International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 5s
DOI: https://doi.org/10.17762/ijritcc.v11i5s.6655
***Article Received**: 02 March 2023 **Revised**: 19 April 2023 **Accepted**: 01 May 2023*

Machine Learning Techniques, Detection and Prediction of Glaucoma– A Systematic Review

[*1]Jincy C Mathew, [2]V. Ilango, [3]V. Asha
[*1]Research scholar, VTU Phd Belgaum, Department of MCA,
New Horizon College of Engineering, Bengaluru, Karnataka 560103, India.
Email: jincycm@newhorizonindia.edu
[2]Professor, Department of Computer Application,
CMR Institute of Technology, Bengaluru, Karnataka 560037, India.
Email: ilango.v@cmrit.ac.in
[3]Professor & Head, Department of MCA, New Horizon College of
Engineering, Bengaluru, Karnataka 560103, India.
Email: v_asha@live.com

Abstract -Globally, glaucoma is the most common factor in both permanent blindness and impairment. However, the majority of patients are unaware they have the condition, and clinical practise continues to face difficulties in detecting glaucoma progression using current technology. An expert ophthalmologist examines the retinal portion of the eye to see how the glaucoma is progressing. This method is quite time-consuming, and doing it manually takes more time. Therefore, using deep learning and machine learning techniques, this problem can be resolved by automatically diagnosing glaucoma. This systematic review involved a comprehensive analysis of various automated glaucoma prediction and detection techniques. More than 100 articles on Machine learning (ML) techniques with understandable graph and tabular column are reviewed considering summery, method, objective, performance, advantages and disadvantages. In the ML techniques such as support vector machine (SVM), and K-means. Fuzzy c-means clustering algorithm are widely used in glaucoma detection and prediction. Through the systematic review, the most accurate technique to detect and predict glaucoma can be determined which can be utilized for future betterment.

Keywords: Glaucoma detection and prediction, Image processing, Machine learning.

I. INTRODUCTION

The term "glaucoma" refers to a variety of conditions that all result in the progressive degeneration of the optic nerve, which progressively worsens vision and eventually renders a person blind [1- 4]. The progression of retinal ganglion cell loss in glaucoma is accompanied by contraction of the visual field (VF), as well as distinctive alterations in the neuroretinal rim tissue in the optic nerve head (ONH) [5-7]. Glaucoma continues to be the biggest cause of permanent blindness in the world despite the existence of viable therapies. By the year 2040, 111.8 million individuals are predicted to have glaucoma, with those in Asia and Africa being disproportionately affected [8-9]. The majority of glaucoma patients are unaware they have the condition because it usually has no symptoms in the early stages. However, early detection and intervention can help reduce visual loss caused by glaucoma [10-13]. Thus, early glaucoma detection is crucial and may be enhanced by the introduction of novel screening, diagnostic, and change monitoring tools [14-15]. Aqueous fluid leakage and optic nerve injury increase the eye's intraocular pressure (IOP), which prevents information from the eye from reaching the brain [16].

The greatest cause of permanent blindness in the world, glaucoma is also linked to a lower quality of life. Risk factors include advanced myopia, frailty, gender, genetics, age, family history, systemic hypotension, smoking, race, systemic hypertension, vasospasm, use of systemic or topical medications, obstructive sleep apnea syndrome, migraine, and most significantly, a high IOP. [17-21].

Although there are many different kinds of glaucoma, open-angle and angle-closure glaucoma are the two basic classifications [22-24]. The patient may experience increasing and rising vision impairment in the later stages of the disease, usually more so in one eye than the other, when the optic nerve has advanced degeneration and there is severe visual loss. Additionally, the affected individual may report decreased night vision. [25-29]. The patient typically experiences peripheral visual loss in such advanced cases, which gradually progresses to affect the central vision [30-34]. Glaucoma can manifest itself in a variety of ways, but historically, it has been split up into two groups: primary or secondary open-angle. Depending on how the anterior chamber angle (ACA) in the eye is configured, there are two basic forms of glaucoma [35-36].

Open angle glaucoma: In clinical practise, primary open-angle glaucoma (ONG) is the most typical form of the disease. It can be distinguished from angle-closure glaucoma (ACG) by the anterior chamber angle's gonioscopic appearance [37]. This is a diagnosis of exclusion since there are no clear ocular or systemic factors that are linked to or precede primary open-angle glaucoma. In the early stages of the disease, it develops slowly and is frequently asymptomatic [38-39]. Three components for the diagnosis of ONG, the anterior chamber must have a normal gonioscopy appearance, the glaucomatous optic disc must cup and be destroyed, and the peripheral vision field must be lost. [40].

Angle-closure glaucoma: A common kind of glaucoma in Asia is known as primary ACG [41], which is characterised by a narrow ACA between the iris and cornea that prevents aqueous fluid from draining properly. As a result, ocular pressure increases, which damages the optic nerve [42-43]. Angle-closure glaucoma diagnosis thus depends on imaging and evaluation of the ACA [44-45]. Angle-closure Pupillary block, a condition where aqueous humour cannot reach the anterior chamber through the pupil, leads to the development of glaucoma [46]. This increased pressure behind the iris causes the iris to bulge anteriorly and obstructs the anterior chamber angle. Any stimulus that causes the pupil to enlarge or the lens to shift anteriorly may lead to acute angle-closure glaucoma [47].

Intense eye discomfort and redness, impaired vision, sighted haloes round lights, headaches, and associated nausea and vomiting are just a few of the extreme acute angle-closure glaucoma symptoms [48]. The nausea and vomiting are sometimes mistaken for gastrointestinal problems, which might delay a prompt diagnosis. IOP levels can get very high in those with acute angle-closure glaucoma [49].

When used to image macular edoema [50], segment retinal layers [51-52] and identify the optic disc/cup [53-54], optical coherence tomography (OCT) offers a clear view of intraretinal morphology and permits noninvasive depth-resolved functional imaging of the retina.

These studies' mainstream can be split into two categories. Researchers manually create features including energy-based features [55], local configuration pattern (LCP) features [56], and higher order spectra (HOS) features [57] using the first type of procedures. Following that, classifiers are created for diagnosis based on these features. For diagnosis, the second category of approaches extracts metrics such the cup-to-disc ratio. These features are determined using a segmentation process that uses manually created features to separate glaucoma-related tissues including the optic disc and optic cup [58].

Recent developments in deep learning and machine learning technologies have made it possible to design new algorithms for automating the diagnosis of eye diseases [59-60], such as glaucoma screening using colour fundus images [61-62] and OCT data [63-64].

Nevertheless, with the addition of ML and DL systems capable of extracting the necessary properties to provide a good diagnosis, the study of medical images in general has made significant progress. Additional stages are needed for these systems, including pre-processing, selecting the best network architecture, and training (which occasionally needs supervision) [65].

A) Key contributions

Detection and prediction of glaucoma using medical images is a challenging and admirable task in the medical domain. The only way to prevent total vision loss is by early detection and prediction of glaucoma that can protect and contribute timely options for doctors to choose effective treatment plans. Therefore, the importance of glaucoma detection, prediction and its benefits motivated me to bring forth a systematic review of glaucoma detection using ML methods. The key contributions of the systematic review are as follows:

- The systematic review of glaucoma detection and prediction using image processing techniques forms future researchers to invent novel glaucoma detection and prediction systems using ML algorithms. In the proposed systematic review, the steps used to detect and predict the glaucoma, ML-based glaucoma detection and prediction are discussed briefly with understandable tabulation. The systematic review is done using recent research papers from 2000 to 2022.
- The main curiosity of the proposed systematic review is to gather more information from recently proposed research works on glaucoma detection and prediction that are not yet reviewed by any authors. The proposed systematic review briefly explains the entire ML techniques for glaucoma detection and prediction.
- There are only rare review papers that discussed developing a glaucoma detection and prediction system using various techniques. Therefore, the primary goal of the suggested systematic review is to compile all recent research publications addressing ML-based glaucoma diagnosis and prediction systems in order to provide a clear notion for future medical advancements. Figure 1 shows the total number of paper reviewed the number of papers reviewed in ML is 128 papers are reviewed. Percentage of the total reviewed papers in Machine Learning – Detection(ML-D) and Machine Learning – Prediction(ML-P) depicted in figure 2 and frequency of several performance metrics is depicted in figure 3. figure 4 gives the flow diagram for total number reviewed.

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 5s
DOI: https://doi.org/10.17762/ijritcc.v11i5s.6655
***Article Received**: 02 March 2023 **Revised**: 19 April 2023 **Accepted**: 01 May 2023*

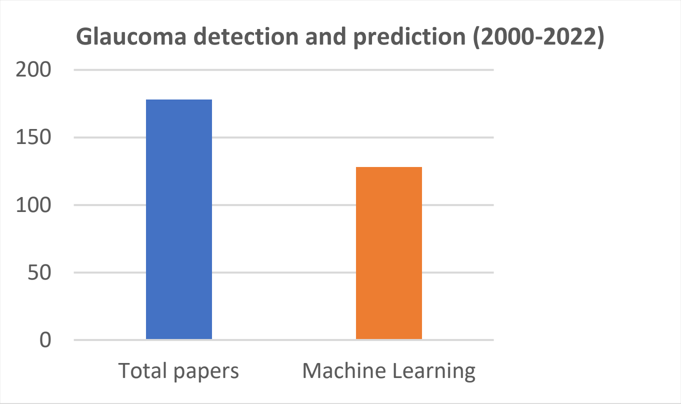

Figure 1: Number of paper reviewed

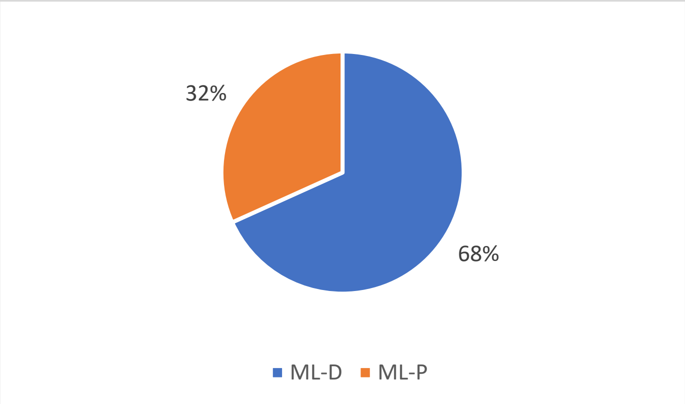

Figure 2: Percentage of the total reviewed papers

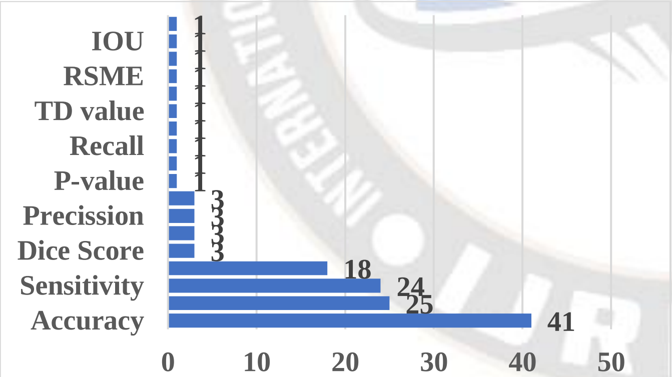

Figure 3: Frequency of several performance metrics.

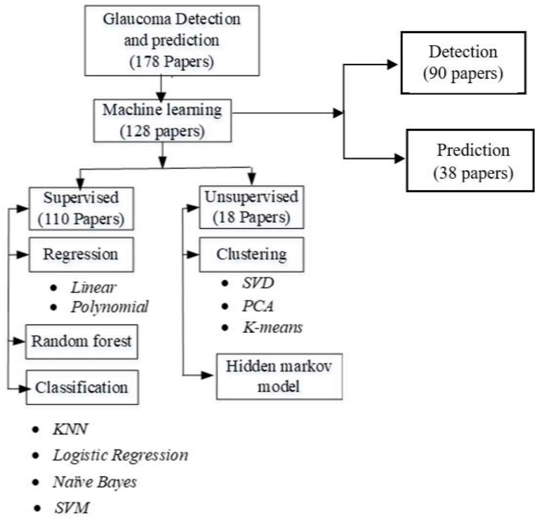

Figure 4: Flow diagram for techniques and total number of papers reviewed

B) Evolution of Machine Learning and different techniques

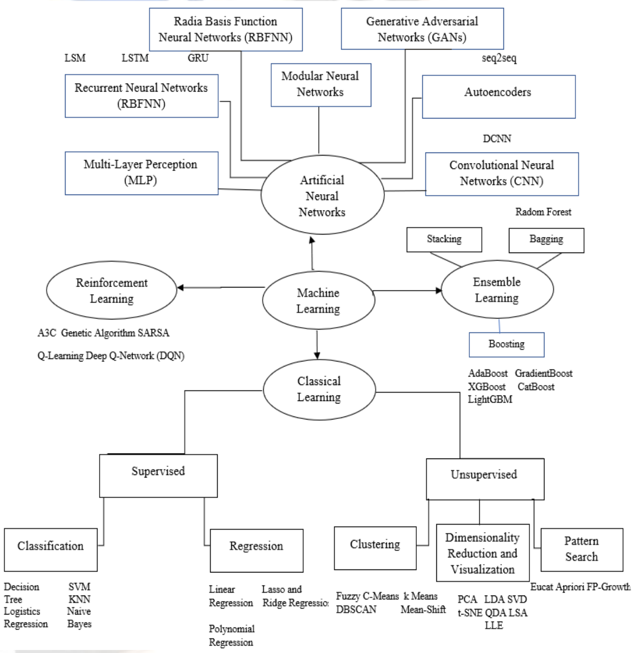

Figure 5: Flow diagram of techniques in ML

A subset of artificial intelligence is machine learning. ML is the study of computer algorithms that get better on their own over time. The study and creation of algorithms that can learn from data and make predictions about data are explored in ML.

Machine learning may modify actions and responses based on additional data, which will increase its efficiency, adaptability, and scalability. figure 5 explains the flow diagram of different techniques used in ML

1. Supervised Learning: In a supervised learning model, the computer picks up knowledge from a labelled dataset in order

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 5s
DOI: https://doi.org/10.17762/ijritcc.v11i5s.6655
***Article Received**: 02 March 2023 **Revised**: 19 April 2023 **Accepted**: 01 May 2023*

to produce anticipated predictions for the reaction to incoming data.

Two types of supervised learning exist:

a) Classification: In classification, data is categorised into several class labels by a computer programme that has been trained on a training dataset.

Types of Classification Algorithms:

- Naive Bayes classifier
- Decision Trees
- Logistic Regression
- K-Nearest Neighbours
- Support vector machine
- Random forest classification

b) Regression: The goal of the regression algorithm is to identify the mapping function to translate the continuous output variable to the input variables (x) (y).

2. Unsupervised Learning: In an unsupervised learning model, the algorithm picks out features, co-occurrences, and underlying patterns on its own to try to make sense of an unlabelled dataset.

Types of Unsupervised Learning:

- Clustering
- Anomaly detection
- Association
- Autoencoders
- Latent variable models
- Neural Networks

3. Reinforcement Learning: Reinforcement learning is a subset of machine learning in which the model learns how to act in a given environment by acting and observing the responses. To maximise the favourable reaction in the specific circumstance, RL performs the proper action. The reinforcement model makes decisions about what steps to take to complete a task, so it is obligated to learn from the event itself.

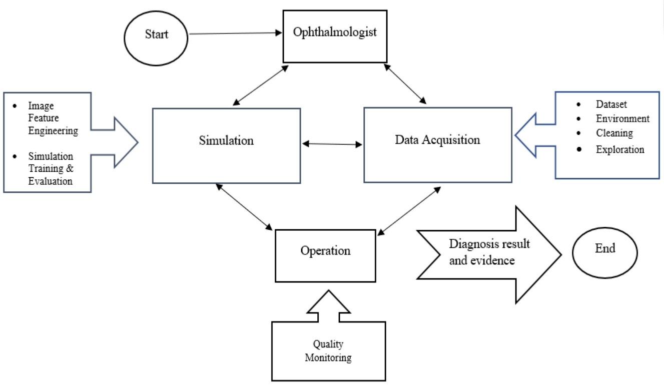

Figure 6: General Architecture of Detection/Prediction of Glaucoma using ML

figure 6 gives a general architecture used of detection/prediction of glaucoma using ML. Following are the steps used in the architecture.

1. Data Acquisition: Data capture is the first stage outlined in the architecture. This entails gathering data, arranging, and grouping case scenarios according to specific criteria that are relevant to decision-making.

2. Data Processing: The data is subsequently forwarded from the data acquisition layer to the data processing layer, where it undergoes extensive integration and processing, including normalisation, cleaning, transformation, and encoding of the data.

3. Data Modelling: It entails choosing from a variety of algorithms that may enable the system to be modified to handle the issue for which the learning is being developed.

4. Execution: The experimenting, testing, and tuning phases of machine learning take place at this stage.

5. Deployment: It is necessary to operationalize ML outputs or to send them for additional exploratory processing. The result can be viewed as a non-deterministic inquiry that needs to be introduced into the system of decision-making.

C) Misclassification Rate

Error Rate is another name for misclassification rate. It is described as the ratio of Total TP+TN+FP+FN to the sum of False Positive and False Negative.

	Actual Positive	Actual Negative
Predicted Positive (PP)	True Positive (TP)	False Positive (FP) (Type 1 Error)
Predicted Negative (PN)	False Negative (FN) (Type 2 Error)	True Negative (TN)

$$Accuracy = \frac{TP + TN}{Total\,Population} \quad (1)$$

$$\Pr ecision = \frac{TP}{PP(TP + FP)} \quad (2)$$

$$\mathrm{Sp}ecificity = \frac{TN}{\mathrm{Actual\,Negative\,(FP + TN)}} \quad (3)$$

$$\mathrm{Error\ Rate/Misclassification\ rate} = \frac{\mathrm{FP + FN}}{\mathrm{Total\,Population}} \quad (4)$$

$$\mathrm{Sensitivity/Recall} = \frac{\mathrm{TP}}{\mathrm{Actual\ Positive(TP + FN)}} \quad (5)$$

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 5s
DOI: https://doi.org/10.17762/ijritcc.v11i5s.6655
Article Received: 02 March 2023 Revised: 19 April 2023 Accepted: 01 May 2023

$$\text{F1 Score} = \frac{2 * (\text{Recall} * \text{Precision})}{\text{Recall} + \text{Precision}} \quad (6)$$

These are the different formulas for handling imbalanced classification datasets

II. REVIEW METHODOLOGY

A) Systematic review stages

The systematic review stages shown in the figure are classified into four points namely: Research queries, data extraction, search strategy, and eligibility criteria. The first stage is research queries, here the research queries on glaucoma detection and prediction using various techniques. The second stage is data extraction, here the details for the given research queries are extracted from various resources. The third stage is the searching strategy, here the terms that are utilized to extract the information are provided. Last in the fourth stage is eligibility criteria, here the inclusion and exclusion criteria are given. Figure 5 shows the systematic review stages.

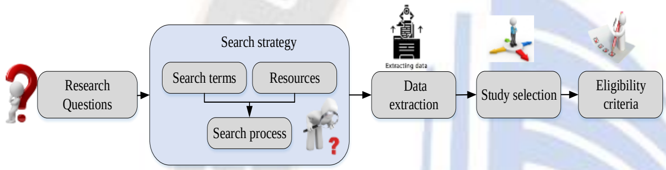

Figure 5: Systematic review stages

B) Research queries

The systematic review is started by stating some research queries that are given below:

RQ1. What is the purpose of a glaucoma detection and prediction?

Ans: The majority of glaucoma patients are unaware they have the condition because it usually has no symptoms in the early stages. However, early detection and intervention can help reduce visual loss caused by glaucoma.

RQ2. What is glaucoma detection and prediction using ML techniques?

Ans: The system's success only hinges on how well the classification algorithm used to categorise newly discovered medical images of normality and abnormality performs.

RQ3: What are the ML detection techniques used in glaucoma?

Ans: Decision tree, Naïve Bayes classifier, Linear regression, Support Vector Machine, KNN, K-means, FCM BPNN.

RQ4: What are the ML prediction techniques used in glaucoma?

Ans: BOSVM, KNN, KF, RFC, Fuzzy Logic, Linear regression, Random Forest Classifier.

RQ5. What are the most popularly used performance metrics to validate the performance of the proposed glaucoma detection and prediction techniques?

Ans: Accuracy, Sensitivity, Specificity, Average, AUC.

RQ6. What causes glaucoma in diabetics?

Ans: Unusual blood vessels that grow out of the retina as a result of diabetic retinopathy can put strain on the eye which can cause a type of glaucoma.

C) Search Strategy

The process we used to create the search keyword was as follows:

- ✓ The research questions are used to determine the main search terms.
- ✓ To replace key words like detection and prediction, new terms were established.
- ✓ The search results are constrained using Boolean operators (ANDs and ORs).
- ✓ The glaucoma detection, prediction, deep learning, and machine learning-related search phrases utilized in this review.

D) Data Extraction

In order to extract the data needed to respond to the research questions, we analyzed the final list of papers in this stage. The review most likely included every recent study on glaucoma diagnosis and prediction from different digital library sources.

The digital libraries (journals and conference papers) that we used for this search are listed below:

Repository	No. of papers referred
Science Direct (https://www.sciencedirect.com)	8
Elsevier (https://www.elsevier.com)	25
IEEE Xplore (https://ieeexplore.ieee.org)	15
Springer (https://www.springer.com)	30
Taylor & Francis	20
ACM	2
Hindawi	10
PubMed	33
American Journal of Ophthalmology	35

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 5s
DOI: https://doi.org/10.17762/ijritcc.v11i5s.6655
***Article Received**: 02 March 2023 **Revised**: 19 April 2023 **Accepted**: 01 May 2023*

E) Study Selection

Based on the search criteria, we initially gathered more than 300 papers. After that, we screened those papers to make sure that our evaluation included only papers that were pertinent to the subject. Below is a description of the filtration and selection procedures:

- ✓ All of the duplicate articles that were gathered from the various digital libraries should be deleted.
- ✓ To prevent any irrelevant papers, use inclusion and exclusion criteria.
- ✓ Review articles should be taken out of the collection of papers.
- ✓ Apply quality evaluation guidelines to only include articles with the necessary qualifications and the best possible responses to our research questions.

F) Eligibility criteria

The following inclusion and exclusion criteria have been met by all research publications evaluated for glaucoma detection and prediction. Table 1 shows the inclusion and exclusion criteria's.

TABLE 1: INCLUSION AND EXCLUSION CRITERIA'S

Inclusion criteria	**Exclusion criteria**
✓ The research papers reviewed only the target of glaucoma detection using image processing techniques	✓ Duplicate publications.
✓ The papers with understandable key objectives.	✓ Studies that were not published in full text
✓ Papers included based on ML techniques for Glaucoma detection and prediction.	✓ Case reports, letters, comments, seminar reports, and review articles.
✓ Only research papers in the English language are preferred.	✓ Remove the articles published before 2000.
✓ Included only	✓ Studies that were not published in English
	✓ Exclude the article that include machine learning not related to the glaucoma detection or prediction

III. STAGES USED IN GLAUCOMA DETECTION USING IMAGE PROCESSING TECHNIQUE

Digital image capture devices are used to take a retinal image as part of the glaucoma diagnostic process. Pre-processing is therefore necessary to equalise anomalies in pictures. The process of feature extraction includes reducing the number of resources needed to accurately describe a huge data set. An important piece of information that may be classified is called a feature [66]. The classification process involves examining an image's characteristics [67]. The dataset is further classified into different classes, such as normal or glaucoma-affected, depending on the analysis. Figure 6 shows the various stages in glaucoma detection and prediction.

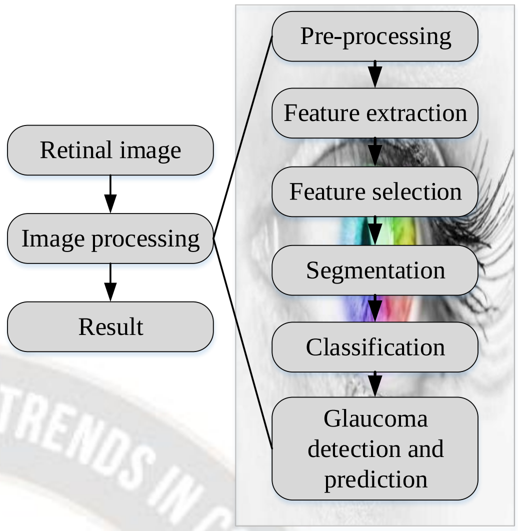

Figure 6: Automated Glaucoma Detection and prediction Generic Process

A) Pre-processing

Using optical image capture techniques, the fundus of the eye is imaged. The primary goals of pre-processing are to reduce pointless artefacts and enhance image quality. The forms of the various pre-processing methods used on the fundus images are listed below. Before measuring and evaluating the feature, there may be artefacts in the photos that need to be addressed after pre-processing [68-70].

Pre-processing was one of the image processing techniques needed for the computational analysis of medical images. The following are some pre-processing procedures:

- ✓ Noise removal
- ✓ Image enhancement
- ✓ Edge detection

In a pre-processing stage, deviations not connected to the glaucoma condition are removed from the photographs in order to highlight these desired characteristics in the input data [71-72]. Typically, interference and other phenomena in medical images provide noise that interferes with the process of measuring parameters in images and data gathering systems [73]. Direct image analysis is challenging due to the minute variations in normal and diseased tissues that may exist due to noise and distortions. No uniform illumination causes shading artefacts that reduce the effectiveness of picture analysis.

By comparing the original image to a reference model, pre-processing is a crucial step that lowers image variation [74]. To remove noise from the fundus image and even out the erratic illuminations seen in retinal images, pre-processing is necessary. It aids in lowering both intra- and inter-image variability [75]. In the pre-processing step, which removes disease-independent variations from the input images, pure glaucomatous changes are highlighted [76]. These include

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 5s
DOI: https://doi.org/10.17762/ijritcc.v11i5s.6655
***Article Received**: 02 March 2023 **Revised**: 19 April 2023 **Accepted**: 01 May 2023*

picture acquisition-related abnormalities like uneven lighting or various ONH localizations as well as retinal features unrelated to glaucoma, including the blood vessel tree [77]. Various pre-processing methods for glaucoma detection are shown in Figure 7.

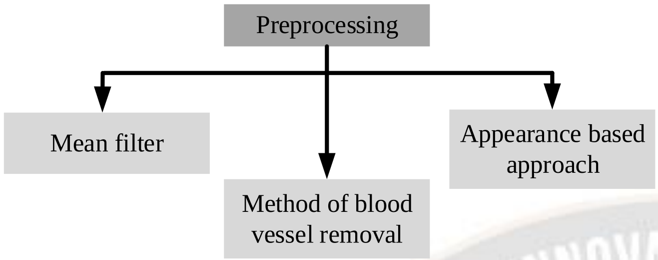

Figure 7: Pre-processing Methods for Glaucoma Detection

Accurate extraction of the optic disc's outline is challenging due to the blood veins that run along it. Since glaucoma disease only slightly affects blood vessels, blood vessels must be excluded from fundus pictures. An extraction of the blood vessels is followed by in painting of the removed blood vessels. The process of filling in a portion of an image based on information outside the portion is known as image in painting. Large areas of the rim are hidden by the major blood artery branches ascending from the optic nerve head (ONH), and their presence complicates study of the visible portions of the ONH. Due to this, OD segmentation may not be as accurate. In order to remove these blood vessel features after blood vessel extraction and before further processing, in painting technique is used.

The region covered by the mask is painted, and the removed blood vessels serve as a mask. The vessel regions in this approach are filled iteratively, layer by layer, from the outside in while the missing pixels receive a weighted average of the nearby values that are already known. Blood vessels can be removed from fundus images using morphological techniques as well. To eliminate the blood vessels, morphological closing via dilatation and erosion is used. The optic disc and blood vessels in the fundus images can be retrieved via image processing [78-79]. These characteristics can give us information that will help us diagnose glaucoma. To segment blood vessels and spatially in paint them to a vessel free image, an appearance based method was implanted in [80]. A vessel-free image following pre-processing is shown in Figure 8.

Figure 8: Vessel in painting on coloured fundus pictures

The main goal of improvement is to transform an image in such a way that the outcome is better than the original image for a certain use. Therefore, methods or strategies for image enhancement may be determined by the specific application. An image's brightness and contrast can be changed to enhance image quality, which is a little more difficult. Calculating a contrast correction factor is the first step.

The precise contrast enhancement itself must be done as the next step. The contrast properties of an image can be changed using a variety of digital processing techniques. The process of taking out noise from an enhanced image is called noise reduction. Image noise removal is one objective in a way that the original picture is preserved discernible. Pre-processing was carried out in [81] utilising a blood vessel removal method. Mean filters were employed in [82] for OCT image pre-processing, which included colour convention, image scaling, and noise removal from the raw image. The three-step pre-processing procedure used to minimise noise is shown in Figure 9.

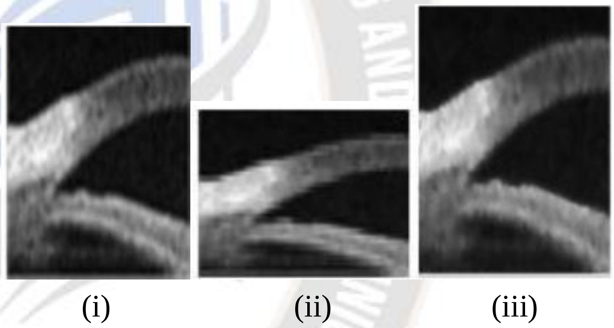

Figure 9: Pre-processing of image. (i) Original image. (ii) Resize image. (iii) Filter image

B) Feature extraction

The most significant and delicate activity is feature extraction**.** System accuracy is mostly dependent on feature quality. To improve the accuracy and efficiency of the glaucoma detection procedure, various automated feature extraction approaches are applied. Different feature extraction methods employed in the glaucoma detection process are shown in Figure. 7. To identify features such as median, mean, and variance, the moment method approach was employed [83]. In [84] variety of extraction techniques, such as the Pixel Intensity Value, Textures, FFT Coefficients, and Histogram Model [85], to detect features like brightness, translation invariance, papilla rim, and cup size are employed.

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 5s
DOI: https://doi.org/10.17762/ijritcc.v11i5s.6655
***Article Received**: 02 March 2023 **Revised**: 19 April 2023 **Accepted**: 01 May 2023*

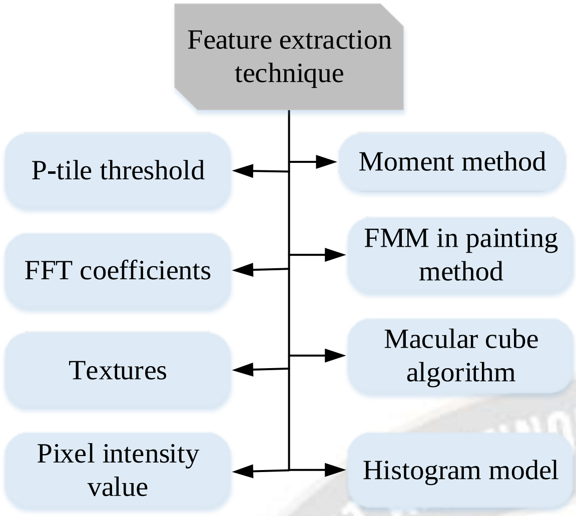

Figure 10: Techniques for Feature Extraction in the Diagnosis of Glaucoma

To identify properties like colour and shape in [86], the P-tile threshold approach was utilised. Using the Macular Cube method, [87] characteristics such macula thickness were extracted. To identify features such cup to disc ratio, neuroretinal rim configuration, and vascular distribution information in [88], sequential FMM in painting method modules were designed. Figure 10 depicts the techniques for feature extraction in the diagnosis of Glaucoma.

C) Feature selection

The process of choosing a subset of pertinent features to be used in model creation is known as feature selection. Various feature selection methods for glaucoma detection are shown in figure 11. In [89], 50 and 34 out of 508 dimensions were found using the Wilcoxon rank sum hypothesis testing feature selection technique. In [90], 30 out of 970 dimensions were identified using the Principle Component Analysis (PCA) approach. According to [91], 29 out of 254 dimensions were found using wrappers and filters.

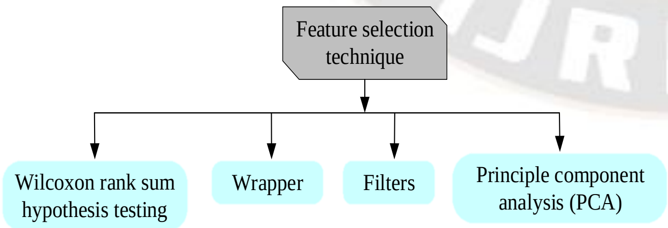

Figure 11: Techniques for Feature Selection in Glaucoma Detection

D) Segmentation

There are several algorithms available for the recognition of various structures such blood vessels, the optic disc, and the macula. Segmenting blood vessels aids in the diagnosis and management of ophthalmologic disorders. The retinal vessels' cross section exhibits Gaussian-shaped variations in grey levels [92]. As a result, blood vessel segmentation is done using a matching filter [93]. The blood vessels are extracted using density analysis in [94]. The segmentation algorithms' performance still needs to be enhanced for better diagnosis. The information present in the blood vessels is captured using wavelet-based techniques in [95] in various sub bands. The removed blood vessels are depicted in Figure. 12.

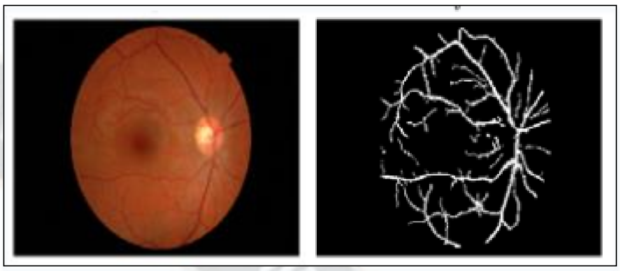

Figure 12: Blood vessel extraction

E) Classification for detecting glaucoma

A crucial computer vision problem that is essential to contemporary technology is image classification. It entails selecting a label or tag from an existing database that was built during training, and applying it to the entire image. On the surface, the procedure appears straightforward, but in reality it includes examining each every pixel in the image to choose the best label for the entire image. The identification of glaucoma involves a variety of image enhancing techniques. The outcomes of the classifiers are used to quantify how well each image-based feature extraction technique can distinguish between glaucoma and non-glaucoma instances.

When the underlying separation model of a classifier closely matches the distribution of the sample data, good results are obtained. We examined many classifiers as the underlying data distribution was unknown. Sensitivity, specificity, and accuracy of these methods for image enhancement have been calculated by employing various classifiers as they are applied to the images. There are numerous methods for classifying data, including support vector machines [96], convolutional neural networks [97] and so on.

F) Glaucoma detection and prediction

Glaucoma detection and prediction is the final stage of an image processing technique. If the patient has glaucoma or not, the final prediction is made at this stage based on the output image. Most cases of early or irreversible blindness are caused by glaucoma [98]. Glaucoma affects around 4% of adults over the age of 40. Most individuals do not recognise they have the disease because there are no symptoms until there are clear indicators of vision loss [99]. It is a neurodegenerative condition that is considered to be the cause of blindness.

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 5s
DOI: https://doi.org/10.17762/ijritcc.v11i5s.6655
***Article Received**: 02 March 2023 **Revised**: 19 April 2023 **Accepted**: 01 May 2023*

Degeneration of the nerves is an irreversible process, hence it causes permanent eyesight loss [100-101]. The only way to prevent total vision loss is by early detection and prediction of glaucoma that can protect and contribute timely options for doctors to choose effective treatment plans. Figure 13 depicts the glaucoma detection and prediction techniques.

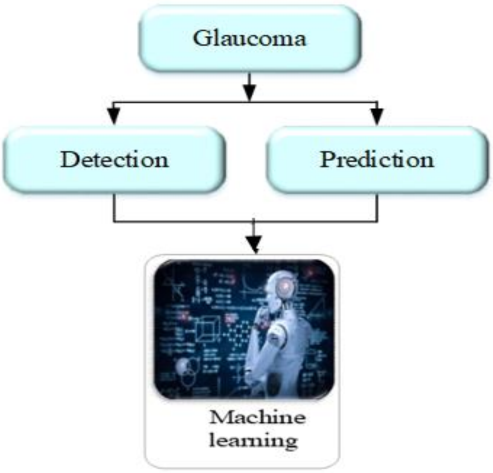

Figure 13: glaucoma detection and prediction technique

IV. GLAUCOMA DETECTION AND PREDICTION USING MACHINE LEARNING TECHNIQUES

Its importance for glaucoma diagnosis and prediction has been shown by the development of new technologies. In this sense, machine learning (ML) methods have shown to be crucial for successful study outcomes. However, the key component of this strategy is the automated task resolution by an intelligent computational system [102]. Images are one sort of data that may be analysed using machine learning (ML), which automates the process of building analytical models [103].In developed glaucoma diagnosis and prediction systems, ML-based methods predominate. The system's success only hinges on how well the classification algorithm used to categorise newly discovered medical images of normality and abnormality performs. Numerous studies have utilised different ML methods to detect and predict glaucoma.

A) Glaucoma detection using machine learning techniques

Zvia et al. [104] examined the application of machine-learning classifiers enhances the detection of glaucoma using OCT. Additionally, the following machine learning classifiers were examined: Support vector machine (SVM), recursive partitioning, and regression tree (RPART). To evaluate the effectiveness of this grading system to currently used measures in assessing glaucoma progression the performance of sensitivity, specificity and accuracy were determined. There was a drawback that if age was a parameter in the machine learning model, it may unfairly affect the results and override the parameters generated by the OCT. The small sample size in our study was another drawback. The results when employing all 38 OCT output data parameters may be impacted by this.

Dey and Bandyopadhyay [105] introduced a unique technique for glaucoma detection utilising digital fundus images. The features were extracted from pre-processed pictures using the PCA approach. In order to train a Support Vector Machine (SVM) classifier, the changed images are fed into it after PCA. This study had two-class prediction problem, normal, healthy eye fundus photos will fall under one class (let's call the positive class), and glaucoma-affected eye fundus images will fall under a different class (say negative class).

Chao-Wei et al. [106] aimed to evaluate performance of Spectral is OCT parameters on glaucoma detection using the SVM classification approach. Our results showed that the SVM technique combined with all OCT features had good performance in detecting the area under the curve of glaucomatous eyes as well as discriminating early, moderate, or severe glaucoma and normal eyes. The study does have certain restrictions. First, people with glaucoma from clinics serve as the typical study population. Additionally, there is a big age difference between the normal group and the glaucoma group in our study individuals. A potential drawback of this study is that the per papillary retinal nerve fibre layer, macula, and optic head OCT data may be influenced by ageing.

Dheeraj et al. [107] revealed quasi-bivariate variational mode decomposition (QB-VMD) from digital fundus pictures, a new and more precise technique for automated glaucoma identification is given. Singular value decomposition (SVD) is applied to all of the chosen characteristics to minimise their dimensionality. Radial basis function (RBF)-based LS-SVM classifier is fed with robust features. For ten FCV, the measured accuracy, sensitivity, and specificity are, 86.13, 84.80, and 87.43 % correspondingly. Glaucoma detection accuracy increased by the PM to 86.13 %. Future proposals may include automated glaucoma identification for big databases with multistage glaucoma utilising deep learning.

Compact variational mode decomposition (CVMD) using fundus pictures Kirar and Agrawal [108] offered as a revolutionary fully variational and adaptable computer based glaucoma diagnostic method. SVM classifier are used to normalise and classify the extracted features. For tenfold cross validation, the resulting accuracy, sensitivity, specificity, precision, and F-measure are 89.18 %, 90 %, 85 %, 93.34 %, and 89.34 %, respectively. The suggested methodology needs to be tested on a large image database. There are numerous uses for it. Diabetes, retinopathy, ovarian cancer, and other illnesses fat in the liver and cancer.

Raghavendra et al. [109] introduced a non-parametric GIST descriptors and optic disc localization to suggest a potential

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 5s
DOI: https://doi.org/10.17762/ijritcc.v11i5s.6655
***Article Received**: 02 March 2023 **Revised**: 19 April 2023 **Accepted**: 01 May 2023*

method for detecting glaucoma. Followed by a novel area-based optic disc segmentation, the Radon transformation is proposed by the approach (RT). The effectiveness of the suggested model was assessed using an effective SVM classifier. We hope to create a deep learning model in the future using a variety of datasets that contain photos of early, moderate, and severe glaucoma. We intend to expand the use of this method to identify more retinal illnesses, such as age-related macular degeneration, maculopathy, diabetic retinopathy, and retinal detachment.

Rahul et al. [110] anticipated a nonlinear technique for automated glaucoma detection. The detailed information provided in the fundus image is easily captured utilising an automated detection approach based on nonlinear higher order statistics (HOS). On fundus imaging, the bispectrum and bicepstrum centre slice is applied. The diagonal of these centre slices is used to derive a number of characteristics. The location sensitive discriminant analysis (LSDA) data reduction approach is used to reduce the number of features. SVM classifier with multiple kernels is fed with the ranking LSDA features for automated glaucoma identification. Using the whole private and public databases, the suggested approach produced classification accuracy of 98.8% and 95%, correspondingly. Future research can expand on this work to detect glaucoma early and other eye conditions including cataract and retinopathy.

Rao et al. [111] proposed a method that glaucomatous images are identified by analysing structural and energy characteristics. These significant textural energy features were discovered by applying energy distribution over the cup to disc ratio. The ANN techniques Normal datasets are used to train Naive Bayes and Multilayer Perceptron (MLP) and Back Propagation (BP). With 89.6% accuracy, Bayes classifies the images in the database. With 97.6% accuracy, the MLP-BP. ANN algorithm identifies the photos in the database. Future upgrades to the device could use artificial intelligence to classify other eye problems.

Tatsuya et al. [112] introduced measurements made with the "Random Forests" technique for spectral domain OCT (SD-OCT). SD-OCT was performed on 126 people's eyes in total OAG patients and 84 healthy people's 84 eyes. Then, by the OCT characteristics of 151 people, including thickness measurements of the macular RNFL (mRNFL), circumpapillary RNFL (cpRNFL), and the combination ganglion cell layer-inner plexiform layer (GCIPL), to discriminate between eyes with glaucoma and healthy eyes, the Random Forests method was applied. The absence of eyes with high myopia from the analysis is one drawback of the current study. The fact that disc metrics, such rim area and vertical cup/disc ratio, were left out of the Random Forests classifier limits the current study's ability to make accurate diagnoses.

Lamiaa. [113] suggested a real-time screening systems to use a wavelet-based glaucoma detection algorithm. To evaluate whether a retinal image is healthy or glaucomatous, a mix of wavelet-based statistical and textural information derived from the detected optic disc region is used. The (K-nearest neighbour's algorithm) KNN classifier was used in the proposed strategy to attain an accuracy of 96.7 %. Future research will evaluate the significance of additional wavelet-based statistical and textural variables to enhance the glaucoma detection method's performance.

Vimal et al. [114] introduced for the diagnosis of glaucoma (GLCM), a grey level co-occurrence matrix method, and CNN clustering are used to complete the classification. Glaucoma detection is solely based on optic CDR estimate. Accuracy obtained was 99.24%. The dynamic evolution of the cup can be depicted in the future using a variety of characteristics, including rim-to-disc ratio, neuroretinal zone, level CDR, and neuroretinal rim width. Using 3D simulation, glaucoma's depth of development can be controlled. Using the zone level values, an accurate prediction can be made in the future.

Javeria et al. [115] focused on using CDR to automatically detect glaucoma in fundus images. For the purpose of detecting the optic disc and optic cup, the region of interest (ROI) is extracted using the intensity weighted centroid approach, pre-processing, and recursively applying k-mean clustering segmentation (OD). The accuracy for glaucoma using the suggested technique is 92 %, while the mean square error for CDR is 0.002. Utilizing OCT pictures, this study can be expanded in the future.

Shetty and Gutte. [116] suggested an approach to separates the optic cup from the optic disc by clustering different parts of the image according to their colour using K-means clustering algorithm (KMC). Lastly, glaucoma is detected using the fractal dimension value obtained from the perimeter algorithm. The suggested algorithm accurately distinguishes between the healthy eye and the eye with glaucoma with a 92 % accuracy. Future applications of this technique include the identification of diabetic retinopathy.

The Simple Linear Iterative Clustering (SLIC) algorithm and KMC for glaucoma detection Mahalakshmi and Karthikeyan. [117] proposed as a method to segment the optic disc and optic cup. When a patient's CDR number reaches 0.6, the ophthalmologist should be consulted for additional patient investigation. By preventing additional eyesight degeneration through prompt medical intervention, this will benefit patients around the world. In the future, we can raise the patient count and evaluate the effectiveness.

Kowsalya et al. [118] presented a method for inspecting images to extract the ROD and assess its glaucoma state. Here, a technique that combines. The removal of the optic disc region from the RGB retinal image is examined using the Firefly

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 5s
DOI: https://doi.org/10.17762/ijritcc.v11i5s.6655
***Article Received**: 02 March 2023 **Revised**: 19 April 2023 **Accepted**: 01 May 2023*

Algorithm, KMC, and Kapur's entropy. Optic disc segmentation is used in the DRIVE database first, and then the RIM-ONE dataset. The suggested technique results in terms of sensitivity, specificity, accuracy RIM-ONE. As a result, clinics may decide to review real-time medical retinal scans in the future.

KMC and the Hough Transformation have been presented Kavya and Padmaja. [119] as a technique to extract the OD for detection of glaucoma. Through the GLCM and Markov Random Field methods, the features are retrieved. Using SVM, the fundus images are divided into the glaucoma and normal classes based on the features extracted. The various feature combinations and raw image quality affect the segmentation and classification's accuracy 86% was achieved by this technique. The quantity of images used to train the SVM affects its accuracy. Understanding the data structure and correctly mapping the class label present the most hurdle.

Chalinee et al. [120] described a technique for automatically calculating the CDR from no stereoscopic retinal fundus pictures produced with a non-mydriatic auto fundus camera, the NIDEK AFC-230. To compare the performance of the determined CDR to the clinical CDR, a set of 44 retinal pictures from Mettapracharak Hospital in Nakhon Pathom, Thailand, were employed. It was discovered that our suggested technique offers 89 % accuracy in the determined CDR findings. The next steps for this project are to improve the cup segmentation method's performance by incorporating a vessel detection and vessel inpainting method.

Antonio et al. [121] provided two automatic techniques for measuring glaucoma and delineating the OD. The Otsu and k-means algorithms, which were used for delineating the region of the optic disc, provide the foundation for the proposed methods. Results from the methodology were encouraging. The Otsu algorithm produced findings that, in the best scenario, had 100% sensitivity, 99.3% specificity, 99.6% accuracy, and a ROC curve of 0.996. Lastly, it is anticipated that the suggested techniques can be included into a computer-aided diagnosis tool to be used in actual situations and can offer a second opinion to a subject matter expert.

Kavitha and Duraiswamy. [122] presented an automated glaucoma detection system using computer-aided fundus pictures. Based on the pallor of fundus images, a novel colour modelling technique, the OC to disc border is proposed to be distinguished using KMC. The fuzzy inference algorithms of adaptive neuro fuzzy inference systems (ANFIS) combine approximate reasoning with the learning capabilities of neural networks. In terms of classification accuracy and convergence speed, the suggested method's performance is contrasted with that of neural networks and SVM classifiers. According to a predetermined clinical procedure, the proposed system can be used for efficient screening in neighbourhood health fairs and can be integrated with current ophthalmologic tests, clinical evaluations, and other risk factors.

T.R. Kausu et al. [123] proposed a model based in population-based glaucoma screening, the evaluation of the optic nerve head using fundus pictures is more advantageous than the evaluation of elevated intraocular pressure. Based on time-invariant feature cup to disc ratio and anisotropic dual-tree complex wavelet transform features, this paper offered a novel approach for glaucoma identification. Fuzzy C-Means clustering is used for optic disc segmentation, and Otsu's thresholding is employed for optic cup segmentation. When compared to earlier research, the results demonstrate that the use of a multilayer perceptron model, the suggested strategy achieved a sensitivity of 98 % and an accuracy rate of 97.67 %.

Mohammed et al. [124] proposed a technique in a reliable way to locate the OD and OC on colour fundus pictures for glaucoma detection using the improved chaotic imperialistic competition algorithm (ICICA). The publicly accessible RIGA dataset was used to assess the performance of the suggested technique. It was discovered that the suggested approach can address some of the KMC algorithm's common issues to produce better outcomes. The final findings were compared with those of KMC using the RMSE parameter in order to assess the efficacy of the suggested approach. The main drawback of the proposed method was less accuracy while in the classification.

Gosh et al. [125] presented a system based on the Grid Color Moment method as a feature vector to extract the colour data and a neural network classifier. Therefore, for automated diagnosis, these features are added to the classifier of the back propagation neural network (BPNN). The suggested approach was evaluated using an open RIM-ONE database with exact gold standards of the optic nerve head. This study categorises photographs of normal and abnormally defective retinas with glaucoma. The accuracy of the experimental results was 87.47 %. As a result, the suggested approach has good accuracy in detecting the early stages of glaucoma.

Arwa et al. [126] presented an algorithm for detecting glaucoma in this article is based on the study of digital fundus pictures utilising RNFL texture feature (coarseness) identified by ensemble RUSBoosted tree classifier. The accuracy of the suggested method was 89.5 %. Future research is advised to create a comprehensive, integrated, automated system to categorise all varieties of glaucoma that may be utilised for follow-up and evaluate various aspects to enhance accuracy and test various classifiers.

Maheswari et al. [127] described a technique for an automated glaucoma diagnosis utilising digital fundus pictures. For image decomposition, the iterative variational mode decomposition (VMD) approach is used. From VMD components, a number of properties are retrieved, including

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 5s
DOI: https://doi.org/10.17762/ijritcc.v11i5s.6655
Article Received: 02 March 2023 Revised: 19 April 2023 Accepted: 01 May 2023

fractal dimensions, Yager entropy, Renyi entropy, and Kapoor entropy. The discriminatory features are chosen using the ReliefF algorithm, and the least squares SVM (LS-SVM) uses these features to classify the data. Utilizing three-fold and ten-fold cross-validation procedures, our suggested method produced classification accuracy rates of 95.19 % and 94.79 %, respectively. Using fundus images, this approach can help ophthalmologists confirm their manual classifications of classes (glaucoma or normal). The performance of the system with large diversified databases, which is a shortcoming of the suggested work.

Raja et al. [128] developed a technique for glaucoma identification employing the best hyper analytic wavelet transform (OHAWT). The procedure involved pre-processing the images, selecting the best transformation, extracting the features, and then classifying the data. To extract features from OHAWT components, pre-processed and altered input fundus images were used. To SVM, robust characteristics were added. 85 % accuracy was claimed utilising 169 pictures. Less detection accuracy was considered as the limitation of this work.

Kolar et al. [129] presented a technique by combining fractal dimensions (FDs) and power spectral characteristics a glaucoma detection system. Different images produced by FDs were given to the SVM with a split test, leaving out one method for results validation. The stated accuracy for 60 images from the local data set was 74.9 %. Less accuracy was the limitation of this technique.

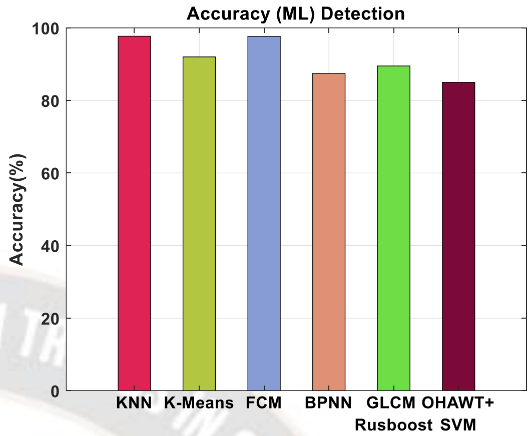

Figure 14: Performance analysis of accuracy parameter for ML detection techniques

Figure 14 depicts the accuracy obtained from different detection technique used in ML. From the graph it is clearly understand that KNN has the higher accuracy value of 97.7%. The obtained accuracy of K-means, FCM, BPNN, GLCM+Rusboost and OHAWT+SVM has the accuracy of 92%, 97.67%, 87.47%, and 89.5% respectively. The comparison table for glaucoma detection using machine learning technique is tubulised in table 2.

TABLE 2: GLAUCOMA DETECTION USING ML TECHNIQUE

Author	Summary	Technique	Objective	Performance	Merits	Demerits/ Research Gap
Zvia et al. [104]	• The use of automated machine classifiers on OCT data could help make this method more effective at spotting glaucomatous abnormalities.	SVM	• The purpose of this study is glaucoma detection using machine-learning classifiers • The technique used to enhances the detection of glaucoma using OCT.	Accuracy, Sensitivity, Specificity	High accuracy	Small sample size
Dey and Bandyopadhyay [105]	• This technique is intended to aid medical professionals in their decision-making regarding the diagnosis of glaucoma.	SVM and PCA	• This technique used to analyse glaucomatous eye and healthy eye • An image processing techniques is employed in digital fundus images of the eye.	Accuracy	Computational efficiency is high	Classification accuracy is less
Chao-Wei et al. [106]	• The use of SVM with Spectralis OCT demonstrates good diagnostic ability in identifying glaucomatous from healthy eyes.	SVM	• With the help of the SVM classification method, the ability of the Spectralis OCT parameters to diagnose glaucoma in our population by examining their diagnostic potential.	AUC	The Taiwanese population shows promise in the treatment of glaucoma	To provide more accurate and reliable estimates for glaucoma diagnosis, larger sample sizes are required.

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 5s
DOI: https://doi.org/10.17762/ijritcc.v11i5s.6655
***Article Received**: 02 March 2023 **Revised**: 19 April 2023 **Accepted**: 01 May 2023*

Dheeraj et al. [107]	• Fundus images from the input are first pre-processed • Then QB-VMD is used to separate the pre-processed images into QB-VMD SBIs. • Radial basis function-based LS-SVM classifier is fed with robust features.	QB-VMD and SVM	• QB-VMD using digital fundus images is used to automatically detect glaucoma.	Accuracy, sensitivity, and specificity	More suitable method to increase the accuracy of glaucoma detection	Future proposals may include automated glaucoma detection for big databases with multistage glaucoma.
Kirar and Agrawal [108]	• From the digital fundus images, the green channel image is recovered and decomposed with CVMD. • For tenfold cross validation with kernel parameter = 2 and 13 features, the achieved classification accuracy is higher.	CVMD and SVM	• CVMD using fundus pictures is suggested as a method for adaptive computer-based and fully variational glaucoma detection.	Accuracy, sensitivity, specificity, precision, and F-measure	Sub band images feature have no noise or interference, a narrow fourier bandwidth, smooth boundaries, a defined direction, and oscillatory characteristics.	The suggested methodology needs to be tested on a large image database
Raghavendra et al. [109]	• Developed model used 1000 fundus images • Achieved the highest accuracy using private dataset. • Model can predict glaucoma in its early stage as it achieves maximum sensitivity	SVM	• Introduced a non-parametric GIST descriptors and optic disc localization to suggest a potential method for detecting glaucoma	Accuracy, sensitivity, specificity	Efficient and computationally less expensive	We intend to expand the use of this method to identify more retinal illnesses
Rahul et al. [110]	• A data reduction approach is used to reduce the number of features needed for automated glaucoma identification. • SVM classifier with multiple kernels is fed with the ranking LSDA features for automated identification.	SVM	• Presented a novel nonlinear technique for automated glaucoma detection	Accuracy	Higher classification accuracy	Early glaucoma detection is not possible
Rao et al. [111]	• In this study, energy distribution over cup to disk ration were applied to find important texture energy features for glaucomatous images. • These energy features are applied to BPNN for effective classification by considering normal subjects extracted energy features.	ANN and MLP-BP	• Proposed a method that glaucomatous images are identified by analysing structural and energy characteristics.	Accuracy	Better accuracy	It cannot be applicable in telemedicine purpose
Tatsuya et al. [112]	• Glaucoma and healthy eyes were distinguished using the Random Forests method. • The thickness of the circumpapillary	Random forest classifier	• Introduced measurements made with the RF technique for SD-OCT	Sensitivity, Specificity	Technique was found to considerably increase SD-capacity OCT's to distinguish	The absence of eyes with high myopia from the analysis is one drawback

	retinal nerve fibre layer, the macular RNFL, and the combined ganglion cell layer-inner plexiform layer were measured using 151 OCT features.				between healthy and glaucoma-affected eyes.	
Lamiaa. [113]	• Researchers have proposed a real-time screening system to use a wavelet-based glaucoma detection algorithm. • The KNN classifier was used to attain an accuracy of 97.7 %.	KNN classifier	• Suggested a real-time screening systems to use a wavelet-based glaucoma detection algorithm	Accuracy-97.7%	Computationally inexpensive	In order to enhance the efficacy of the glaucoma detection technique, future work will investigate the value of additional wavelet-based textural and statistical aspects.
Vimal et al. [114]	• Finding or detecting abnormalities on the retinal image early on is incredibly difficult and time-consuming for ophthalmologists. • This approach encourages the employment of a methodology that combines manual elements with deep learning in an Equal ratio.	KMC and GLCM	• For the diagnosis of glaucoma GLCM, a grey level co-occurrence matrix method, and CNN clustering are used to complete the classification.	Accuracy, sensitivity, specificity	Accurate segmentation and classification	Using the zone level values, an accurate prediction can be made in the future.
Javeria et al. [115]	• For the purpose of detecting the OD and OC, the ROI is extracted using the intensity weighted centroid approach • Pre-processing, and recursively applying KMC segmentation.	K-means clustering	• Focused on using CDR to automatically detect glaucoma in fundus images	Accuracy MSE	More reliable and accurate	Utilizing OCT pictures, this study can be expanded in the future.
Shetty and Gutte. [116]	• The proposed work segments the optic cup which is distinct from optic disc by clustering various portions of the image based on its color using KMC for the detection of glaucoma.	K-means clustering	• Suggested an approach to separates the OC from the OD by using KMC algorithm for the glaucoma detection	Accuracy-92%	Accurately distinguishes between the healthy eye and the eye with glaucoma	Future applications of this technique include the identification of diabetic retinopathy
Mahalakshmi and Karthikeyan [117]	• Method to segment OC and OD using SLIC for glaucoma detection are proposed. • OC and OD are then used to compute the CDR for screening patients with the condition.	SLIC and KMC	• The KMC for glaucoma detection and the SLIC algorithm were recommended for segmenting the OD and OC.	CDR ratio	The retinal fundus camera image can identify glaucoma in early stage	Less efficient
Kowsalya et al. [118]	• The OD region of a retinal image is an important area for studying how the brain processes light.	KE, K-means and FA	• Introduced a method for inspecting images to extract the ROD and assess its glaucoma state.	Accuracy, sensitivity, specificity	Achieving the superior statistical and image similarity values.	Clinics may decide to review real-time medical retinal scans in the future

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 5s
DOI: https://doi.org/10.17762/ijritcc.v11i5s.6655
***Article Received**: 02 March 2023 **Revised**: 19 April 2023 **Accepted**: 01 May 2023*

	• Here, a technique that combines KE, KMC, and FA is studied for extracting the OD out from RGB retinal images.					
Kavya and Padmaja [119]	• It uses different features like GLCM and MRF to segment them. • The algorithm increases by applying the technique on region of interest.	GLCM, MRF and SVM	• KMC and the Hough Transformation have been presented as a technique to extract the optic disc for detection of glaucoma	Accuracy	The texture features clearly depict the differences between images of health and disease.	The key difficulty is correctly mapping the class label to the data structure.
Chalinee et al. [120]	• In this study, we have presented a method to calculate the CDR automatically from fundus images. • The performance of our approach is evaluated using the distance between the calculated CDR and manually graded CDR.	K- means, Canny algorithm	• Described a technique for automatically calculating the CDR from no stereoscopic retinal fundus pictures • Produced with a non-mydriatic auto fundus camera, the NIDEK AFC-230	Accuracy-89%	Simple to understand	Less accuracy
Antonio et al. [121]	• The findings could be included in a computer-aided diagnosis tool that can offer a second opinion to a subject matter expert, they say. • It is anticipated that the suggested techniques can be used in actual clinical trials.	K-means and OST	• Provided two automatic techniques for measuring glaucoma and delineating the optic disc.	Accuracy sensitivity specificity ROC	Higher accuracy	Computationally expensive
Kavitha and Duraiswamy. [122]	• The OC to OD border is proposed to be distinguished using KMC. • The fuzzy inference algorithms of ANFIS combine approximate reasoning with the learning capabilities of neural networks. • In terms of classification accuracy and convergence speed, the suggested method's performance is superior to that of SVM	ANFIS and K-means	• Presented an automated glaucoma detection system using computer-aided fundus pictures	Accuracy, Convergence time	In order to accurately detect glaucoma, the features considered are clinically significant.	Computationally expesive
T.R. Kausu et al. [123]	• A technique for glaucoma detection based on the cup-to-disk ratio of time-invariant features. • The FCM clustering algorithm was used for optical disc segmentation. Findings show that the suggested technique had a 98% sensitivity and a 97.67% accuracy rate.	FCM	• A technique for diagnosing glaucoma is provided based on anisotropic dual-tree complex wavelet transform features and time-invariant cup-to-disc ratio data. • Otsu's thresholding is utilised for optic cup segmentation, whereas the FCM clustering	Accuracy - 97.67% Sensitivity- 98%	Higher accuracy	Other eye diseases such diabetic retinopathy, macular edoema, and retinal haemorrhage can be detected using the approach in future.

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 5s
DOI: https://doi.org/10.17762/ijritcc.v11i5s.6655
Article Received: 02 March 2023 Revised: 19 April 2023 Accepted: 01 May 2023

			method is employed for optic disc segmentation.			
Mohammed et al. [124]	• This approach can address some of the K-means clustering algorithm's common issues to produce better outcomes. • The effectiveness of the proposed strategy was evaluated by comparing the end results with those of K-means clustering using the RMSE parameter.	K-means and ICICA	• Proposed a technique in a reliable way to locate the OD and OC on colour fundus pictures for glaucoma detection using the ICICA.	AccuracyRMSE	Simple to understand and implement	The main drawback of the proposed method was less accuracy while in the classification.
Gosh et al. [125]	• This work proposes an automated system based on both Grid colour Moment method and a feature vector to extract the color features (non-morphological) and neural network classifier. • Features are fed to the BPNN classifier for automated diagnosis of glaucoma.	BPNN	• Proposed a narrative automated glaucoma diagnosis and classification system • A neural network classifier and feature vector based on the Grid Color Moment method are used to extract nonmorphological colour features.	Accuracy-87.47%	Early stage glaucoma detection is possible	Noise may lead to undesired final result
Arwa et al. [126]	• The method was tested on a set of158 images composed of 118 healthy retina images and 40 glaucomatous images. • This algorithm uses texture analysis based on co-occurrence matrix and Tamara features to detect the presence or absence of eye blemishes.	GLCM RUSboost.	• Presented an algorithm for detecting glaucoma. • This article is based on the study of digital fundus pictures utilising RNFL texture feature (coarseness) identified by ensemble RUSBoosted tree classifier	AUC-93% Accuracy-89.5%	Higher accuracy for glaucoma detection	Future research is advised to create a comprehensive, integrated, automated system to categorise all varieties of glaucoma that may be utilised for follow-up and evaluate various aspects to enhance accuracy and test various classifiers
Maheswari et al. [127]	• Images are processed by a machine that uses the least squares support vector machine (LS-SVM) to classify them. • The discriminatory features are chosen using the ReliefF algorithm. • Images are analysed for fractal dimensions, Yager entropy, Renyi entropy, and Kapoor entropy.	LS-SVM, VMD and 2D-EWT	• Suggested a technique for automatic glaucoma detection. • To shorten the computation time and produce photos with the same dimensions, all 505 input photographs were scaled and pre-processed.	Acccuracy Sensitivity Specificity	Effective feature extraction technique is used	The performance of the system 270 may suffer with large, diversified databases, which is a shortcoming of the suggested work.
Raja et al. [128]	• The procedure involved pre-processing the images, selecting the best transformation, extracting the features, and then classifying the data.	OHAWT and SVM	• Developed a technique for glaucoma identification employing the best OHAWT	Accuracy-85%	Easy to implement	Less detection accuracy

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 5s
DOI: https://doi.org/10.17762/ijritcc.v11i5s.6655
***Article Received**: 02 March 2023 **Revised**: 19 April 2023 **Accepted**: 01 May 2023*

	• 85 percent accuracy was claimed utilising 169 pictures.					
Kolar et al. [129]	• Split testing was used to feed various FD-generated images to the SVM while excluding one approach for validation.	SVM	• Presented a technique by combining fractal dimensions (FDs) and power spectral characteristics as a glaucoma detection system	Accuracy-74.9%	Less computational time	Less accuracy

B) Glaucoma prediction using machine learning technique

Sally et al. [130] presented For 385 POAG patients from a single academic institution, models were created using structured EHR data using a multivariable logistic regression (MVLR), random forests (RF), and artificial neural networks (ANN). For each model, the Youden Index, sensitivity, specificity, and mean area under the receiver operating characteristic curve (AUC) were determined to assess performance. We found and interpreted the systemic variables influencing the predictions. This strategy offers a chance for the development of automated risk prediction within the EHR based on systemic data to support clinical decision-making in the future.

Koichiro et al. [131] developed a classifier based on OCT measurements to predict the VF impairment in glaucoma suspects using Random Forest (RF) algorithm. Individual decision tree AROCs, GCL+IPL, rim area, m-RNFL, and cp-RNFL were all notably lower than the overall AROC from the RF classifier. Deficiency of a normative population to serve as a benchmark was this study's primary flaw.

A method developed by Shuldiner et al. [132] that uses a preliminary VF test and a ML algorithm to identify eyes that would develop glaucoma quickly. The neural network model was also trained utilising age, summary measures, reliability metrics, and point-wise threshold data. When trained on initial VF data, rapid progression was foreseen by the SVM model. It may be possible to forecast patients who are most likely to advance quickly with even greater accuracy by adding more clinical data to the existing model is the future scope.

The use of ML and elastic net logistic regression (ENR) Kouros Nouri-Mahdavi et al. [133] used RNFL and GCIPL thickness as well as RNFL and GCIPL change rates at the central 24 superpixels and three eccentricities to forecast the development of VF. Several ML models, such as Naive Bayes, RF, and SVM, were explored, and the model with the highest AUC was chosen. We showed that baseline and longitudinal structural data can accurately confirm or predict the evolution of functional glaucoma with clinically significant precision. If our methods are further improved, doctors may have access to an invaluable tool for predicting functional development and making treatment decisions in glaucoma.

Eswari and Balamurali. [134] introduced a machine learning model, an intelligent prediction system is created to predict glaucoma. Bayesian optimization support vector machine (BOSVM) is integrated into a local real-time dataset of diabetic people in this proposed system, and it accurately predicts glaucoma with 96.6 %, 0.83 in the AUC for the training set, and 97.3 % accuracy with 0.943, 0.951, and 0.943, 0.951 of sensitivity and specificity. This model will soon be used with a sizable real-time dataset and numerous classifiers in place of binary classifiers.

Sharifi et al. [135] proposed a ML method for predicting glaucoma and identifying its risk factors. The Cross-Industry Standard Process for Data Mining (CRISP-DM) methodology is used to create the data analysis pipeline for this project. Several machine learning models, including as Bagging Ensemble, Decision Trees (DTs), K-Nearest Neighbors (K-NN), SVM, RFs, and Extra Trees (ETs), were developed for the classification step of predicting glaucoma. Utilizing longitudinal data gathered over a 5-year period, we may predict future glaucoma trends and changes in cohort study participants.

Two Kalman filters (KF) were constructed Mohammed et al. [136] to forecast mean deviation (MD) and pattern standard deviation values 36 months in the future for patients with OAG and glaucoma suspects: Both a KF with tonometry and perimetry data (KF-TP) and a KF with tonometry, perimetry, and global RNFL data (KF-TPO) were used. Prediction accuracy (proportion of MD values predicted within the 95% repeatability interval) across the models, differences. There are a few restrictions on our study. The first is that higher sample sizes might improve the performance of our models.

Christopher et al. [137] introduced a model to predict the glaucoma based on relevance vector machine classifier. A Bayesian model called the RVM learning classifier uses Bayesian inference to make probabilistic predictions practise procedure. When the baseline confocal scanning laser ophthalmoscope (CSLO) and standard automated perimetry (SAP) readings were analysed, RVM was better able to predict which eyes would develop glaucoma in the future than the CSLO and SAP global indices. The main drawback of this technique was an overestimation or underestimation of the number of progressors found using this method.

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 5s
DOI: https://doi.org/10.17762/ijritcc.v11i5s.6655
***Article Received**: 02 March 2023 **Revised**: 19 April 2023 **Accepted**: 01 May 2023*

Supriya et al. [138] used a comprehensible, discrete state space model to model and predict longitudinal glaucoma data. A continuous-time hidden markov model (CT-HMM) model, based on the atypical order of temporal data taken during appointments, depicts the continuous change in structural and functional measures. Comparing our results to earlier work that used the average RNFL thickness, we achieve a mean absolute error reduction of 74%.This research will be helpful for precisely predicting the geographic distribution and pace of tissue ageing. Correct intervention based on more precise prognosis may help to advance glaucoma clinical care.

KF algorithm was proposed by Gian- Gabrial et al. [139] to be used in a method for normal tension glaucoma (NTG) prediction. KF is a potential method that can be used to create tailored predictions and learn the future course of the disease in groups of glaucoma patients. We assessed the suggested method's RSME value and prediction error distribution. If the accuracy of our predictions is directly generalizable to patients with NTG living in other nations, more study is required to make that determination.

Elfattah et al. [140] developed a more precise prediction model for the onset of primary ONG due to ocular hypertension using the RF technique. According to experimental findings, the random forest method produced better prediction outcomes, with an overall accuracy of 93%. In future we can extend this work with improving accuracy.

Isaac et al. [141] created a clinical decision support model for glaucoma with an open angle. The provided approach combines supervised learning classification with the results of interacting multiple model Kalman filtering. When the Kalman filtering results were included as extra features in the supervised learning model, the performance area under the curve (AUC) of our model increased by almost 7% (rose from 0.752 to 0.819). Future research may be able to enhance our methodology by including techniques for the disease's dynamic control.

Figure 15 depicts the Performance analysis of accuracy parameter for ML prediction techniques. From the graph it is clearly understand that KF has the higher accuracy value of 95%. The obtained accuracy of BOSVM, KNN, and RFC has the accuracy of 92%, 83.56%, 95%, and 93% respectively. The comparison table for glaucoma prediction using ML technique is tubulised in table 3.

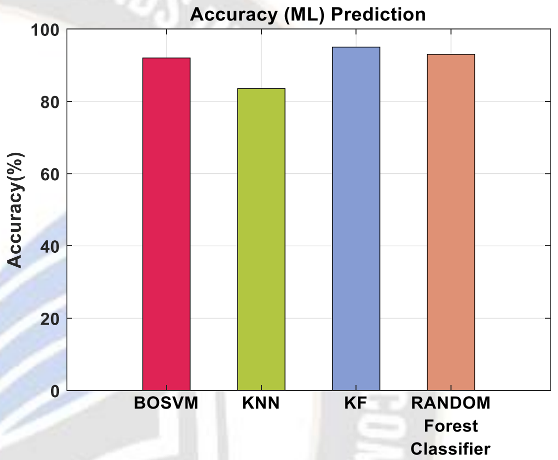

Figure 15: Performance analysis of accuracy parameter for ML prediction techniques

TABLE 3: GLAUCOMA PREDICTION USING ML TECHNIQUE

Author	Summary	Techniques	Objective	Performance	Merits	Demerits/ Research Gap
Sally et al. [130]	• We find and interpret the systemic variables influencing the predictions as well as the individual factors that affect their relative sensitivity and effectiveness.	ANN,MVLR, RF	• To anticipate the need for surgical intervention in individuals with POAG by leveraging systemic data in electronic health records (EHR).	Youden Index, sensitivity, specificity, and AUC	Not appropriate in real time application	Automatic prediction is not possible
Koichiro et al. [131]	• The Random Forest approach of analysing OCT measurements • Gives a precise indication of whether perimetric degeneration is present in glaucoma suspects.	RFC	• Based on OCT measurements, a classifier was developed using the "RF" algorithm to identify VF impairment in glaucoma suspects.	Sensitivity Specificity	Accurate prediction	Lack of a normative population to act as a reference
Shuldiner et al. [132]	• Additionally, age, summary metrics, reliability metrics, and point-wise threshold data were used to train the neural network model.	SVM	• Introduced a technique based on a preliminary VF test, MLA can identify eyes that will develop glaucoma rapidly	Accuracy,AUC	Prediction accuracy is high	Adding more clinical data to the existing model is the future scope

	• The SVM model AUC 0.72 successfully predicted quick development when trained on initial VF data.					
Kouros Nouri-Mahdavi et al. [133]	• Used ML technique to predict the evolution of functional glaucoma with clinically significant precision. • Showed that baseline and longitudinal structural data can accurately confirm or predict the development of glauco-metastasis	Naive Bayes, Random Forests, and SVM	• GCIPL and RNFL change rates at the central 24 superpixels and three eccentricities, together with ENR and ML, were used to predict the progression of VF using baseline circumpapillary RNFL and macular GCIPL thickness.	AUC Precision	Precisely predict the glaucoma	Valuable tool is needed to predict glaucoma
Eswari and Balamurali [134]	• This proposed system uses BOSVM • Given an AUC of 0.83 in the training set, which accurately predicts glaucoma 96.6 % of the time. With respect to sensitivity and specificity, the test had an accuracy of 97.4 %.	BOSVM	• Introduced a machine learning model • An intelligent prediction system is created to predict glaucoma	Accuracy sensitivity, specificity, and AUC	Early prediction of glaucoma possible	Large Real time dataset application is not possible
Sharifi et al. [135]	• For this study, a data analysis pipeline based on the CRISP-DM technique has been created. • Data sampling, pre-processing, classification, assessment, and validation are the pipeline's key steps. • For each stage of the data analysis, various machine learning models were created.	DTs, K-NN, (SVM, RFs, ETs, and Bagging Ensemble techniques	• Outlined a machine learning method model for glaucoma prediction and risk factor identification.	Accuracy - 83.56 Sensitivity - 82.21, Specificity - 81.32, and an AUC -88.54	Simple to understand	We may predict future glaucoma trends and changes in cohort study participants
Mohammed et al. [136]	• There are two KFs: one with KF-TP, and the other KF-TPO. • Prediction accuracy (proportion of MD values predicted within the 95% repeatability interval) across the models, differences.	Kalman filtering algorithm	• Two KF were designed to predict MD and pattern SD values for patients with OAG and glaucoma suspects 36 months in the future.	Accuracy-95%	Higher prediction accuracy	Higher sample size is required for prediction
Christopher et al. [137]	• A Bayesian model has been developed to predict which eyes will develop glaucoma in the future. • It is better able to predict this than the CSLO and SAP global indices	RVM	• Introduced a model to predict the glaucoma based on RVM classifier.	Sensitivity Specificity Accuracy AUROC	Higher accuracy	Overestimation or underestimation of the number of progresses found using this method
Supriya et al. [138]	• A CT-HMM model, based on the atypical order of temporal data taken during appointments, depicts the continuous change in structural and functional measures. • Comparing our results to earlier work that used the average RNFL	CT-HMM	• Used a comprehensible, discrete state space model to model and predict longitudinal glaucoma data.	MAE	Precisely predicting the geographic distribution and pace of tissue ageing	Correct intervention based on more precise prognosis may help to advance glaucoma clinical care in future

	thickness, we achieve a mean absolute error reduction of 74%.					
Gian-Gabrial et al. [139]	• KF is a potential method that can be used to create tailored predictions and learn the future course of the disease in groups of patients.	KF algorithm	• Projected a method for the prediction NTG using KF algorithm	RSME	Less dependence on operator expertise	Reduced accuracy due to the sample size
Elfattah et al. [140]	• Established a more accurate prediction model using a random forest methodology for the progression of ocular hypertension to primary open angle glaucoma. • The two parts of our strategy are prediction and risk factor calculation. • Before moving on to the prediction phase, where a random forest approach is used for classification, we first determine the risk factors related to the outcome.	RFC	• Developed a more precise prediction model for the onset of primary ONG due to ocular hypertension using the RF technique.	Accuracy-93%	Better prediction accuracy	In future we can extend this work with improving accuracy.
Isaac et al. [141]	• The provided approach combines supervised learning classification with the results of interacting multiple model Kalman filtering. • When the Kalman filtering results were included as extra features in the supervised learning model	Kalman filtering algorithm	• Created a clinical decision support model for glaucoma with an open angle.	AUC	Successfully proactive disease stages prediction	Future research may be able to enhance our methodology by including techniques for the disease's dynamic control.

V. OPEN CHALLENGES

From the systematic review proposed in the paper, it is well clear that ML techniques are becoming more attention from the authors because of their ability to detect and predict glaucoma more accurately. Even though, the computational intelligence of ML techniques are increasing, still they are dealt with a large number of issues. This section outlines a number of scientific issues that previous studies on the early detection of glaucoma have been unable to address. However, improving the effectiveness of various glaucoma detection tools also calls for a lot of work.

VI. CONCLUSION

In the systematic review a survey on glaucoma detection and prediction using ML techniques are discussed clearly. The systematic review provides detection and prediction from the year 2000-2022. Two tabulations are drawn to indicate various techniques using ML for detection and prediction of glaucoma. The systematic review shows some important applications of ML techniques in the medical domain utilized in today's glaucoma detection and prediction research. Basic phases like pre-processing, feature extraction, selection, classification, segmentation, classification detection, and prediction are used in image processing approaches to detect glaucoma. The method of image processing is also beneficial for separating the ROI from the retinal fundus image. It is also explained how to recognise certain aspects in retinal pictures. Images that are healthy or have glaucoma are classified automatically using a ML model that incorporates features that were retrieved. DL is a growing trend in automated applications and is, in reality, of utmost importance. Authors across the world are working hard to enhance these techniques by exploring various possible ways. However, using more sources would have further improved this evaluation.

REFERENCE

[1] J. L. Wiggs, & L. R. Pasquale, "Genetics of glaucoma," Human molecular genetics vol. 26, no. R1, pp. R21-R27, 2017.

[2] R. Lim, & I. Goldberg, The Glaucoma Book: A Practical, Evidence-Based Approach to Patient Care, (Chapter 1, p. 3) (2010).

[3] R. J. Casson, G. Chidlow, J. P. Wood, J. G. Crowston, & I. Goldberg, "Definition of glaucoma: clinical and experimental concepts," Clinical & experimental ophthalmology vol. 40, no. 4, pp. 341-349, 2012.

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 5s
DOI: https://doi.org/10.17762/ijritcc.v11i5s.6655
***Article Received**: 02 March 2023 **Revised**: 19 April 2023 **Accepted**: 01 May 2023*

[4] R. R. Bourne, "The optic nerve head in glaucoma," Community Eye Health vol. 19, no. 59, pp. 44, 2006.

[5] C. W. McMonnies, "Glaucoma history and risk factors," Journal of optometry vol. 10, no. 2, pp. 71-78, 2017.

[6] R. J. Casson, G. Chidlow, J. P. Wood, J. G. Crowston, & I. Goldberg, Defnition of glaucoma: Clinical and experimentalconcepts. Clin. Exp. Ophthalmol. Vol. 40, pp. 341–349, 2012. https://doi.org/10.1111/j.1442-9071.2012.02773.x.

[7] D. R. Anderson, Collaborative normal tension glaucoma study. Curr Opin Ophthalmol. Vol. 14, pp. 86–90, 2003.

[8] C. Bowd, R. N. Weinreb, J. M. Williams, & L. M. Zangwill, The retinal nerve fiber layer thickness in ocular hypertensive, normal, and glaucomatous eyes with optical coherence tomography. Arch Ophthalmol. Vol. 118, pp. 22–26, 2000.

[9] R. R. Bourne, The optic nerve head in glaucoma, Commun. Eye Health. Vol. 19, no. 59, () pp. 44–45, 2006.

[10]. D. L. Budenz, K. Barton, J. Whiteside-de Vos, J. Schiffman, J. Bandi, W. Nolan, & Tema Eye Survey Study Group. Prevalence of glaucoma in an urban West African population: the Tema Eye Survey. JAMA Ophthalmol. Vol. 131, pp. 651–658, 2013.

[11]. A. Hennis, S. Y. Wu, B. Nemesure, R. Honkanen, M. C. Leske, & Barbados Eye Studies Group. Awareness of incident open-angle glaucoma in a population study: the Barbados Eye Studies. Ophthalmology. Vol. 114, pp. 1816–1821, 2007.

[12]. R. S. Harwerth, L. Carter-Dawson, E. L. Smith, G. Barnes, W. F. Holt, & M. L. Crawford, Neural Losses Correlated with Visual Losses in Clinical Perimetry. Invest Ophthalmol Vis Sci. vol. 45, pp. 3152–3160, 2004.

[13]. M. Ulieru, O. Cuzzani, S. H. Rubin, & M. G. Ceruti, "Application of soft computing methods to the diagnosis and prediction of glaucoma." In Smc 2000 conference proceedings. 2000 ieee international conference on systems, man and cybernetics.'cybernetics evolving to systems, humans, organizations, and their complex interactions'(cat. no. 0, vol. 5, pp. 3641-3645, 2000. IEEE.

[14] R. Asaoka, H. Murata, K. Hirasawa, Y. Fujino, M. Matsuura, A. Miki, & M. Araie, Using deep learning and transform learning to accurately diagnose early-onset glaucoma from macular optical coherence tomography images. Am J Ophthalmol. Vol. 198, pp. 136–145, 2019.

[15] J. E. Morgan, N. J. L. Sheen, R. V. North, Y. Choong, & E. Ansari, "Digital imaging of the optic nerve head: monoscopic and stereoscopic analysis," British Journal of Ophthalmology, vol. 89, no. 7, pp. 879–884, 2005.

[16] E. Balan, C. Venkatesan, M. G. Sumithra, M. Akila, & M. Manikandan, "Method for detecting cup to disk ratio for the prediction of glaucoma disease–A review," 2020.

[17] P. Harasymowycz, C. Birt, P. Gooi, L. Heckler, C. Hutnik, D. Jinapriya, & R. Day, "Medical Management of Glaucoma in the 21st Century from a Canadian Perspective," J Ophthalmol. pp. 6509809, 2016. 10.1155/2016/6509809

[18] A. P. Rotchford, J. F. Kirwan, M. A. Muller, G. J. Johnson, & P. Roux, "Temba glaucoma study: a population-based cross-sectional survey in urban South Africa," Ophthalmology. Vol. 110, pp. 376–82, 2003.

[19] S. Thomas, W. Hodge, & M. Malvankar-Mehta, "The cost-effectiveness analysis of teleglaucoma screening device," PLoS One. Vol. 10, pp. e0137913, 2015. 10.1371/journal.pone.0137913

[20] C. Imrie, & A. J. Tatham, "Glaucoma: the patient's perspective," Br J Gen Pract. Vol. 66, pp. e371-373, 2016. 10.3399/bjgp16X685165

[21] H. Hashemi, M. Mohammadi, N. Zandvakil, M. Khabazkhoob, M. H. Emamian, M. Shariati, & A. Fotouhi, "Prevalence and risk factors of glaucoma in an adult population from Shahroud, Iran," J Curr Ophthalmol. Vol. 31, pp. 366-372, 2018. 10.1016/j.joco.2018.05.003.

[22] R. N. Weinreb, C. K. Leung, J. G. Crowston, F. A. Medeiros, D. S. Friedman, J. L. Wiggs, & K. R. Martin, "Te pathophysiology and treatment of glaucoma: a review," JAMA vol. 311, pp. 1901–1911, 2014.

[23] M. T. Leite, L. M. Sakata, & F. A. Medeiros, "Managing glaucoma in developing countries," Arq. Bras. Ofalmol. Vol. 74, pp. 83–84, 2011.

[24] A. Hennis, S. Y. Wu, B. Nemesure, R. Honkanen, M. C. Leske, et al. "Awareness of incident open-angle glaucoma in a population study: the Barbados Eye Studies," Ophthalmology vol. 114, pp. 1816–1821, 2007.

[25] R. Susanna, C. G. De Moraes, G. A. Cioffi, & R. Ritch, "Why do people (still) go blind from glaucoma?. Transl," Vis.Sci. Technol. Vol. 4, no. 1, 2015.

[26] P. Founti, A. L. Coleman, M. R. Wilson, F. Yu, E. Anastasopoulos, A. Harris, & F. Topouzis, Overdiagnosis of open-angle glaucoma in the general population: the Tessaloniki Eye Study. Acta Ophthalmol. Vol. 96, pp. e859–e864, 2018.

[27] V. Grau, J. C. Downs, and C. F. Burgoyne, ''Segmentation of trabeculated structures using an anisotropic Markov random field: Application to the study of the optic nerve head in glaucoma,'' IEEE Trans. Med. Imag., vol. 25, no. 3, pp. 245–255, Mar. 2006.

[28] H. A. Quigley and A. T. Broman, ''The number of people with glaucoma worldwide in 2010 and 2020,'' Brit. J. Ophthalmol., vol. 90, pp. 262–267, Mar. 2006.

[29] F. Fumero, S. Alayon, J. L. Sanchez, J. Sigut, and M. Gonzalez-Hernandez, ''RIM-ONE: An open retinal image database for optic nerve evaluation,'' in Proc. 24th Int. Symp. Comput.-Based Med. Syst., pp. 1–6, 2011.

[30] D. S. W. Ting, C. Y.-L. Cheung, G. Lim et al., "Development and validation of a deep learning system for diabetic retinopathy and related eye diseases using retinal images from multiethnic populations with diabetes," JAMA, vol. 318, no. 22, pp. 2211–2223, 2017.

[31] F. A. Medeiros, L. M. Zangwill, C. Bowd, and R. N. Weinreb, ''Comparison of the GDx VCC scanning laser polarimeter, HRT II confocalscanning laser ophthalmoscope, and stratus oct optical coherence tomographfor the detection of glaucoma,'' Arch. Opthalmol., vol. 122, pp. 827–837, Jun. 2004.

[32] P. Naithani et al., ''Evaluation of optical coherence tomography and Heidelberg retinal tomography parameters in detecting early and moderate glaucoma,'' Invest. Ophthalmol. Vis. Sci., vol. 48, pp. 3138–3145, Jul. 2007.

[33] L. M. Ventura, N. Sorokac, R. De Los Santos, W. J. Feuer, and V. Porciatti, ''The relationship between retinal ganglion cell function and retinal nerve fiber thickness in early glaucoma,'' Invest. Ophthalmol. Vis. Sci., vol. 47, pp. 3904–3911, Sep. 2006.

[34] R. S. Harwerth and H. A. Quigley, ''Visual field defects and retinal ganglion cell losses in patients with glaucoma,'' Arch. Opthalmol., vol. 124, pp. 853–859, Jun. 2006.

[35] J. De Fauw, J. R. Ledsam, B. Romera-Paredes et al., "Clinically applicable deep learning for diagnosis and referral in retinal disease," Nature Medicine, vol. 24, no. 9, pp. 1342–1350, 2018.

[36] E. J. Higginbotham, & D. A. Lee, Clinical guide to glaucoma management. Woburn, MA: Butterworth Heinemann, pp. 156-70, 2004.

[37] J. S. Distelhorst, & G. M. Hughes, "Open-angle glaucoma." American family physician vol. 67, no. 9, pp. 1937-1944, 2003.

[38] H. A. Quigley, S. K. West, J. Rodriguez, B. Munoz, R. Klein, & R. Snyder, "The prevalence of glaucoma in a population-based study of Hispanic subjects: Proyecto VER," Arch Ophthalmol. Vol. 119, pp. 1819–26, 2001.

[39] S. Y. Shen, T. Y. Wong, P. J. Foster, J.-L. Loo, M. Rosman, S.-C. Loon, W. L. Wong, S.-M. Saw, and T. Aung, "The prevalence and types of glaucoma in malay people: The singapore malay eye study," Investigative Ophthalmology and Visual Science, vol. 49, no. 9, p. 3846, 2008.

[40] Y. H. Kwon, J. H. Fingert, M. H. Kuehn, & W. L. Alward, "Primary open-angle glaucoma," New England Journal of Medicine vol. 360, no. 11, pp. 1113-1124, 2009.

[41] R. Sihota, N. C. Lakshmaiah, H. C. Agarwal, R. M. Pandey, and J. S. Titiyal. "Ocular parameters in the subgroups of angle closure glaucoma." Clinical & experimental ophthalmology vol. 28, no. 4, pp. 253-258, 2000.

[42] 'Types of Glaucoma',http://www.glaucoma.org/glaucoma/types-ofglaucoma.php, Access Date: 12 January 2016.

[43] 'Diseases and Conditions Glaucoma', http://www.medicinenet.com/tunnel_vision/symptoms.htm, Access Date: 13 January 2016

[44] P. Tarongoy, C. L. Ho, & D. S. Walton, "Angle-closure glaucoma: the role of the lens in the pathogenesis, prevention, and treatment," Survey of ophthalmology vol. 54, no. 2, pp. 211-225, 2009.

[45] P. J. Foster, & G. J. Johnson, "Glaucoma in china: how big is the problem?" Br. J. Ophthalmol., vol. 85, no. 11, pp. 12771282, 2001.

[46] S. Salim, "The role of anterior segment optical coherence tomography in glaucoma," Journal of Ophthalmology, pp. 1–9, 2012.

[47] M. Nongpiur, B. Haaland, D. Friedman, S. Perera, M. He, L. Foo, M. Baskaran, L. Sakata, T. Wong, and T. Aung, "Classification algorithms based on anterior segment optical coherence tomography measurements for detection of angle closure," Ophthalmology, vol. 120, no. 1, pp. 48–54, 2013.

[48] C. Leung and R. Weinreb, "Anterior chamber angle imaging with optical coherence tomography," Eye, vol. 25, no. 3, pp. 261–267, 2011.

[49] I. Lai, H. Mak, G. Lai, M. Yu, D. Lam, and C. Leung, "Anterior chamber angle imaging with swept-source optical coherence tomography: Measuring peripheral anterior synechia in glaucoma," Ophthalmology, vol. 120, no. 6, pp. 1144–1149, 2013.

[50] N. Wang, H. Wu, Z. Fan, "Primary angle closure glaucoma in Chinese and Western populations," Chin Med J, vol. 115, pp. 1706-15, 2002.

[51] M. E. Nongpiur, J. Y. Ku, & T. Aung, "Angle closure glaucoma: a mechanistic review," Current opinion in ophthalmology vol. 22, no. 2, pp. 96-101, 2011.

[52] Y. Ikuno, K. Sayanagi, T. Oshima, F. Gomi, S. Kusaka, M. Kamei, M. Ohji, T. Fujikado, and Y. Tano, "Optical coherence tomographic findings of macular holes and retinal detachment after vitrectomy in highly myopic eyes," American Journal of Ophthalmology, vol. 136, no. 3, pp. 477–481, 2003.

[53] A. Bagci, M. Shahidi, R. Ansari, and M. Blair, "Thickness profiles of retinal layers by optical coherence tomography image segmentation," American Journal of Ophthalmology, vol. 146, no. 5, pp. 679–687, 2008.

[54] M. K. Garvin, M. D. Abramoff, X. Wu, S. R. Russell, T. L. Burns, ` and M. Sonka, "Automated 3-D intraretinal layer segmentation of macular spectral-domain optical coherence tomography images," IEEE Transactions on Medical Imaging, vol. 28, no. 9, pp. 1436–1447, 2009.

[55] K. Lee, M. Niemeijer, M. K. Garvin, Y. Kwon, M. Sonka, and M. Abramoff, "Segmentation of the optic disc in 3-D OCT scans of ` the optic nerve head," IEEE Transactions on Medical Imaging, vol. 29, no. 1, pp. 159–168, 2010.

[56] H. Fu, D. Xu, S. Lin, D. W. K. Wong, and J. Liu, "Automatic Optic Disc Detection in OCT Slices via Low-Rank Reconstruction," IEEE Transactions on Biomedical Engineering, vol. 62, no. 4, pp. 1151–1158, 2015.

[57] M. C. Leske, A. Heijl, M. Hussein, B. Bengtsson, L. Hyman, E. Komaroff, & Early Manifest Glaucoma Trial Group. "Factors for glaucoma progression and the effect of treatment: the early manifest glaucoma trial." Archives of ophthalmology 121, no. 1, pp. 48-56, 2003.

[58] U. R. Acharya, S. Bhat, J. E. Koh, S. V. Bhandary, H. Adeli, "A novel algorithm to detect glaucoma risk using texton and local configuration pattern features extracted from fundus images," Computers in biology and medicine vol. 88, pp. 72–83, 2017.

[59] K. P. Noronha, U. R. Acharya, K. P. Nayak, R. J. Martis, S. V. Bhandary, "Automated classification of glaucoma stages using higher order cumulant features," Biomedical Signal Processing and Control, vol. 10, pp. 174–183, 2014.

[60] M. S. Haleem, L. Han, J. van Hemert, B. Li, "Automatic extraction of retinal features from colour retinal images for glaucoma diagnosis: A review," Computerized medical imaging and graphics vol. 37, no. 7, pp. 581– 596, 2013.

[61] J. De Fauw, J. R. Ledsam, B. Romera-Paredes et al., “Clinically applicable deep learning for diagnosis and referral in retinal disease,” Nature Medicine, vol. 24, no. 9, pp. 1342–1350, 2018.

[62] M. R. K. Mookiah, U. R. Acharya, H. Fujita et al., “Local configuration pattern features for age-related macular degeneration characterization and classification,” Computers in Biology and Medicine, vol. 63, pp. 208–218, 2015.

[63] B. AI-Bander, W. AI-Nuaimy, M. A. AI-Taee, and Y. Zheng, “Automated glaucoma diagnosis using deep learning approach,” in Proceedings of 14th International MultiConference on Systems, Signals & Devices, Marrakesh, Morocco, March 2017.

[64] R. Asaoka, K. Hirasawa, A. Iwase et al., “Validating the usefulness of the “random forests” classifier to diagnose early glaucoma with optical coherence tomography,” American Journal of Ophthalmology, vol. 174, pp. 95–103, 2017.

[65] S. Maetschke, B. Antony, H. Ishikawa, G. Wollstein, J. S. Schuman, and R. Garvani, “A feature agnostic approach for glaucoma detection in OCT volumes,” 2018, http://arxiv. org/abs/1807.04855.

[66] J. Ker, L. Wang, J. Rao, and T. Lim, ‘‘Deep learning applications in medical image analysis,’’ IEEE Access, vol. 6, pp. 9375–9389, 2018.

[67] S. Yousefi, M.H. Goldbaum, M. Balasubramanian, T.P. Jung, R.N. Weinreb, F.A. Medeiros, C. Bowd, Glaucoma progression detection using structural retinal nerve fiber layer measurements and functional visual field points. IEEE Trans Biomed Eng vol. 61, no. 4, pp. 1143–1154, 2013.

[68] A. Sarhan, J. Rokne, & R. Alhajj, "Glaucoma detection using image processing techniques: A literature review," Computerized Medical Imaging and Graphics vol. 78, pp. 101657, 2019.

[69] C. B. Anusorn, W. Kongprawechnon, T. Kondo, S. Sintuwong, & K. Tungpimolrut, "Image processing techniques for glaucoma detection using the cup-to-disc ratio," Science & Technology Asia pp. 22-34, 2013.

[70] I. Qureshi, "Glaucoma detection in retinal images using image processing techniques: a survey," International Journal of Advanced Networking and Applications vol. 7, no. 2, pp. 2705, 2015.

[71] M. Madhusudhan, N. Malay, S. R. Nirmala, & D. Samerendra, "Image processing techniques for glaucoma detection," In International conference on advances in computing and communications, pp. 365-373. Springer, Berlin, Heidelberg, 2011.

[72] R. Bock, J. Meier, L. G. Nyúl, J. Hornegger, & G. Michelson, "Glaucoma risk index: automated glaucoma detection from color fundus images," Medical image analysis vol. 14, no. 3, pp. 471-481, 2010.

[73] Y. Xu, L. Duan, S. Lin, X. Chen, D.W.K. Wong, T.Y. Wong, J. Liu, (2014) “Optic cup segmentation for glaucoma detection using low-rank superpixel representation,” In: International conference on medical image computing and computer-assisted intervention. Springer, Cham, pp. 788–795.

[74] I. N. Bankman, “Ed., Handbook of Medical Image Processing and Analysis,” Baltimore, MD, USA: The Johns Hopkins Univ. Press, pp. 1084–1098, 2000.

[75] S. R. Nirmala, M. K. Nath, and S. Dandapat, ‘‘Retinal image analysis: A review,’’ Int. J. Comput. Commun. Technol., vol. 2, pp. 11–15, Jul. 2011.

[76] R. C. Gonzalez, “Digital Image Processing,” PHI, New Delhi-110001: Prentice Hall of India, Second ed., 2006.

[77] W. H, H. W, G. KG, and L. ML, “An effective approach to detect lesions in color retinal images,” pp. 1–6, August 2000. Conference on Computer Vision and Pattern Recognition, IEEE,

[78] U. R. