,j) \frac{(i-\mu_x)(j-\mu_y)}{\sigma_x \sigma_y} \quad (3.23)$$

where, μ and σ are mean and standard deviation respectively.

$$\mu_x = \sum_{i=0}^{N_g-1} \sum_{j=0}^{N_g-1} i * p(i,j), \quad \mu_y = \sum_{i=0}^{N_g-1} \sum_{j=0}^{N_g-1} j * p(i,j) \quad (3.24)$$

$$\sigma_x = \sqrt{\sum_{i=0}^{N_g-1} \sum_{j=0}^{N_g-1} i^2 * p(i,j)}, \quad \sigma_y = \sqrt{\sum_{i=0}^{N_g-1} \sum_{j=0}^{N_g-1} j^2 * p(i,j)} \quad (3.25)$$

10. Different variant

$$\text{Different variant} = \text{Variance of } p_{x-y} \quad (3.26)$$

11. Different entropy

$$\text{Different Entropy} = - \sum_{i=0}^{N_g-1} p_{x+y}(i) \log p_{x+y}(i) \quad (3.27)$$

12. Information to measure correlation 1

$$\text{inf1} = \frac{HXY2 - HXY1}{\max(HX, HY)} \quad (3.28)$$

Where HX , and HY are entropies of p_x , and p_y respectively.

$$HXY1 = - \sum_{i=0}^{N_g-1} \sum_{j=0}^{N_g-1} p_x(i,j) \log \{ p_x(i) p_y(j) \} \quad (3.29)$$

$$HXY2 = - \sum_{i=0}^{N_g-1} \sum_{j=0}^{N_g-1} p_x(i)p_y(j) \log \{ p_x(i) p_y(j) \} \quad (3.30)$$

13. Information measure correlation2

$$inf2 = (1 - \exp[HXY2 - HXY])^{\frac{1}{2}} \quad (3.31)$$

$$HXY = - \sum_{i=0}^{N_g-1} \sum_{j=0}^{N_g-1} p_x(i,j) \log p_x(i,j) \quad (3.32)$$

3.3.2 Image gradient

Image gradient applies to directional changes in image color or intensity, which plays a crucial role in image processing. Mathematically, It is an image gradient in a discrete form, where a two-dimensional function $F(x,y)$ the partial derivative can be represented as the Equation (3.33) (Jacobs and David, 2005).

$$\frac{\partial F(X,Y)}{\partial x} = \lim_{\epsilon \rightarrow 0} \frac{F(x+\epsilon,y) - F(x,y)}{\epsilon} \quad (3.33)$$

For discrete data, the gradient can approximate using finite differences essentially for x-direction as Eq. (3.34) given below.

$$X: \quad \frac{\partial F(X,Y)}{\partial x} \approx \frac{F(x+1,y) - F(x,y)}{1} \quad (3.34)$$

It can be approximated by moving one index point in the x-direction, $F(x+1, y)$, i.e., discrete samples of moving from one column to another while keeping y constant. It approximates the difference between a given pixel and a subsequent pixel in the x-direction, $F(x+1, y) - F(x, y)$. For y-direction, refer to Eq. (3.35).

$$Y: \quad \frac{\partial F(x,y)}{\partial y} \approx F(x, y+1) - F(x, y) \quad (3.35)$$

Besides, this approximation enables us to determine the differences between sample images and exploit derivatives for these images (Wu et al., 2018). The following example expresses how the image gradient is calculated.

Assume the sample sub-image in Figure 3.22, in each interesting point, the gradient can calculate the neighborhood of partial pixel (here, E) and traverse to both image dimensions.

20	30	30	20	10
20	20	20	10	13
3	A	B	C	0
20	D	E	F	9
10	G	H	I	9
10	0	9	9	9
10	0	9	9	9

Figure 3.22. Sub image example to compute gradient.

“Gradient” can be described as a metric to determine changes in image function. That is, changes in intensity correspond to changes in x - or y -direction (Ding et al., 2017). Mathematically, the image gradient can be measured using Eq. (3.36).

$$\nabla F = \left[\frac{\partial F}{\partial x}, \frac{\partial F}{\partial y} \right] \quad (3.36)$$

where $\frac{\partial F}{\partial x}$ is the derivative of function F , representing an image, concerning x , and $\frac{\partial F}{\partial y}$ is the derivative of function F , concerning y . This is essentially how to evaluate the changes in image function F in both x - and y -directions.

Assume a simple examples. “A to B” represents a simple ramp image starting with dark (0) to pure white (255), (Figure 3.23).

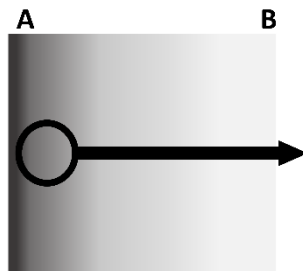


Figure 3.23. Image with horizontal ramp from A to B.

At circle point, measure the changes in this image function with respect to how it is change in neighborhood for the x-direction (toward arrow end). All of the change in direction for the x-direction, none for the y-direction.

This is a highly simple case that can be represented as Eq. (3.37).

$$\nabla F = \left[\frac{\partial F}{\partial x}, 0 \right] \quad (3.37)$$

Intensity variation may be in the y-direction (Figure 3.24), “A to B” ramp image turning from black (0) to white (255).

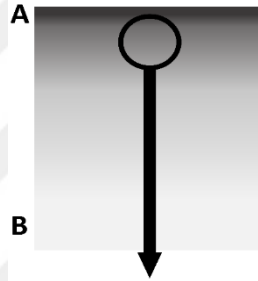


Figure 3.24. Image with vertical ramp from A to B.

In such a case, no change would occur in the x-direction that appears to be fixed, whereas some changes would occur in the y-direction (Eq. (3.38)).

$$\nabla F = \left[0, \frac{\partial F}{\partial y} \right] \quad (3.38)$$

Combining these two cases would yield the case shown in Figure 3.25.

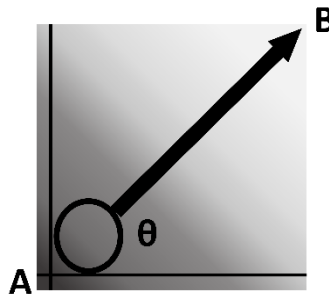


Figure 3.25. Image with 45° ramps from A to B.

Accordingly, when changes occur in both directions, the gradient would be at a θ angle. That is, the gradient point in the direction of the angle is the fastest increase in

intensity, less so in x- and y-directions (Gonzalez e al., 2004), as expressed in Eq. (3.39).

$$\nabla F = \left[\frac{\partial F}{\partial x}, \frac{\partial F}{\partial y} \right] \quad (3.39)$$

Thus, the gradient direction can be computed by inverting the tangent (Eq. (3.40)).

$$\theta = \tan^{-1} \left[\frac{\partial F}{\partial y}, \frac{\partial F}{\partial x} \right] \quad (3.40)$$

The magnitude of this vector is measured by Eq. (3.41)

$$\|\nabla F\| = \sqrt{\left(\frac{\partial F}{\partial x}\right)^2 + \left(\frac{\partial F}{\partial y}\right)^2} \quad (3.41)$$

Hence, the gradient of an image at any point can be defined from the vector magnitude and angle (Yang et al., 2018).

3.3.3 IG-GLCM algorithm

The cornea can be affected by a large number of diseases. An interesting part of treatment is to detect these diseases at early stages. For this purpose, an intelligent system capable of prompting and accurately detecting diseases is developed by employing a machine learning algorithm. The IG-GLCM algorithm has been proposed to extract features of cornea images (four corneal maps) taken by Pentacam. The maps are explored separately to define the normality of a certain part of the cornea.

In the proposed method, the GLCM algorithm is utilized to present intensity co-occurrence combinations in a given image by determining texture measurements and changes in the intensity of a certain pixel. It is employed to extract the features of all cornea images from the dataset to train the system to diagnose new incoming cases. The time taken for feature extraction can be a burden on the system. About 90% of the

total diagnostic time is spent on training. This can be a principal challenge facing these systems because fast training is considered a critical benefit of such systems. As with other machine learning systems, this system also must be trained to accurately and swiftly diagnose diseases due to a wide range of data points.

This challenge can be overcome by using a novel technique (IG-GLCM) to circumvent time-consuming for train the system and obtain high performance. To this end, the image is processed prior to its feature extraction, where the image sharpness is measured by calculating the image gradient in different directions, and the GLCM algorithm is applied to generated images.

The multi-class SVM algorithm is also proposed as a classifier to diagnose corneal integrity by learning each class separately.

3.3.4 Practical experiment

A group of clinical diseases diagnosis by testing each map individually using multi-class SVM. In this work, we conducted a set of experiments in order to diagnose accurately and reliably, the results are displayed in the section 4.3.

3.4 Local Information Pattern Descriptor for Corneal Diseases Diagnosis (LIP)

Many types of images contain attributes called texture, which can be defined as areas in the image that contain a spatial distribution of various intensities and colors. For instance, the X-ray of the human brain is a "texture" image (Zhang and Rusinkiewicz, 2018; Castellano et al., 2004), as it contains different spatial distributions of healthy and damaged tissues. This is because these characteristics of texture play a vital role in the diagnosis process. The same applies to many computer vision applications such as medical image analysis (Gupta et al., 2020; Aliyu et al., 2019; Kahya, 2019), satellite image analysis (Demir et al., 2018), factory image analysis (Guo, 2018), and computer graphics (Braz et al., 2017; Zulkeflie et al., 2019). In the sixties of the last century, many proposals were put forward on the issue of discrimination texture (Herrington et al., 2018). However, most of them failed in real-world applications to provide a good performance that meets the real-time requirements due to the complex

calculation (Saeed et al., 2020). Recently, effective local descriptive has been developed, where the description vectors are easy to calculate, for example local binary pattern (LBP) (Ojala et al., 2020; Tang et al., 2013). It was used in many modern applications like face recognizing (Zhang and Hua, 2015), expression faces analysis (Nigam et al., 2019; Sotoodeh et al., 2019), retrieve components from images or videos (Xiang et al., 2018) etc. LBP is a simple and easy method to extract local features from images by giving values to the pixels in sub-image, which represent logic outputs of its comparison with the center of the sub-image. This code however, is converted from binary to Decimal. The most important properties of LBP are easy to apply in the true-world, it is not affected by the different lighting, ease of calculation, and the speed (Pietikäinen et al., 2011).

3.4.1 LBP algorithm

The basic idea of LBP did not change in all previous researches in this field (Ojala et al., 2020) that the approach remains just thresholding the center of the sub-image. The center intensity was excluded that it is not used in estimating the LBP. In this case, the neighbors compensated by certain weights according to their locations in the sub-image, whereas the center are values expressing the real intensity on the center of sub-image, hence, their exclusion is considered a loss in the amount of information, which could regard as an essential factor of classification, discrimination, and diagnosis. Besides, the values of contrast were also to overcome the image rotation problem (Saeed et al., 2020). Therefore, the focus of LBP calculations was only on pattern. The problem is that patterns can be repeated in different locations of the image, or maybe the same pattern is present in an image of the different categories. In reality, these similar patterns have been calculated in completely different intensities. Losing this information determines the utilization of LBP description in some applications that use datasets contain images with little textures.

In this work, we suggest a new algorithm to gain the local information to defeat the loss of information from the image as well as to solve the problem of image rotation. The proposal is based on utilizing the sub-image center intensity to estimate neighbors' weights that can be used to calculate Contrast Based Centre (CBC) value, which is calculated from Equation (3.42), see Figure 3.26.

$$CBC = \frac{1}{P} (\sum_{i=0}^{P-1} C^{T_i}) \quad (3.42)$$

where, P is number of samples, C is the center of sub-image, and T is the threshold value of sub-image.

12	13	8		1	1	0		9 ¹	9 ¹	9 ⁰	
15	9	12		1	C	1		9 ¹	C	9 ¹	
5	2	1		0	0	0		9 ⁰	9 ⁰	9 ⁰	

CBC=5

Figure 3.26. Calculating the CBC value.

The CBC in the Figure 3.26 calculated as:

$$CBC = \frac{1}{8} * [9^0 + 9^1 + 9^1 + 9^1 + 9^0 + 9^0 + 9^0 + 9^1] = 5$$

On the other hand, weights are estimated using the center value as a base for the exponent T. The T represents the value of shareholding for each pixel. As for the CBC, however, it is the neighbor's weights. Thus, the CBC value per se is a constant value, and would not be affected by image rotation, therefore it is a solution to the image rotation problem. Further, to distinguish between to sub-image with a size of 3×3 having the same CBC value, we suggest calculating the Local pattern (LP) for each block, the sum of neighbors' intensity transitions, from one into the sub-image center's value, and vice versa. Figure 3.27 illustrate the whole structure of the LIP algorithm.

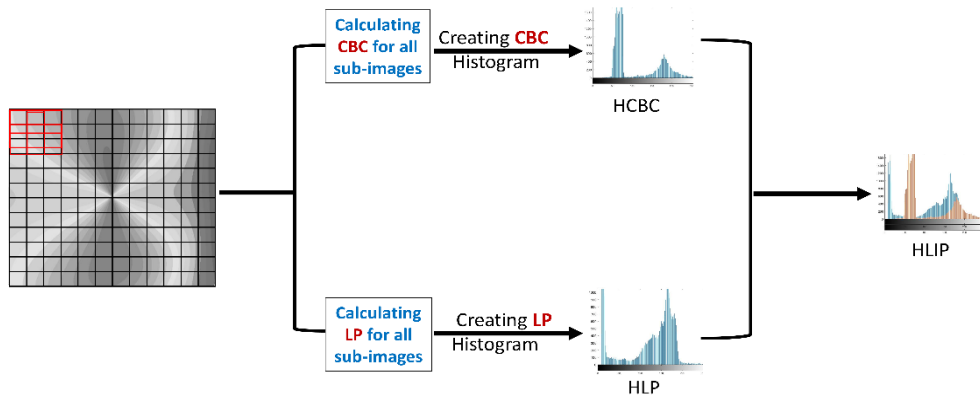


Figure 3.27. Structure of the LIP algorithm.

To simplify the calculation and understanding, let's select a 3×3 sub-image. Since LBP thresholding 3 x 3 neighbors, as Figure 3.28, of each pixel with the value of center,

which is incapable to describing more detailed information, the LIP uses the information of the center of each sub-image.

