A Seminar Report on:

"Cataract Detection and Grading based on Retinal Images using Deep Learning"

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Rupa G. Mehta

17th Nov 2020

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Contents

List of Tables

List of Figures

List of Symbols

π	Mathematical Constant having value 3.1415926535
$\sum$	Summation Notation

List of Abbreviations

ANN	Artificial Neural Network
ARMD	Age Related Macular Degeneration
BRA	Big Ring Area
CNN/ConvNet	Convolutional Neural Network
DFT	Double Fourier Transform
DL	Deep Learning
DM	Data Mining
EPC	Edge Pixel Count
FC	Fully Connected
GGCM	Gray Gradient Co-occurrence Matrix
GLCM	Gray Level Co-occurrence Matrix
HSI	Hue Saturation Intensity
KNN	k-Nearest Neighbours
LDA	Linear Discriminant Analysis
LOCS III	Lens Opacity Classification System
ML	Machine Learning
PCA	Principal Component Analysis
PSC	Posterior Subcapsular Cataract
RGB	Red Green Blue
ROC	Receiver Operation Characteristic
ROI	Region of Interest
SRA	Small Ring Area
SVM	Support Vector Machine
WCGS	Wisconsin Cataract Grading System
WHO	World Health Organization

Abstract

Visual impairment, generally termed as vision loss, is described as an inability to see, wherein rectification is not possible using aids such as lens or glass adoption. Various recognized causes include cataract, glaucoma, Age Related Macular Degeneration (ARMD), uncorrected refractive errors, trachoma, and diabetic retinopathy. Cataract has been known as one of the significant reasons for visual impairment worldwide, covering around 50% of blindness cases. A cataract is characterized by a blurred and foggy vision, which leads to partial or complete loss of eyesight if turned severe. The availability of knowledgeable ophthalmologists and proper treatment facilities is a must to cure the impairment timely. Moreover, people residing in rural or underprivileged areas find it difficult to avail of good quality resources and services at a feasible cost. It is indispensable to detect cataract with high precision and a shorter time to reduce the chances of its severe effects.

This study mainly focuses on discussing and comparing various available methods for cataract detection and grading based on retinal images using the concepts of Deep Learning. Different models and architectures are surveyed, and a comparative analysis is conducted to reach a more feasible and accurate solution. The whole process of cataract detection and grading involves retinal image acquisition, preprocessing, feature extraction, model preparation, and model deployment and testing. Removal of patients' personalized information available at retinal image heads frames the basic necessity to preprocess the data. Eclipse fitting and homogenization are some of the methods that are used for the same. Apart from the Literature Survey and Case Studies conducted, some Convolutional Neural Network (CNN/ConvNet) architectures like NasNet, Inception, EfficientNet, DenseNet, and sequential models are also implemented to generate real-time results. The generated custom results are compared to make the information and conclusions more comprehensive. An image processing technique for cataract grading based on geometrical and morphological transformations, contouring, and bit-wise manipulations in image vectors has also been proposed and implemented using the OpenCV library of Python. The output produced by employing the said algorithm depicts the percentage of cataract present in the input image.

Keywords: Retinal Diseases - Cataract Detection - Cataract Grading - Feature Extraction - Image Processing - Fundus Images

Chapter 1

Introduction

Eye inevitably is an essential sense organ. It provides them the ability to visualize and interpret their surroundings. It has been a proven fact that 80% of what one perceives is communicated through sight. If any of the other sense organs get malfunctioned or stop working, then the eyes are enough to protect the being from landing in danger. According to the prevailing situation, vision loss or degradation, and cases of blindness are on a continuous increase worldwide. Hence, their timely detection and prevention have become an enormous challenge for medical professionals, research scientists, and concerned organizations. Cataract, glaucoma, ARMD, uncorrected refractive errors, trachoma, and diabetic retinopathy are some of the central eye disabilities that have been encountered so far. Among these, cataract has been stated as the most prevalent reason for blindness.

Cataract is known to cover more than 50% cases of blindness. According to the World Health Organization (WHO) report of 2015, 20 million people suffer from moderate to chronic cataract, and 60% of them are the residents of underprivileged localities. This study is focused on analyzing the medical images and the available methodologies for cataract detection to devise and conclude an efficient solution. Medical images are a specific type of non-text information related to the diagnosis of various medical abnormalities. The modality under study is a retinal image. **Figure 1.1** depicts a sample retinal image. Retinal images are primarily utilized by

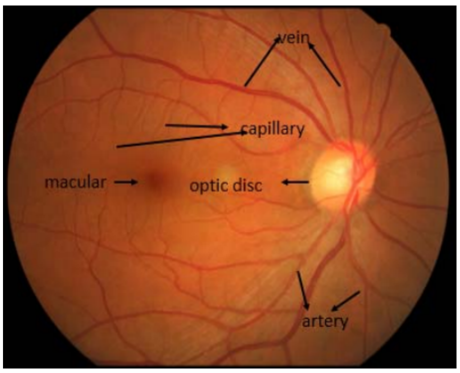

Figure 1.1: A sample Retinal Image [3]

primary eye-care physicians and ophthalmologists to detect or identify an epidemic eye. Moreover, amendments in the retinal vascular features like tortuosity, branching angle, and vessel width help identify the cardiovascular issues and cases of hypertension. The study of retinal images very well demonstrates visual impairment and their severity, and hence they are necessary for the ophthalmologists' discoveries and treatment procedure.

The processing of retinal images for information retrieval plays a vital role in detecting various medical scenarios dependent on them. This research is mainly constructed around interpreting and utilizing the retinal images for cataract detection and grading using some deep learning models.

1.1 Motivation

Cataract is a lens opacification issue that occurs due to protein denaturation leading to impaired vision. The number of diagnosed cataract cases is increasing at a breakneck pace. An efficient method for detecting cataract at the early stages is in dire need. Traditional methods for cataract detection are based on fundus images and dependent on ophthalmologists. The efficiency is relatively low here and cost-ineffective due to the less availability of quality doctors than the growing cataract cases. Moreover, the people dwelling in underprivileged and less developed areas find it very difficult to get their diagnosis done in a cost-efficient manner.

It all defines the need for an automated system for cataract detection to increase diagnosis efficiency and effectiveness. The easy to use and open-source availability of such a system will help both the medical community and affected patients to utilize the utility at their ease.

Apart from detection, it is indispensable to get well acquainted with the degree of cataract a person is suffering from cataract so that proper medication can be advised to him for his early recovery. It arises the need to develop a utility for grading the severity of cataract.

Hence, this seminar survey is highly motivated by the requirement of reducing the prevailing condition of vision loss due to cataract by employing an automated solution for its detection, thus reducing the burden on the doctors' community.

1.2 Objectives

This study explores the existing ways to preprocess the retinal images efficiently and subsequently structure their results in a detection model using machine learning techniques. After that, a comprehensive study on cataract grading techniques has been conducted to calculate the severity of the cataract. Some custom results are also generated to propose a pipeline that collectively works for cataract detection and grading purposes.

1.3 Contribution

In this seminar report, an in-depth survey has been conducted of pre-existing literature regarding the various techniques of cataract detection and grading to fulfill the project objectives hitherto discussed. A comparative study has been drawn based on these methods. Some of the algorithms are implemented, and their comparison report has been prepared. An algorithm for percentage calculation of cataract has been devised in the subsequent study.

1.4 Organization of seminar report

Chapter one explains a brief overview of the seminar subject, the motivation behind choosing this topic, its objectives, and the contribution towards this topic.

Chapter two describes the theoretical background involving the medical terminologies related to cataract, its various types, and reasons for its formation. The scope is further expanded to discuss the procedure of cataract detection and grading. A brief overview about the architecture of CNN/ConvNet concludes the chapter.

Chapter three literature survey for the study undertaken. It involves various literature methods for cataract detection and grading. A detailed emphasis has been laid on the existing methodologies and modules, and the scope and technologies involved in developed systems have been explained in depth.

Chapter four is based on a case study. It involves the detailed explanation of the algorithm that was found to be the best after **Chapter three**.

Chapter five includes the experimental analysis, simulation and results of some CNN architectures.

Chapter six presents the conclusions drawn by stating the most suitable methods for the defined purpose and future enhancements of the project.

Chapter 2

Theoretical Background

This chapter attempts to drive focus on the theoretical background required to understand the approach to analyzing the process of cataract detection and grading. Here the medical terminology, specifically regarding the epidemic eye, cataract types, severity, and methods to detect and treat it, is discussed to create the base required to understand further discussion. Afterward, a basic flowline of automated detection systems is explained with the help of a block diagram. A section of the chapter is utilized for explaining the architecture and operation of CNN/ConvNet.

2.1 Overview

Lenticular opacity or lens opacification is termed as cataract in medical terminology that further leads to low vision [12]. It is a type of eye disorder that leads to more severe visual impairment if not treated at the early stages. This all raises a need for early detection and improving the availability and presence of good quality eye care centers [12]. The extensive study that has been carried out in this regard proclaims that half of the blindness cases are contributed by cataract alone [13–16]. Efficient treatment and pre-detection can significantly reduce the agonies of the cataract patients, but professional ophthalmologists' unavailability in underdeveloped regions hamper the treatment process [17].

2.2 Types of Cataract

There exist three types of cataract based on the location of protein denaturation or deposition in or around the lens of the eye, viz. Nuclear Cataract, Cortical Cataract, and Posterior Subcapsular Cataract (PSC) [2].

2.2.1 Nuclear Cataract

It develops on the nucleus of the lens, as justified by its name. It is mainly observed to occur in the aged people [2]. More commonly this type of cataract serves an impact on distance vision and gets more intensified with aging due to an increase in the cloudiness and yellowish texture of the eye with time.

2.2.2 Cortical Cataract

It develops in the cortex of the lens. This type of cataract occurs in the surrounding region or periphery of the lens [2]. It mainly occurs in a spoke-like fashion and characterized by white wedge opacities. It leads to blurred vision and a vision with only one eye at a time known as monocular diplopia.

2.2.3 Posterior Subcapsular Cataract

It develops in the back regions of the eye lens. It initializes with a tiny opaque spot at the back of the lens and soon gets enlarged with time. People having diabetes or consuming steroids frequently are more prone to this type [2]. It leaves an impact on the reading vision of the patient.

2.3 Classes of Cataract

Cataracts can be classified into four classes, viz., normal or non-cataractous, mild, moderate, and severe, as mentioned in [3–5, 18]. **Figure 2.1** demonstrates the degree of cataract from sample images of patients tested for the same.

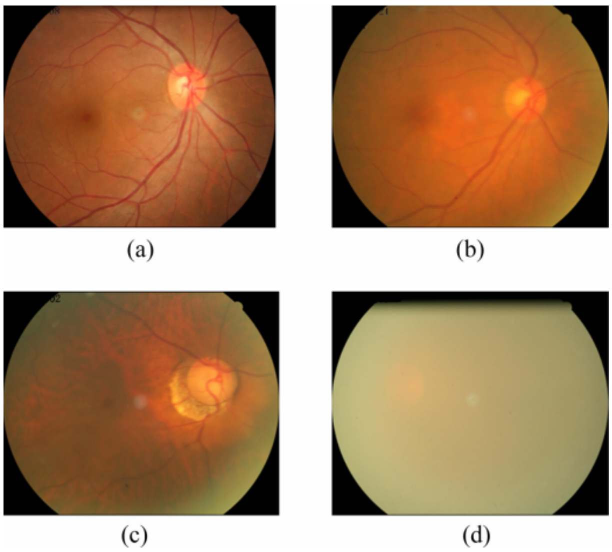

Figure 2.1: Fundus images for each class. (a) Normal; (b) Mild; (c) Moderate; (d) Severe [4]

Retinal fundus images, blood vessels (small and large), and optic disk collectively demonstrate the cataract degree, a patient is suffering from [18]. As shown in (a), the optic disk and large and small blood vessels have clear visibility, thus accounting for a non-cataractous eye. In (b), a number of vessels are clearly visible along with the optic disk, whereas in (c), only large blood vessels can be located hence justifying the mild and moderate cataract cases respectively. However, (d), a severe cataract image is almost opaque, and nothing can be adequately seen.

