OPTISCAN-SMART CORNEAL TOPOGRAPHY DESKTOP APPLICATION-A DEEP LEARNING OPHTHALMIC DIAGNOSTIC ASSISTANT.

by

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APPROVAL BY BOARD OF EXAMINERS

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AUTHORS DECLARATION

I take full responsibility of the research work conducted during the thesis titled "**Optiscan-Smart Corneal Topography Desktop Application-A Deep Learning Ophthalmic Diagnostic Assistant.**"

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Mr.Tufail Shah

DEDICATION

This research work is dedicated to our beloved Parents and Teachers, Friends and University supporting staff who supported and motivated us in tough times and made us into what we are today.

ABSTRACT

“Optiscan" presents a novel artificial intelligence desktop program designed to improve the effectiveness of corneal topography report analysis in the field of ophthalmology. Through the automation of crucial data point extraction and topographic map interpretation, Optiscan considerably enhances the precision and effectiveness of ophthalmological diagnosis and therapy. Improved patient care could result from the application's potential to completely change how ophthalmologists diagnose their patients. The project entails building Optiscan from beginning to end and developing the AI model that powers its operations following integrating it into the desktop environment.

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LIST OF ABBREVIATIONS AND SYMBOLS

AI	Artificial Intelligence
CNN	Convolutional Neural Network
OCR	Optical Character Recognition
CTSP	Corneal Thickness Spatial Profile
PTI	Percentage Thickness Increase
ReLU	Rectified Linear Unit
LSTM	Long Short-Term Memory
MLP	Multi-Layer Perceptron
SMART	Specific Measurable Achievable Relevant and Time bound
WBS	Work Breakdown Structure
APP	Application
D	Diapoter
μ	Micro Diaopter

1 INTRODUCTION

There has been substantial progress in the field of medical diagnostician where enhancement in areas like image processing has been achieved. Consequently, Optiscan meets the problem of the accurate supervised machine-learning models for the design of the eye topographical image. Topography involving measurement of the corneal curvature, height, and warpage topography is invaluable, in the management of diseases such as keratoconus and astigmatism. A particular part of our project is the complex application of artificial intelligence, computer vision, and image analysis to improve eye health identification and diagnosis. Some objectives are associated with enhanced performance and efficiency in analyzing medical images to achieve better outcomes that can be beneficial to patients' lives. In this paper, activities that include scope definition, methods, relevant diagrams, training details, and assessment results of the models are explained in detail. We also demonstrate a sample of the desktop application that might be more specifically tailored to eye care practitioners, its real-life potential to affect medical diagnostics and decision-making included. This study reveals how Optiscan has contributed to the development of machine learning and medical imagery analysis for enhancing healthcare practices.

1.1 Project Vision:

The vision of this project is to create an intelligent desktop application based on artificial intelligence and computer vision capabilities that can automate the process of analyzing corneal topography reports.

1.2 Problem Statement

Practitioners of eye care sometimes find the task cumbersome and time-consuming in interpreting corneal topography reports, hence delaying their around diagnosis with high accuracy on these disorders. Data extraction manually and map interpretation create problems that influence the quality of diagnoses. The problem can be overcome by automating these tasks through artificial intelligence to speed up and simplify the diagnostic process to achieve desired health outcomes, which is what this "Optiscan" project will ultimately do.

1.3 Goals and Objectives:

1.3.1 Goals:

- To develop a desktop application equipped with a trained AI model with computer vision techniques on the dataset of corneal topography images.
- To carry out automatic data extraction, identifying key points from corneal topography reports through this application.
- To use AI-augmented interpretation of topographic maps to increase the accuracy in diagnosis.
- To improve the diagnostic process in ophthalmology by giving a better and faster tool for eye doctors.

1.3.2 Objectives:

- To develop the foundation for Optiscan, focused on easy desktop application functionality.
- To train the AI model to capture important data points accurately from corneal topography reports
- To apply algorithms for automated interpretation of topographic maps, creating insightful visualization.
- To validate Optiscan's effectiveness through rigorous testing and refinement procedures.

1.4. Project Scope

In our project scope their our various componets such as:

1.4.1. Application Development

The development of this app includes its user interface, data processing, and AI algorithm integration and efficient diagnostic results.

1.4.2. AI Model Training:

For the app to work, an efficient AI model has to be trained to interpret corneal topography reports correctly.

1.4.3. Data Integration:

In order to read corneal topography reports, the application must seamlessly integrate with a variety of ophthalmological data sources and devices.

1.4.4. User-friendly Interface:

As medical specialists have lesser know how with computer based systems, the proposed application will be built in the simplest way to be handled for the convenience of eye care doctors.

1.4.5. Continuous Performance Optimization and Testing:

Once the application is developed continuous techniques and tests will be run to check the the performance of the system. To ensure the maximum optimization of the app any anomaly or malfunction will be fixed and rechecked.

1.4 Methodological Strategy

Optiscan project follows a systematic approach that involves the development of the model, identification of suitable datasets, training of the learned model, model testing, and finally the integration of the tool into a single computing environment that can operate on a desk top application. The given objective follows the comprehensive study plan to improve ‘algorithms for topographic image analysis and diagnosis of eye diseases. ’

1.4.1 Data Collection and Preparation

Patient records totaling over 50,000 were samples in this study and were sourced from Hashmani Clinics. This dataset covers numerous pathologies, and therefore this study is effective in training and test the models. In the process of data collection, the following approaches were used to deal with missing reports, blurred images, and irregularities. Clinical specialists analyzed the patient images at the remote end by manually labeling the pathological changes and the corneal topography measures including curvature and elevation maps.

1.4.2 Data Preparation

Preparing the models was done before training was carried out, the following activities were performed. The images were standardized to a particular size, in addition, there were created more samples using data augmentation techniques in order to achieve the best train accuracy.

1.4.3 Model Development

Seven distinct models were developed and trained to address different aspects of the Optiscan project. Each model was trained to detect various features in the reports and each feature was highlighted to us by the doctor according to their importance in the diagnosis.

1.4.4 Integration into Desktop Application

To make the developed models easily usable, they were embedded in a desktop application with the aid of CustomThinker to enable the creation of a good GUI. This interface also makes it is easy to input/output data and perform various manipulations on it. To ensure that the result derived from the various models could be easily understood and manipulated for further diagnostic analysis, the output generated was in the form of PDF reports using FPDF2.

1.4.5 Evaluation and Assessment

The evaluation, and assessment were important for making sure that the models align with the needs that were pinpointed during the needs assessment. This phase made concrete the integrated models as well as their applicability in a real business environment and the realization of the concept of a GUI-based desktop application.

1.5 Work Distribution

The project comprised two main parts: Research and implementation were the two processes that had to be conducted concurrently to integrate practice and theory into the interventions. The research phase was concerned with studying such techniques more and the possible ways to apply them in medical image processing and creating the corresponding methodologies in the context of corneal topography. At the same time, the implementation phase consisted of integrating these theoretical constructs into functional components of the Optiscan desktop application. To ensure that this duality is done efficiently the tasks were divided among the team members based on their abilities the undertakings were categorized. The section headed by one member was responsible for conducting the research in theoretical framework and made sure that the available research approaches and methods were critically reviewed and practiced. The other member well conversant with software development and system integration dealt with the implementation aspects, writing down the methodologies, developing the application frontend, and carrying out the integration of the various systems. Such division of work let us to make the most use of our experience, avoid delays, and check continuity of the research and its implementation.

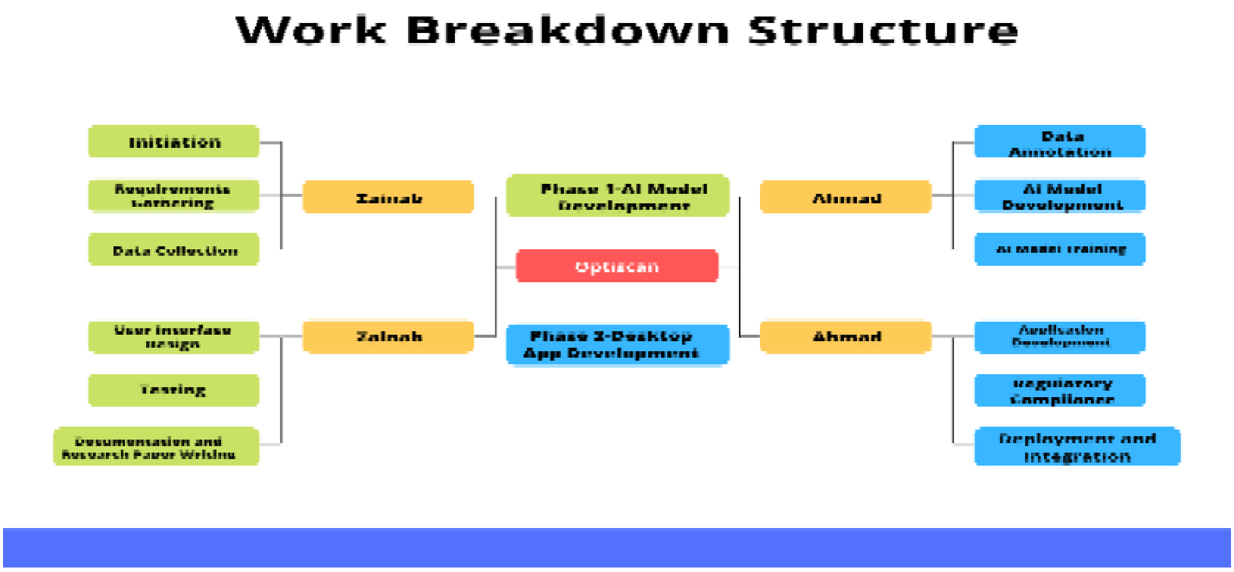


Fig 1: Work Break down Structure

2 BACKGROUND INFORMATION

2.1 Purpose of Corneal Topography

Corneal Topography an important evaluation tool that takes tomography or images of the first aspect of the eye, the corneal surface. It is crucial in the assessment and treatment of a wide variety of ocular pathologies with primary uses in keratoconus, astigmatism, and pre-/post-refractive surgery care. Topographical analysis of the cornea produces graphical representations of the same, including its contour, or accurately referred to as its map.

2.1.1 Elements of Corneal Topography:

These reports usually comprise a sequence of figures and charts, meaning different characteristics of the corneal surface. The images show tonal variations of curved patterns using different colors to distinguish changes in altitude or plane on the corneal surface. The graphs likely depict corneal thickness topography, the relief of the eye's upper surface and other characteristics.

2.1.2 Interpreting Corneal Topography Reports

Furthermore, it is relevant to understand a brief explanation of the reports is needed for their proper comprehension. In other words, the color maps must be interpreted to get an accurate of the corneal curvature and the graphs have to be scrutinized to detect any abnormal trends. This complexity explains why more advanced tools such as Optiscan that incorporate the use of artificial intelligence in interpreting analysis and subsequently feeding the clinician with accurate information are very useful.

2.2 Medical Imaging and Artificial Intelligence.

Medical image processing is an important area in health care as it improves the diagnostic stage of health care by offering accurate, thorough exploration of different body parts without having to conduct invasive procedures. It encompasses processes for getting and working on medical images from the imaging procedures like X-ray, MRI, CT, and Ultrasound. All these images assist the health care practitioners in diagnosing and managing diseases as they avail information which may not be easily seen by the human eyes.

2.2.1 AI Application for Medical Imaging

AI in the last decade has brought a drastic change in medical image analysis. Of the AI techniques, ML and DL are specifically useful for pattern and anomaly identification in medical images. One type of deep learning models has been widely popular due to its capability to learn features of images or pictures; these models are called Convolutional Neural Networks (CNNs). Such models can identify abnormal situations, diagnose diseases, and in some cases, forecast patients' outcomes with a certain degree of efficacy.

Therefore, imaging using AI is not merely about the diagnosis of various diseases. It is also applied to assess a patient's treatment plan, the progression of disease and for the concept of prescriptive medicine. Through the application of AI in medical image processing, health care facilities can gain more accurate, efficient and precise results in the shortest time possible, thereby promoting enhanced patients' care and quality.

2.3 Application of Particular Machine Learning Models in Medical Imaging

2.3.1 Anomaly Detection with Autoencoders

Autoencoder is a kind of artificial neural network, which takes advantage of the ability to study efficient codings of offered data. These are mainly applied in cases of dimensionality reduction as well as feature extraction. On the anomaly detection using autoencoders, the model encodes data to decode it and initially learns to reconstruct the input data perfectly. The extent of difference between the original and the reconstructed data is the measure of anomaly. In medical imaging this approach was presented and the idea is to add to reconstructed image points that differ significantly from the original image.

2.3.2 KDE Analysis for Identifying Abnormal Patterns

Kernel Density Estimation (KDE) is a method of approximating an unknown probability density function of a real valued random variable. In the case of the anomaly detection, the use if KDE can be applied to assess the probable density of normal data points. If a new data point falls in the areas of low density, these are labeled as anomalies. This method is especially useful in MRI where uncommon picture appears may suggest a pathologic state.

2.3.3 Optical Character Recognition (OCR) is the technical process of Text Recognition in Reports.

OCR is a technique that expedites the conversion of paper documents, scanned PDFs, the image captured through digital cameras, and another such forms into an editable data format. The OCR systems employ machine learning methods in order to identify the text in an image and extract it. In medical imaging, OCR consists of converting textual content from image-based medical reports for better organization and analysis.'

2.3.4 CNN's for Sign Detection in Numeric Values of Report

CNNs are deep learning structures that have the main function of analyzing data that has a grid-like structure, namely images. CNNs are used in the identification of image features such as symptoms or particularities in medical reports through the detection of signs/symbols. These networks also entail the use of several layers that help in learning patterns of images required for classifying purposes, and this makes the networks to be suitable for recognizing such symbols as plus and minus signs in medical charts.

2.3.5 Colored Feature Detection in Reports using CNN

Color detection, on the other hand, is mostly used in applications that require the isolation of certain colors from an image. Usually, in medical imaging, various values/parameters are depicted by different colors. Technology-based systems that are used for coloring recognition work on the principle where pixel values of an image are analyzed to detect the presence and distribution of specific colors.

2.3.6 Understanding and Analyzing Medical Graph Understanding

Various graphs in medical reports are frequently used to display key information that may include the patient’s status, disease, or treatment efficacy. To comprehend these graphs, one requires to review and analyze such aspects as the highest values of the graphs, main trends, and other important data. These graphical elements are the basis for analysis and interpretation of various medical imaging and the deep learning models help in the diagnosis and treatment plan of the diseases. CNNs are used to classify properties of graph and then to do further detection and diagnosis.

2.4 Analysis:

Including more sophisticated artificial intelligence models within the medical image processing paradigm is a radical disruption to the overall conventional healthcare diagnostics, and treatment paradigms. Using techniques like anomaly detection with autoencoders, kernel density estimation, optical character recognition, and convolutional neural networks, medical consultants can huge accuracy and scalability when interpreting huge medical images. These technologies help in reducing the time taken in the analysis of corneal topography reports necessary in the diagnosis and management of diseases such as; keratoconus, and astigmatism. This is vital because small and unremarkable irregularities are picked up by the automated systems thus improving the reliability of diagnoses and decreasing on human interventions. Further, digitization of medical report and extracting textual data from such report through OCR helps in smooth data handling which is critical in situations where patients are to be attended to. The available color detection algorithms and the methods to understand the particularities of graphs add depth to the analysis with options to comprehend numerous medical issues and treatment processes. Admittedly, the above-mentioned advanced AI models do not only facilitate the diagnostic process but also improve the application of the so-called ‘individual approach’ in medical work. Thus, the healthcare providers are in a position to offer better care, bring about better results for the patients as well as contribute to the optimization of the various processes in the healthcare delivery system. This concomitance between AI and medical imaging shows another progress that AI has brought into medicine as it paints the vision of improved efficiency between the use of technology and advanced medical solutions in enhancing the medical research.

3 LITERATURE REVIEW / RELATED WORK

Over the years, a number of scientific papers have been published and have made substantial improvements to the field of corneal topography analysis and diagnostic tools based on deep learning approaches. In the recent work of Saluja et al. [1] (2020), the researchers proposed a deep learning approach for curvature and elevation mapping with the corneal topography. Another study done by Zhang and Wang [2] identified how text extraction from medical reports could be accomplished employing the recurrent neural networks (RNNs); thus offering information on probable automated data extracting strategies.

Owing to the detection of signs, Jiang et al. [3] (2018) introduced a model to detect positive and negative sign documents in medical reports, thus stressing the need to recognize values correctly. Regarding color detection in corneal maps, Lee and Park [4] (2021) proposed the utilization of CNNs for recognition of color-coded values, which was helpful in more accurate and sophisticated feature extraction.

Using the example of Chen et al. [5](2017), which was focused on applying graph understanding models, it was possible to identify that such models were crucial for interpretation of the graphical information and their impact on the further strategies of diagnostics and choices within the medical field.

Research in creating user-friendly desktop applications is a field that is as vibrant today as it was years ago. Wang and Li [6](2020) also presented a simple yet powerful GUI-based tool that is designed specifically for the practicing ophthalmologist and effortlessly merges deep learning models with everyday tasks. Other remarkable contributions are given by Liu et al. [7] (2019) who worked on anomaly detection in medical imaging and Kim et al. [8] (2021) who applied color features for ophthalmic diagnostic. This adds more values to the corneal topography analysis and diagnostic help through deep learning advances.

The Summary of some of the papers we reviewed for our projects are as followed

3.1 Applications of Corneal Topography and Tomography: A Review

Authors: Rachel Fan MBBS, Tommy CY Chan FRCS, Gaurav Prakash MD, Vishal Jhanji MD FRCOphth

Year: 2017

Research Question:

- The research goals of the paper are aimed at exploring and explaining the use of corneal topography and tomography in clinical settings. To delineate the multiple areas of ophthalmology practice wherein corneal imaging is key, a full review of its utility in clinical decision making will be given. These objectives involve analyzing development of ectasia, appraising surgery results as well as dealing with postoperative complications following refractive interventions.

Methodology:

- The methodology applied in this paper is a narrative approach which entails synthesizing all the empirical works about the clinical aspects of corneal topography. By taking such an approach, authors can, comparatively speaking, systematically review and recap the findings, diagnoses and assessments about corneal imaging.
- This book offers a comprehensive insight into the clinical use of corneal topography for different sub specialities of ophthalmology through its systematic review and synthesis of available evidence.

Key Findings:

The review highlights the indispensable character of corneal topography within the current ophthalmic procedures. The paper emphasizes the importance of corneal visualization in diagnosing and monitoring progression of ectasia, in evaluating surgical outcomes after refractive procedures, in managing complications after refractive surgeries and earlier cataract surgery and intraocular lens power calculation. The criteria for diagnosis, the assessment methods and the implications for the clinicians were elucidated by the authors via a comprehensive literature analysis in each of the aforementioned areas.

3.2 Title: Pentacam: Principle and Clinical Applications

Authors: Rajeev Jain, SPS Grewal

Year: May-August 2009

Research Question:

- The main objective of the paper is to assess the principle of the Pentacam technology, and explain its common applications in ophthalmology.

Methodology:

- The authors take us through a thorough assessment of Pentacam technologies, synthesizing existing literature and clinical expertise and explain the principles and clinical uses.
- They elaborate the modus operandi of Pentacam in the determination of corneal parameters, anterior chamber dynamics, and intraocular structures. Furthermore, they provide stations and comparison studies to point out the effectiveness of Pentacam in different clinical settings.

Key Findings:

- Pentacam provides an important instrument for diagnosing keratoconus, screening for glaucoma and, configuring corneal collagen crosslinking or intraocular lens implantation procedures.
- The technology enables improvement of the precision in terms of the intraocular lens calculations, especially of the eyes with previous refractive surgery or complex clinical conditions.
- The Pentacam SR used within High-Resolution Pentacam has sharper imaging and more accurate layer evaluation of cornea and intra-ocular structures, which may have positive effect on the assessment stage of refractive surgeries.

- This paper highlights that Pentacam is a highly valuable device necessary for ophthalmic practice. In terms of anterior segment anatomy and dynamics, its ability to offer valuable information offers a great variety of applications for diagnosis, treatment planning, and follow-up care in different ocular diseases.

3.3 Title: Characteristic of Entire Corneal Topography and Tomography for the Detection of Sub-clinical Keratoconus with Zernike Polynomials using Pentacam

Authors: Zhe X1, Weibo Li, Jun Jiang, Xiran Zhuang, Wei Chen, Mei Peng, Jianhua Wang, Fan Lu, Meixiao Shen & Yuanyuan Wang

Year: 2017

Research Questions:

The research questions addressed in the paper include:The research questions addressed in the paper include:

- Regarding the effectiveness of particular indices based on corneal topography and tomography in the early detection of keratoconus (KC), especially the subclinical KC, what is the deepest explanation?
- How is the methodology that can calculate the corneal surface features and thickness number distributed?
- What are the strengths and disadvantages in implementing Zernike polynomials fitting analysis and discriminant functions for distinguishing departing from the normal corneas, subclinical KC, and KC corneas?

Methodology:

The methodology involves:

- Involving KC patients with normal subjects from a hospital medical center.
- Performing slit lamp examinations, with pachymetry measurement using Pentacam HR.
- Based on several criteria, subjects are classified into normal, subclinical KC and KC groups respectively.

- Through the fitting analysis of Zernike polynomials for the purpose of determining corneal surface elevations and distribution of thickness.

Key Findings

- Uses a comprehensive approach comprising of corneal topography and tomography to assess elusive changes in the early stages of keratoconus.
- Consist of Zernike polynomials fitting analysis which is an innovative approach of quantification of corneal surface traits.
- The discriminant functions are used to separate corneas that are normal, subclinical KC, and KC corneas objectively.
- The performance of all the indices based on corneal imaging is compared with the early KC.

3.4 Title: Improving automatic liver tumor segmentation in late-phase MRI using multi-model training and 3D convolutional neural networks;

Research Questions:

The research questions addressed in the paper include:The research questions addressed in the paper include:

- Can particular indices, derived from the corneal topography and tomography, play their role in early diagnose keratoconus (KC) disease?
- What techniques are used to measure non-uniform corneal surface characteristics and thickness distribution?
- To what extent the use of the Zernike polynomials fitting analysis and discriminant functions in separating the corneas of normal individuals, subclinical keratoconus (KC), and KC corneas is appropriate?
-

Methodology:

The methodology involves:

- Recruitment of both KC patients and normal subjects from a local medical center.
- Conduct corneal examinations of the oculars, including corneal topography. Using Pentacam HR system.
- Place each subject in a normal, subclinical KC, or KC group based upon particular criteria.
- Employing the Zernike polynomials to fit the analysis of corneal surface elevations and distribution of thickness by means of inquiry.
- Building discriminant functions by stepwise line discrimination analysis, which will categorize groups based on Zernike RMS metrics and Pentacam metrics.
-
- **Key Findings:**
- The eye mapping (corneal topography and tomography) is the basis to assess the KC development in early stages.
- Brings the Zernike polynomials fitting analysis, a new approach to measure corneal surface properties.
- Deploys discriminative functions that provide an objective way to distinguish a cornea as a normal one, a subclinical KC, and a KC cornea.
- Generates information on the indexing effectiveness of different indicators from the corneal image modalities in the detection of the early stages of KC.

3.5 Title: Deep Learning for Predicting Refractive Error From Retinal Fundus Images

Author: Avinash V. Varadarajan, Ryan Poplin, Katy Blumer, Christof Angermueller, Joe Ledsam, Reena Chopra,Pearse A. Keane, Greg S. Corrado, Lily Peng,1 and Dale R. Webster

Year: 2018

Research Question:

- What is the predictive power of deep learning models on refractive error from central retinal fundus images, and what associated features are crucial for these predictions?

Methodology

- Data Collection: The study employed retinal fundus images from two datasets, UK biobank and AREDS, to train and validate deep learning models for classifying refractive errors.
- Model Training: CNNs and the attention mechanism were used by the deep learning models for prediction of refractive error.
- Analysis: The attention maps were created to highlight the geometrical features that highly correlated with refractive error in retinal fundus images. The survey also evaluates the influence of eye diseases (cataract surgery or AMD) on predictive performance.

Key Findings

- Focus on Fovea: The attention maps showed a perfect focus on the fovea for all refractive errors which imply its key role in model prediction.
- Effect of Eye Diseases: From the model accuracy, we could tell that excluding the subjects with cataract surgery and/or AMD yields a slight yet considerable improvement.
- Differences between Data Sets: A model accuracy variation was noted between the UK Biobank and AREDS datasets. This is possibly attributed to the factors like image quality and abnormal macular pathology.

3.6 Title: Image reconstruction using priors from deep learning

AUTHOR: DEVI AYYAGARI, NISHA RAMESH, DIMITRI YATSENKO,TOLGA TASDIZEN, AND CRISTIAN ATRIANVIEW MEDICAL, SALT LAKE CITY, USA, BAYLOR COLLEGE OF MEDICINE, HOUSTON, USA, SCIENTIFIC COMPUTING AND IMAGING INSTITUTE.

YEAR: 2018

Research Question

- The study purpose is focused on overcoming the problem of not enough data tomography, with a particular interest in the functionality of Cone Beam Tomosynthesis Fluoroscopy (CBT-fluoroscopy). The key issue here is returning better reconstructions in tomographic imaging in the case of data insufficiency taking into account the obvious classical inverse, poor-conditioned, or under-determined nature of the problem.

Methodology

- The presented strategy brings into play a new scheme which uses CNN based regularizers in an iterative reconstruction algorithm. The goal here is to harness the full capabilities and potential of the machine learning while eliminating the biases that could be encoded in the machine.
- They implement this by using CT datasets acquired virtually in the CBT-fluoroscopy device, simulating the training process. For the training of two separate CNNs coupled with thepseudospecial and morphological iteration algorithms, 'early CNN' and 'late CNN' are used. For both models U-Net architecture is used, one for the convolutional encoder and one for
- Author: Devi Ayyagari, Nisha Ramesh, Dimitri Yatsenko,Tolga Tasdizen, and Cristian AtrianView medical, Salt Lake City, USA, Baylor College of Medicine, Houston, USA, Scientific Computing and Imaging Institute.
  Year: 2018

KEY FINDINGS

Visual comparison of reconstructions made at different stages of the process illustrates the efficiency of the proposed approach in removing geometrical distortions and misalignments that usually arise by limited data. The progress of reconstructions goes from having the early stages with major distortions to the later stages with better quality and fewer biases. In turn, the CNN at the last stage performs boosts the reconstructions by smoothing the structures obtained at the first stage.

The quantitative analysis indicates the progressive improvement of reconstruction quality and consistency with the measurements as the rest of the process completes.

3.7 Review Summary Table

No.	Tiltle	Year	Publication	Summary	Assistance in the Project
1.	• **Applications of Corneal Topography and Tomography: A Review** •	2017	Wiley	Reached a consensus on different methodological approaches represented by corneal topography and tomography in ophthalmology.	Gives in-depth analysis of corneal topography and how it is applied in ophthalmology, informing comprehension about its use as a diagnostic tool and treatment planning.
2.	• **Pentacam: Principle and Clinical Applications**	2009	Indian Journals	How PENTCAM is a powerful tool for making	Offers a detailed understanding of the Pentacam technology, its working principles, and its clinical

				diagnostic repots.	applications, crucial for developing a desktop application for analyzing corneal topography reports
3.	• **Characteristic of entire corneal topography and tomography for the detection of sub-clinical keratoconus with Zernike polynomials using Pentacam,**	2017	Scientific Reports	Explores roles of the Zernike polynomials and Pentacam for diagnosing subclinical keratoconus.	Illustrates the efficiency of Pentacam and Zernike polynomials in detecting early signs of keratoconus which will be eventually used as basis for corneal health assessment algorithms in the desktop application.
4.	Improving automatic liver tumor segmentation in late-phase MRI using multi-model training and 3D • **convolutional neural networks;**	2021	Scientific Reports	Investigates the improvement of liver tumor segmentation in fase MRI late through multi-model training and 3D convolutional neural networks (CNNs)	Provides a way to make more advanced techniques for liver tumor segmentation in MRI scans, which may help doctors to be more accurate and efficient when using a desktop application to read and analyze medical images.
5.	• **Deep Learning for Predicting**	2018	IOVS	Demonstrates the use of deep learning models to predict	Provides insights into leveraging deep learning for image-based predictions,

	Refractive Error From Retinal Fundus Images			refractive error from retinal fundus images with high accuracy.	relevant for developing algorithms in the desktop application to analyze corneal topography reports.
6.	• **Image Reconstruction using Priors from Deep Learnin**	2018	SPIE Digital Library	Proposes a novel framework to improve the quality of image reconstruction by embedding (CNNs) as regularizers within an iterative reconstruction algorithm.	Offers insights into using deep learning for improving image reconstruction quality, which can be relevant for enhancing the accuracy of corneal topography analysis in the desktop application.

***Table 1**: Summary Table of Research Work*

4 DEVELOPMENT

One of the diagnostic procedures used in ophthalmology is Corneal topography through which a detailed map including the curvature of the cornea can be made. To this end, Mauch et al noted that through assessment of corneal topography, it becomes possible for clinicians to identify cases of astigmatism, keratoconus, and irregular corneal matter that make treatment planning and monitoring possible.

In the Optiscan project, we had five kinds of corneal topography images of the left eye, the right eye of the patients. These imaging that to a large extent act as full spectrum eye care screening are heavily scrutinized using well-developed models which even can detect basic data that are essential in diagnosing and planning the subsequent treatment. These images and their parameters and behaviours together were collected from the eye care specialists to put all the findings into bio clinic meanings of normal and abnormal or noab ranges.

Following are the 5 different types of images/analysis of each eye in topography report.

4 Maps Refractive: These describe the contour of the corneal surface in light of curvature and power when defining people's visual acuity and any veering off from the standard curvature ever again.

Belin/Ambrosio Enhanced Ectasia: These images show the external and superior aspect of corneal thickness and relief: the abnormal form is a feature of ectatic corneal pathology such as keratoconus, and is crucial during surgical interventions.

Fourier-Analysis: While dealing with corneal irregularity in concordance, Fourier analysis helps in determining HOAs and surface topographical surface roughness on visual clarity.

Zernik Analysis Wavefront Aberration Cornea Front: These impacts include stigmatism, spherical aberration, and other higher orders associated with front surface of influence, on corneal optics.

Zernik Analysis - Wavefront Aberration Cornea Back: If the location of a considerable irregularity at the back surface is examined in detail, the observer will get a glimpse at the posterior corneal irregularities that do impact optical quality and visual quality.

Like above mentioned, all the described types of images demonstrate the certain aspects of the structure and refractive characteristics of the cornea, its irregularities, and aberrations, the availability of the set of images for diagnosis and evaluation of individuals is of pivotal importance for ophthalmologists and optometrists. By integrating these analyses into out desktop specific application it provides for more accurate and effective diagnostic plans as well as enhancement of the basic overall assessment of various corneal disorders.

4.1 Model Training.

4.1.1 Anomaly Detection Model:

The first system that we made is an anomaly detection system that actually has 3 deep learning models working inside it, that was implemented in our Optiscan project and its objective was to identify anomalies in the QS in the corneal topography reports. The field QS is available in the 4 Maps Refractive image of the presented report; it depicts the reliability of the report under consideration as the result of imagery through the Pentacam device. Thus when the QS appears against a white background with the text 'OK' in any case if there exists variation in either text color or background one would be made to understand that it is an unreliable report.

There are two main indications of the report being realiable: if the color of the text is white and the words on the QS are ‘OK’ other than this any variation in the colour of the background of this text means that the report might be unreliable. To achieve this, we employed three distinct models: These models are an Autoencoder, Autoencoder-Decoder, and Kernel Density Estimation or KDE model.

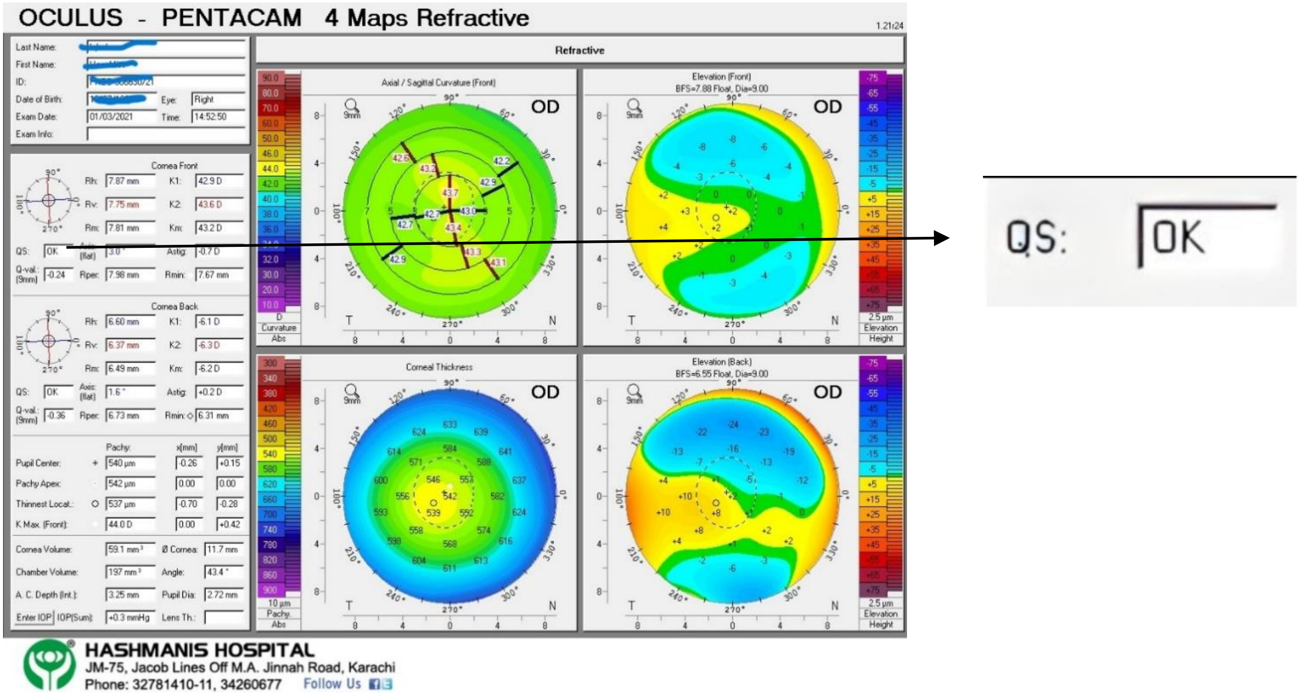


Fig 2: 4 Maps Refractive analysis and QS Field

4.1.1.1 Dataset

- Training Set: 7,000 images
- Validation Set: 1,000 images
- Test Set: 2,000 images

4.1.1.2 Data Preprocessing

In order to pre-process the inputs, every image was rescaled to 16×16 pixels and normalized. Different techniques of data augmentation were applied, from the ImageDataGenerator class of keras in order to increase the number of samples, and thus increase the quantity of data to use during training.

4.1.1.3 Models Architecture

4.1.1.3.1 Autoencoder Model:

4.1.1.3.1.1 Imports and Data Preparation:

We begin importing necessary libraries like random, glob, os, joblib, PIL, matplotlib, numpy and tensorflow. We defined constants for image dimension with respect to number of nodes and number of node with respect to batch size 50. We used data augmentation and data rescaling features of keras Machine learning library to initialize an ImageDataGenerator

4.1.1.3.1.2 Data Generators:

In the following sections, we explain our use of training, validation, and anomaly data generators in the form of ImageDataGenerator. flow_from_directory function, where the paths to the datasets and the target size are specified as 16x16 pixels.

4.1.1.3.1.3 Model Structure:

We instantiated a Convolutional Autoencoder model using TensorFlow/Keras' Sequential API module. The model had coupled Conv2D, and MaxPooling2D layers as well as UpSampling2D layers.

4.1.1.3.1.4 Model Compilation and Summary:

We use Adam optimizer and mean squared error as loss function for compiling our model and displayed a summary of the building model parameters.

4.1.1.3.2 Encoder Model

The Encoder model was fitted with training and validation generators using the fit method. After training we have stored the meodel.

4.1.1.3.2.1 Monitoring Performance:

We used Training loss and Validation Loss, and Mean Squared Error (MSE) plots against epochs to monitor model training.

4.1.1.3.2.2 Model Evaluation:

To begin with, we gave some predictions on a set of training images and explained original versus reconstructed images. The model was then tested using validation and anomaly datasets for evaluation purposes.

After that, we took the trained weights of the Autoencoder and built an encoder model from it, we also printed the summary of the model and saved the model as encoder_model. h5.

4.1.1.3.3 Kernel Density Estimation (KDE) Model

4.1.1.3.3.1 Fitting the KDE:

The images were flattened by unstacking them and the KDE model was then fitted by using a Gaussian kernel on these vectors. The KDE model includes the results of the study and was saved under the name kde_model. joblib.

4.1.1.3.3.2 Calculating Metrics:

Therefore, we utilized the encoder and KDE models to establish a function that can determine the density and reconstruction error of images in batches. Hence, these above metrics were computed for regular batches as well as anomaly batch to find out difference.

4.1.2 Overall working of the Models Anomaly Detection Module

In our Optiscan project, the anomaly detection system was designed to sequentially process corneal topography images using three interconnected models: An Autoencoder, An Encoder Model, and Kernel Density Estimation (KDE) model. Here’s how the overall workflow operates:Here’s how the overall workflow operates:

- **Encoding Phase:** We pre-process the image and then feed it to the Autoencoder model. This model contains several convolutional layers followed by down sample layers with a specific goal of reducing dimensions to capture relevant features when design.

- **Feature Extraction:** The Autoencoder therefore transforms the picture to a latent space of a lower dimension, thus capturing salient perceptual characteristics. This latent representation is useful for deciding what can be considered to be an anomaly.
- **Reconstruction Phase:** Consequently, the encoded image is processed in the Encoder model which has been explained above. This model is designed to work in reverse of the encoding process for image reconstruction using up-sampled and convolutional layers.
- **Reconstruction Error Calculation**: It is the measure of the difference between the original image and the reconstructed image that is used to calculate the amount of error in the given reconstructed image. Introduction The equation below shows the reconstruction error, where a higher value implies that the image in question may not be normal, as measured by the distance of its features to the mean of the normal data.

- **Density Estimation:** The encoded features carried out from the Autoencoder are flattened and incorporated into the KDE model. In the process of classification, the KDE model, which is trained on normal images, gives the density of how likely the features of the given image are to have been encoded.
- **Density Calculation:** The KDE model determines the probability density of encoded features for a given image. A low-density value implies that the features of images are abnormal; they are remote from the mean value of the data distribution.

4.1.2.1 Anomaly Detection Decision

- **Combining Metrics:** The legitimacy of an image as an anomaly involves decision making that combines the aspects of reconstruction error as well as density.
- **High Reconstruction Error:** It implies that if the image reconstruction error is greater than a prescribed value, then there are features in an image that have not been found in normal images.
- **Low Density Estimate**: The KDE model will further have a low density estimate of the features encoded if the image is an anomaly making it a strong hint that the image is an anomaly.

- **Anomaly Criteria:** Anomaly detection of an image is based on criteria that meet high reconstruction error as well as low-density estimation. This double criterion which defines membership to these groups allows for a reliable and solid detection mechanism.

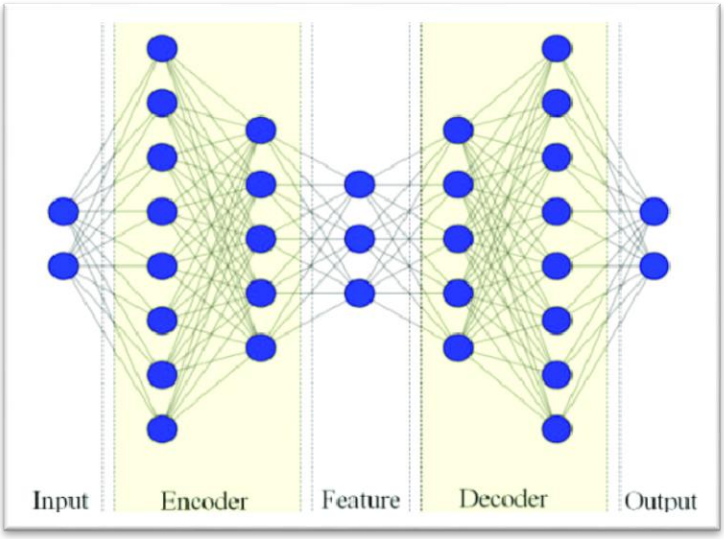


***Fig 3*: Anomaly Detection Model Generic Architecture**

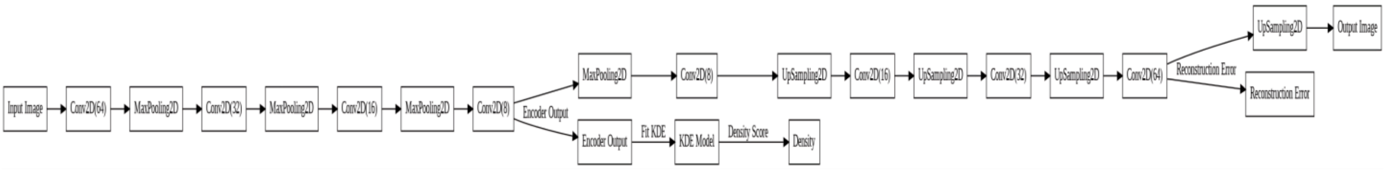
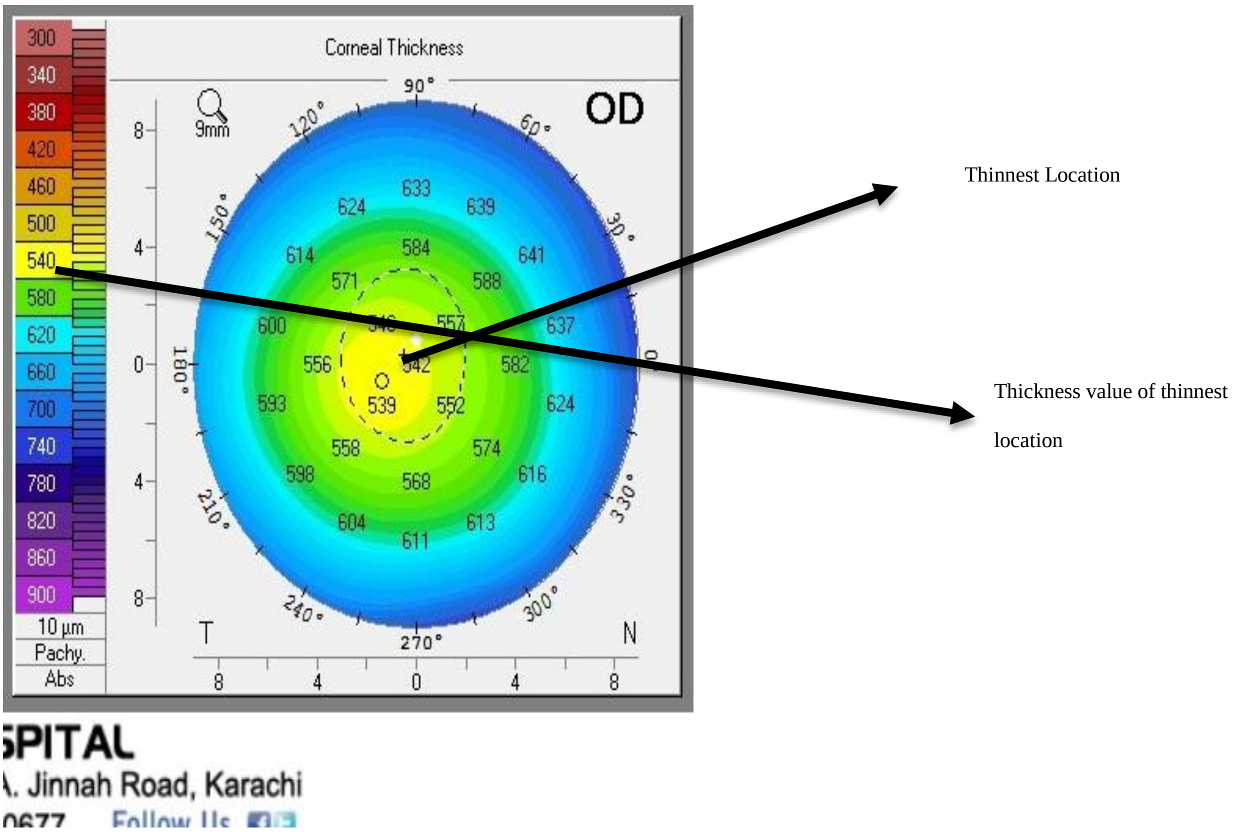


***Fig 4*: Anomaly Detection Model Architecture Made in Optiscan**

4.1.3 Corneal Thickness Classification Model:

The second model that could be drawn out from our study involving Optiscan is on the classification of corneal thickness. This one has also implemented the Convolutional Neural Network (CNN) model for analysing a specialised layer of the refractive OCT, which is the corneal thickness map. In layman's terms the first step involves determining a small circle referred to as the circle of least diameter which localizes the least amount of tissue on the cornea. This circle tends to exist in an area of color like yellow within a map; it is the thinnest section of a cornea or the colour of which the circle is. Perhaps the colour used could be assigned to the number on the colour chart placed on the extreme left of the map. This is the actual corneal thickness value that is frequently referred to as minimum corneal thickness and is commonly the parameter that is normally obtained and presented.



[Fig 5](#): Corneal Thickness Map and Its Values

4.1.3.1 Dataset:

The dataset consists of images of the corneal thickness divided into equal 16 classes including only planar map images. The classes are labeled as follows: [300, 340, 380, 420, 460, 500, 540, 580, 620, 660, 700, 740, 780, 820, 860, 900].

- Training Set: 7,584 images
- Validation Set: 1,072 images
- Test Set: 2,160 images

4.1.3.2 Data Augmentation:

To eradicate places of overemphasise of the features and improve on the probability of the model, several data augmentation pre-processing was used. Among them included rotation, flipping and shifting while making sure it was not one of the inputs used during training of the network.

4.1.3.3 Model Architecture:

For that reason the method was trained using three-convolution layers with max-pooling layers, flattening and the CNN architecture with two layers of density. To solve for overfitting of the model, the use of the dropout layer was included during the training and only the training set was implemented.

4.1.3.4 Training and Validation:

The suggested model was trained using Adam every 50 iterations and categorical cross-entropy loss was applied. Making the learning rate zero is not very useful for training purposes because as a matter of fact,(setting the learning rate) is done in an ideal way as follows. 0001. Some strategies like checkpoints and early stopping were used to avoid over-fitting.

4.1.3.5 Results:

The training accuracy that was achieved was 93%

4.1.4 Corneal Elevation Classification:

The third model we trained project concerns establishing the categories of elevation level in refractive maps. The refractive dataset includes two elevation maps: elevation back and elevation front are two forms of maps that are critical in any corneal report. Both maps have a '+' symbol in its center to facilitate the identification of the appropriate elevation grade. This model aims to locate the + sign, in which it resides, and then match the area in which the + is located with a representation of elevation in color code indicating a numerical value according to the color-coding chart provided.

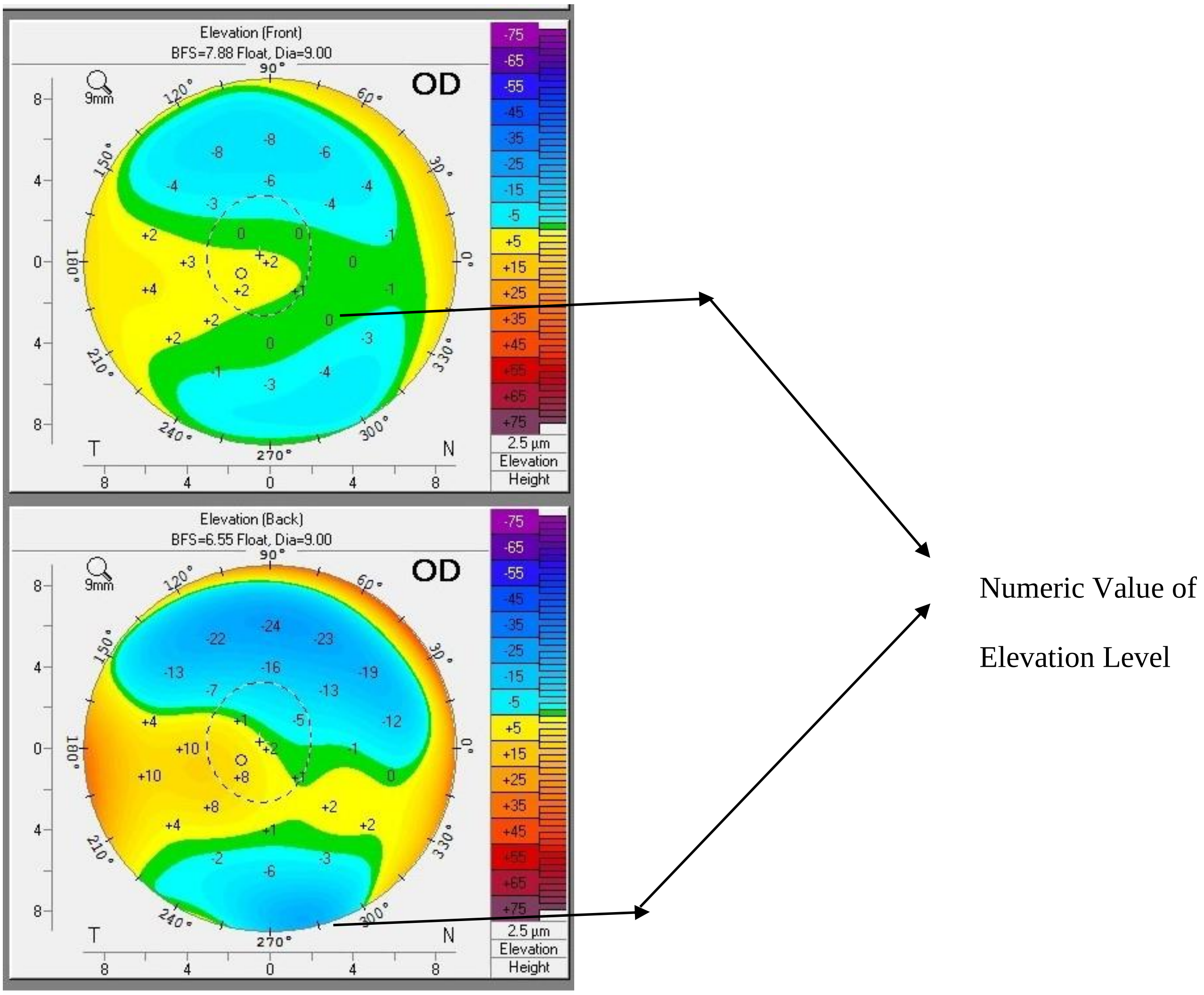


Fig 6 : Elevation Maps of Cornea

4.1.4.1 Data Set

The data set consists of elevation images which were classified into 16 classes covering elevation range of -75 to +75. The class label of each sample is the elevation of the area where it is found, divided into ranges. This dataset is further divided into training data, validation data and testing data set to maintain its competency.

- Training Set: 15,120 images
- Validation Set: 2,160 images
- Test Set: 4,320 images

4.1.4.2 Model Architecture:

Three Convolutional Layers: These layers are followed by max-pooling layers for feature extraction.

Flatten Layer: The next layer transforms the scaled feature maps from the 2D dimension to the 1D dimension.

Two Dense Layers: These layers are used for classification with the intent of avoiding overfitting of the parameters and hence incorporating dropout.

4.1.4.3 Model Compilation and Training:

A learning rate of 0.0035 for maximum optimization. Regular check-points were also used to write down the models which came closest to the minimum of the validation loss.

4.1.4.4 Performance:

By the time the training was complete the trained model was pulling a training accuracy 87. 50%. This means that the model is useful in classifying elevation images accurately

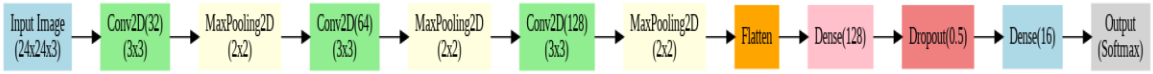
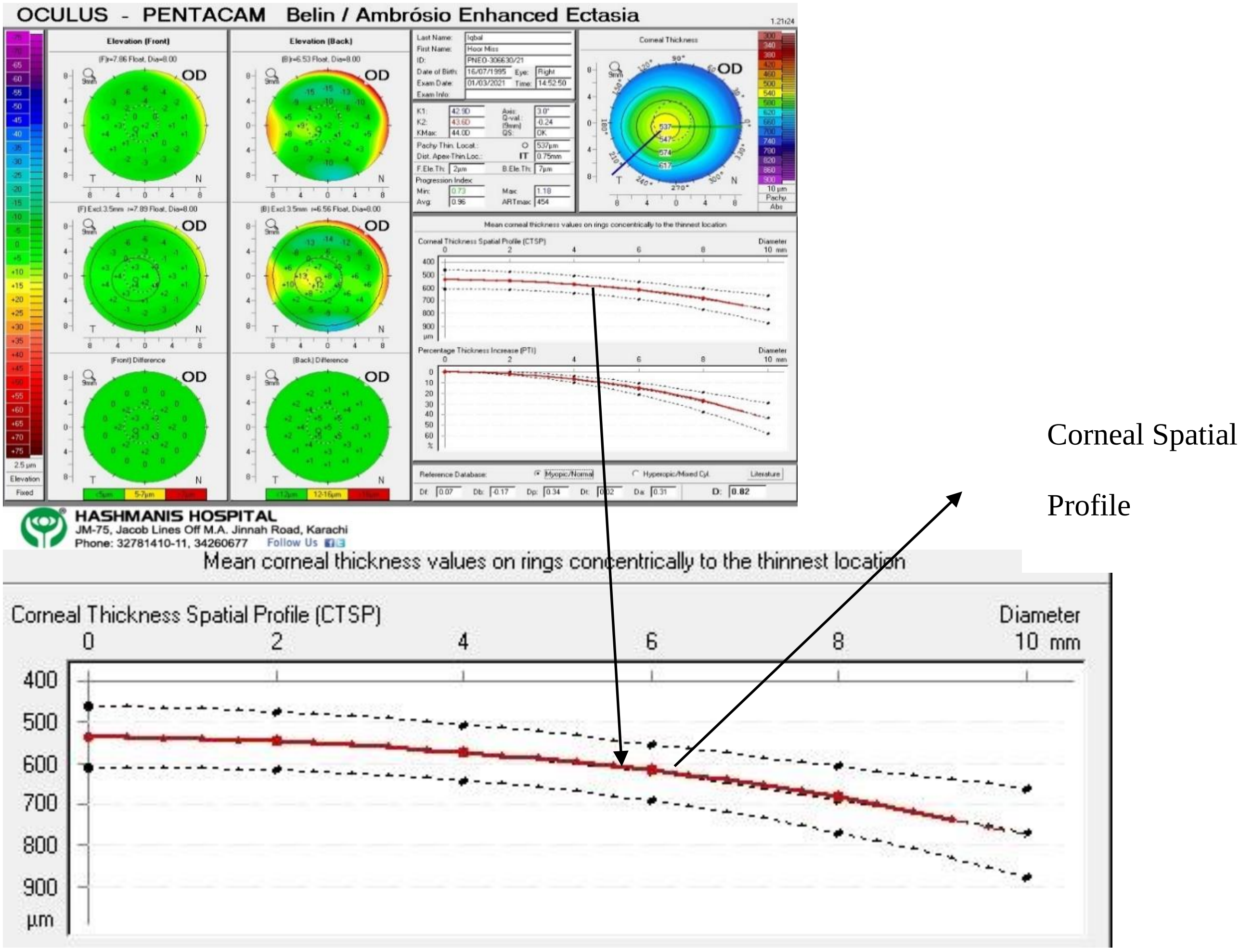


***Fig 7* : Corneal Elevation Classification Model architecture**

4.1.5 Corneal Thickness Spatial Profile (CTSP)

Corneal thickness at the minimum measured point and the mean of the thicknesses measured on 22 circles concentric with the minimum point and having their diameter increased at 0 is called CTSP analysis. The CTSP ramp resigns a corneal-thickness spatial profile in 4 mm steps as compared with the older SAT ramp, which steps 0. 25 mm between 1. 25 and 4. 25 mm. The idea of this model is to see whether or not the red line matches any of the reading fitting lines; if not, then it should approach before the 6-mm mark as that signifies corneal failure.



[Fig 8](#) : Belin/Ambrosio Enhanced Ectasia-CTS Analysi

4.1.5.1 Dataset

To accomplish the research objectives of using the CTSP model for identifying corneal thickness spatial profiles from the medical images, the model was trained, validated, and tested on dataset of corneal topography images. The dataset was divided as follows:The dataset was divided as follows:

- Training Set: 2,800 images
- Validation Set: 400 images
- Test Set: 800 images

4.1.5.2 Convolutional Neural Network (CNN)

The CTSP model used a notably complex CNN model, abbreviated as Convolution–Pooling–Convolution–Pooling–Fully Connection–Classification, which includes several numbers of convolutional and pooling layers and fully connected layers that used for classification. In this model, extra layers like Batch normalization and Dropout layers were incorporated in order to enhance the model performance and to reduce issues to do with the overfitting of the model.

4.1.5.3 Model Training and Evaluation

The long short-term memory (LSTM) in the CTSP model was trained using the Adam optimizer algorithm and binary cross entropy loss. Early stopping and checkpoint callback functions were used to track the model and save in the best performing models. As concluded from the results of the model had high training accuracy of 94%.

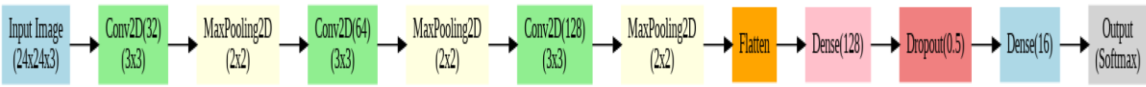


***Fig 9*: Corneal Thickness Spatial Profile**

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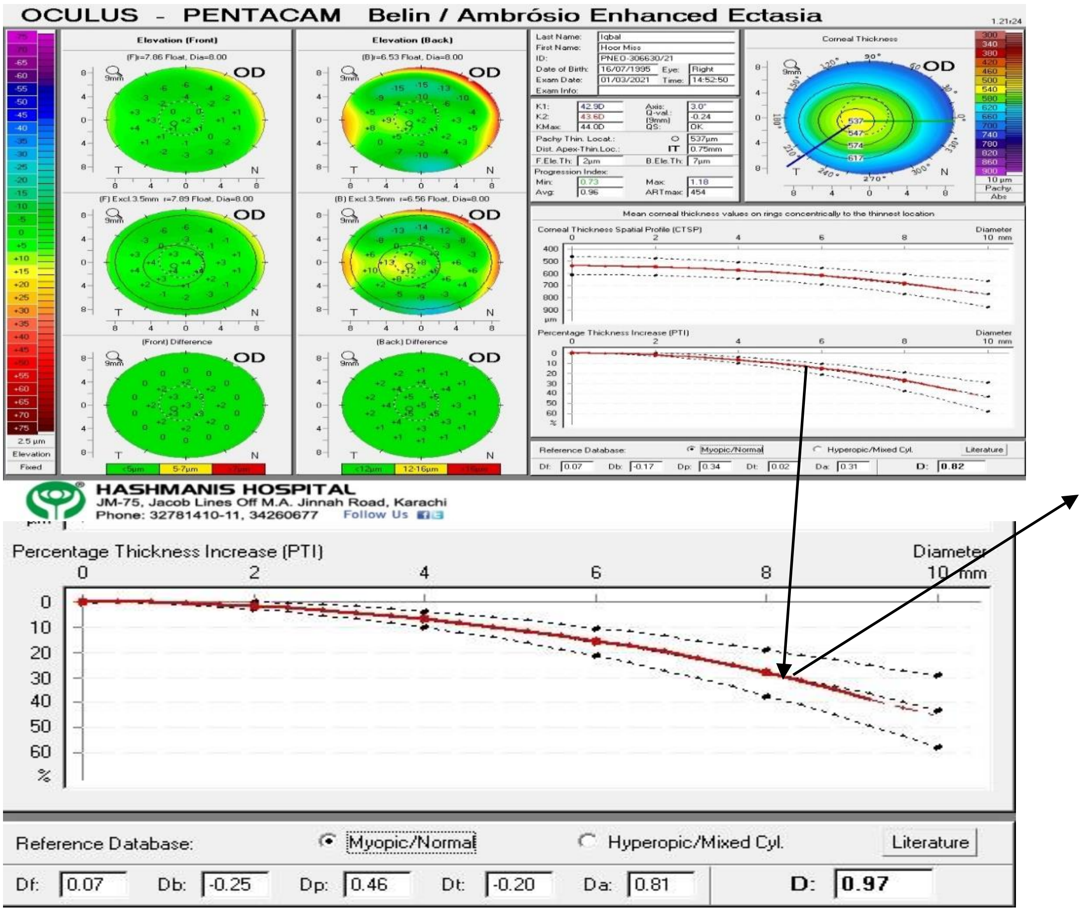
4.1.6 PTI Model:

The measurement that describes the shape of the cornea is the Percentage Thickness Index (PTI) where the percentage is the thickness increase from the thinnest point to the periphery. Five differential parameters –Change in anterior elevation from a standard reference surface to an enhanced reference surface (Df), Change in posterior elevation (Db), Corneal thickness at the thinnest point (Dt), Displacement at the thinnest point (Da), Pachymetric progression (Dp). The main purpose of this model, like the CTSP model is to determine whether the red graph line is aligned with any of the dotted line if not, it is to deviate before the 6 mm mark the main objective is to analyze the shifting and fluctuations in the thickness of the cornea at a different elevation.



Percentage Thickness Increase

***Fig 10*: Belin/Ambrosio Analysis with PTI Graph**

4.1.6.1 Dataset

The PTI model was trained, validated, and tested on a dataset consisting of 4,000 medical images categorized into two classes: As a result, it becomes possible to define the difference between normal and abnormal behavior while considering the given criteria. The dataset was divided into:

- Training Set: 2,800 images
- Validation Set: 400 images
- Test Set: 800 images

4.1.6.2 Image Preprocessing

In the image processing for this problem, the images were pre processed then normalized thus rescaling the images; other data augmentation was also done for the models to be sensitive to minor changes. The following operations that we are going to include in our list; rotation both horizontal and vertical flipping.

4.1.6.3 Convolutional Neural Network (CNN)

The PTI model used an architecture of CNN that had multiple convolutional as well as one or many middle layers of pooling structures and fully coupled layers for classification of the sample. Some measures taken to overcome overfitting in the structure were the integration of layers of Batch Normalization as well as the incorporation of the Dropout layers into the establishment of the network.

4.1.6.4 Model Training and Evaluation

To train the model it was important to apply the early stopping approach as well as the checkpoint callbacks for managing the model's progress. This it further allowed the model to learn with the training accuracy of 95% for a better performance. and 86% accuracy of the test respectively.

When assessed the percent of thickness variations in corneal topography report, the PTI model splendid training & test result exhibited the usefulness of the model. The representation of the model with training and validation metrics amplified for data ensured the soundness of the model.

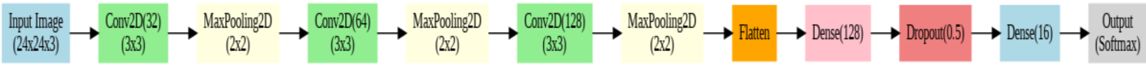


Fig 11: Model architecture of PTI Model

4.1.7 Sign Model-Classification of Plus Minus Sign:

The Sign Model in our Optiscan project consists of a deep learning Convolutional Neural Network (CNN) which is used to decipher and annotate signs before numerals in Corneal Topography reports. This model trained using TensorFlow and Keras on a variety of images to detect indicators, which could be crucial for decision making; moreover, the image enhancement techniques can help our desktop application in enhancing its analytical Capabilities.

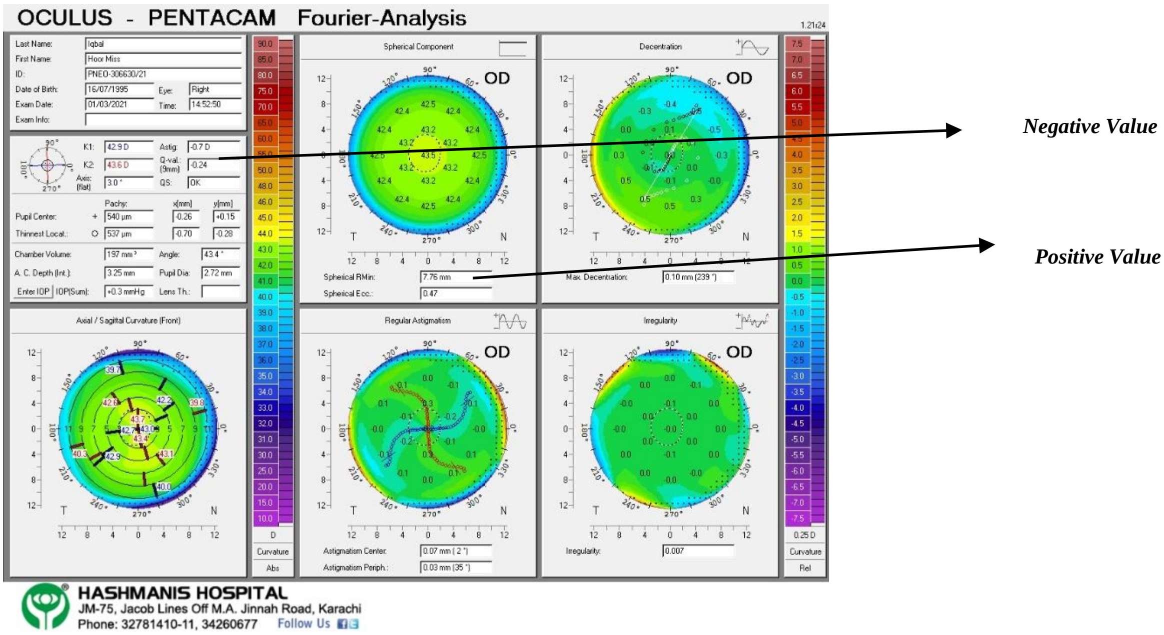


Fig 12 : Fourier Analysis with Positive and Negative Numeric Values

4.1.7.1 Dataset Preparation

The dataset for the sign model was an organized formation of folders for training, validation, and testing. The different pictures they were shown were then tagged as plus or minus symbol. After that, the ImageDataGenerator class from the Keras library was applied to the images for further preprocessing. The pixel values were normalized so that they were in the range from 0 to 1.

4.1.7.2 Model Architecture

The model employed the application of Convolutional Neural Network (CNN) with a sequentially incorporated layer. The architecture consisted of: The model comprises the following layers: Four Conv2D layers, all of which are followed by the ReLU activation and same padding.

Four MaxPooling2D layers should be used to decrease the size of the unsqueezed feature maps.

A Flatten layer Step 5: to reduce the shape of 2D matrices into 1D vector.

The same is the architecture of two Dense layers using ReLU activation with the final layer being softmax activation to classify into three classes namely Class_A, Class_B, and Class_C.

4.1.7.3 Compilation and Training

The model was trained with the help of Adam's optimizer, categorical cross-entropy loss function and accuracy measure was kept as the metrics. The learning rate was set to 1e-5 in the implementations. The prominent feature of training was early stopping to prevent overfitting and model checkpointing to save the model with the least validation loss.

4.1.7.4 Evaluation

The model was then tested using a different set of data of equal size as before with the purpose of evaluating its performance. The model was tested on both training and test datasets, and loss and accuracy were used as the evaluation metrics, and an average test set accuracy of 92% was observed.

4.1.8 Text OCR for Numeric Value Recognition:

The text OCR model used in this work employs deep learning methods to precisely capture and segment the textual numeric values in images. Here, the model is trained on a new dataset augmented for data diversification, and features the use of convolutional neural networks (CNNs) for feature extraction and classification. Since the feature map responds to various image transformations and the model is built based on solid principles of computer science, it shows high ability in recognizing and analyzing numeric text within the images, which is beneficial for working with the data.

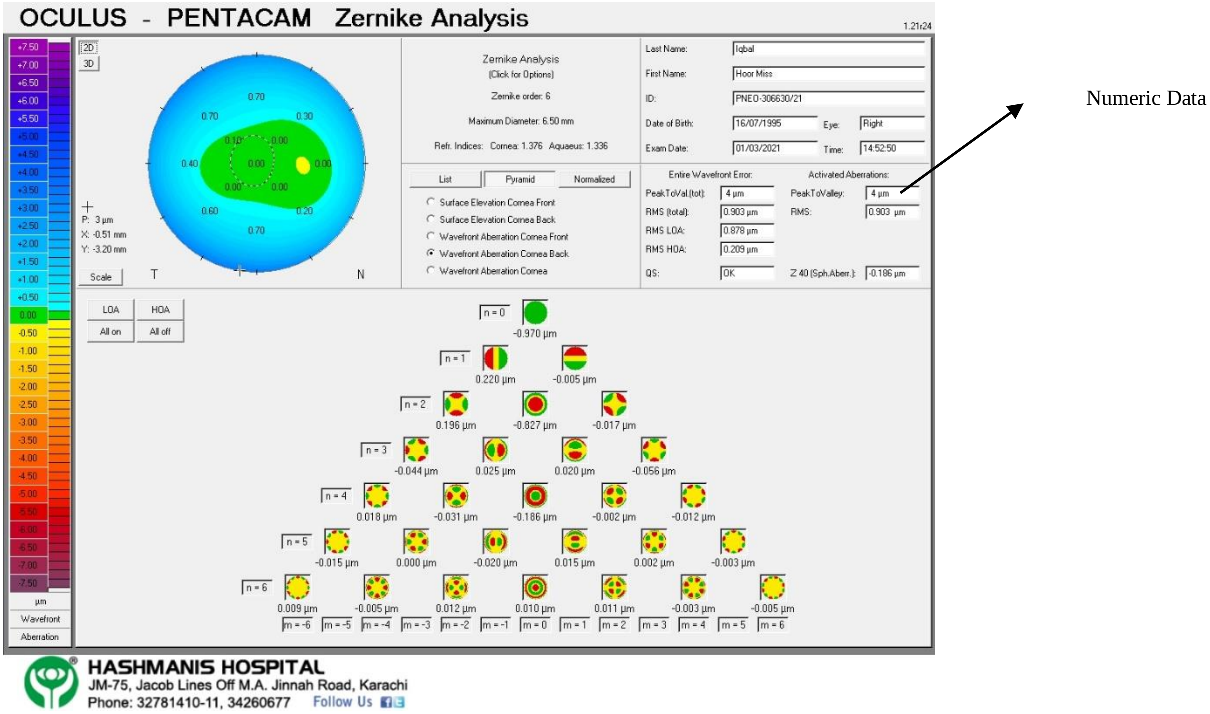


***Fig 13**: Zernik Analysis with Numeric Values*

4.1.8.1 Dataset

The dataset used for the text model contained images of numbers that were written in different forms including ordinary typed texts, handwritten texts, scanned as well as photographed texts. The dataset was divided into training, validation, and test sets with a total of 14,000 images: For training the model, the user selected 9,800 images, for validation 1,400 images were selected while for testing of the model, 2,800 images were used.

4.1.8.2 Convolutional Neural Network (CNN)

The text recognition model proposed did use multiple CNN layers in extracting feature specific and pooling layers for the same before followed by density layers for classification purposes. Thus, Adam optimizer was used for training and categorical cross entropy loss function was applied.

4.1.8.3 Model Training and Evaluation

CNN model was trained on the training dataset, and the experiments of the model were conducted on the validation and tested dataset. The procedures that were followed during the training process include early stopping techniques as well as model checkpointing. Errors were tested on the test dataset with the model able to achieve high accuracy of 88% .

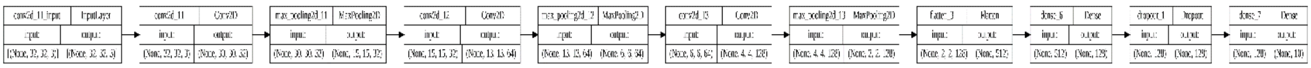
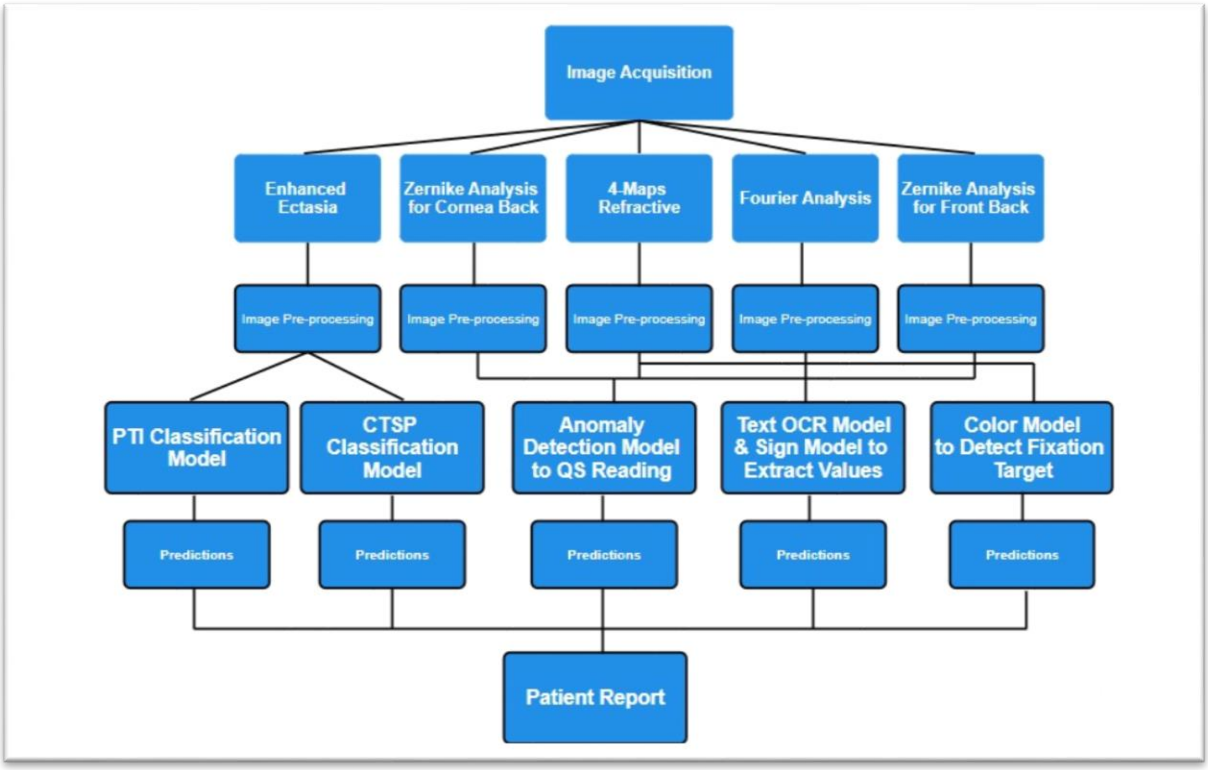
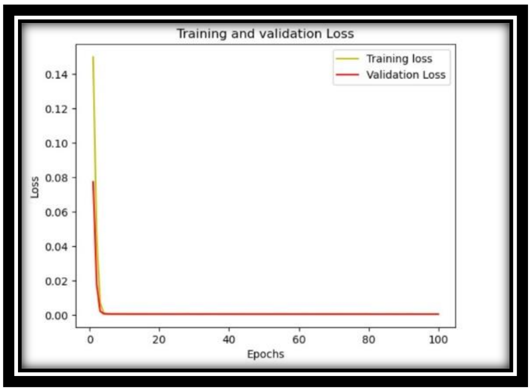


***Fig 14**: Model Architecture of OCR Model*



[Fig15](): Over all Image Processing of all models

4.1.9 Performance Metrics Of Models



Anomaly Detection Model

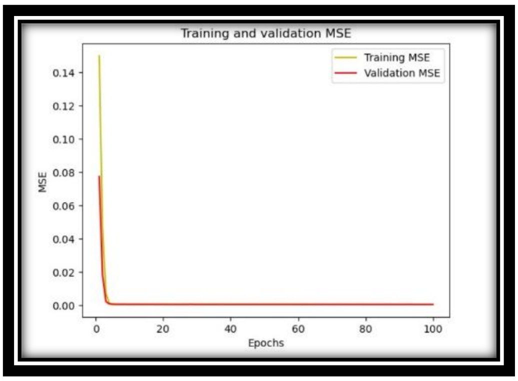
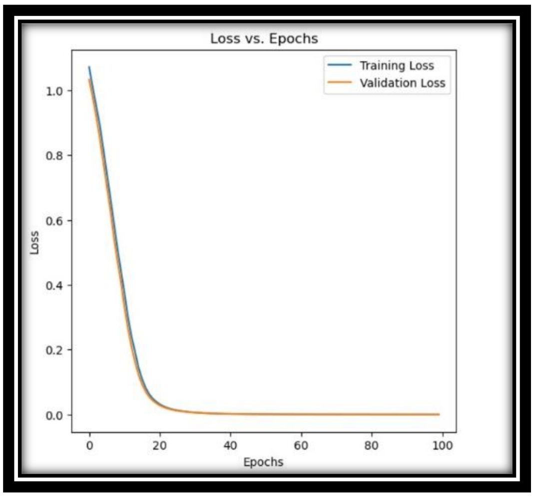


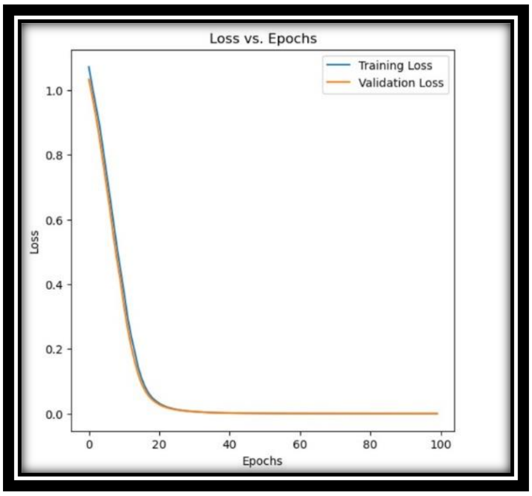
Fig 16: Training Validation Loss of Anomaly Model

Fig17 : MSE of Anomaly Model

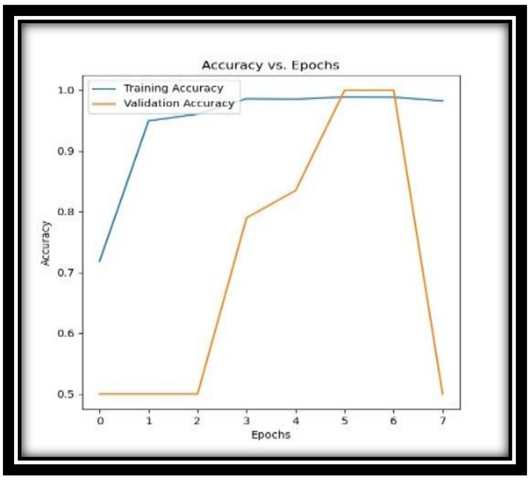


[Fig 18](#): Training Validation Loss of Sign Model

Sign Recognition Model

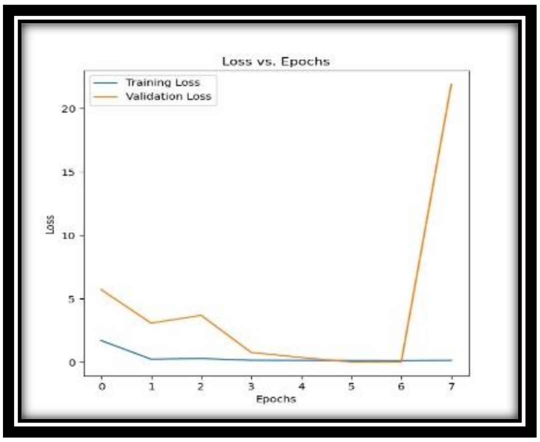


[Fig 19](#): MSE of Sign Model

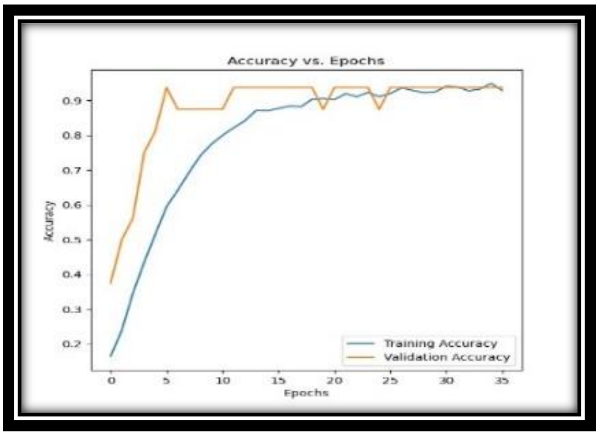


[Fig 20](#): Training Validation loss of CTSP Model

CTSP Model

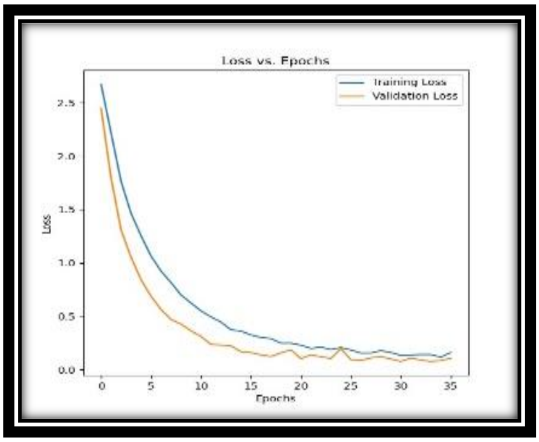


[Fig 21](#): MSE of CTSP

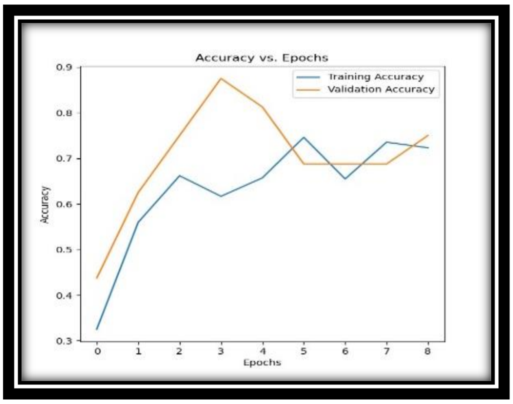


[Fig 22](#): Training Validation Loss of Corneal Thickness Model

Corneal Thickness Model

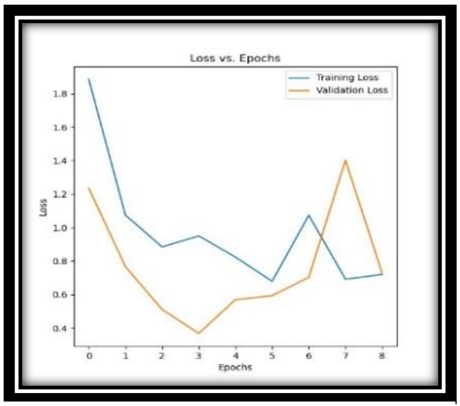


[Fig 23](#): MSE of Corneal Thickness Model

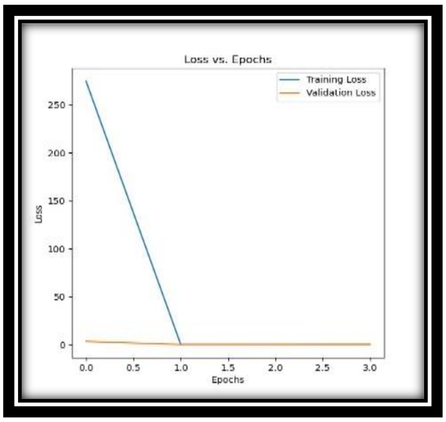


[Fig 24](#): Training Validation Loss of Corneal Elevation Model

Corneal Elevation Models

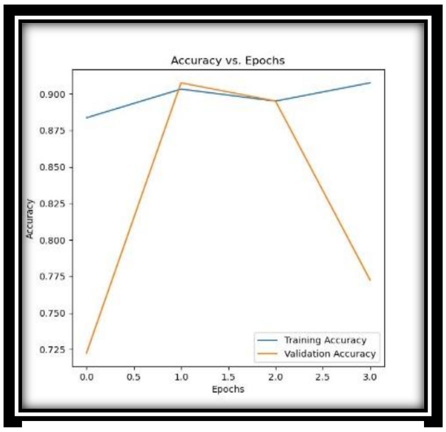


[Fig 25](#): MSE of Corneal Elevation Model

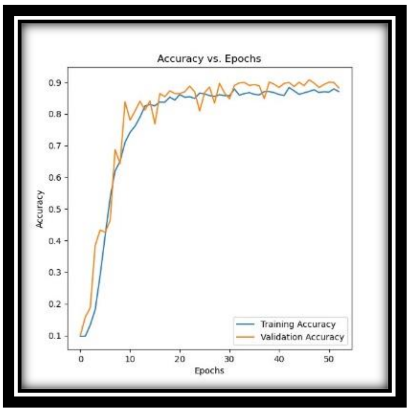


[Fig 26](#): Training Validation Loss of PTI Model

PTI Model

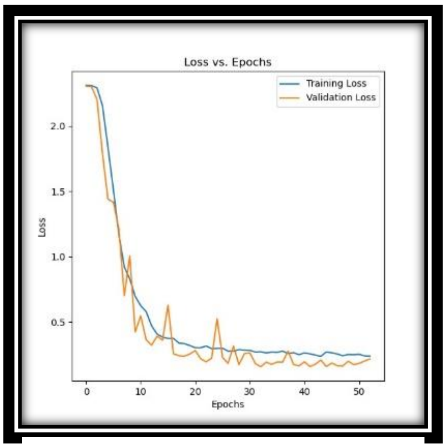


[Fig 27](#): MSE of PTI Model



[Fig 28](#): Training Validation Loss of Text Model

Text Recognition Model



[Fig 29](#): MSE of Text Model

4.1.9.1 Model Performance Analysis:

The specific performance of all models in the Optiscan project is described in some figures, which depict the loss and other performance indicators in training and validation phases. Specifically, for the Anomaly Detection Model, figures for training loss and validation loss are used to illustrate that the two decrease with each epoch, which demonstrates proper learning and fine generalization ability without over-learning. The graphs for the Sign Recognition Model also depict an ascending trend for both loss and accuracy which indicate the model's stability in sign classification. The Corneal Thickness Classification Model shows a slow decay of loss and a simultaneous rise in accuracy, which implied a high potential in detecting the alterations in corneal thickness. As for the Corneal Elevation Classification Model, the loss graphs for the model reveal a well-controlled training process, and the accuracy graphs demonstrate the model's performance in classifying the elevation levels properly. It can be seen from the loss graphs of CTSP Model that training is done without much overfitting and the accuracy graphs that high performance is achieved in spatial analysis of corneal thickness profile. In relation to the PTI Model, what is depicted here is well managed training where the losses are depicted by graphs that depict a downward trend and accuracy portrayed by a graph showing the correct identification of the thickness in the cornea on an upward trend. Finally, the graphs of the Text OCR for Numeric Value Recognition Model show that the training process was efficient; that is, the loss is reducing, the accuracy is increasing; all these features prove that the model can accurately recognize the numeric text. A 100% accuracy reported for some of the models including Anomaly Detection and Sign Recognition Models does not imply overfit, but the basic and clean nature of the given data that made it easier for the models to reach such figures.

4.2 Application Development

The training of the models then their implementation into the desktop application was an important factor in making sure that Optiscan would effectively function on the user interface of the desktop. This required designing a GUI for the tool, handling the computational processes involved in making inferences with models and producing detailed reports to accompany the same.

4.2.1 User Interface and Functionality

The UI was created with the aid of the Tkinter GUI framework, and implemented with additional features of the customtkinter version. Some of the jobs include loading images, making predictions and showing the results. One of the great features is that the interface enables the users to choose between different corneal maps and analyses provided including the Four Map, The Enhanced Estasia map the Fourier Analysis, and the Zernik Corneal maps.

Key functions within the interface include:

4.2.1.1 Active Button Management

Used in order to integrate with the TechEditor_IconClick event and adjust the UI accordingly to which button is currently selected through setting and color attributes as well as updating images.

4.2.1.2 File Dialogs and Messages:

Used for file selecting and appearing messages for the user.

4.2.1.3 Model Integration

Anything related to managing the incorporation of the machine learning models into the application was in ML. py. Model: This script has the functionality of loading the pre-trained models and then making predictions on processed input images.

To optimize the model, these models were loaded using TensorFlow and Joblib during the application runtime for better inference.

4.2.2 Report Generation

The report. Bot written in py script is also responsible for generating accurate reports on pdf format through making use of the FPDF. It defines the reports as consisting of analysis results and corneal map visualizations.

Key functionalities include:

4.2.2.1 Table Creation:

It involves such specific functionalities as creating the tables in the PDF based on certain conditions and requirements which will present the analysis results in such coordinated ways.

4.2.2.2 Image Handling:

Integration of visual representations engendered by the models comprising the allegedly correct Four Map, the Enhanced Estasia, Fourier Analysis, and Zernik Cornea maps.

According to the definition of the report function, the program should take a dictionary of image paths and generate an extensive report, containing both textual and graphical information.

4.3 Over all Implementation Details

The development process involved several critical steps:

4.3.1 Model Loading:

In loading each model, their specific frameworks were used to facilitate this process to allow for the most efficient and effective outcomes.

4.3.2 User Interface Design:

With the usage of a library customtkinter, the application features a clean and well-thought-out interface that enables easy navigation and interaction.

4.3.3 Function Integration:

Basic functionalities were incorporated into the graphical user interface for receiving inputs from the user, performing model analysis to arrive at the output, and updating the changes in the displayed output.

4.3.4 Report Generation:

The corresponding control was integrated to create the automatic generation of reports, which would prove to be very useful for users, giving them a comprehensive report on a specific matter, using the FPDF library to generate clean and professional PDF reports.

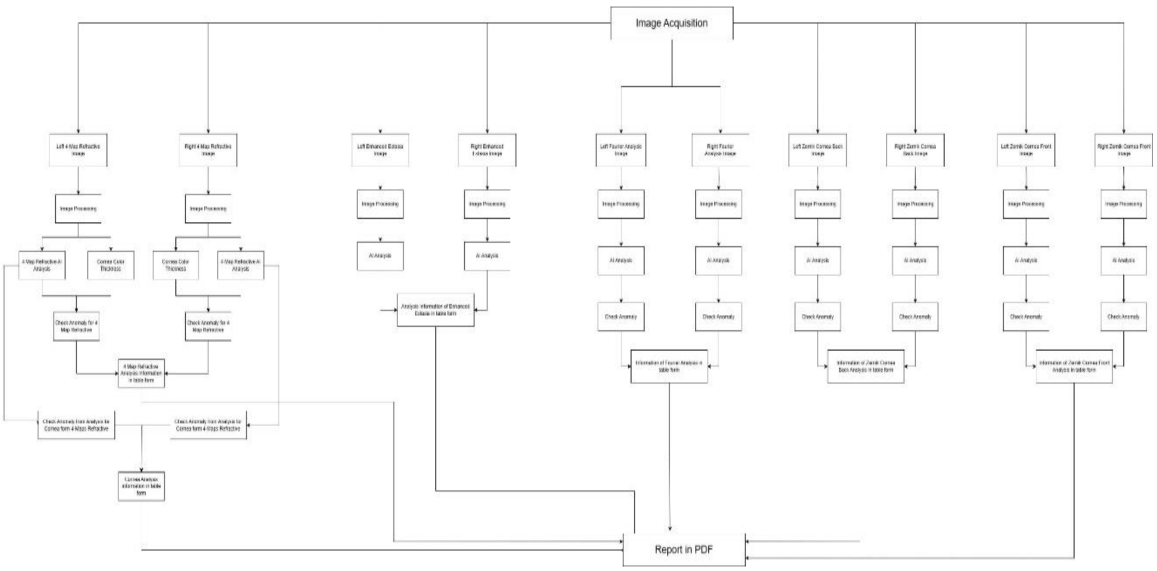


***Figure 30**: Flow Diagram of Optiscan*

5 RESULTS AND DISCUSSIONS

Optiscan application is a clear example of the efficiency of implementing a number of robust artificial intelligence models into a single system that analyzes corneal topography reports and issues elaborate PDF reports. This chapter presents the outcome of the performance of the Optiscan application in terms of each model's accuracy and efficiency in enhancing the overall functionality of the system. Analyzing these findings, we illustrate how proposed application can contribute to increasing diagnostic effects and aiding in the treatment of patients in ophthalmology field.

5.1 Models Performance

Model Name	Architecture	Image Input	Accuracy
Anomaly Detection Model	Convolutional Autoencoder	QS Fields	100%
Corneal Thickness Classification	Convolutional Neural Network (CNN)	Corneal Thickness Map	93.75%
Corneal Elevation Classification	CNN with MaxPooling and Dense Layers	Corneal Elevetaion Map	87.5%
Corneal Thickness Spatial Profile (CTSP) Model	Complex CNN with LSTM layers	CTSP Graph	94.71%
Percentage Thickness Index (PTI) Model	CNN with Batch Normalization and Dropout	PTI Graph	95.61%
Sign Model - Plus Minus Sign Classification	Sequential CNN	Data set of +,-	100%
Text OCR for Numeric Value Recognition	CNN with Dense Layers	Data set of all numeric values	87.79%

Table 2: Summary of Models

5.1.1 **Discussion**:

The above table shows the good working and structure of the following AI models applied in Optiscan application. All models, beginning with the Anomaly Detection Model, Corneal Thickness Classification, Corneal Elevation Classification, etc. , reveal high accuracy, which demonstrates how appropriately trained are these models for their stated functions. This also shows the efficiency and accuracy in using the Optiscan system on corneal topography report analysis and interpretations.

5.2 Application's Performance and Report Generation

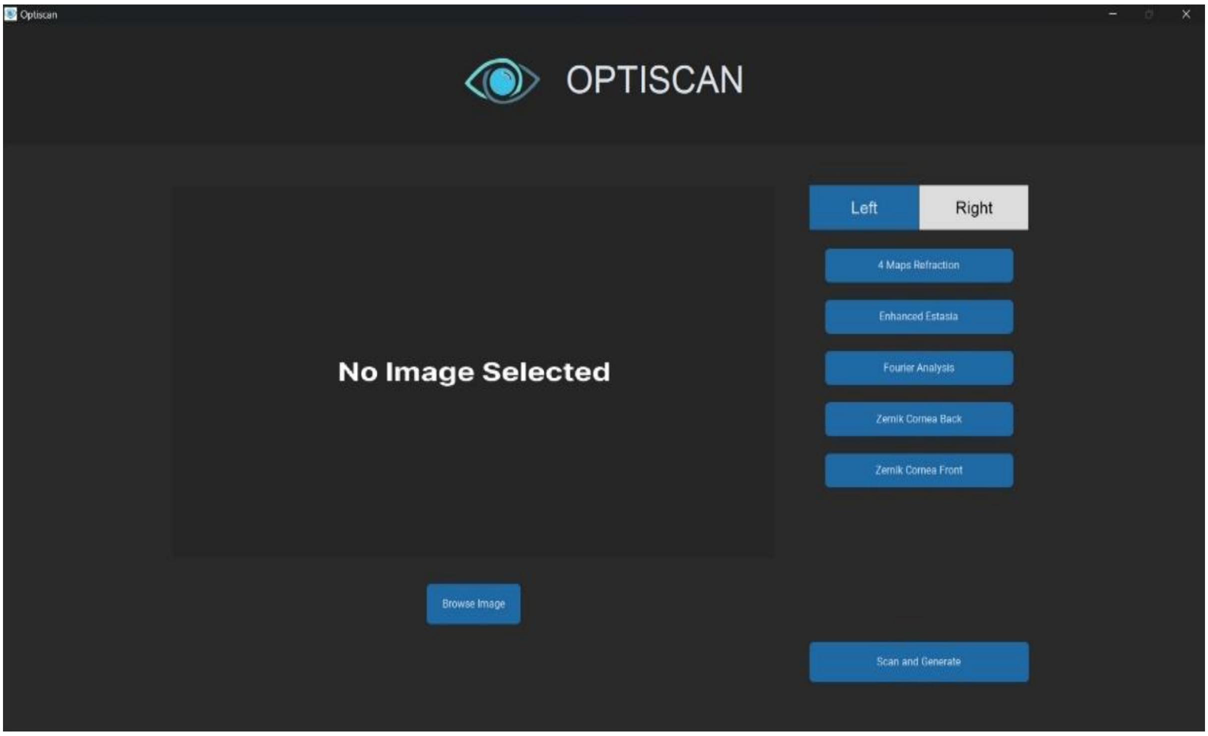


***Fig 31*: UI of Optiscan**

Optiscan Report

Patient Name : Khalil Mehwish Miss
Birth Date : 30/04/1996
Exam Date : 16/02/2021
Time : 19:06:11

4-Maps Refractive

The report for the right eye is ready reliably.
The report for the left eye is ready reliably.

Maps	Right Eye	Left Eye
Corneal Elevation Front Map	The Fixation Target is at +5µm	The Fixation Target is at +5µm
Corneal Elevation Back Map	The Fixation Target is at +5µm	The Fixation Target is at +5µm
Pupil Center Value from Corneal Thickness Map	Pupil Center Value is at 540mm	Pupil Center Value is at 660mm

Analysis for Cornea form 4-Maps Refractive

The report for the right eye is ready reliably.
The report for the left eye is ready reliably.

	Right Eye	Left Eye
Shape	Prolate	Prolate
Q-Analysis	-0.37	-0.28
K1 Range	Normal	Normal
K1 Analysis	45.0 D	44.4 D
K2 Range	Normal	Normal

Fig 32: Report Generated by the Optiscan Application

5.3 Discussion

The image of the user interface of the Optiscan application preview shows a layout suggesting simplicity in its usage as well as in input of data. It must have features of data entry for submitting medical images, setting up analysis parameters and display of the analysis in progress. Likewise, the output that Optiscan users receive in PDF format after the analysis contains all the results of the calculations and visualizations for corneal health factors. In combination, these things showcase the functionality of the application and provide confidence to the healthcare professionals for using Artificial Intelligence in growing the diagnoses and efficiency of work in the cases of ophthalmologic illnesses.

6 PROJECT MANAGEMENT

6.1 Project Life Cycle

Software project development is generally divided into various crucial phases that are as follows: These stages are important in order to ensure orderly and proper conduct of the software project with the intended objectives met.

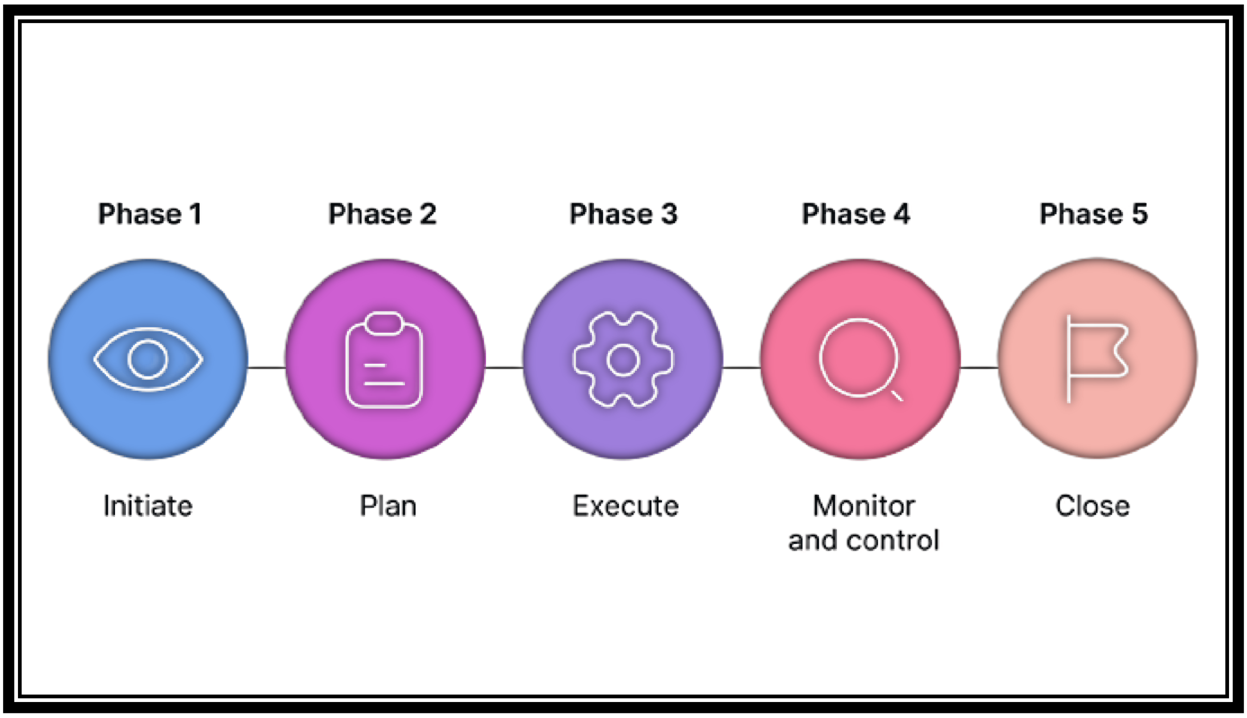


Fig 33: Optiscan Project Lifecycle Phases

6.1.1 Initialization

As stated before, in any software development project, including the "Optiscan" project, the initial stage is the Project Initialization. Below are the detailed description of the activities as well as issues to consider at this stage of the project.

6.1.1.1 Identifying the Goal

First of all the team defined clear goals of the project and described them as fully as possible. In the case of Optiscan, the objective was to create an AI-based corneal topography analysis software. Specifically, the goal of this was to solve the problems that ophthalmologists faced in reliably interpreting topography reports.

6.1.1.2 Stakeholder Engagement:

Thus, if several entities are involved, interaction with them and in particular ophthalmologists is a must. The responses received from the doctors were used to understand the difficulties faced and the expectations of other eye health specialists. This engagement enabled the team to define significant stakeholders as the project's organization, eye doctors, and patients.

6.1.1.3 Needs Evaluation:

What follows are the main discussions that the team had with these ophthalmologists, where a needs assessment was conducted systematically. This meant understanding potential concerns and problems existing in the field of ophthalmology among the specialists. The group also investigate the potential positive side of applying an AI technology such as faster and more efficient topography report analysis.

6.1.1.4 Definition of the Objective:

Project goals were defined at a strategic level during the PI phase when the team put together this project. In the list of goals that were addressed, one can identify such objectives as increased accuracy of diagnoses and the automation of the topography report. These goals acted as the project's over arching ideas, and also the foundation for further planning and progression.

6.1.1.5 Research and the 3R Model:

It is evident that this is a group of people that is very committed to carrying out their investigations effectively. "3R: The research model proposed is the "Research, Read and Review" model. Most probably, the information about the area of ophthalmology, specifically corneal topography, existing software, and AI-associated developments was researched for this model. The "Research" step introduces a generalist approach to sustaining an up-to-date status of the most recent innovations in the industry.

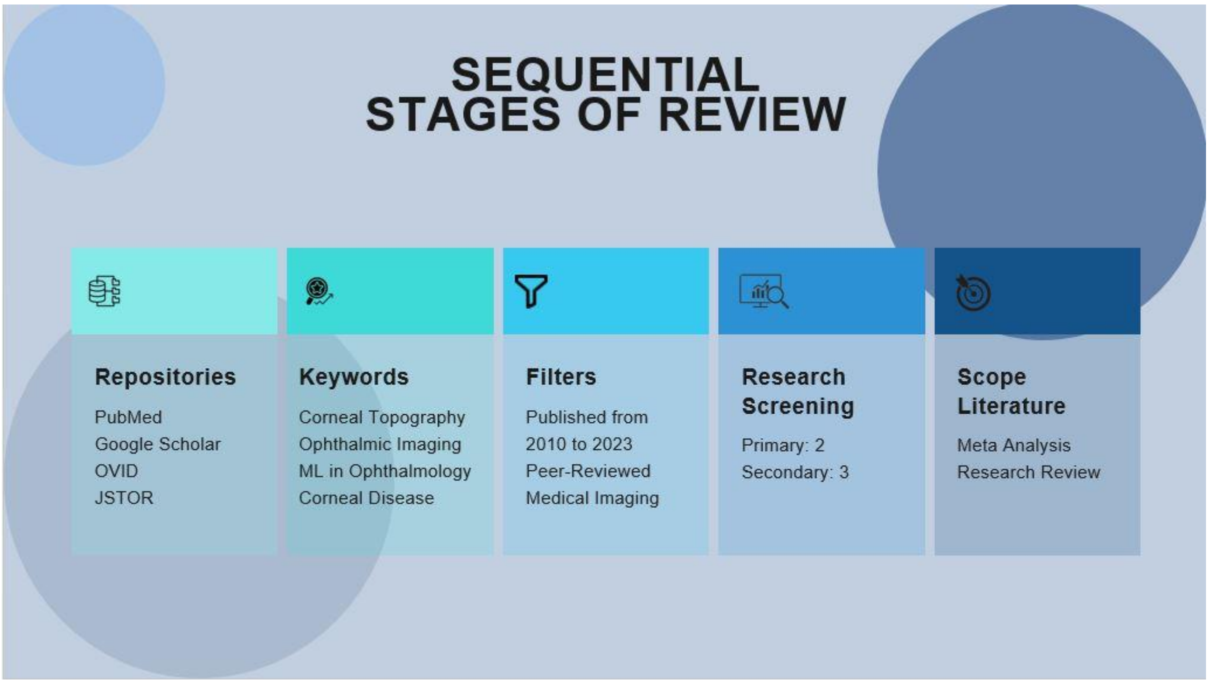


Fig 34: Research Flow Diagram

6.1.2 Project Planning

Project planning offers a roadmap of how the project is to transform from one stage to another; this leads to accomplishment of set goals on time. Following activities sgioiw what we did in this phase.

6.1.2.1 Gantt Chart:

As a whole, a Gantt chart reflects the project schedule with tasks on a time line. It illustrated how the various tasks are interrelated and provides a brief explanation of the gradual advancement of project's work. In Our Project Gantt chart to indicating the start and end date of each phase, task, and a milestone would be shown. It would as well guarantee that deadlines are met a factor that is crucial in health care projects that contain time-sensitive phases through arranging the concepts of activities, their interrelation and the phase of the project into visions.

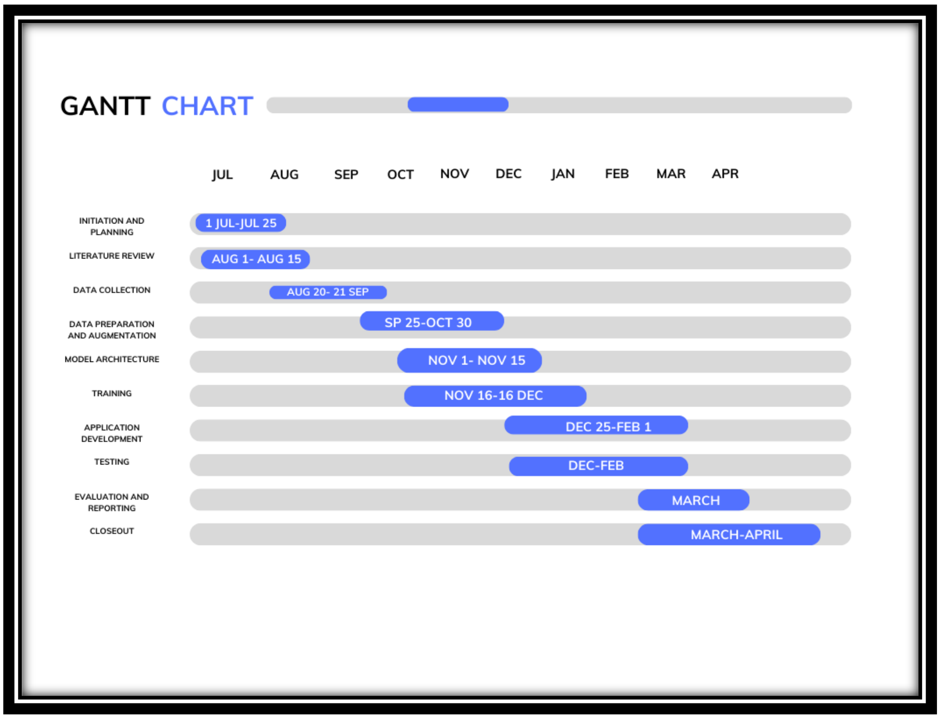


Fig 35 Gantt Chart of Optiscan

6.1.2.2 Figuring Out SMART Goals:

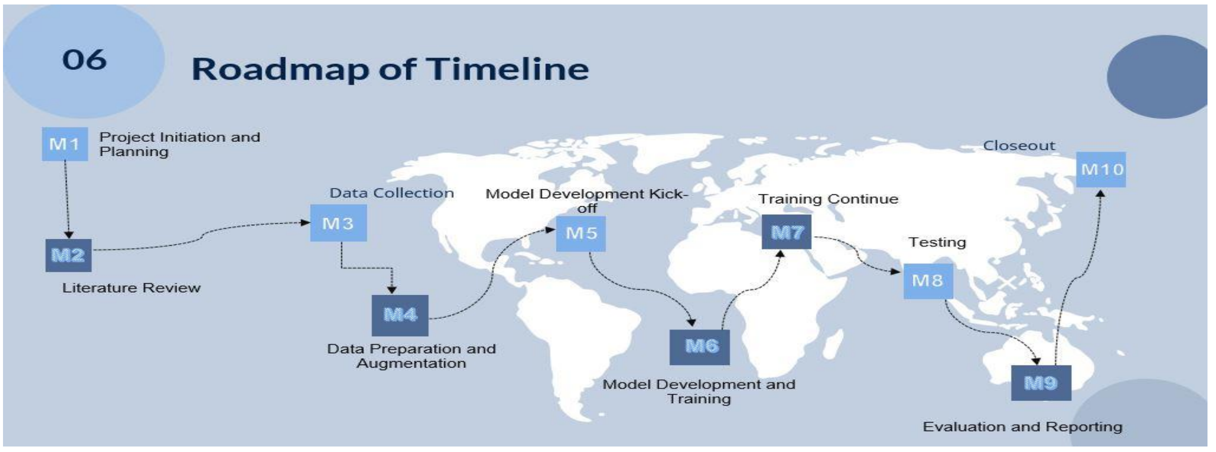
SMART is an acronym which is an abbreviation of Specific, Measurable, Achievable, Relevant, and Time bound. This is how the objective of the 'team' is established. Here, the aims were to raise the accuracy rate of topographical analysis to 95% and decrease the duration of diagnoses by 20%. These objectives helped the team to have more specific targets to work towards due to the fact that the project will have been set on accurate and measurable course.

6.1.2.3 Establishing Project Parameters:

As for the project definition, it is highly important to define where project begins and ends clearly. Next, we explained what the AI application can do and cannot do as well as what can be considered inclusion or exclusion. Therefore, through this action, the problem of scope creep is likely to be addressed hence the objectives of the project can be met.

6.1.2.4 Project Timeline:

Activities and their timeline are important parts of project management as the latter also requires the identification of key project milestones. It is likely that the work was divided into steps called the data collection, development of a model, and integration of software. Milestones are especially used as control points to ensure that progress is being made and that the overall project is on schedule. Below is the breakdown of the timeline of our project.



[Fig 36](#): Timeline Roadmap of Optiscan

6.1.3 Execution:

In the Execution phase of the "Optiscan" project, it transition from the planning of what needs to happen to the creating and programming of the actual AI application. During this stage, there are several important things to do and think about:

6.1.3.1 AI Model Development:

The team ensured it familiarizes the AI model with several datasets of corneal topography reports which will enable it to identify important features associated with topographic maps. This is because preprocessing of the data, feature engineering as well as modeling will often be inculcated in the training process.

6.1.3.2 Application Development:

The project team will initiate the process of creating that application to incorporate the use of artificial intelligence as per the laid down plans in consultation with other interested parties. This is due to elements such as Requirements specifications, coding, the software architectural design, and the User Interface/User Experience design. Analyzing and recognizing the meaning of topographic maps will be easier for the AI model if the deep learning methods are integrated into the AI model.

6.1.3.3 Working Together with Eye Specialists:

The second improvement that is important at the Execution stage is the cooperation with ophthalmologists. The group will also consult some eye specialists concerning some affairs as well. This shall remain very important since the feedback from the ophthalmologists shall help make improvements on the effectiveness of the application, increase on it's clinical relevance plus aid in the meeting certain medical demands.

6.1.4 Controlling:

By following the approach of the "Optiscan" team, during the Controlling phase of project management, the team continuously logs and prevents measures vital to the project. Below is a thorough summary of the major tasks and things to think about during this stage:

6.1.4.1 Monitoring Development Milestones:

The project schedule is important to review periodically to ascertain the point the team is at concerning development. This implies tracking different activities' conditions, comparing them with the plan, as well as adjusting the schedule. In this manner problems that would otherwise cause project delays are swiftly dealt with and this helps in ensuring the timely completion of the project.

6.1.4.2 Performance Monitoring:

The steady significance of the actual models and the application cannot be understated, so it's important to monitor its efficiency. This entails the assessment of the model's performance, accuracy, and precision together with the usability of the application. The remaining group will be solved if there are particular issues or ineffacies discovered; the entire group will work to make these points better. This could include enhancing the lines of code, addressing some of the issues regarding usability or even fine-tuning the artificial intelligence tool.

Risk Identification and Mitigation: Controlling phase requires the identification of the possible hazards in the process of completing the plan.

Collecting data on possible threats is one of the crucial steps in the Controlling phase. This involves assessing and measuring risks for instance unforeseen computer problems, glitches in the software, and privacy issues on data. Outcomes for preventive measures will be drafted to minimise the likelihood of such risks if they materialise in future. This might involve implementing safety measures, contingency measures and processes in case of unfavorable conditions.

6.1.4.3 Successful Interaction:

Thus, one has to maintain communication with all the appropriate stakeholders. This means constant communication with the relevant authorities, ophthalmologists, and all other stakeholders to whom one has to report periodically. Actually, it is important to be proactive and respond to any matter shortly, it may be an issue, comment, or concern. That is why, contracts that guarantee the creation of a project conforming to regulations and the expectations can be ensured by effective communication.

6.1.5 Closing:

In order to ensure that all the activities developed in the scope of this project have been completed, reviewed, and archived, Our project requires a closure phase. Here's a more thorough breakdown of the tasks and things to think about in this stage:Here's a more thorough breakdown of the tasks and things to think about in this stage:

6.1.5.1 Finishing Project Tasks:

Evaluating that every task in a project is accomplished is the prime concerned in the Closing phase. This includes the finalization of the Optiscan application including development, test and deployment and at the same occasion of all the related documentation.

6.1.5.2 Project Evaluation:

The entire effectiveness of the project will be assessed by the panel at the Closure phase during our Final Defense Presentation. This involves a comparison of what the project has produced and the objectives and requirements explained during the system planning phase. This is an opportunity to determine how effectively the goals of the project were achieved and whether the presented project solved the problem stated at the beginning of the initiation, namely the improvement of corneal topography analysis.

6.1.5.3 Deliverables and Records:

Sharing the results of the project with other people and required stakeholder including the team members, managers, and other relevant persons is called final defense. This presentation could include general information about the project: objectives, work plan, results.

6.1.5.4 Preparing a Research Paper:

As earlier noted, the team commences the writing of the research paper on the Closing phase of the project. This paper will therefore highlight on the methodology implemented in the project, the results observed and the conclusion derived from it. It is also an opportunity to communicate the findings of the larger scientific and medical field on lessons learned in implementing the Optiscan project as well as the impact.

7 FUTURE WORK AND CONCLUSION

7.1 Future Work:

In the future, we plan to add more opthomoligical of other test reports and enhance its effectiveness within the application. These additional reports and their management therefore offer a more complete set of diagnostic tools for the eye health practitioners. The end-result envisioned, therefore, is the creation of a comprehensive diagnostic tool that can r range from diagnosing various ocular diseases, and help increase the effectiveness of diagnoses made in ophthalmology subsequently, thus, positively affecting the health of patients in the field of ophthalmology further.

7.1.1 Optical Coherence Tomography (OCT) Scans:

OCT is an imaging process that doesn’t use radiation or inject a radiopharmaceutical, and can produce images of the retina that are cross-sectional through light wave interference. These layers shall then be checked for macular degeneration, diabetic retinopathy and other ailments of the retinal and our method shall entail the use of convolutional neural networks (CNNs) and autoencoders. It will also integrate deep learning algorithms that will enhance the detection of signals of the above ailment through alterations in the layers of the retina that could be negligible.

7.1.2 Fundus Photography:

A fundus photograph is a large image of reflected light seen through the pupil and the interior anatomy of an eye including a retina, optic disk, macula as well as the pole at the back of the eye.Utilizing recent advancements in deep learning techniques, one can identify and distinguish among numerous ailments such as glaucoma, diabetic retinopathy, and hypertensive retinopathy from the fundus images. Our models will concentrate in making an effort to detect such typical patterns and deviations that may correspond to such conditions.

7.1.3 Visual Field Tests:

Visual fields refer to the range of a patients’ vision, particularly, the central vision which is the field and the peripheral vision. These tests aid in the diagnosis of glaucoma alongside other optic neuropathies and are quite useful. In this way, it is recommended to decode the interpretations of the visual field maps by means of artificial intelligence algorithms, that is, which areas are not preserved and could have been lost and what might have caused their degeneration. Some of the measures that we envisage on are having models that would be in a position to identify specific patterns of visual field loss that is characteristic of certain types of optic neuropathy.

7.1.4 **Fluorescein Angiography:**

For stagnant infers to injecting a fluorescent compound called fluorescein into the bloodstream and thereafter capturing images of the dye circulation through the blood vessels of the retina. In ophthalmology this test is used for diagnosing and following up diseases, which include retinal vein occlusion, diabetic retinopathy and macular degeneration. Utilizing the image enhancement strategies and artificial neural networks, we want to monitor the blood flow of the retina and obtain information about the possible view pursh near me blockages or leakages in retinal vessels. These models will be designed to identify such variations effectively to help its later diagnosis and management of such diseases.

7.1.5 **Integrating Diagnostic Tools:**

Since all these test images are quite different from one another in terms of format and content, models such as CNNs, autoencoders, and kernel density estimation can be applied to the analysis of each kind of eye test images. If the parameters/in characteristics of the tools are compatible those are useful inputs integrating these additional diagnostic tools to our application will not be a problem. The idea is that each of the diagnostic modules will specifically designed for certain types of images – this will allow to make sure that our application is as flexible as possible, and to provide detailed analysis in the widest possible range of eye tests.

Combining these diagnostic tools will make an ideal place to provide eye care professionals with different tools that would be very useful in their practice. This platform will not only help in the timely identification of the ocular diseases but also in observation and management of the diseases. We envision that having a highly functional and reliable diagnostic assistant will help bring positive impact on the field of ophthalmology, most specially, in addressing patients' needs and ensuring that effective and fast diagnoses are provided to them.

7.2 Conclusion:

To Conclude, Optiscan project can be considered as the precise development in the sphere of corneal topography analysis and its use in eye care. As shown in this thesis, significant problems in the interpretation and use of corneal imaging data have been solved during the process of creating and using multiple machine learning models simultaneously. the

Surveying the current methodologies and technologies in corneal topography, our team began the project insisting on the improvements in the accuracy and efficiency of calculations. Using state of the art algorithm in machine learning specifically CNNs and anomaly detection models, we were able to create tool set that is designed to extract, analyze and interpret data accurately from corneal images.

Among the achievements accomplished in the case are the development of the models for evaluation of non-typical tendencies in quality scores, text recognition from medical reports, detection of the signs for values' identification, colors' analysis of color-coded data, and graph mining for complete reports' analysis. Some of the models described above were built into a friendly user GUI on the desktop application with help of CustomThinker, while to produce high resolution PDF-reports, FPDF2 was used.

Thus, extensive evaluation was conducted on a large dataset gathered from Hashmani Clinics, proving the efficiency and application of the developed models in real-world conditions. These results suggest that the Optiscan system not only enhances diagnostic capabilities but also enhances the productivity for operation eye care experts, thus making the practical clinical decisions much more accurate and helpful for patient's recovery.

As for the future improvements, the enlargement of the database with a vast variety of clinical situations can be considered as one of the potential directions for improvement; algorithms' fine-tuning to achieve even higher accuracy; as well as the possibilities to implement AI-based findings in practice immediately into the software, used in clinics.

Conclusively, as highlighted by the Optiscan project, it is a specifically valuable development in the diagnosis of illnesses, as well as an illustration of how machine learning can reshape healthcare. Thus, we can act as a link between conventional diagnostic tools and modern technology so as to expand the availability and effectiveness of eye care worldwide.

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