In contrast to LBP that does not care about the intensity of the sub-image, the LIP uses the center intensity to estimate the LIP code value to gain more details from the image information and pattern.

A selected 3x3 sub-image, Figure 2.28, $I(A_0)$ is the center of sub-image, where the thresholding is representing $f(.,.)$ which can represent by Equation (3.43).

$$f(I(A_0), I(A_i)) = \begin{cases} 0 & \text{if } I(A_i) - I(A_0) < 0 \\ 1 & \text{Otherwise} \end{cases} \quad i = 1, 2, 3, \dots, 8 \quad (3.43)$$

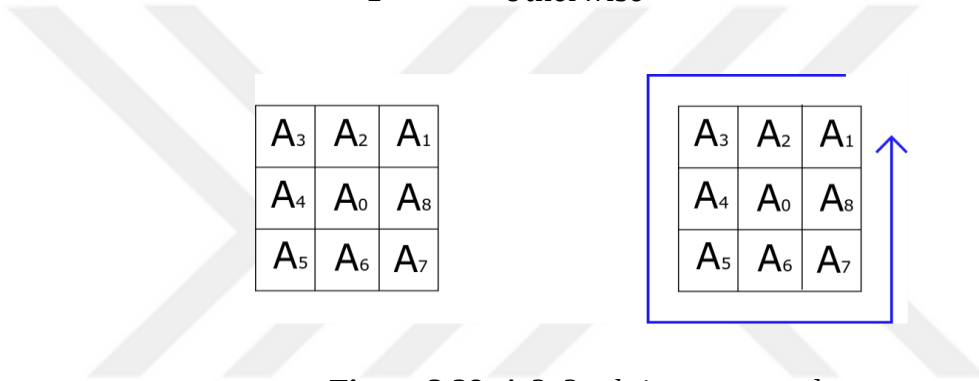


Figure 3.28. A 3x3 sub-image example.

Consequently, the local information CBC code for a sub-image can be representing as in Equation (3.44).

$$\text{CBC}(A_0)\text{code} = \{f(I(A_0), I(A_1)), f(I(A_0), I(A_2)), \dots, f(I(A_0), I(A_8))\} \quad (3.44)$$

where $f(.,.)$ is binary code function.

Finally, the CBC, is defined as summation of all neighbors' binary code function (as exponent) for with respect to center's value (as basis). It can be formally calculated in Equation (3.45). It can be formally calculated in Equation (3.).

$$\text{CBC} = \text{LI}_{A_0} = \frac{1}{P} \sum_{i=0}^{P-1} C^{f(A_0, A_i)} \quad (3.45)$$

From the Equation (3.45) the bit-binary for a specific sub-image still 8-Bits. The lowest value of CBC is 8, when the all neighbors' intensities are lower than C , whereas the highest CBC is $8C$ when the all neighbor's intensities higher than C .

Therefor this method gives realistic information of sub-image. Moreover, rotate the image with specific angle α , where $\alpha = 45, 90, 135, 180, 225, 270$, and 315 , not effect the value of the CBC code. The reason for this the constant relationship between the center and the neighbor, see Figure 3.29.

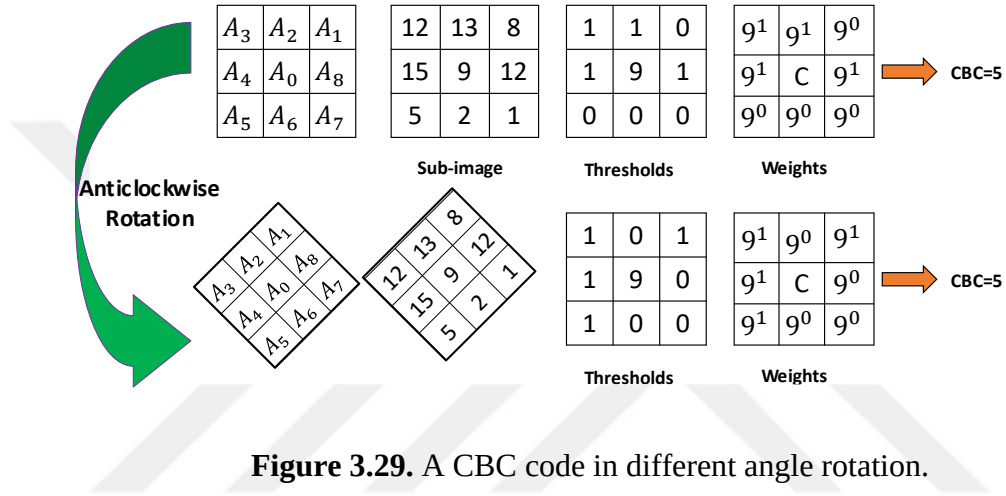


Figure 3.29. A CBC code in different angle rotation.

Let the CBC in angle $\alpha = 0$ is CBC_0° therefore rotate the sub-image with angle $\alpha = 45$ the CBC_{45° still same, Equation (3.46) and (3.47) illustrate the CBC invariant in case anticlockwise image rotation.

$$I(A_0)_{0^\circ} = f((A_0)_{0^\circ}, (A_1)) \quad (3.46)$$

$$I(A_0)_{45^\circ} = f((A_0)_{0^\circ}, (A_{1+1})) \quad (3.47)$$

Therefore, the general Equation is formed as in (3.48) and (3.49).

$$I(A_i)_{\theta^\circ} = f((A_0), (A_{(i+z) \bmod 8})) \quad i = 1, 2, \dots, 8. \quad (3.48)$$

$$\text{where, } z = \begin{cases} \theta \bmod 44 & \text{anticlockwise rotation} \\ 8 - (\theta \bmod 44) & \text{clockwise rotation} \end{cases} \quad (3.49)$$

The CBC is still a constant value in different angle rotation. So, the general CBC formula in different angle is given in Equation (3.50).

$$CBC_{\theta} = \{f(A_0, A_{(1+z) \bmod 8}), f(A_0, A_{(2+z) \bmod 8}), \dots, f(A_0, A_{(8+z) \bmod 8})\} \quad (3.50)$$

Generally, it also can be written in another formula as in Equation (3.51).

$$CBC_{A_0 \theta} = \frac{1}{P} \sum_{i=1}^P C^{f(A_0, A_{(i+z) \bmod 8})} \quad (3.51)$$

The flaw for use this method is that the sub-images may have the same CBC despite they have different neighbors (pattern) as clarified in Figure 3.30. To distinguish between two sub-images with a size of 3×3, therefore we suggest calculating local pattern (LP) for each block image, which is the number of changes in neighbor's intensity values, i.e. changing from values highest than the center to values less than the center and vice versa. The LP of a sub-image can be calculated by Equation (3.52).

$$LP = \sum_{i=1}^{i=P-1} XOR(I(A_i), I(A_{i+1})) \quad (3.52)$$

where, P is the number of samples.

It also could be represented the number of transitions of the neighbors' values from the of center to one, or vice versa. See Figure 3.31.

15	6	3	12^1	12^0	12^0	CBC=6.5 LP=3
13	12	17	12^1	C	12^1	
2	10	18	12^0	12^0	12^0	

15	13	10	12^1	12^1	12^0	CBC=6.5 LP=4
6	12	17	12^0	C	12^0	
2	3	18	12^0	12^1	12^1	

Figure 3.30. Calculation of the LP from different sub-images.

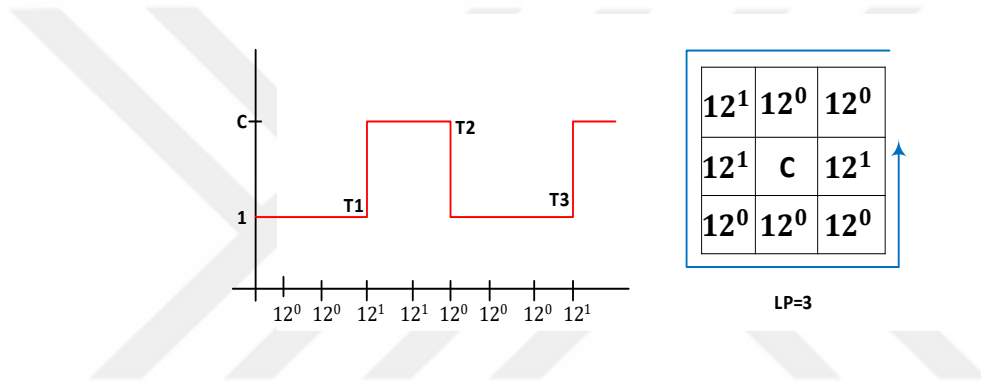


Figure 3.31. Calculate the Local pattern from sub-image.

Finally, the histogram for both pattern and CBC value are calculated, where it to preserve the information about the distribution of the LP patterns and CBC.

The two histograms concatenate to be represented the histogram of local information and patterns (HLIP) which is denoted as the feature vector. It can be calculated by the Equation (3.53).

$$HLIP = \{HCBC(R_i) + HLP(R_i) \mid i = 1, \dots, P\} \quad (3.53)$$

where, $HCBC$ is the histogram of local features extracted from region R_i . HLP is the histogram of patterns calculated from region R_i . See Figure 3.32.

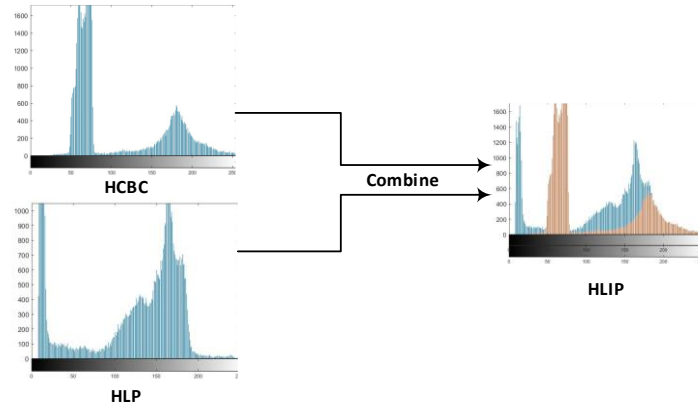


Figure 3.32. Histogram illustration of local information pattern.

3.4.2 Practical experiments

The image of the human cornea was used as an input to the system. The image of the cornea consists of four maps (Sinjab, 2018), see Figure 3.15. First is called sagittal map, it gives information about Astigmatism disease. The second which is called Corneal Thickness map reads the thickness of the cornea in divergent places of the cornea and gives the coordinates of the pupil center. The third and fourth maps (Elevation Front and Elevation Back) provide information about the cornea's anterior and posterior surface. Thus, a group of clinical diseases can be diagnosed by testing each map individually using SVM, naïve Bayes, Decision tree algorithms. In this work we conducted four types of experiments in order to diagnose accurately and reliably set of cornea disease. All results are present in Section 4.4.

4. RESULTS AND DISCUSSIONS

In this chapter, the results and discussions of each study will be presented separately.

4.1 SWFT Algorithm

4.1.1 Results

This section compares the SWFT achievements to those of the standard SIFT in controlled experiments. The evaluation of the diagnosis of the different corneal diseases is calculated as well. Support vector machine (SVM) are exploited as a classification tool to diagnose cornea diseases. In the real world, there are many numbers of patient cases available. Therefore, to build a system that simulates reality and to assess the effect of classification accuracy when the training size is different, the practical experiments are conducted in four different scenarios as following, 10% of dataset for training and 90% for testing, 50% of dataset for training and 50% for testing, 70% of dataset for training and 30% for testing, or 90% of dataset for training and 10% for testing. The results are obtained using cross-validation for each strategy. Tables 4.1, 4.2, 4.3, and 4.4 show the comparison of the results between the proposed and the standard algorithms using the four different strategies.

The proposed algorithm also examined using two other classifiers, the naive Bayes, and the K-Nearest Neighbors (KNN) classifiers, as it applied using the four maps of corneal topography, taking into account the balancing of data in case a big gap between the numbers of the instances in classes. The accuracy of the diagnosis calculated as well as estimate the cross-validation error for both classifiers using 10-fold cross-validation, the results shown in Table 4.5.

Table 4.1. Achievements of the algorithm on the sagittal map for diagnosis the corneal astigmatism using all strategies (%).

Measurements	Strategies of dataset							
	10%90%		50%50%		70%30%		90%10%	
	SIFT	SWFT	SIFT	SWFT	SIFT	SWFT	SIFT	SWFT
Recall	67.47	89.47	80.39	84.15	85.48	91.37	83.86	88.29
Precision	61.90	80.95	76.63	78.70	81.53	81.53	78.86	85.56
Accuracy	69.23	84.61	77.17	80.30	82.20	85.59	80.11	85.99
1-precision	38.09	19.04	23.36	21.29	18.64	18.64	21.13	14.43
Specificity	63.60	80.00	73.68	76.28	78.57	80.00	76.43	83.43

Table 4.2. Achievements of the algorithm on the corneal thickness map to diagnosis corneal-thinning disease using all strategies (%).

Measurements	Strategies of dataset							
	10%90%		50%50%		70%30%		90%10%	
	SIFT	SWFT	SIFT	SWFT	SIFT	SWFT	SIFT	SWFT
Recall	71.73	77.48	76.19	80.76	79.36	87.09	75.0	85.95
Precision	65.02	69.48	70.79	74.33	74.62	76.05	68.18	77.27
Accuracy	66.39	69.05	74.22	78.22	75.20	80.00	70.00	81.81
1-precision	34.97	30.51	29.20	25.66	25.37	23.94	31.80	22.72
Specificity	60.00	58.86	72.50	76.03	70.68	73.01	65.0	79.16

Table 4.3. Achievements of the algorithm on the corneal elevation front map for diagnosis the cornea-isolated-land disease using all strategies (%).

Measurements	Strategies of dataset							
	10%90%		50%50%		70%30%		90%10%	
	SIFT	SWFT	SIFT	SWFT	SIFT	SWFT	SIFT	SWFT
Recall	94.66	96.47	96.59	100	96.15	100	96.96	100
Precision	82.60	85.09	95.50	97.19	93.45	97.19	94.11	97.14
Accuracy	82.33	85.57	93.69	97.74	91.72	97.74	92.85	97.67
1-precision	17.30	14.90	4.49	2.80	6.54	2.80	5.88	2.85
Specificity	53.71	59.32	82.60	89.79	75.86	89.66	77.77	88.88

Table 4.4. Achievements of the algorithm on the corneal elevation back map to diagnosing the like tang diseases using all strategies (%).

Measurements	Strategies of dataset							
	10%90%		50%50%		70%30%		90%10%	
	SIFT	SWFT	SIFT	SWFT	SIFT	SWFT	SIFT	SWFT
Recall	91.59	92.21	93.75	96.12	90.58	95.40	96.42	100
Precision	79.56	82.11	78.94	81.57	84.61	91.20	90.00	93.33
Accuracy	75.00	77.63	83.40	86.30	84.61	91.66	91.66	95.83
1-precision	20.43	17.88	21.05	18.00	15.38	8.79	10.00	6.66
Specificity	15.15	18.33	71.68	75.00	75.86	85.96	85.0	90.00

Table 4.5. Accuracy of cornea disease diagnosis by applying the proposed algorithm on all corneal topography maps (%), and Loss cross-validation error.

Maps \Methods	Naive Bayes Classifier				KNN Classifier			
	Accuracy (%)		c-Validation		Accuracy (%)		cross validation	
	SIFT	SWFT	SIFT	SWFT	SIFT	SWFT	SIFT	SWFT
Sagittal	81.0	98.7	0.29	0.25	82.8	92.1	0.34	0.13
C. Thickness	47.0	92.8	0.51	0.34	73.1	78.5	0.34	0.26
Elevation Front	98.7	99.7	0.16	0.02	98.1	98.7	0.32	0.01
Elevation Back	82.6	99.8	0.24	0.01	91.4	92.4	0.17	0.14

Our proposal also examined on three common datasets, namely Skin Cancer MNIST: HAM10000 (Tschandl et al., 2018), Chest X-Ray Images (Pneumonia) (Kermany et al., 2018), and MIAS MiniMammographic Databases (Suckling et al., 2005). It should be noted that the Skin Cancer MNIST dataset contains several categories. therefore, it is classified on the basis of category. For example, Benign keratosis (bkl), Dermatofibroma (df), Melanocytic nevi (nv), and Basal cell carcinoma (bcc). For comparison and testing, each of the two categories selected separately. whereas the Chest X-Ray and MIAS MiniMammographic datasets labeled as normal and abnormal. The proposed algorithm and the standard SIFT are used to be compared. Finally, the accuracy of the diagnosis calculated using three classifiers, the Naive Bayes, KNN, and SVM classifiers, and the results as shown in Table 4.6.

Table 4.6. Accuracy of diagnosis comparing between the proposed algorithm and standard SIFT examined and employing indifferent classifiers (%).

	Chest X-Ray		MIAS MiniMammographic		Skin Cancer MNIST					
classifier	Normal VS abnormal		Normal VS abnormal		Bkl VS df		Bcc VS bkl		Bcc VS nv	
	SIFT	SWFT	SIFT	SWFT	SIFT	SWFT	SIFT	SWFT	SIFT	SWFT
SVM	93.40	95.80	73.00	72.50	73.50	75.80	70.70	75.40	89.10	94.90
Naive Bayes	91.00	94.80	81.40	83.30	90.70	94.20	89.00	96.50	95.50	98.50
KNN	94.00	93.10	73.10	73.90	80.70	85.70	81.50	84.50	90.00	94.50

Figure 4.1 (a-d) plots recall and precision to illustrate the comparison results of practical experiments between the SIFT and SWFT algorithms using sagittal, corneal thickness, elevation front, and elevation back maps, which clearly shows how the proposed algorithm outperforms its counterpart.

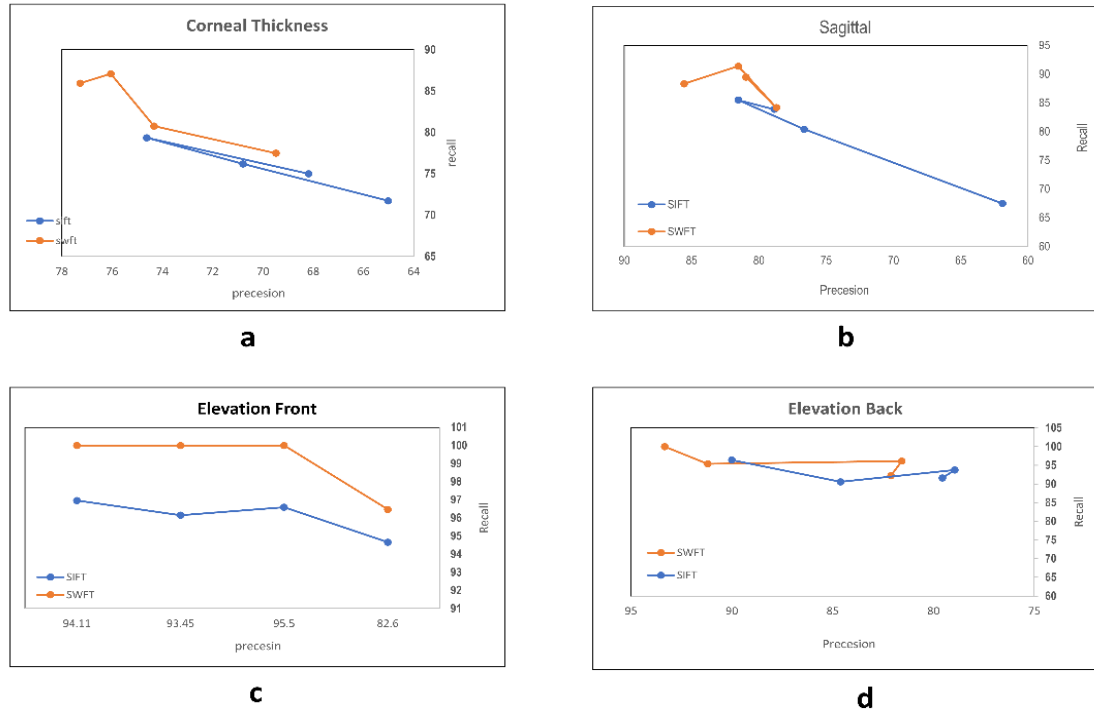


Figure 4.1. Plotting the Compression of SIFT and SWFT performance with different strategies for a) Sagittal map. b) Corneal Thickness map. c) Elevation front map d) Elevation back map.

4.1.2 Discussion

The previous section showed that the SWFT algorithm, in general, is significantly has high accuracy and reliability compared to the standard SIFT local feature descriptor. From the Tables above, the probability of correct diagnosis (recall) using the proposed algorithm with various strategies gives more realistic results than the standard algorithm, where, the recall average values for diagnosing cornea diseases for all strategies and maps are 91.54, and 86.01 using SWFT and SIFT respectively. The statistics tell that the proposed algorithm detect better the relevant diseases among the retrieved instances via testing using all the strategies, where, the precision average values for diagnosing cornea diseases using all maps are 84.29, and 79.76 using SWFT and SIFT respectively. The accuracy metric refers to the correct predictions of the proposed algorithm. The reports indicate the SWFT algorithm achieved the highest performance among all cases examined to detect both true results (positive and negative) for all the strategies, where the average accuracy values are 84.85 and 80.61 using SWFT and SIFT algorithms respectively.

The SWFT algorithm achieved a lower percentage of the false detection cases relative

to the overall cases compared with the standard SIFT algorithm, where the average of represents the false detection values (1-precision) are 15.68, and 20.22 using SWFT and SIFT algorithms respectively. The results also showed a system using SWFT algorithm achieves a higher percentage in detecting healthy corneas that are correctly diagnosed as not having any disease than using SIFT algorithm via using all strategies, the average of specificity are 75.23, and 68.63 using SWFT and SIFT algorithms respectively. Figure 4.1 indicates that the proposed algorithm outperformance the standard algorithm even when examed with different datasets, except in very rare cases. The reason might be attributed to the nature of the data that trained. Despite the minor errors, it still an algorithm that has an explicit positive impact on improving the efficiency of the system performance, especially with the corneal topography datasets.

4.2 Multi-Subbands Wavelet with SIFT Algorithm for Local Feature Extraction

4.2.1 Results

The proposed method applied on a set of corneal topography represents the important content of the cornea. The two dimensions wavelet transform applied on the original input maps (sagittal, cornea, elevation front, and elevation back) individually, which produce a set of subbands (LL, LH, HL, HH) that contains certain characteristics extracted from the original image. The only one subband of the wavelet has been exploit to extract the feature that represent the whole corneal maps, this single wavelet subband acquisition by decomposition the corneal image into one level using DWT. Tables 4.7 to 4.22 show the results of applying the proposed method on the dataset. The results evaluated using five different metrics (i.e. Recall, Precision, Accuracy, 1-Precision, and Specificity), in different strategies (ratio of training and testing set) i.e. 30%70%, 50%50%, 90%10%, 10%90% training/testing sets.

Table 4.7. Cornea diagnosis in different subbands and SIFT using SVM classifier with 70%30% strategies using sagittal map (%).

Sagittal	Recall	Precision	Accuracy	1-Precision	Specificity
S-LL	75.80	72.30	72.03	27.69	67.85
S-LH	88.35	80.33	84.40	19.64	81.03
S-HL	88.35	80.33	84.40	19.64	81.03
S-HH	90.16	84.61	86.44	15.38	82.45
SIFT	85.48	81.53	82.20	18.64	78.57

Table 4.8. Cornea diagnosis in different subbands and SIFT using SVM classifier with 50%50% strategies using sagittal map (%).

Sagittal	Recall	Precision	Accuracy	1-Precision	Specificity
S-LL	78.78	81.30	83.75	18.69	79.59
S-LH	78.78	82.85	84.61	17.12	81.25
S-HL	90.00	84.11	86.29	15.88	82.47
S-HH	89.42	86.91	87.92	13.08	86.40
SIFT	80.39	76.63	77.17	23.36	73.68

Table 4.9. Cornea diagnosis in different subbands and SIFT using SVM classifier with 90%10% strategies using sagittal map (%).

Sagittal	Recall	Precision	Accuracy	1-Precision	Specificity
S-LL	80.95	77.72	77.5	22.72	73.68
S-LH	84.21	72.72	77.5	27.27	71.42
S-HL	88.88	72.72	80.00	27.27	72.72
S-HH	90.00	81.81	85.00	18.18	80.00
SIFT	83.86	78.86	80.11	21.13	76.43

Table 4.10. Cornea diagnosis in different subbands and SIFT using SVM classifier with 10%90% strategies using sagittal map (%).

Sagittal	Recall	Precision	Accuracy	1-Precision	Specificity
S-LL	90.96	82.98	86.27	17.01	81.66
S-LH	90.44	82.98	85.99	17.01	81.56
S-HL	89.95	82.98	85.15	17.01	81.25
S-HH	89.94	82.98	85.71	17.01	81.46
SIFT	67.47	61.90	69.23	38.09	63.60

Table 4.11. Cornea diagnosis in different subbands and SIFT using SVM classifier with 70% 30% strategies using corneal thickness map (%).

Corneal Thickness	Recall	Precision	Accuracy	1-Precision	Specificity
S-LL	79.68	76.11	76.03	23.88	71.92
S-LH	81.66	73.13	76.03	26.86	70.49
S-HL	48.74	74.62	75.51	25.37	72.58
S-HH	86.88	79.10	81.96	20.89	77.04
SIFT	79.36	74.62	75.2	25.37	70.68

Table 4.12. Cornea diagnosis in different subbands and SIFT using SVM classifier with 50% 50% strategies using corneal thickness map (%).

Corneal Thickness	Recall	Precision	Accuracy	1-Precision	Specificity
S-LL	78.84	73.21	74.25	26.78	69.38
S-LH	82.07	77.67	78.21	22.32	73.95
S-HL	80.00	75.47	76.53	24.52	72.95
S-HH	83.49	76.78	78.71	23.21	73.73
SIFT	76.19	70.79	74.22	29.2	72.5

Table 4.13. Cornea diagnosis in different subbands and SIFT using SVM classifier with 90%10% strategies using corneal thickness map (%).

Corneal Thickness	Recall	Precision	Accuracy	1-Precision	Specificity
S-LL	76.19	66.66	69.04	33.33	61.90
S-LH	80.00	66.66	71.42	33.33	63.63
S-HL	76.19	66.66	69.04	33.33	61.90
S-HH	80.95	77.27	77.5	22.72	73.68
SIFT	75.00	68.18	70.00	31.8	65.00

Table 4.14. Cornea diagnosis in different subbands and SIFT using SVM classifier with 10%90% strategies using corneal thickness map (%).

Corneal Thickness	Recall	Precision	Accuracy	1-Precision	Specificity
S-LL	76.47	47.17	56.22	52.80	42.65
S-LH	76.71	71.42	72.13	28.57	67.23
S-HL	74.19	67.98	69.12	32.01	63.88
S-HH	75.93	69.95	71.03	30.04	65.92
SIFT	71.73	65.02	66.39	34.97	60.00

Table 4.15. Cornea diagnosis in different subbands and SIFT using SVM classifier with 70%30% strategies using elevation front map (%).

EF	Recall	Precision	Accuracy	1-Precision	Specificity
S-LL	100	96.26	96.99	3.73	86.65
S-LH	100	96.26	96.99	3.73	86.65
S-HL	100	94.39	95.48	5.60	81.25
S-HH	100	93.85	95.06	6.14	80.00
SIFT	96.15	93.45	91.72	6.54	75.86

Table 4.16. Cornea diagnosis in different subbands and SIFT using SVM classifier with 50%50% strategies using elevation front map (%).

EF	Recall	Precision	Accuracy	1-Precision	Specificity
S-LL	100	96.08	96.86	3.91	86.27
S-LH	100	96.08	96.86	3.91	86.27
S-HL	100	39.85	95.06	6.14	80.00
S-HH	100.	96.08	96.86	3.91	86.27
SIFT	96.59	95.5	93.69	4.49	82.6

Table 4.17. Cornea diagnosis in different subbands and SIFT using SVM classifier with 90%10% strategies using elevation front map (%).

EF	Recall	Precision	Accuracy	1-Precision	Specificity
S-LL	100	94.28	95.34	5.71	80.00
S-LH	100	94.28	9.34	5.71	80.00
S-HL	100	88.90	90.69	11.24	66.66
S-HH	100	94.28	95.34	5.71	80.00
SIFT	96.96	94.11	92.85	5.88	77.77

Table 4.18. Cornea diagnosis in different subbands and SIFT using SVM classifier with 10%90% strategies using elevation front map (%).

EF	Recall	Precision	Accuracy	1-Precision	Specificity
S-LL	100	96.68	97.51	3.10	88.88
S-LH	100	96.89	97.51	3.10	88.88
S-HL	100	93.16	94.52	6.82	78.43
S-HH	100	94.40	95.52	5.59	81.63
SIFT	94.66	82.6	82.33	17.3	53.71

Table 4.19. Cornea diagnosis in different subbands and SIFT using SVM classifier with 70%30% strategies using elevation back map (%).

EB	Recall	Precision	Accuracy	1-Precision	Specificity
S-LL	97.46	84.61	88.88	15.38	78.46
S-LH	95.29	89.01	90.27	10.98	83.05
S-HL	97.53	86.81	90.27	13.18	80.95
S-HH	92.94	86.81	87.50	13.18	79.66
SIFT	90.58	84.61	84.61	15.38	75.86

Table 4.20. Cornea diagnosis in different subbands and SIFT using SVM classifier with 50%50% strategies using elevation back map (%).

EB	Recall	Precision	Accuracy	1-Precision	Specificity
S-LL	98.85	92.02	93.86	7.97	85.29
S-LH	97.14	98.47	91.70	10.52	84.15
S-HL	98.48	85.52	90.04	14.47	79.81
S-HH	95.71	88.15	90.04	11.84	82.17
SIFT	93.75	78.94	83.4	21.05	71.68

Table 4.21. Cornea diagnosis in different subbands and SIFT using SVM classifier with 90%10% strategies using elevation back map (%).

EB	Recall	Precision	Accuracy	1-Precision	Specificity
S-LL	92.30	80.00	83.33	20.00	72.72.
S-LH	92.85	86.66	87.5	13.33	80.00
S-HL	98.65	86.66	85.41	13.33	78.94
S-HH	92.30	80.00	83.33	20.00	72.72
SIFT	96.42	90.00	91.66	10.00	85.00

Table 4.22. Cornea diagnosis in different subbands and SIFT using SVM classifier with 10%90% strategies using elevation back map (%).

EB	Recall	Precision	Accuracy	1-Precision	Specificity
S-LL	59.8	84.67	87.55	15.32	77.89
S-LH	59.16	86.13	88.74	13.86	79.56
S-HL	93.62	85.76	87.32	14.23	78.68
S-HH	93.75	87.59	88.47	12.40	80.89
SIFT	91.59	79.56	75.00	20.43	51.15

From all values, the highest and lowest differences are clarifying that the proposed method performance is improved, which can be considered sufficiently enough evidence of the novelty of the proposed method as it can be seen in Figure 4.2.

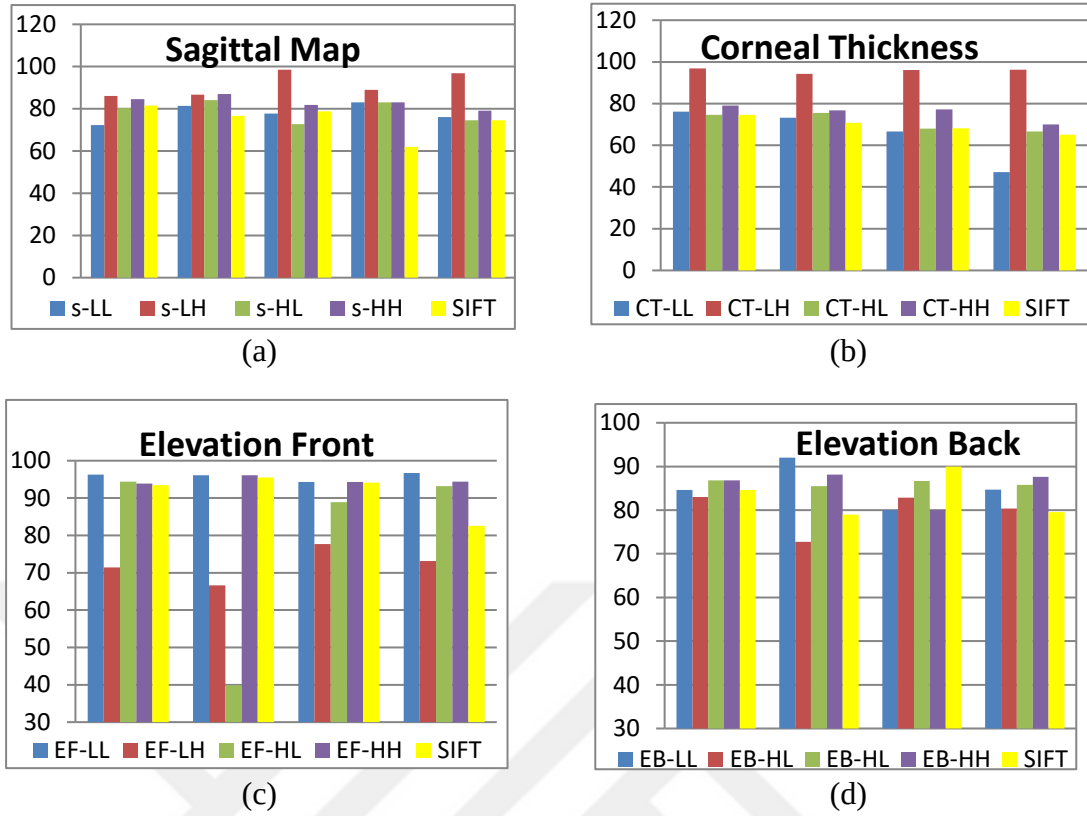


Figure 4.2. Results of precision in different strategies and subbands (a) sagittal map (b) Corneal Thickness map (c) Elevation Front map (d) Elevation Back map.

4.2.2 Discussion

Results of proposed method have been represented in Table 4.7-4.22. As it can be seen the proposed method Accuracy and recall metric is always higher than the standard SIFT algorithm. In some sets, the difference is higher than 14%.

For the "Recall" metric results, Tables show that extracting features from HH-SIFT for all types of cornea maps in different strategies often gives satisfactory results that represent the performance for the proposed methods even higher than the standard SIFT algorithm results have been obtained for all experiments. The Tables also show that it is extremely rare that the highest "Recall" of the system has been recorded from extracting data from SIFT-LL. The results have recorded that the highest difference between the proposed and the standard algorithm with respect to the Sagittal, corneal thickness, Elevation front, Elevation back maps are 23.49, 7.25, 5.34, 6.95, respectively, and the lowest difference are 4.69, 4.74, 3.04, and 2.16 respectively. While second metric "precision" were indicating that using SIFT-HH subband mostly

gives the high values as a measure of system performance, and the next highest values obtained by using the SIFT-LH subband. Only one experiment indicates the SIFT standard gives highest precision which is in 90%10% strategy. The highest differences between the proposed and the standard algorithm with respect to the Sagittal, corneal thickness, Elevation front, Elevation back maps are 21.28, 9.09, 14.29, and 19.98 respectively, and the lowest differences are 2.95, 4.48, 0.17, and -3.34 respectively. Whereas, the accuracy become high through exploit the SIFT-HH and next is by exploit SIFT-LH, while only one test refers to high accuracy using SIFT in 90%10% strategy, and one when 50%50% strategy. Tables recorded that the highest difference between the proposed and the standard algorithm with respect to the Sagittal, corneal thickness, Elevation front, Elevation back maps are 17.04, 7.5, 15.18, and 13.74 respectively, and the lowest differences are 4.24, 4.40, 2.19 and -4.16 respectively.

Finally, the specificity measurement indicates that using SIFT-HH subband gives highest values and next are SIFT-LH and SIFT-LL subbands sequentially. The highest differences between the proposed and the standard algorithm with respect to the Sagittal, corneal thickness, Elevation front, Elevation back maps are 18.06, 17.68, 35.17, and 28.85 respectively, and the lowest difference between them is 3.75, 0.45, 3.67 and -5.00 respectively.

4.3 IG-GLCM Algorithm

4.3.1 Results

In this section, a proposed IG-GLCM algorithm is applied with 1-distance and several degrees (0°, 45°, 90°, and 135°) and multi-class SVM to the collected dataset containing normal/abnormal cornea cases. Each 1-distance and individual degree applied to all four corneal images (sagittal, corneal Thickness, Elevation Front, and Elevation Back) then calculate the average metrics values. This algorithm was also employed to reduce execution time. The performance was evaluated by calculating several measurements, such as accuracy, execution time, specificity, and sensitivity. To increase the confidence of the system evaluation and verify that IG-GLCM does not work in isolation from other techniques, the proposed method was examined using several methods, including wavelet transform, discrete cosine transforms, and Fourier transform with different angles. Additionally, a comparison between the proposed and the standard algorithm have been done. Worth mentioning, the algorithms are running

on the computer has CPU Core (TM) i7-5500U, 2.4 GHz, and RAM 16 GB DDR4. Tables 4.23-4.26 reports the average result of applying methods on four corneal maps. Figure 4.3 represent the linear graph of time-consuming.

Moreover, IG-GLCM measured the gradient in both horizontal (Gx) and vertical directions (Gy). This is followed by applying the GLCM algorithm to each separate direction (method 1 and 2 in Tables 5-8) and calculating the metrics mentioned above. We go further, to showing how efficiency the proposed method, where the system trained by applied the gradient directions followed by apply wavelet, DCT, or FFT techniques independently. Thus, employ the IG-GLCM to extract features from images (methods 3-6) applied to the four corneal maps. The average metrics are calculated and reports in Tables 4.27-4.30. The results illustrated as graph in Figure 4.4.

Finally, image analysis is performed using a single-level wavelet transform and generated coefficients (LL, LH, HL, HH). The IG-GLCM algorithm is then applied to each of the coefficients to examine its impact on execution speed and accuracy, as presented in Table 4.31.

Table 4.23. Comparison of the performance of applying different techniques with distance 1 and angle 0^0 .

Method	Time	Accuracy	Sensitivity	Specificity
GLCM	751.633	80.05	77.79	97.77
IG-GLCM	85.83	92.34	92.20	94.44
IG-GLCM + FFT	97.581	82.81	82.17	87.77
IG-GLCM +DCT	133.318	92.346	91.65	97.78

Table 4.24. Comparison of the performance of applying different techniques with distance 1 and angle 45^0 .

Method	Time	Accuracy	Specialty	Specificity
GLCM	823.441	79.42	77.65	93.33
GLCM + Gradient	88.48	91.46	90.94	95.55
GLCM + Gradient + FFT	107	93.65	94.2	90.1
GLCM+ Gradient +DCT	132.227	93.601	93.35	95.55

Table 4.25. Comparison of the performance of applying different techniques with distance 1 and angle 90^0 .

Method	Time	Accuracy	Specialty	Specificity
GLCM	673.904	81.806	79.63	98.88
GLCM + Gradient	85.46	92.47	91.93	96.66
GLCM + Gradient + FFT	108.15	87.31	86.3	93.3
GLCM+ Gradient +DCT	129.7265	93.224	92.29	95.55

Table 4.26. Comparison of the performance of applying different techniques with distance 1 and angle 135^0

Method	Time	Accuracy	Specialty	Specificity
GLCM	668.12	79.171	77.08	95.55
GLCM + Gradient	86.70	92.34	92.22	93.33
GLCM + Gradient + FFT	108.1	87.87	87.03	93.26
GLCM+ Gradient +DCT	133.195	91.21	90.65	95.55

Table 4.27. Comparison of the performance of applying different techniques with gradients in x, & y axis with distance 1 and angle 0^0 .

Method	Time	Accuracy	Specialty	Specificity
1. IG-GLCM using Gx	89.44	92.24	91.46	97.4
2. IG-GLCM using Gy	92.8	92.33	92.6	90.1
3. IG-GLCM using Gx+FFT	95.83	81.39	80.6	86.01
4. IG-GLCM using Gx+DCT	130.0	81.74	82.04	79.7
5. IG-GLCM using Gy+ FFT	92.001	72.92	70.69	82.32
6. IG-GLCM using Gy+ DCT	136.011	85.92	85.02	91.7

Table 4.28. Comparison of the performance of applying different techniques with gradients in x, & y axis with distance 1 and angle 45^0 .

Method	Time	Accuracy	Specialty	Specificity
1. IG-GLCM using Gx	79.44	92.54	91.78	97.40
2. IG-GLCM using Gy	87.62	93.24	96.8	69.94
3. IG-GLCM using Gx+FFT	97.14	79.94	79.7	81.8
4. IG-GLCM using Gx+DCT	130.87	84.32	84.05	86.01
5. IG-GLCM using Gy+ FFT	102.7	87.81	78.90	78.2
6. IG-GLCM using Gy+ DCT	123.50	83.76	83.89	82.90

Table 4.29. Comparison of the performance of applying different techniques with gradients in x, & y axis with distance 1 and angle 90^0 .

Method	Time	Accuracy	Specialty	Specificity
1. IG-GLCM using Gx	80.02	93.50	93.33	94.18
2. IG-GLCM using Gy	85.84	93.37	95.16	81.86
3. IG-GLCM using Gx+FFT	88.67	80.55	78.6	92.7
4. IG-GLCM using Gx+DCT	131.42	89.12	89.37	87.56
5. IG-GLCM using Gy+ FFT	95.85	77.56	77.45	78.23
6. IG-GLCM using Gy+ DCT	126.44	83.13	83.89	87.23

Table 4.30. Comparison of the performance of applying different techniques with gradients in x, & y axis with distance 1 and angle 135^0 .

Method	Time	Accuracy	Specialty	Specificity
1. IG-GLCM using Gx	86.53	91.70	91.06	95.84
2. IG-GLCM using Gy	93.32	92.75	93.07	90.67
3. IG-GLCM using Gx+FFT	95.87	79.37	79.06	80.93
4. IG-GLCM using Gx+DCT	131.96	84.87	84.78	85.49
5. IG-GLCM using Gy+ FFT	91.39	76.37	76.08	78.23
6. IG-GLCM using Gy+ DCT	128.6	83.48	38.49	83.41

Table 4.31. performance of different subbands wavelet with IG-GLCM algorithm.

Method	TIME	Accuracy	Specialty	Specificity
LL_GLCM	231.1689	89.58	89.25	92.22
LH_GLCM	237.6176	85.9473	87.41	74.44
HL_GLCM	237.8271	88.833	88.82	88.88
HH_GLCM	231.115	83.56	83.30	85.55

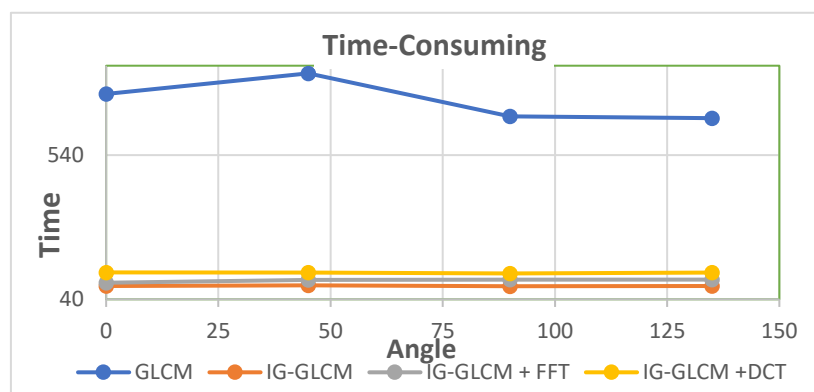


Figure 4.3. Chart for measurements of cost time for different methods.

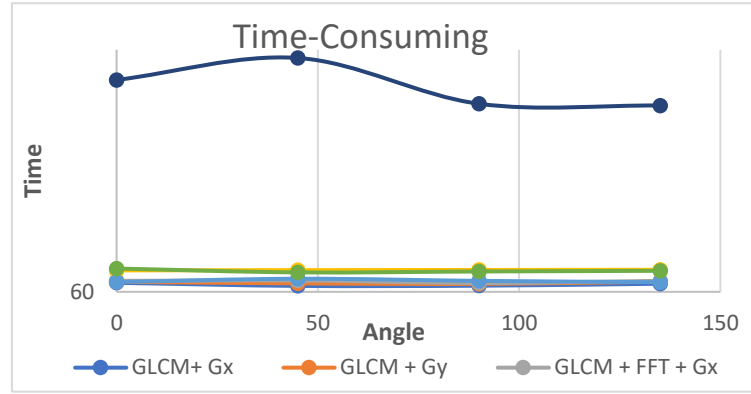


Figure 4.4. Chart for measurements cost time for proposed and different methods.

4.3.2 Discussion

The proposed method was evaluated using the corneal topography dataset. According to Tables 4.23 to 4.26, the proposed method contributed to a reduction in execution time (diagnosis of corneal disease), and a reduction in the average time needed for feature extraction from various angles (0° , 45° , 90° , and 135°) about 88%.

The proposed method led to a reduction in execution time, whether used alone or in conjunction with other techniques. The results indicated an 82% and 85% decrease in the average time using DCT and FFT, respectively. On the other hand, using the standard algorithm, the maximum and minimum time spent on diagnosis was recorded at 45° and 135° , respectively. An essential contribution of the present research is reducing execution time for diagnostic systems using the GLCM algorithm.

The proposed method was shown to have yielded more accurate results than the standard algorithm regarding diagnosis accuracy. The average diagnostic accuracy was increased by 12, 7, and 12.5% using GLCM with Gradient, DCT and FFT methods, respectively. The maximum and minimum accuracy using the GLCM were recorded at 90° and 45° , respectively. Besides, the specificity and sensitivity values indicated a nearly 18 and 20% improvement, respectively, when the proposed method was used alone, and 20 and 12%, respectively, when DCT and FFT methods were used together. Therefore, another contribution of this research is improved accuracy.

According to Tables 4.27 to 4.30, using a horizontal gradient (Gx) and a vertical gradient (Gy) has contributed to improved system performance. By applying Gx with

GLCM (method 1), the average execution time less than applying Gy (method 2), in contrast, method 2 reports a higher average performance in terms of accuracy, sensitivity, and specificity.

Regarding to using Gx or Gy with FFT or DCT techniques (methods 3-6). Generally, Tables 4.27 to 4.30 reports that method 3 consume less average execution time. Applying FFT with Gx, supplies less time-consuming than applying FFT with Gy. Moreover, it supplies higher ratios in terms of accuracy, sensitivity, and specificity. On the other hand, utilizing DCT with Gx is more time-consuming while provides higher ratios of accuracy, sensitivity, and specificity as comparison with using DCT with Gy.

Table 4.31 shows that less time is spent on using wavelet sub-bands by applying the standard GLCM algorithm. Here, the mean execution time is reduced by 68%, thereby improving corneal disease's diagnostic accuracy. Despite using wavelet subbands, the time spent was reduced, and the diagnostic accuracy was increased. Nonetheless, using gradient increases system efficiency regarding accuracy and speed.

Accordingly, the present research's most vital contribution is using the proposed algorithm in real time applications especially diagnostic systems.

4.4 LIP Algorithm

4.4.1 Results

A set of investigations were conducted on a set of data in order to diagnose different cornea diseases. The outputs of applying the suggested method were compared with the results of applying the standard algorithm using the same set of data. In the real-life data about the patients can be available and in different quantities. Besides, a system that can simulate the reality can be also be built. This system evaluates the range of the impact of the data number differences on the system performance. Therefore, experiments were conducted in four scenarios; 10% with 90%, 20% with 80%, 30% with 70%, and 50% with 50% of the data for training and for test respectively. (see Tables 4.32 to 4.35).

Table 4.32. Achievements comparison of the LIP and LBP to corneal diagnosis by applying all strategies on the sagittal map (%).

	20%80%		30%70%		50%50%		70%30%		80%20%	
	LBP	LIP	LBP	LIP	LBP	LIP	LBP	LIP	LBP	LIP
Recall	62.1	75.3	64.6	80.7	70.4	81.1	76.1	83.9	61.6	76.3
Precision	98.4	92.0	92.9	90.9	93.6	92.5	96.4	95.8	96.0	94.2
Accuracy	67.0	79.6	68.9	83.4	75.5	84.4	81.9	87.9	65.7	81.2
Specificity	94.4	87.7	83.3	87.6	88.0	89.7	94.0	94.2	86.9	90.8

Table 4.33. Achievements comparison of the LIP and LBP to corneal diagnosis by applying all strategies on the Corneal thickness map (%).

	20%80%		30%70%		50%50%		70%30%		80%20%	
	LBP	LIP	LBP	LIP	LBP	LIP	LBP	LIP	LBP	LIP
Recall	50.9	62.2	50.8	68.1	0	65.8	0	53.9	0	64.9
Precision	100	70.3	100	69.9	0	45.1	0	45.7	0	52.8
Accuracy	50.9	63.1	50.8	68.1	65.8	73.2	65.7	68	65.6	74.0
Specificity	0	64.3	0	68.1	65.8	75.5	65.7	73.8	65.6	77.5

Table 4.34. Achievements comparison of the LIP and LBP to corneal diagnosis by applying all strategies on the Elevation front map (%).

	20%80%		30%70%		50%50%		70%30%		80%20%	
	LBP	LIP	LBP	LIP	LBP	LIP	LBP	LIP	LBP	LIP
Recall	78.2	81.6	77.4	84.2	78.2	80.5	59.3	66.4	91.7	93.1
Precision	89.3	86.3	90.5	90.6	89.8	91.3	89.8	92.6	99.4	99.4
Accuracy	82.0	83.2	81.9	86.4	82.1	84.4	78.3	83.6	91.6	93.0
Specificity	87.2	85.1	88.3	89.3	87.7	89.6	94.3	96.1	90.0	92.3

Table 4.35. Achievements comparison of the LIP and LBP to corneal diagnosis by applying all strategies on the Elevation back map (%).

	20%80%		30%70%		50%50%		70%30%		80%20%	
	LBP	LIP	LBP	LIP	LBP	LIP	LBP	LIP	LBP	LIP
Recall	70.5	75.0	72.6	84.0	71.8	72.6	72.9	76.8	69.5	71.9
Precision	96.9	95.0	98.1	94.1	87.9	83.9	87.5	82.1	90.1	89.5
Accuracy	75.2	79.2	78.0	85.5	76.9	76.3	77.6	78.7	75.2	77.3
Specificity	92.1	90.0	95.5	88.8	84.7	81.3	84.6	80.9	85.9	86.1

The proposed algorithm also tested using three other classifiers, naive Bayes, decision tree, and the K-Nearest Neighbors (KNN) classifiers, as it applied using the four maps of corneal topography. The accuracies are calculated as shown in Table 4.36.

Table 4.36. Accuracy of cornea disease diagnosis apply proposed algorithm on all corneal topography maps (%).

	KNN		D.T.		N.B.	
	LBP	LIP	LBP	LIP	LBP	LIP
Sagittal	90.8	90.0	96.4	97.4	84.6	94.4
C. Thickness	95.8	96.2	99.0	98.7	85.3	93.9
Elevation Front	95.8	96.2	99.0	98.7	85.3	93.9
Elevation Back	92.5	92.0	97.1	98.5	75.7	89.0

Furthermore, our proposal also tested on four common datasets, namely Skin Cancer MNIST: HAM10000 (Tschandl et al., 2018), Chest X-Ray Images (Pneumonia) (Kermany et al., 2018), MIAS MiniMammographic Databases (Suckling et al., 2005) and LISC dataset (Rezatofghi and Zadeh, 2011) which included samples that taken from peripheral blood. It should be noted that the Skin Cancer MNIST dataset contains several categories. therefore, it is classified on the basis of category. For example, Benign keratosis (bkl), Dermatofibroma (df), Melanocytic nevi (nv), and Basal cell carcinoma (bcc). For comparison and testing, each of the two categories selected separately. The Chest X-Ray and MIAS MiniMammographic datasets labeled as normal and abnormal. The proposed algorithm and the standard LBP are used to be compared. Finally, the accuracy of the diagnosis calculated using three classifiers, the Naive Bayes, KNN, and SVM classifiers, and the results as shown in Table 4.37.

Table 4.37. Accuracy of diagnosing cornea for the proposed and standard SIFT (%).

Dataset	Diagnosing Type	SVM		D.T.		N.B.	
		LBP	LIP	LBP	LIP	LBP	LIP
MiniMammographic	malignant/benign	84.5	82.0	95.0	100	82.0	91.5
Chest X-Ray	Normal/ Pneumon	89.5	89.9	95.1	98.3	74.5	75.0
Skin Cancer MNIST	bcc/bkl	79.5	87.5	96.0	98.5	64.0	72.5
	bcc/mel	77.0	80.0	92.0	96.1	72.0	63.0
	mel/bkl	78.0	82.0	97.0	97.0	73.5	76.5
	mel/nv	87.5	96.0	99.0	97.5	79.5	80.5
	vasc/bcc	78.0	76.5	94.5	93.0	69.5	80.0
	vasc/bkl	77.5	84.5	94.5	97.0	69.5	70.5
	df/bkl	77.5	85.5	94.5	96.5	69.5	77.5
	df/bcc	75.0	77.5	93.5	98.0	66.0	80.0
LISC	baso/mono	78.1	88.0	97.0	99.0	87.1	88.1
	baso/lymp	96.1	97.1	98.0	100	90.4	99.0
	baso/neut	93.8	94.8	100	100	96.1	99.0

4.4.2 Discussion

The results have been obtained by applying the standard LBP and the suggested LIP algorithms in various strategies (data training and testing percentages). Using a group of metrics to assess the system's performance extremely helped to understand the algorithm's behaviors and the proposed as well. Results reflect that applying the proposed algorithm provides high diagnostic accuracy as compared to applying standard LBP in all the experiments and strategies. In Table 4.32, the sagittal images were used to diagnose the existent of corneal Astigmatism disease. We observed when low rate training data, the results of the Specificity using LIP are slightly less than the standard LBP, whereas increasing training data, led to increasing specificity rates permanently. It indicates to response of the proposed algorithm for improving the performance when increasing the training data more than its counterpart. Additionally, once applying LIP, we note ameliorating the precision results when increasing the number of training rates while losing the improvement in the standard algorithm. Finally, as is clearly visible, we find in any conditions the LIP outperforms the LBP in terms of accuracy and precision.

Table 4.33 refer to the efficiency of the algorithms to diagnose corneal thinness and Pupil deviation from the cornea center. The results report that applying standard LBP on the Corneal Thickness maps is unsatisfying as compared with LIP. Apply LBP shows the classifier biased to classify both categories to one class, which can be called comprehensive bias. It is evident either from the precision ratio is 100% and the specificity is zero, or when both recall and precision are 0%, as well as the value of accuracy and specificity are similar.

The Elevation Front map is used for diagnosing the anterior corneal surface such as isolated land, and like tang shape diseases. Table 4.34 tales that diagnosis accuracies and specificities using the LBP algorithm are less than using the proposed LIP. On the other hand, we observed the results of recall and precision are impacted using high training data rate while applying LIP, which led to outperforming the standard LBP.

Table 4.35 presents the potential of LIP for diagnosing the posterior corneal surface condition such as normal, isolated land, and like tang shape. We note that some metrics

values slightly low when using the proposed algorithm due to the scarcity of abnormal corneal elevation-back images.

Strongly notable from Table 4.36, implement the LIP to all types of maps provides higher diagnostic rates than the LBP even when using different classifiers.

Table 4.37 points out the LIP outperforms the standard algorithm even in cases examined with different datasets, except in rare cases, the reason might be attributed to the nature of the data that trained and the LIP behavior, it tends to improve skillfully when available suitable numbers of training data are. Despite the minor errors, LIP stills a promising algorithm that has an explicit positive impact on improving the efficiency of the system performance.

Generally, the reports of the above-mentioned Tables reflect the LIP aptitude to diagnose the corneal condition. This may be attributed to the failure of LBP to extracting suitable characteristics which might help the system to achieve satisfactory performance.

5. CONCLUSION AND FUTURE WORK

5.1 Conclusion

The use of computer-aided is essential for increasing accuracy and rapidity for diagnosing corneal diseases. The most significant part of the diagnostic systems is extracting the features from medical images, which is one of the most powerful techniques to increase the reliability of such systems. Accordingly, this work focused on extracting local features from medical images using the proposed SWFT algorithm, which is an alternative representation for the local features descriptor for the SIFT algorithm. Precise extraction of the features considerably helps eliminate the diagnosis mistakes due to erroneous data that may occur for any reason thus maintain the safety of patients' eyes, preventing damage, and aid specialists make the right decisions. Compared to the standard representation, the expensive experiments indicate the SWFT algorithm is more distinctive, a significant achievement for real-world applications, and it is efficient in extracting features from images thus increasing the efficiency of the system. Employing wavelet transform as a multiresolution analysis to produce images with different scales has a significant and clear impact on the extracting more distinct features that boost the system's ability to outperforms the standard SIFT descriptor and achieving a high performance for distinguishing between categories. Ultimately, the use of machine-learning algorithms to diagnose corneal diseases using corneal topography has yielded impressive results, so we recommend using them by ophthalmologists to help giving more accurate and immediate decisions.

Corneal diseases can be diagnosed accurately and promptly using machine learning techniques. Due to the nature of medical imagery of corneal topography, it is interpreted as texture images. Thus, data extraction methods from image textures (e.g., GLCM) and classification (Multi-class SVM) yielded good results. The calculation of image gradients before data extraction provided support for this is algorithm. This was because it significantly reduced the time spent on image feature extraction and increased diagnostic accuracy, thereby improving system efficiency even if it was utilized with other methods. consequently, the proposed method considered a robust method to reducing time execution. From this rostrum, we recommend to employ it in the real-time applications.

In general, corneal diseases directly and seriously affect the susceptibility of the human eye vision. Therefore, it has become necessary to build an automatic system that helps diagnose these diseases. The most important stage in building these systems is to extract features from the medical images, particularly the local features of the images. Utilizing the image center in extracting the local features, increases the diagnosis accuracy, hence, it is used in the proposed LIP, besides involving the pattern to calculate feature vector as well. In this manner, image information can be preserved and not lost as it is essential for the diagnostic process.

LIP is a fast, reliable, easy to calculate, and less time-consuming method. It can be used by applications that need real-time processing. Besides, it can be applied with the systems where real features description is required accurately and in detail. Finally, we recommend using such a system in the hospitals and eye health centers to help ophthalmologists in the thorough, reliable, and fast clinical diagnosis of corneal disease.

5.2 Future Work

For future work, we will be creating a new map that is friendlier, easy to be trained, and adaptive, to help the ophthalmologists with the behavior procedure. Moreover, evaluating the most popular algorithms that fit with such case studies and mostly it will be expected to be in multiclass hyper. Finally, we suggest new methods training for diagnosis, train the ophthalmologists, and evaluate the possibility of using such a map. A deep learning techniques will be employed to create a mentioned image, where the Conditional generative adversarial (CGAN) (Mirza and Osindero, 2014) model has ability to synthesis a new images based on the conditional input images. It is widely utilized in numerous researches since it can produce realistic output images and accept image “y” instead of noise, for generating output images.

REFERENCES

- Abdel-Hakim, A.E. and Farag, A.A., 2006. CSIFT: A SIFT descriptor with color invariant characteristics. In 2006 IEEE computer society conference on computer vision and pattern recognition, 2, 1978-1983.
- Accardo, P.A. and Pensiero, S., 2002. Neural network-based system for early keratoconus detection from corneal topography, *Journal of biomedical informatics*, 35, 3, 151-159.
- Acharya, U.R., Raghavendra, U., Fujita, H., Hagiwara, Y., Koh, J.E., Hong, T.J., Sudarshan, V.K., Vijayanathan, A., Yeong, C.H., Gudigar, A. and Ng, K.H., 2016. Automated characterization of fatty liver disease and cirrhosis using curvelet transform in biology and medicine, 79, 250-258.
- Achirul Nanda, M., Boro Seminar, K., Nandika, D. and Maddu, A., 2018. A comparison study of kernel functions in the support vector machine and its application for termite detection. *Information*, 9, 1, 1-14.
- Agarwal, S. and Roth, D., 2002. Learning a sparse representation for object detection. In *European conference on computer vision*, 113-127.
- Alhwarin, F., Ristić–Durrant, D. and Gräser, A., 2010. VF-SIFT: very fast SIFT feature matching. *Pattern Recognition Symposium*, 222-231.
- Ali Hasan, S. and Singh, M.D., 2014. Novel Algorithm to Differentiate Astigmatism from Keratoconus, Doctoral dissertation, Thapar University, department of electrical and instrumentation engineering, Punjab, India.
- Ali, A.H., Ghaeb, N.H. and Musa, Z.M., 2017. Support vector machine for keratoconus detection by using topographic maps with the help of image processing techniques, *IOSR Journal of Pharmacy and Biological Sciences*, 12, 6, 50-58.
- Aliyu, H.A., Razak, M.A.A. and Sudirman, R., 2019. Normal and abnormal red blood cell recognition using image processing, *Indonesian Journal of Electrical Engineering and Computer Science*, 14, 1, 100-104.
- Ambrósio, R. and Belin, M.W., 2010. Imaging of the cornea: topography vs tomography, *Journal of refractive surgery*, 26, 11, 847-849.
- Ambrósio, R., Dawson, D.G., Salomão, M., Guerra, F.P., Caiado, A.L.C. and Belin, M.W., 2010. Corneal ectasia after LASIK despite low preoperative risk: tomographic and biomechanical findings in the unoperated, stable, fellow eye, *journal of refractive surgery*, 26, 11, 906-911.
- Amiri, M., Lina, J.M., Pizzo, F. and Gotman, J., 2016. High frequency oscillations and spikes: separating real HFOs from false oscillations, *clinical Neurophysiology*, 127, 1, 187-196.

- Anooj, P.K., 2012. Clinical decision support system: Risk level prediction of heart disease using weighted fuzzy rules, *Journal of King Saud University-Computer and Information Sciences*, 24, 1, 27-40.
- Antonie, M.L., Zaiane, O.R. and Coman, A., 2001. Application of data mining techniques for medical image classification, In *Proceedings of the Second International Conference on Multimedia Data Mining*, 94-101.
- Arbelaez, M.C., Versaci, F., Vestri, G., Barboni, P. and Savini, G., 2012. Use of a support vector machine for keratoconus and subclinical keratoconus detection by topographic and tomographic data, *Ophthalmology*, 119, 11, 2231-2238.
- Artal, P., Berrio, E., Guirao, A. and Piers, P., 2002. Contribution of the cornea and internal surfaces to the change of ocular aberrations with age, *JOSA A*, 19, 1, 137-143.
- Artal, P., Berrio, E., Guirao, A. and Piers, P., 2002. Contribution of the cornea and internal surfaces to the change of ocular aberrations with age, *JOSA A*, 19, 1, 137-143.
- Arya, K.V., Rajput, S.S. and Upadhyay, S., 2019. Noise-robust low-resolution face recognition using sift features. In *Computational Intelligence: Theories, Applications and Future Directions-Volume II* (pp. 645-655). Springer, Singapore.
- Bagherinia, H., Chen, X., Flachenecker, C., Angeles, R., Burger, D., Caroline, P., Dishler, J., Tanzer, D., Schanzlin, D. and Reeder, K., 2008. Support Vector Machine (SVM)-Based Classification of Corneal Topography, *Investigative Ophthalmology and Visual Science*, 49, 13, 1023-1023.
- Bauer, J., Sünderhauf, N. and Protzel, P., 2007. Comparing several implementations of two recently published feature detectors, *IFAC Proceedings Volumes*, 40, 15, 143-148.
- Bay, H., Tuytelaars, T. and Van Gool, L., 2006. Surf: Speeded up robust features, In *European conference on computer vision*, 404-417.
- Bergman, S., 1970. The kernel function and conformal mapping, 5, 21-24, *The kernel function*, American Mathematical Soc, providence, rhode Island, USA.
- Bessho, K., Maeda, N., Kuroda, T., Fujikado, T., Tano, Y. and Oshika, T., 2006. Automated keratoconus detection using height data of anterior and posterior corneal surfaces, *Japanese journal of ophthalmology*, 50, 5, 409-416.
- Bevilacqua, V., Simeone, S., Brunetti, A., Loconsole, C., Trotta, G.F., Tramacere, S., Argentieri, A., Ragni, F., Criscenti, G., Fornaro, A. and Mastronardi, R., 2017. A computer aided ophthalmic diagnosis system based on tomographic features, In *International Conference on Intelligent Computing*, 598-609.

- Bharath, I., Devendiran, S. and Mathew, A.T., 2018. Bearing condition monitoring using tunable Q-factor wavelet transform, spectral features and classification algorithm, *Materials Today, Proceedings*, 5, 5, 11476-11490.
- Bhosale, N.V. and Kanade, S.S., 2018. A Comparative Analysis on Hardware System of 2D Discrete Wavelet Transformation for the Image Denoising Application, In *International Conference on Intelligent Data Communication Technologies and Internet of Things*, 1076-1087.
- Bhushan, N., Rao, A.R. and Lohse, G.L., 1997. The texture lexicon: Understanding the categorization of visual texture terms and their relationship to texture images, *Cognitive Science*, 21, 2, 219-246.
- Bishop, C.M., 2006. Pattern recognition and machine learning, pp: 137-179, *Linear Models for Classification*, springer, New York, NY, USA.
- Braz, J., Magnenat-Thalmann, N., Richard, P., Linsen, L., Telea, A., Battiato, S. and Imai, F. eds., 2017. Computer Vision, Imaging and Computer Graphics Theory and Applications, 11th International Joint Conference, VISIGRAPP, Rome, Italy.
- Brody, J., Waller, S. and Wagoner, M., 1994. Corneal topography: History, technique, and clinical uses. *International ophthalmology clinics*, 34, 3, 197-207.
- Brown, M. and Lowe, D.G., 2002. Invariant Features from Interest Point Groups. In *BMVC*, 4, 1-12.
- Carvalho, L.A., 2005. Preliminary results of neural networks and Zernike polynomials for classification of videokeratography maps, *Optometry and vision science*, 82, 2, 151-158.
- Carvalho, L.A.V.D. and Barbosa, M.S., 2008. Neural networks and statistical analysis for classification of corneal videokeratography maps based on Zernike coefficients, a quantitative comparison. *Arquivos brasileiros de oftalmologia*, 71, 3, 337-341.
- Castellano, G., Bonilha, L., Li, L.M. and Cendes, F., 2004. Texture analysis of medical images, *Clinical radiology*, 59, 12, 1061-1069.
- Cavas-Martínez, F., Bataille, L., Fernández-Pacheco, D.G., Cañavate, F.J. and Alió, J.L., 2017. A new approach to keratoconus detection based on corneal morphogeometric analysis, *PLoS One*, 12, 9, 0184569.
- Chandra, T.G., Nasution, A.M. and Setiadi, I.C., 2019. Melanoma and nevus classification based on asymmetry, border, color, and GLCM texture parameters using deep learning algorithm. In *AIP Conference Proceedings*, 2193, 1, 050016.

- Chastang, P.J., Borderie, V.M., Carvajal-Gonzalez, S., Rostène, W. and Laroche, L., 2000. Automated keratoconus detection using the EyeSys videokeratoscope. *Journal of Cataract & Refractive Surgery*, 26, 5, 675-683.
- Cheng, Q., Shao, K., Li, C., Li, S., Li, J. and Shao, Z., 2018. A distributed system architecture for high-resolution remote sensing image retrieval by combining deep and traditional features, 10789, 413-432.
- Dadi, H.S. and Pillutla, G.M., 2016. Improved face recognition rate using HOG features and SVM classifier, *IOSR Journal of Electronics and Communication Engineering*, 11, 04, 34-44.
- Dai-Hong, J., Lei, D., Dan, L. and San-You, Z., 2019. Moving-object tracking algorithm based on PCA-SIFT and optimization for underground coal mines, *IEEE Access*, 7, 35556-35563.
- Daubechies, I., 1990. The wavelet transforms, time-frequency localization and signal analysis, *IEEE transactions on information theory*, 36, 5, 961-1005.
- Demir, I., Koperski, K., Lindenbaum, D., Pang, G., Huang, J., Basu, S., Hughes, F., Tuia, D. and Raskar, R., 2018. A challenge to parse the earth through satellite images, In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition Workshops*, 172-181.
- Dharmalingam, S., Lenin, K. and Krishnan, P.N., 2020. Comparative analysis of cylindrical thread and straight square profile pin on ultimate tensile strength of AA8011/AZ31B in friction stir butt welding, *Materials Today, Proceedings*, 21, 523-526.
- Ding, S., Zhao, X., Xu, H., Zhu, Q. and Xue, Y., 2017. NSCT-PCNN image fusion based on image gradient motivation, *IET Computer Vision*, 12, 4, 377-383.
- Doi, K., 2007. Computer-aided diagnosis in medical imaging, historical review, current status and future potential, *Computerized medical imaging and graphics*, 31, 5, 198-211.
- Dong, J., Liu, W. and Zhu, Y., 2019. Application of SIFT feature vector matching algorithm in binocular stereo vision system, In *Fifth Symposium on Novel Optoelectronic Detection Technology and Application*, 11023, 437-442.
- Elshinawy, M.Y., 2010. Pre-CAD normal mammogram detection algorithm based on tissue type. Ph.D. thesis, Department of Electrical and Computer Engineering Howard University.
- Fawcett, T., 2006. An introduction to ROC analysis, *Pattern recognition letters*, 27, 8, 861-874.

- Friedman N. Pearls for Interpreting Corneal Topography Maps. 2013. URL Address: <http://www.opthalmologyweb.com/Featured-Articles/142292-Pearls-for-Interpreting-Corneal-Topography-Maps/>.
- Friedman, J.H., 1998. Data Mining and Statistics, What's the connection, Computing science and statistics, 29, 1, 3-9.
- Fujita, H., Uchiyama, Y., Nakagawa, T., Fukuoka, D., Hatanaka, Y., Hara, T., Lee, G.N., Hayashi, Y., Ikeda, Y., Gao, X. and Zhou, X., 2008. Computer-aided diagnosis, the emerging of three CAD systems induced by Japanese health care needs, Computer methods and programs in biomedicine, 92, 3, 238-248.
- Fung, G.M. and Mangasarian, O.L., 2005. Multicategory proximal support vector machine classifiers. Machine learning, 59,1, 77-97.
- Gao, Y., Wu, Q., Li, J., Sun, J. and Wan, W., 2017. SVM-based automatic diagnosis method for keratoconus, Second International Workshop on Pattern Recognition, International Society for Optics and Photonics, 10443, 177-181.
- García-García, Á., Melián, R., Carreras, H., Rodríguez-Hernández, V., Reñones, J. and Estévez, B., 2019. Corneal dioptric power and astigmatism: A comparison between colourcolour light-emitting diode based and Scheimpflug technology topography, Archivos de la Sociedad Española de Oftalmología, 94, 6, 273-280.
- Gonzalez, R.C., 2004. Digital Image Processing Using Matlab-Gonzalez Woods & Eddins. pdf. Education.
- Guo, W., 2018. Automated Characterization of Plant Growth and Flowering Dynamics Using RGB Images, In Smart Plant Factory, 385-393.
- Gupta, M., Konar, D., Bhattacharyya, S. and Biswas, S., 2020. Computer Vision and Machine Intelligence in Medical Image Analysis, International Symposium, ISCM, 992.
- Haralick, R.M. and Shanmugam, K., 1973. Computer classification of reservoir sandstones, IEEE Transactions on Geoscience Electronics, 11, 4, 171-177.
- Hashemi, H. and Mehravaran, S., 2010. Day to day clinically relevant corneal elevation, thickness, and curvature parameters using the Orbscan II scanning slit topographer and the Pentacam scheimpflug imaging device. Middle East African journal of ophthalmology, 17, 1, 44-45.
- Herrington, J., Maddess, T., Coy, D., Carle, C., Sabeti, F. and Barbosa, M., 2018. Learning Complex Texture Discrimination. Journal of Vision, 18, 10, 260-260.
- Hidalgo, I.R., Rodriguez, P., Rozema, J.J., Dhubhghaill, S.N., Zakaria, N., Tassignon, M.J. and Koppen, C., 2016. Evaluation of a machine-learning classifier for keratoconus detection based on Scheimpflug tomography, Cornea, 35, 6, 827-832.

- Hsu, C.W. and Lin, C.J., 2002. A comparison of methods for multiclass support vector machines, *IEEE transactions on Neural Networks*, 13, 2, 415-425.
- Hu, Y., Zhao, C.X. and Wang, H.N., 2008. Directional analysis of texture images using gray level co-occurrence matrix, *IEEE Pacific-Asia workshop on computational intelligence and industrial application*, 2, 277-281.
- Huang, Z.C., Chan, P.P., Ng, W.W. and Yeung, D.S., 2010. Content-based image retrieval using color moment and Gabor texture feature, *International conference on machine learning and cybernetics*, 2, 719-724.
- Issarti, I., Consejo, A., Jiménez-García, M., Hershko, S., Koppen, C. and Rozema, J.J., 2019. Computer aided diagnosis for suspect keratoconus detection, *Computers in biology and medicine*, 109, 33-42.
- Issarti, I., Rozema, J. and Consejo, A., 2018. Corneal modeling and Keratoconus identification, *Biomath Communications Supplement*, 5, 1.
- Jacobs, D., 2005. Image gradients. *Class Notes for CMSC*, 426.
- Jimi, F., Kehong, W., Dongqing, Y. and Yong, H., 2019. Gas flow status analysis in additive manufacturing based on texture of molten pool images, 179, 385-394.
- Kaestner, C.A.A., 2013. Support vector machines and kernel functions for text processing, *Revista de Informática Teórica e Aplicada*, 20, 3, 130-154.
- Kahya, M.A., 2019. Classification enhancement of breast cancer histopathological image using penalized logistic regression. *Indonesian Journal of Electrical Engineering and Computer Science*, 13, 1, 405-410.
- Kamdi, V.D., Raut, A.D., Pardakhe, V. and Jagtap, V.A., 2018. A Study of SURF features for Face recognition, *International Journal of Electronics, Communication and Soft Computing Science and Engineering*, 90-94.
- Kashyap, N. and Sinha, G.R., 2012. Image watermarking using 3-level discrete wavelet transform, *Int. Journal of Modern Education and Computer Science*, 4, 3, 50-51.
- Ke, Y. and Sukthankar, R., 2004. PCA-SIFT: A more distinctive representation for local image descriptors. In *Proceedings of the 2004 IEEE Computer Society Conference on Computer Vision and Pattern Recognition, CVPR*, 2, II-II.
- Kermamy, D., Zhang, K. and Goldbaum, M., 2018. Labeled optical coherence tomography and Chest X-Ray images for classification. *Mendeley data*, 2, 2.
- Khalaf, M., Hussain, A.J., Alafandi, O., Al-Jumeily, D., Alloghani, M., Alsaadi, M., Dawood, O.A. and Abd, D.H., 2019. An application of using support vector machine based on classification technique for predicting medical data sets, In *International Conference on Intelligent Computing*, 11644, 580-591.

- Klyce, S.D., 1984. Computer-assisted corneal topography. High-resolution graphic presentation and analysis of keratotomy, *Investigative ophthalmology and visual science*, 25, 12, 1426-1435.
- Koh, J.E., Acharya, U.R., Hagiwara, Y., Raghavendra, U., Tan, J.H., Sree, S.V., Bhandary, S.V., Rao, A.K., Sivaprasad, S., Chua, K.C. and Laude, A., 2017. Diagnosis of retinal health in digital fundus images using continuous wavelet transform (CWT) and entropies, *Computers in biology and medicine*, 84, 89-97.
- Kononenko, I., 2001. Machine learning for medical diagnosis, history, state of the art and perspective, *Artificial Intelligence in medicine*, 23, 1, 89-109.
- Koza, J.R., Bennett, F.H., Andre, D. and Keane, M.A., 1996. Automated design of both the topology and sizing of analog electrical circuits using genetic programming, *In Artificial Intelligence in Design*, 96, 151-170.
- Krig, S., 2016. Image pre-processing. *In Computer vision metrics*, 35-74.
- Kulkarni, P., Stranieri, A. and Ugon, J., 2016. Texture image classification using pixel N-grams, *IEEE International Conference on Signal and Image Processing*, 137-141.
- Kurniawan, R., Yanti, N. and Nazri, M.Z.A., 2014. Expert systems for self-diagnosing of eye diseases using Naïve Bayes, *International Conference of Advanced Informatics: Concept, Theory and Application*, 113-116.
- Lackner, B., Schmidinger, G., Pieh, S., Funovics, M.A. and Skorpik, C., 2005. Repeatability and reproducibility of central corneal thickness measurement with Pentacam, Orbscan, and ultrasound, *Optometry and vision science*, 82, 10, 892-899.
- Lane, F., Azad, R.M.A. and Ryan, C., 2016. Principled evolutionary algorithm search operator design and the kernel trick, *IEEE Symposium Series on Computational Intelligence*, 1-9.
- Lavric, A. and Valentin, P., 2019. KeratoDetect, keratoconus detection algorithm using convolutional neural networks, *Computational intelligence and neuroscience*, 8162567, 1-9.
- Li, C., Huang, Y. and Zhu, L., 2017. Color texture image retrieval based on Gaussian copula models of Gabor wavelets. *Pattern Recognition*, 64, 118-129.
- Li, Q., Cai, W., Wang, X., Zhou, Y., Feng, D.D. and Chen, M., 2014. Medical image classification with convolutional neural network, *13th international conference on control automation robotics & vision*, 844-848.
- Liu, L., Chen, J., Fieguth, P., Zhao, G., Chellappa, R. and Pietikäinen, M., 2019. From BoW to CNN, Two decades of texture representation for texture classification, *International Journal of Computer Vision*, 127, 1, 74-109.

- Liu, Y., Lian, J., Bartolacci, M.R. and Zeng, Q.A., 2014. Density-based penalty parameter optimization on C-SVM. *The Scientific World Journal*, 851814, 1-9.
- Lopes, B.T., Ramos, I.C., Dawson, D.G., Belin, M.W. and Ambrósio Jr, R., 2016. Detection of ectatic corneal diseases based on pentacam, *Zeitschrift für Medizinische Physik*, 26, 2, 136-142.
- Lopes, B.T., Ramos, I.C., Salomão, M.Q., Guerra, F.P., Schallhorn, S.C., Schallhorn, J.M., Vinciguerra, R., Vinciguerra, P., Price Jr, F.W., Price, M.O. and Reinstein, D.Z., 2018. Enhanced tomographic assessment to detect corneal ectasia based on artificial intelligence, *American journal of ophthalmology*, 195, 223-232.
- Lowe, D.G., 1999. Object recognition from local scale-invariant features, In *IEEE international conference on computer vision*, 2, 1150-1157.
- Ludwig, P.E., Motlagh, M. and Sevensma, K., 2017. *Anatomy, Head and Neck, Eye Cornea*, 29262108.
- Maeda, N., Klyce, S.D. and Smolek, M.K., 1995. Comparison of methods for detecting keratoconus using videokeratography. *Archives of Ophthalmology*, 113, 7, 870-874.
- Maeda, N., Klyce, S.D. and Smolek, M.K., 1995. Neural network classification of corneal topography, Preliminary demonstration, *Investigative ophthalmology & visual science*, 36, 7, 1327-1335.
- Maity, R. and Suman, M., 2019. Predictability of hydrological systems using the wavelet transformation: Application to drought prediction. *A changing World*, 109-137.
- Mallat, S.G., 1989. A theory for multiresolution signal decomposition: the wavelet representation, *IEEE transactions on pattern analysis and machine intelligence*, 11, 7, 674-693.
- Marsolo, K., Twa, M., Bullimore, M.A. and Parthasarathy, S., 2007. Spatial modeling and classification of corneal shape, *IEEE Transactions on Information Technology in Biomedicine*, 11, 2, 203-212.
- Masala, G.L., 2006. Computer aided detection on mammography, *World Academy of Science, Engineering and Technology*, 15, 1, 1-6.
- Masters, B.R. ed., 1990. Noninvasive diagnostic techniques in ophthalmology, , pp. 1-16, Barry R. Masters (Editor), *Ophthalmic Image Processing*, New York, USA.
- McAlinden, C., Khadka, J. and Pesudovs, K., 2011. A comprehensive evaluation of the precision (repeatability and reproducibility) of the Oculus Pentacam HR, *Investigative ophthalmology and visual science*, 52, 10, 7731-7737.

- Meng, Y., Ye, C., Yu, S., Qin, J., Zhang, J. and Shen, D., 2019. Sugarcane node recognition technology based on wavelet analysis, *Computers and Electronics in Agriculture*, 158, 68-78.
- Mikolajczyk, K., Tuytelaars, T., Schmid, C., Zisserman, A., Matas, J., Schaffalitzky, F., Kadir, T. and Van Gool, L., 2005. A comparison of affine region detectors, *International journal of computer vision*, 65, 1, 43-72.
- Mirza, M. and Osindero, S., 2014. Conditional generative adversarial nets, *arXiv preprint arXiv*, 1-7.
- Morel, J.M. and Yu, G., 2008. On the consistency of the SIFT method, 1-17.
- Morel, J.M. and Yu, G., 2009. ASIFT: A new framework for fully affine invariant image comparison, *SIAM journal on imaging sciences*, 2, 2, 438-469.
- Mun, S., Park, S., Han, D.K. and Ko, 2017. Generative adversarial network based acoustic scene training set augmentation and selection using SVM, 93-97.
- Mundar, D., Jakus, M. and Matotek, D., 2012. Quantitative research methods participation in the information sciences papers in Croatia. In *Central European Conference on Information and Intelligent Systems*, 77-78.
- Nemeth, G., Vajas, A., Kolozsvari, B., Berta, A. and Modis Jr, L., 2006. Anterior chamber depth measurements in phakic and pseudophakic eyes: Pentacam versus ultrasound device. *Journal of Cataract & Refractive Surgery*, 32, 8, 1331-1335.
- Nigam, S., Singh, R. and Misra, A.K., 2019. Local binary patterns based facial expression recognition for efficient smart applications, In *Security in Smart Cities, Models, Applications, and Challenges*, 297-322.
- Noaman, K.M., Muharram, A.A. and Alqubati, I.A., 2014. Diagnosis of poor eyesight based on support vector machine and artificial neural networks, *Journal of Emerging Trends in Computing and Information Sciences*, 5, 10.
- Nowak, E., Jurie, F. and Triggs, B., 2006. Sampling strategies for bag-of-features image classification. In *European conference on computer vision*, 490-503.
- Ojala, T., Pietikäinen, M. and Harwood, D., 1996. A comparative study of texture measures with classification based on featured distributions, *Pattern recognition*, 29, 1, 51-59.
- Ojala, T., Pietikainen, M. and Maenpaa, T., 2002. Multiresolution gray-scale and rotation invariant texture classification with local binary patterns, *IEEE Transactions on pattern analysis and machine intelligence*, 24, 7, 971-987.
- Oliveira, C.M., Ribeiro, C. and Franco, S., 2011. Corneal imaging with slit-scanning and Scheimpflug imaging techniques, *Clinical and Experimental Optometry*, 94, 1, 33-42.

- Park, Y. and Guldmann, J.M., 2020. Measuring continuous landscape patterns with Gray-Level Co-Occurrence Matrix (GLCM) indices, 109, 105802-105803.
- Pereira, C.R., Pereira, D.R., Silva, F.A., Masieiro, J.P., Weber, S.A., Hook, C. and Papa, J.P., 2016. A new computer vision-based approach to aid the diagnosis of Parkinson's disease, *Computer Methods and Programs in Biomedicine*, 136, 79-88.
- Perissutti, P., Accardo, A.P., Pensiero, S. and Salvatat, M.L., 1998. November. Automatic keratoconus detection by means of a neural network: comparison between a monocular and a binocular approach, In *Proceedings of the 20th Annual International Conference IEEE Engineering in Medicine and Biology Society, Biomedical Engineering Towards the Year 2000 and Beyond*, 3, 1397-1399.
- Piorkowski, A., Nurzynska, K., Gronkowska-Serafin, J., Selig, B., Boldak, and Reska, D., 2017. Influence of applied corneal endothelium image segmentation techniques on the clinical parameters, *Computerized Medical Imaging and Graphics*, 55, 13-27.
- Potthast, C., Breitenmoser, A., Sha, F. and Sukhatme, G.S., 2018. Active multi-view object recognition and online feature selection. In *Robotics Research*, 471-488.
- Quisling, S., Sjoberg, S., Zimmerman, B., Goins, K. and Sutphin, J., 2006. Comparison of Pentacam and Orbscan IIz on posterior curvature topography measurements in keratoconus eyes, *Ophthalmology*, 113, 9, 1629-1632.
- Rafi, M. and Mukhopadhyay, S., 2018. Texture description using multi-scale morphological GLCM, *Multimedia Tools and Applications*, 77, 23, 30505-30532.
- Rahimy, E., 2018. Deep learning applications in ophthalmology, *Current opinion in ophthalmology*, 29, 3, 254-260.
- Rehman, I., Hazhirkarzar, B. and Patel, B.C., 2019. *Anatomy, head and neck, eye*.
- Rezatofighi, and H. S. Zadeh, 2011. Automatic recognition of five types of white blood cells in peripheral blood, *Computerized Medical Imaging and Graphics*, 35. 4, 333-343.
- Rhif, M., Ben Abbes, A., Farah, I.R., Martínez, B. and Sang, Y., 2019. Wavelet transform application for/in non-stationary time-series analysis: a review, *Applied Sciences*, 9, 7, 1345-1346.
- Saeed, A., Khan, M.J., Shahid, H., Naqvi, S.I., Riaz, M.A., Khan, M.S. and Amin, Y., 2020. An Accurate Texture Complexity Estimation for Quality-Enhanced and Secure Image Steganography, *IEEE Access*, 8, 21613-21630.

- Saika, M., Maeda, N., Hirohara, Y., Mihashi, T., Fujikado, T. and Nishida, K., 2013. Four discriminant models for detecting keratoconus pattern using Zernike coefficients of corneal aberrations. *Japanese journal of ophthalmology*, 57, 6, 503-509.
- Saito, T. and Rehmsmeier, M., 2015. The precision-recall plot is more informative than the ROC plot when evaluating binary classifiers on imbalanced datasets, *PloS one*, 10, 3, 0118432-0118433.
- Salih, N. and Hussein, N., 2018. Human corneal state prediction from topographical maps using a deep neural network and a support vector machine. *International Journal of Current Research*, *International Journal of Current Research*, 10, 11, 75461-75467.
- Schölkopf, B., Smola, A.J. and Bach, F., 2002. Learning with kernels, pp. 25-55, support vector machines, regularization, optimization, and beyond, MIT press, Cambridge, London, England.
- Schwiegerling, J. and Greivenkamp, J.E., 1996. Keratoconus detection based on videokeratoscopic height data, *Optometry and vision science*, official publication of the American Academy of Optometry, 73, 12, 721-728.
- Seitz, B., Langenbucher, A., Hager, T., Janunts, E., El-Husseiny, M. and Szentmáry, N., 2017. Suppl-1, M7, penetrating keratoplasty for keratoconus–excimer versus femtosecond laser trephination. *The open ophthalmology journal*, 11, 225-256.
- Sharma, N. and Aggarwal, L.M., 2010. Automated medical image segmentation techniques, *Journal of medical physics/Association of Medical Physicists of India*, 35, 1, 3-4.
- Silverman, R.H., Urs, R., RoyChoudhury, A., Archer, T.J., Gobbe, M. and Reinstein, D.Z., 2017. Combined tomography and epithelial thickness mapping for diagnosis of keratoconus, *European journal of ophthalmology*, 27, 2, 129-134.
- Silverman, R.H., Urs, R., RoyChoudhury, A., Archer, T.J., Gobbe, M. and Reinstein, D.Z., 2014. Epithelial remodeling as basis for machine-based identification of keratoconus. *Investigative ophthalmology & visual science*, 55, 3, 1580-1587.
- Singh, A., Zarei-Ghanavati, M., Avadhanam, V. and Liu, C., 2017. Systematic review and meta-analysis of clinical outcomes of Descemet membrane endothelial keratoplasty versus Descemet stripping endothelial keratoplasty/Descemet stripping automated endothelial keratoplasty, *Cornea*, 36, 11, 1437-1443.
- Sinjab, M.M., 2012. Corneal topography in clinical practice (Pentacam System). Basics and Clinical Interpretation Jaypee Brothers Medical Publishers (P) Ltd., London, England.

- Sinjab, M.M., 2018. Corneal Tomography in Clinical Practice (Pentacam System), corneal power Maps, pp. 36-51, Basics & Clinical Interpretation. Jaypee Brothers Medical Publishers, London, England.
- Smadja, D., Touboul, D., Cohen, A., Doveh, E., Santhiago, M.R., Mello, G.R., Krueger, R.R. and Colin, J., 2013. Detection of subclinical keratoconus using an automated decision tree classification. *American journal of ophthalmology*, 156, 2, 237-246.
- Smolek, M.K. and Klyce, S.D., 1997. Current keratoconus detection methods compared with a neural network approach, *Investigative ophthalmology and visual science*, 38, 11, 2290-2299.
- Souza, M.B., 2011. Supervised learning network as an aid in the detection of keratoconus, Doctoral dissertation, University of São Paulo, Brazilian.
- Souza, M.B., Medeiros, F.W., Souza, D.B. and Alves, M.R., 2008. Detection of keratoconus based on a neural network with Orbscan, *Arquivos brasileiros de oftalmologia*, 71, 6, 65-68.
- Souza, M.B., Medeiros, F.W., Souza, D.B., Garcia, R. and Alves, M.R., 2010. Evaluation of machine learning classifiers in keratoconus detection from orbscan II examinations, *Clinics*, 65, 12, 1223-1228.
- Starck, J.L., Murtagh, F. and Fadili, J., 2015. Sparse image and signal processing: Wavelets and related geometric multiscale analysis, pp. 16-43, *The wavelet Transform* Cambridge university press, London, England.
- Subasi, A. and Yaman, E., 2019. EMG signal classification using discrete wavelet transform and rotation forest, In *International Conference on Medical and Biological Engineering*, 29-35.
- Suckling, J., Parker, J., Dance, D., Astley, S., Hutt, I., Boggis, C., Ricketts, I., Stamatakis, E., Cerneaz, N., Kok, S. and Taylor, P., 2015. Mammographic image analysis society, database, 1. 21.
- Suykens, J.A., Van Gestel, T. and De Brabanter, J., 2002. Least squares support vector machines pp. 20-68, *Support Vector Machine*, World scientific, New Jersey, USA.
- Tang, H. and Tang, F., 2012. AH-SIFT: Augmented histogram based SIFT descriptor, In *2012 19th IEEE International Conference on Image Processing*, 2357-2360.
- Tang, H., Yin, B., Sun, Y. and Hu, Y., 2013. 3D face recognition using local binary patterns. *Signal Processing*, 93, 8, 2190-2198.
- Toutounchian, F., Shanbehzadeh, J., Khanlari, M. and Stage, A.R., 2012. Detection of keratoconus and suspect keratoconus by machine vision, In *Proceedings of the International MultiConference of Engineers and Computer Scientists*.

- Tschandl, P., Rosendahl, C. and Kittler, H., 2018. The HAM10000 dataset, a large collection of multisource dermatoscopic images of common pigmented skin lesions. *Scientific Data*, 5, 180161-180162.
- Twa, M.D., Parthasarathy, S., Bullimore, M.A., Roberts, C., Mahmoud, A.M., Tom Raasch, O.D. and Schanzlin, D.J., 2000. Automated decision tree classification of keratoconus from videokeratography, *Investigative Ophthalmology and Vision Science*, E-Abstract, 1082, 46-47.
- Twa, M.D., Parthasarathy, S., Raasch, T.W. and Bullimore, M.A., 2003. Decision tree classification of spatial data patterns from videokeratography using Zernike polynomials. In *Proceedings of the SIAM International Conference on Data Mining*, 3-12.
- Twa, M.D., Parthasarathy, S., Roberts, C., Mahmoud, A.M., Raasch, T.W. and Bullimore, M.A., 2005. Automated decision tree classification of corneal shape. *Optometry and vision science: official publication of the American Academy of Optometry*, 82, 12, 1038-1039.
- Udomhunsakul, S. and Wongsita, P., 2004. Feature extraction in medical MRI images, In *IEEE Conference on Cybernetics and Intelligent Systems*, 2004, 1, 340-344.
- Ulyanov, D., Vedaldi, A. and Lempitsky, V., 2017. Improved texture networks: Maximizing quality and diversity in feed-forward stylization and synthesis, *IEEE Conference on Computer Vision and Pattern Recognition*, 6924-6932.
- Valdés-Mas, M.A., Martín, J.D., Rupérez, M.J., Peris, C. and Monserrat, C., 2014. Machine learning for predicting astigmatism in patients with keratoconus after intracorneal ring implantation, In *IEEE-EMBS International Conference on Biomedical and Health Informatics*, 756-759.
- Valdés-Mas, M.A., Martín-Guerrero, J.D., Rupérez, M.J., Pastor, F., Dualde, C., Monserrat, C. and Peris-Martínez, C., 2014. A new approach based on machine learning for predicting corneal curvature (K1) and astigmatism in patients with keratoconus. *Computer methods and programs in biomedicine*, 116, 1, 39-47.
- Verma, M. and Raman, B., 2018. Local neighborhood difference pattern: A new feature descriptor for natural and texture image retrieval. *Multimedia Tools and Applications*, 77, 10, 11843-11866.
- Vidal, M. and Amigo, J.M., 2012. Pre-processing of hyperspectral images. Essential steps before image analysis. *Chemometrics and Intelligent Laboratory Systems*, 117, 138-148.
- Wan, Q., Wang, D., Ye, H., Tang, J. and Han, Y., 2017. A review and meta-analysis of corneal cross-linking for post-laser vision correction ectasia, *Journal of current ophthalmology*, 29, 3, 145-153.

- Wilson, S.E. and Ambrosio, R., 2001. Computerized corneal topography and its importance to wave front technology. *Cornea*, 20, 5, 441-454.
- Wirawan, A., Kwoh, C.K., Chew, P.T.K., Aquino, M.C.D., Loon, S.C., See, J., Zheng, C. and Lin, 2012. Feature selection for computer-aided angle closure glaucoma mechanism detection. *Medical Imaging and Health Informatics*, 2, 4, 438-444.
- Wu, W., Zhang, Y., Wang, Q., Liu, F., Chen, P. and Yu, H., 2018. Low-dose spectral CT reconstruction using image gradient ℓ_0 -norm and tensor dictionary, *Applied Mathematical Modelling*, 63, 538-557.
- Xie, B., Qin, J., Xiang, X., Li, H. and Pan, L., 2018. An Image Retrieval Algorithm Based on Gist and Sift Features. *IJ Network Security*, 20, 4, 609-616.
- Yacoub, M.A., Mohamed, A.S. and Kadah, Y.M., 2006. A cad system for the detection of malignant tumors in digitized mammogram films, In *Proc. 3rd Cairo International Biomedical Engineering Conference*, 1-5.
- Yamaguchi, T., Shimizu, E., Yagi-Yaguchi, Y., Tomida, D., Satake, Y. and Shimazaki, J., 2017. A novel entity of corneal diseases with irregular posterior corneal surfaces: concept and clinical relevance, *Cornea*, 36, S53-S59.
- Yang, A.Y., Chow, J. and Liu, J., 2018. Focus: sensory biology and pain: corneal innervation and sensation: the eye and beyond. *The Yale journal of biology and medicine*, 91,1, 13-14.
- Yang, Q., Zhang, Y., Zhao, T. and Chen, Y., 2018. Single image super-resolution using self-optimizing mask via fractional-order gradient interpolation and reconstruction, *ISA transactions*, 82, 163-171.
- Ye, D., Sun, L., Yang, Z., Che, W. and Tan, W., 2017. Determination of bruised potatoes by GLCM based on hyperspectral imaging technique, *International Conference on Service Systems and Service Management*, 1-6.
- Yousefi, S., Yousefi, E., Takahashi, H., Hayashi, T., Tampo, H., Inoda, S., Arai, Y. and Asbell, P., 2018. Keratoconus severity identification using unsupervised machine learning. *PLoS One*, 13, 11, 0205998-025999.
- Zhang, L. and Rusinkiewicz, 2018. Learning to detect features in texture images, *Proceedings IEEE conference on vision and pattern recognition*, 6325-6333.
- Zhang, Y. and Hua, C., 2015. Driver fatigue recognition based on facial expression analysis using local binary patterns. *Optik*, 126, 23, 4501-4505.
- Zhu, W., Zeng, N. and Wang, N., 2010. Sensitivity, specificity, accuracy, associated confidence interval and ROC analysis with practical SAS implementations, *NESUG proceedings: health care and life sciences*, Maryland, 19, 67-68.

CURRICULUM VITAE

Name and Surname: Samer Kais Jameel AL-SALIHI
Address: BAGHDAD, IRAQ

EDUCATION INFORMATION

Undergraduate: AL-Mansur University, 1997-2003, IRAQ.
Master: B.A.M.U. University, 2009-2012, INDIA.
Ph.D.: Aksaray University, 2016-2021, TURKEY.

PROFESSIONAL EXPERIENCE AND AWARDS

1. University of Raparin-lecturer.
2. Member in computer science research group.

PUBLICATIONS PRESENTATIONS AND PATENTS

1. Jameel, S.K., Aydin, S. and Ghaeb, N.H., 2020. Machine Learning Techniques for Corneal Diseases Diagnosis: A Survey. International Journal of Image and Graphics, p.2150016.
2. AL-SALIHI, S. A. M. E. R., AYDIN, S., & HUSSEIN, N. (2021). SWFT: Subbands wavelet for local features transform descriptor for corneal diseases diagnosis. Turkish Journal of Electrical Engineering & Computer Sciences, 29(2), 875-896.
3. AL-SALIHI, S.K., AYDIN, S. and GHAEB, N.H., LIP: local information pattern descriptor for corneal diseases diagnosis.