2.4 Risk Factors for Cataract

There are several reasons which result in cataract formation. Various factors are responsible for the denaturation of protein, leading to the lens's opacification [18]. Some of them are as mentioned below:

2.4.1 Aging

The eye lens is majorly composed of water and proteins. As a person starts getting older, these proteins start forming chunks leading to blurriness in the vision [19]. It mainly occurs in people having an age of fifty years and above. Mechanisms such as denaturation of proteins, fiber cell membrane and oxidative damages, elevated calcium, glutathione deficiency, abnormal lens epithelial cell migration, etc., are significant causes for senile cataracts [20].

2.4.2 Trauma

Cataracts can also be caused due to blunt and penetrating eye injuries [19, 20]. Electric shock, chemical burns, ionizing radiations, and entry of foreign particles in the eye lead to damage to the eye lens capsule, paving the way for inner lens swelling leading to protein degeneration.

2.4.3 Diabetes

Diabetic patients are 60% more prone to develop cataracts than others [19]. A person suffering from diabetes will have an imbalance in his glucose level which leads to increased glucose content in the aqueous humor of eyes, which is responsible for transmitting nutrients to the eye including oxygen and glucose. These increased sugar levels cause swelling which subsequently results in low vision [19].

2.4.4 Smoking

The toxins present in smoke produced during the consumption of cigarettes leads to the oxidation of cells. When this oxidation occurs in the eye lens cells, it results in cataract [19]. Nuclear opacities generally get enhanced due to these reasons [20].

2.5 Flow of Cataract Detection Process

Any classification process follows three necessary steps, viz. Preprocessing, Feature Extraction, and Classifier Construction, and so is there for the cataract classification process, as shown in the **Figure 2.2** [2, 3, 5]. These are the basic building blocks for classification problems and are discussed in the subsequent sections.

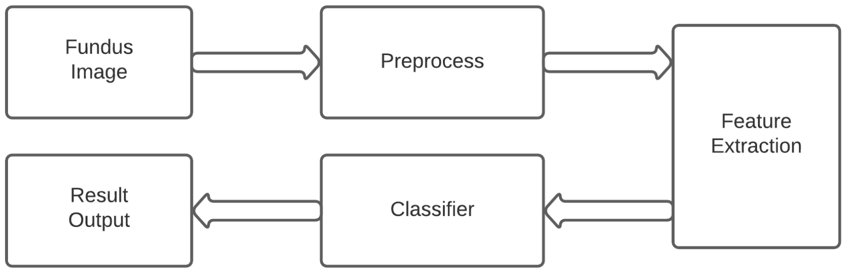

Figure 2.2: Cataract Classification Process Flow [5]

2.5.1 Preprocessing

The noise gets accumulated in any image during acquisition and transmission processes [21]. Hence, it becomes essential to preprocess the images before feeding them further in the pipeline to reduce the noise or enhance the image, thereby increasing the image quality [3]. The techniques utilized for preprocessing largely depend on the type of images and the purpose of their use.

2.5.2 Feature Extraction

Any classifier builds upon by taking into consideration some factors relevant to any input data. These factors are generally termed as features in the domain of Data Mining (DM) [22]. There are lots of features present in any data. Sometimes the availability of features of less importance decreases the quality of the model built and makes them computationally inefficient. Hence, it becomes necessary to perform dimensionality reduction on such type of data. It reduces the high dimensional space of sample data to lower dimensions so that the reduced features collectively represent the whole data without any significant loss [3].

2.5.3 Classifier

Classification is a process of mapping the given data to their corresponding labels [23]. Once a classifier is trained, it automatically identifies to which category a given data point belongs [3]. It frames the backbone for any automated classification or detection systems involving Machine Learning (ML).

2.6 Convolutional Neural Networks

A CNN/ConvNet is a typical Deep Learning (DL) model. It takes in input data and consequently assigns some trainable weights and biases to various features present. The preprocessing requirement for a ConvNet is comparatively much lesser than other classification algorithms. In CNN, filters can be learned during training as compared to some primitive filters' methods. An analogy exists between a CNN pattern and a human brain neuron pattern. The visual cortex organization inspires such brain neuron patterns.

CNN comparatively involves fewer parameters and uses already existing weights, resulting in a better fitting to the image dataset for a developed architecture [24]. In other words, the training of the network is done in a manner to understand the hidden features of the image thoroughly. A typical CNN would look like, as shown in **Figure 2.3**.

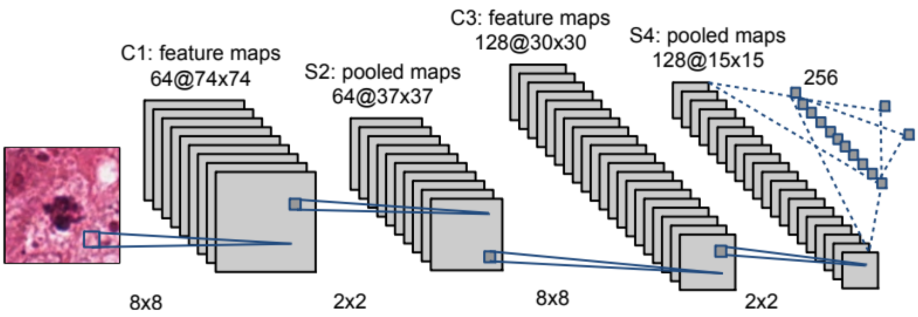

Figure 2.3: A typical Convolutional Neural Network [6]

The components of a CNN/ConvNet will be discussed in the following sections.

2.6.1 Input Layer

This is the initial layer in the network where images of varied formats (i.e., RGB, HSV, YCbCr, grayscale, etc.) are fed. These images can either be of training or testing sets. The images fed should be scaled to the same input size before feeding them forward in the network.

2.6.2 Convolution Layer

In this layer, innumerable filters are present to conduct convolution operation on input tensors. It outputs a feature map. As explained in **Figure 2.4**, the convolution operation performs ele-

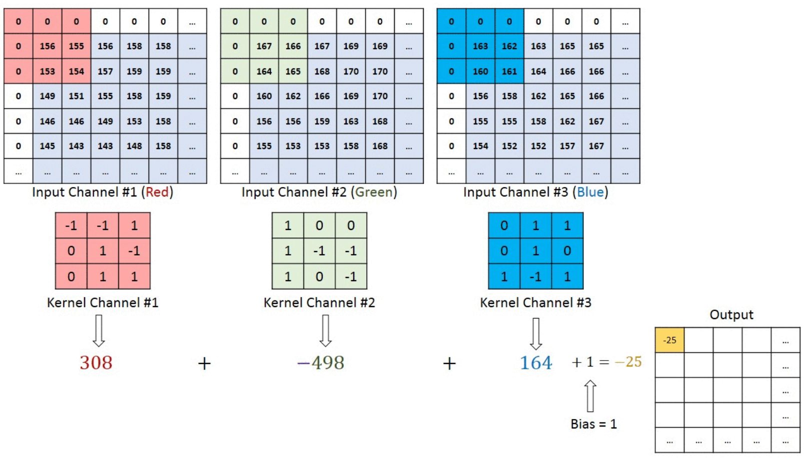

Figure 2.4: Convolution Operation [7]

ment-wise multiplication of matrix elements and filter values on each channel of the image and, after that, sums up the results of each channel to fill the corresponding cell with the resultant value. Hence, it constitutes the most crucial part of the network.

2.6.3 Activation Layer

The output of the convolution layers is fed to this layer in order to incorporate non-linearity in the network. Various activation functions that are used in this layer are tanh, sigmoid, reLU, and leaky ReLU.

2.6.4 Pooling Layer

This layer reduces the number of features when the input tensors are large. It results in dimensionality reduction of the feature map [25]. In this layer, various functions that can be used are min pooling, max pooling, sum pooling, and average pooling. Some of these are illustrated in **Figure 2.5**.

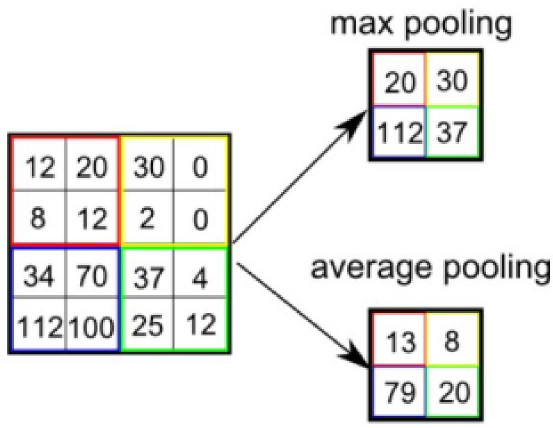

Figure 2.5: Max Pooling and Average Pooling [8]

2.6.5 Fully Connected Layer

The pooling layer's output is flattened in a single-dimensional vector and given to the Fully Connected (FC) Layer. Afterward, it is fed to the output layer.

2.7 Performance Measures for Classification Problems

Confusion Matrix (refer to **Figure 2.6** is utilized to evaluate the performance of a classifier. It is a two-dimensional matrix viz., Actual and Predicted. It consists of four parameters that are used to calculate different measures: True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN) [26].

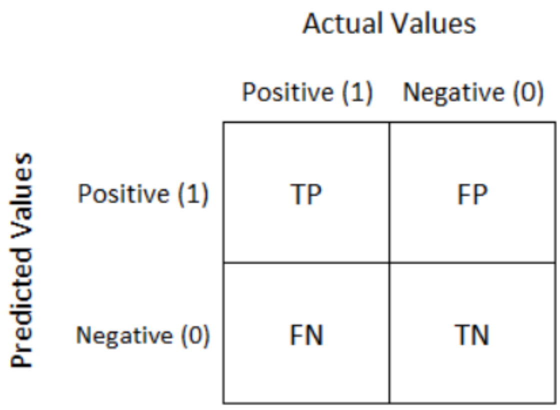

Figure 2.6: Confusion Matrix [9]

Following performance measures are studied based on Confusion Matrix:

- Classification Accuracy: It gives a measure about the correct predictions made by the classifier out of all the predictions and is given by the formula:

$$ClassificationAccuracy = \frac{TP+TN}{TP+FP+FN+TN} \tag{2.1}$$

- Recall/Sensitivity: It is described as a probability that the test tuple sets to positive in the unhealthy population. It is represented by:

$$Sensitivity = \frac{TP}{TP+FN} \tag{2.2}$$

- Specificity: It is described as a probability that the test tuple sets to negative in the healthy population and calulated as follows:

$$Specificity = \frac{TN}{TN+FP} \tag{2.3}$$

- Precision: It gives the ratio of correct positive predictions and is found as:

$$Precision = \frac{TP}{TP+FP} \tag{2.4}$$

Chapter 3

Literature Survey

This chapter explains the essential core concepts, pertaining to the project, viz. about different existing cataract detection and grading techniques in brief detail. A comparative study has been conducted and results are consolidated to reach the most efficient solution.

3.1 Clinical Cataract Detection and Grading Systems

Li et. al. suggested that clinical Cataract diagnosis involves Slit-lamp imaging and Scheimpflug imaging techniques [27]. It is developed on a protocol known as Lens Opacity Classification System (LOCS III). This is a very intricate procedure which is required to be performed by very experienced ophthalmologists hence poses a challenge to be conducted in less developed regions.

Caixinha et. al. conducted a study and concluded that use of ultrasound back-scattering signal can improve the assessment accuracy and during the survey they achieved better system's accuracy but with a small training data [28–31]. But use of such techniques was soon found to be very much cost-inefficient and complicated hence a need of optimizing them in terms of cost and operation was felt.

Rosenthal et. al. investigated the use of fundus images to grade nuclear cataracts [32], as the fundus cameras are quite easy to operate for technologists, or even patients themselves. The method proposed here was used to grade cataract severity by making a comparison between clinical and examiner's grades. It proved to be a better technique than the classical slit-lamp investigation ones.

3.2 SVM Classifier based on Lens Structure

Li et. al. collected slit-lamp images and used them to investigate the methods for automatic nuclear and cortical detection and grading systems [1].

3.2.1 Automatic Cortical Cataract Grading System

Retro-Illumination images are captured and considered for this study. Preprocessing of these images is done through canny and laplacian edge detection techniques. It results in the extraction of Region of Interest (ROI). Spoke-like features help in differentiating between cortical and PSC cataract opacities. Hence, some local thresholding and edge detection methodologies were applied both in angular and radial directions. Cortical opacities were obtained by subtracting the angular opacities from the radial ones [1]. Now, the area is calculated and the grade is assigned as per the rules (suggested in [33]) described in the **Table 3.1**.

Table 3.1: Ground Truth for Cortical Cataract Grading [1]

Cortical Grade	Total Opacities (%)
1	0–5%
2	5–25%
3	25–100%

3.2.2 Automatic Nuclear Cataract Grading System

In the study, the Wisconsin Cataract Grading System (WCGS) [33], a clinical grading system, is used as a ground truth. The grades here are from 0.1 to 5 where a grade value less than 3 is considered as the normal case. Preprocessing involves thresholding and horizontal and vertical profile clustering for ellipse extraction on a slit-lamp image. After this, the Active Shape Model is employed for contour extraction. 24 landmark points are marked in this manner. Support Vector Machine (SVM) classification model was trained on six-dimensional feature space. **Figure 3.1** demonstrates the comparison between the results obtained from the ground

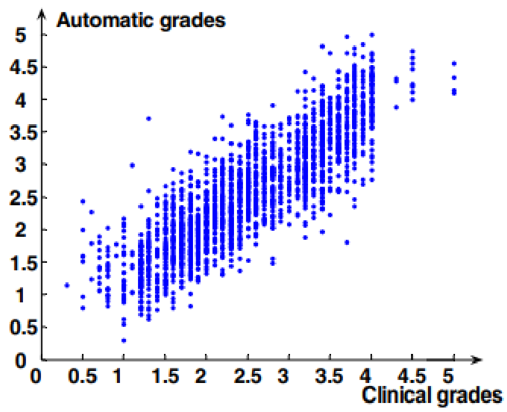

Figure 3.1: Comparison between the results of proposed system and ground truth [1]

truth and the proposed method. Error histogram for automatic grading of nuclear cataract was plotted.

3.3 Backpropagation Neural Network Classifier

Meimei et. al. studied the BP Neural Network classifier for Automatic Cataract Classification based on retinal images [3]. The G channel of Red Green Blue (RGB) color space was extracted, for it demonstrates the best contrast between the foreground and background [34]. As discussed in [3], preprocessing of the fundus images involves the following steps:

- The G channel of the image undergoes Top-Bottom Hat Transformation [35] to enhance the contrast between the blood vessels and the foreground. This transformation takes place when the original image is used to subtract the opening or closing image. When the operation is done on the opening image, it is referred to as Top Hat Transformation else Bottom Hat Transformation.
- The resultant operates for histogram equalization to improve the image quality, also known as improved Top-Bottom Hat Transformation (refer to **Figure 3.2**).

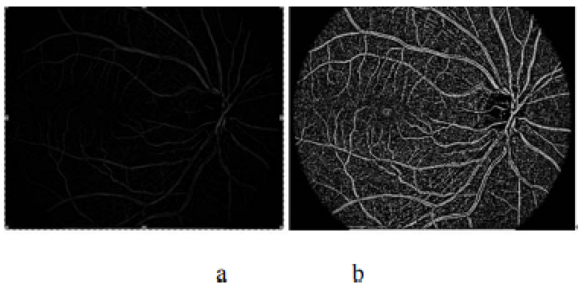

Figure 3.2: Images after (a) Normal and (b) Improved Top-Bottom Hat Transformation [3]

- The noise in the image is reduced using a Trilateral filter

Preprocessing is followed by feature extraction. The network uses Luminance, Gray Level Co-occurrence Matrix (GLCM), and Gray Gradient Co-occurrence Matrix (GGCM) features. Luminance resembles the white pixel ratio in the image. GLCM is used to extract features such as angular second moment, correlation, entropy, contrast, etc.. GLCM does not provide edge features such as little gradient dominance, large gradient dominance, gray heterogeneity, gradient heterogeneity, energy, etc.. These features are extracted using GGCM.

BPNN Classifier is used to serve the classification purpose. It is a two-layer network, and ten neurons are used in the hidden layer [3]. Confusion Matrix and Receiver Operation Characteristic (ROC) are used for evaluation purposes of four-class classification.

3.4 LDA with Adaboost Algorithm as a Classifier

As discussed in [10] by Zheng et. al., the G-channel of the fundus images was extracted and processed for extracting features using two-dimensional Double Fourier Transform (DFT). The resultant here was called Fourier images. These images were divided into 10 subsets and a ten-fold cross-validation techniques was used during training. Principal Component Analysis (PCA) was used for dimensionality reduction to reach a 300-dimension feature space.

Linear Discriminant Analysis (LDA) classifier, also known as *Fischer Linear Discrimination* was used for classification purpose. The Adaboost algorithm was employed with LDA and a total of 100 Adaboost iterations were processed in each fold. the one-vs-one strategy along with voting was used for four-class classification.

The average accuracy out of ten folds was considered to evaluate the classifier's performance in both two-class and four-class classification.

3.5 SVM Classifier based on SRA, BRA, EPC, and Object Perimeter Features

Nayak proposed a method in which a three-class SVM classifier is built to classify the normal, cataract, and post-cataract images. The images undergo preprocessing to shift from RGB to Hue Saturation Intensity (HSI) color space so that the mean intensity can be normalized [36] [37]. Features such as Small Ring Area (SRA), Big Ring Area (BRA), Edge Pixel Count (EPC) and Object Perimeter are extracted from the normalized images. The SVM classifier was used for classification purposes.

3.6 Backpropagation Classifier along with Fuzzy Means Feature Extraction Technique

Acharya et. al. studied a backpropagation-based Artificial Neural Network (ANN) classifier algorithm for three-class, viz., normal, cataract and post-cataract classification [38]. Histogram equalization is used for preprocessing the optical images. The aim is to convert the input image to a flat histogram. A flat histogram is a uniform intensity representation of an image obtained by reassigning all intensity image pixel values using monotonic, non-linear mapping [37].

After preprocessing, the Fuzzy K-means Clustering algorithm performs the feature extraction operation by taking six initial cluster centers initially. It takes RGB vector as an input to group the regions [39]. For each class, they got 18 features by employing the algorithm on RGB channels. During training, the output existed in the range 0 to 1.0 [38]. While during testing it gets normalized to 0 or 1.0 by utilizing a threshold at 0.5.

For measuring the performance of the classifier, classification accuracy, sensitivity, specificity, and positive predictive accuracy were taken into consideration.

3.7 KNN based Classification Method

Fuadah et. al. conducted a study to improve the accuracy of the existing systems for cataract detection and grading using statistical texture analysis of the eye images and k-Nearest Neighbours (KNN) algorithm [40]. From the input eye images, pupil area (ROI) was extracted manually and converted to grayscale. These 8-bit format grayscale images are used to extract features like contrast, dissimilarity and uniformity using GLCM [41, 42].

During classification, feature extraction results of both training and testing data were plotted in same multi-dimensional space and a comparison between the features of both was done to predict the correct class for each query entry data. KNN supervised machine learning algorithm [43] was incorporated to classify the images using majority voting, i.e., if *k=1* the object had been assigned the class of its nearest data point [40].

Accuracy of the classifier was obtained using the confusion matrix.

3.8 Conclusion of Prior Works

The method investigated in [10], having Adaboost classifier along with PCA and DFT feature extraction techniques, has shown better results for detection and grading of cataract, compared to others, as depicted by **Table 3.2**. Fundus Retinal Images are processed in this algorithm. However, the technique proposed in [40] is also reaching to considerable results by making use of KNN method for classification.

The conducted survey has made the fact quite clear that SVM classifier's performance can be comparatively increased to a good extent if the preprocessing techniques are improved and more significant features like SRA, BRA, EPC, and Object Perimeter are included in the system [1, 36].

If the classification process involves the use of ANN architectures, then clustering extracts better features to train rather than GGCM [3, 38]. The detailed analysis of the most efficient method surveyed here will be carried out in the following chapters.

Table 3.2: Comparison of Cataract Detection Techniques [2]

Reference	Preprocessing Operations	Feature Extraction	Classification Methods
[1]	Nuclear Cataract: Lens Localization Cortical Cataract: Converted to Polar Coordinate, Local Thresholding	Intensity inside lens and sulcus, color on posterior reflex, intensity ratio	SVM
[3]	Convert to Green Channel, Improved Top Bottom Hat Transformation, Trilateral Filter	24 features from GLCM and 15 features from GGCM	Back Propagation
[10]	Resizing and Localization of Fundus Image	PCA and Spectrum from 2D DFT Fundus Image	LDA with Adaboost Algorithm
[36]	Image Normalization, RGB to HSI Transformation	Small Ring Area, Big Ring Area, EPC, Object Perimeter	SVM
[38]	Histogram Equalization	6 clusters are extracted by using Fuzzy Means Algorithm	Back Propagation
[40]	Obtain ROI, RGB to Grayscale conversion	Contrast dissimilarity and uniformity using GLCM	KNN Method

Chapter 4

Case Study

This chapter focuses on the detailed explanation of the most efficient algorithm observed after the conduction of Literature Survey viz., *LDA with Adaboost Algorithm as a Classifier* [10]. Zheng et. al. in this proposed work made use of an image sample set consisting 460 fundus images belonging to four classes of cataract i.e., Normal, Mild Moderate, and Severe. Since, the existing clinical technologies were using the slit-lamp images for LOCS III, and WCGS, these technologies needed to be implemented by advanced ophthalmologists. This made their usage complicated and expensive for a large population [10].

As any Machine Learning classification system involves the preprocessing, feature extraction, and classifier training and testing steps therefore the subsequent sections of the chapter will deal with the technologies adopted in each of these.

4.1 Preprocessing

Initially, the G-channel of the fundus images were extracted because it is the best contrast measure observed so far [34]. Moreover, these images are said to constitute the details of the original fundus images. Apart from this, patient's personal information was cropped to maintain their privacy. The resultant images of preprocessing are as shown in **Figure 4.1**.

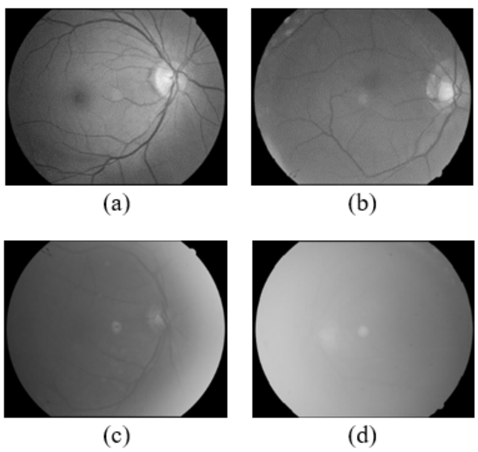

Figure 4.1: G-channel fundus images (a) Normal; (b) Mild; (c) Moderate; (d) Severe [10]

4.2 Feature Extraction

The lens-opacities in cataract act as low-pass filter which absorb and scatter the light rays propagating through the eye lens [10]. So, the two-dimensional DFT [44] was applied to all the resultant images of preprocessing to get the spectrogram which is in Fourier or frequency domain. For an *m*n* sized image, the 2-D DFT is represented by:

$$F(k,l) = \sum_{i=0}^{n-1} \sum_{j=0}^{m-1} f(i,j) e^{-i2\pi(\frac{ki}{n}+\frac{lj}{m})} \tag{4.1}$$

where $f(i,j)$ is the image in spatial domain and the exponential term is the basis function corresponding to each point $F(k, l)$ in the Fourier space [10]. Here, sine and cosine waves are base functions with increasing frequencies. The output is known as Fourier image and is as shown in **Figure 4.2**, demonstrating (a) for Normal, (b) for mild, (c) for moderate, and (d) for severe cataract grades.

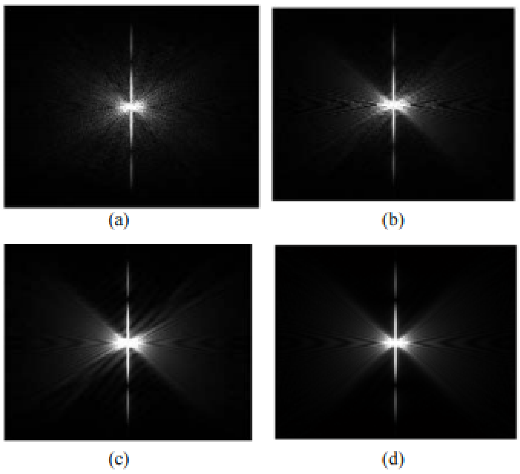

Figure 4.2: Results of 2-D DFT on Fundus Images [10]

4.3 Dimension Reduction

Dimensionality reduction using PCA was performed to reach a 300-dimensional feature space. PCA is a widely used dimensionality reduction method that sees a projection to best represent the data in a least square sense [45]. The error observed after dimension reduction is 0.36% as observed.

4.4 Classifier Building

All the Fourier images were divided into ten equal-sized subsets in a random permutation. During training, a ten-fold cross-validation technique was used, i.e., for each subset consider it as the testing set and nine others together as the training set to train the classifier. Firstly, dimensionality reduction was performed. Then LDA classifier was used to train for this fold. LDA, also known as *Fischer Linear Discrimination*, is used to find a projection that separates the data in the best least square sense [45]. 100 Adaboost iterations were adopted for each fold.

Figure 4.3 shows that every two class of cataract fundus images are separable in one-dimension. The one-vs-one strategy is used for four-class classification. It means any two-classes were adopted from the training set to train the classifier, then decide samples in the testing set into these two classes. Thus, 6 decisions were made for 6 combinations and voting classification was used to predict the result. The same process was repeated for the ten folds.

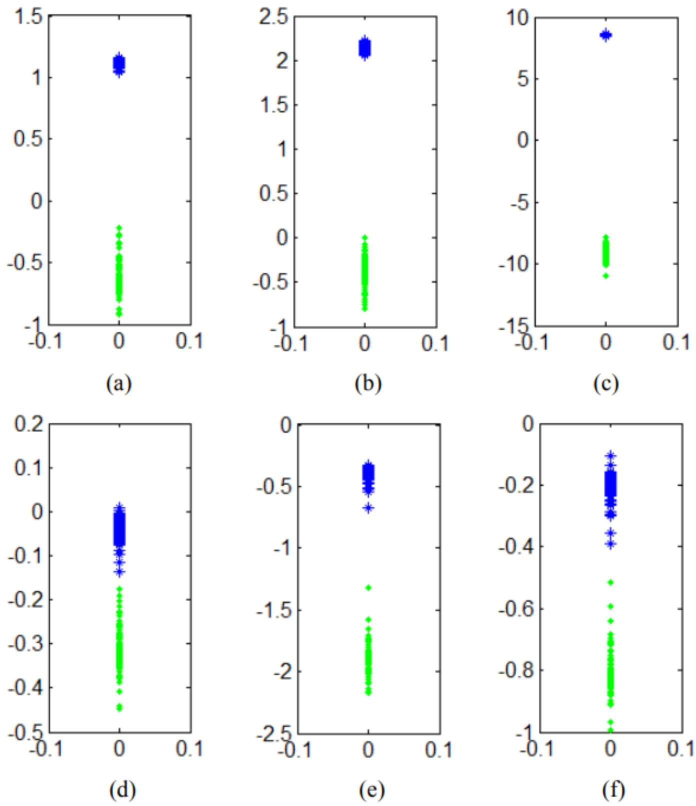

Figure 4.3: Visualization of pairwise 1-dimensional separability of fundus images with different levels of cataract. (a) normal vs mild; (b) normal vs moderate; (c) normal vs severe; (d) mild vs moderate; (e) mild vs severe; (f) moderate vs severe. [10]

4.5 Evaluation of the Classifier

The average accuracy of ten folds was considered to evaluate the classifier's performance in both two-class and four-class classification. This model possessed an accuracy of 95.22% for two-class classification and 81.52% for four-class classification.

4.6 Conclusion

In this work, it is observed that mist in a cataract eye is the most important factor under consideration for classification and grading purposes and hence acts a filter for 2-D DFT. As cataract increases, mist gets thicker and low frequency components increase. So, the frequency patterns act as quality features for training the classifier.

Chapter 5

Experimental Analysis, Simulation and Results

This chapter explains firstly the structure of the dataset and image preprocessing, secondly different architectures that were trained are quoted along with their comparative accuracy analysis then the architecture of the best model is explained and finally the training process is described. The data preparation step is inspired from [46] with slight modifications. The last section of the chapter is dedicated to the discussion of an image processing process to calculate percentage of cataract in an epidemic eye.

5.1 Dataframe

The datasets available in [47] and [48] are used together for the training purpose. The image in the dataset are preprocessed and a table or a dataframe is created which contains 2 columns. One column for the image path, and second column is the label, it is '1' for cataract and '0' otherwise.

5.2 Architectures under study

Overall seven machine learning architectures (see **Table 5.1**) were implemented using keras

Table 5.1: Comparative performance analysis of implemented models

Architecture	Optimizer	Number of Trainable Parameters	Accuracy (%)
DenseNet121	RMSProp	6,955,906	38.83%
NasNetMobile	Adam	5,584,092	76.21%
DenseNet121	Adam	8,532,354	88.83%
EfficientNetB0	Adam	4,010,110	90.29%
EfficientNetB5	Adam	28,344,882	90.77%
EfficientNetB7	Adam	63,792,082	92.23%
InceptionV3	Adam	22,334,850	93.20%

backend on the given dataset and their testing accuracies were compared. It has been observed that the *Adam* optimizer fits best with the retinal images. As shown in the table, the best results are obtained through InceptionV3 but EfficientNet series have also exhibited the comparable results. In EfficientNet series networks a positive slope has been observed in the accuracy with the version but the number of trainable parameters also increase exponentially making it computationally less feasible than InceptionV3. So, InceptionV3 along with *Adam* optimizer has been concluded to be the best model among the studied ones.

5.3 Architecture of InceptionV3

InceptionV3 is a CNN architecture which is basically an improved version of Inception Family. Label Smoothing, Factorized 7 x 7 convolutions, and the use of an auxiliary classifier are some of the acquired improvements [49]. Its architecture is as shown in **Figure 5.1**. It works on Transfer Learning methodology.

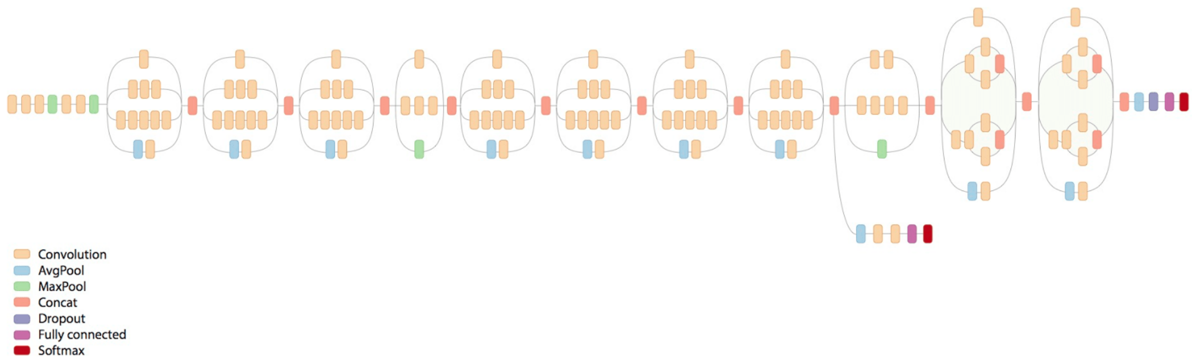

Figure 5.1: InceptionV3 Architecture [11]

5.4 Process Flow

The process proposed for two-class classification of cataract is as shown in **Figure 5.2**. The network was trained on the dataset consisting of 1026 images of two categories viz., cataract and normal. The data is split into three sets, i.e., train, validation, and test sets having 697, 123,

Figure 5.2: Classification Process Flow

and 206 images respectively. The input image size used here is 192(height)x256(width). *Adam* optimizer is used with a learning rate of 1e-3. The following steps were followed sequentially:

1 A dataframe was made containing two columns, one for images and other for label. The label is '1' if the image pair is positive for cataract or '0' otherwise.

2 The image is preprocessed using ImageDataGenerator having parameters; horizontal_flip = True, height_shift_range = 0.1, and fill_mode = 'reflect'.

3 The images from a row of the dataframe, after preprocessing as mentioned above, is passed through the training network for given number of epochs until the model converges. Two callback functions, EarlyStopping and ReduceLROnPlateau, are used.

5.5 Results of InceptionV3

The InceptionV3 model was set to train for 100 epochs but early stopping was conducted at 44^{th} epoch with a validation accuracy of 93.50% and training accuracy of 99.71%. 93.20% testing accuracy was observed when the model was evaluated on the test set. The given two graphs demonstrate the training trends between losses and accuracies (see **Figure 5.3**).

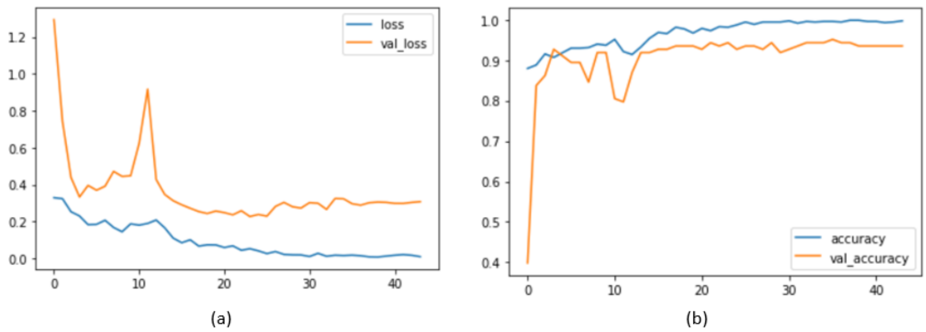

Figure 5.3: Training plots

5.6 Method to calculate percentage of Cataract in an epidemic eye

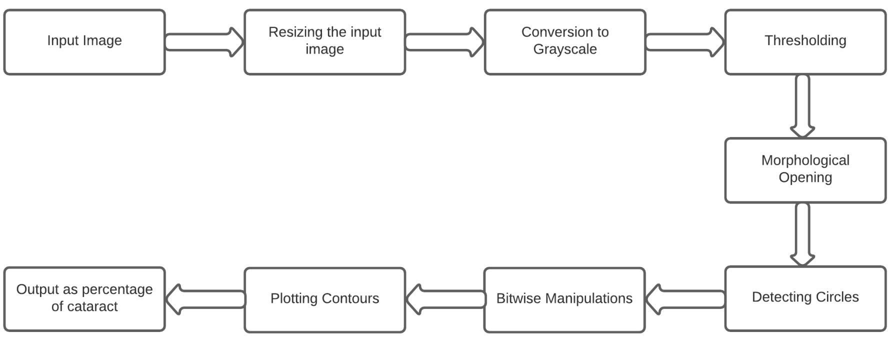

Figure 5.4: Flow of the process for calculating percentage of cataract

An image processing technique for calculating the percentage of cataract in an epidemic eye based on geometrical and morphological transformations, contouring, and bit-wise manipulations in image vectors has been studied. The whole flow is as shown in **Figure 5.4**. This has been implemented using the OpenCV library of Python.

Chapter 6

Conclusion and Future Work

As the availability of advanced technologies and experienced ophthalmologists is found to be sparse in the developing and underdeveloped regions, it gives a rise to the need of more advanced yet efficient diagnosis techniques for the treatment of pandemic eyes. The severity of eye disease increases as the time passes so it has become very necessary to treat the patient as early as possible to reduce the chances of myopia (short-term effects) and ultimately blindness.

The study suggests that there exist various efficient automatic methods for cataract detection and grading purposes that too at no cost, it implies the scope of improvements in the concerned domain. The implementation of machine learning algorithms has made it significant to note that CNN architectures can prove to be a huge success while operating with fundus images.

Further advancements in the project encompasses the extension of its domain by combining multiple approaches for feature extraction to the proposed algorithm as surveyed through in Literature Review. This whole flow aims to develop an automated cataract detection and grading techniques with feasible computation efficiency and comparable results thereby decreasing the overall operational, maintenance and availability cost as compared to traditional clinical methods.

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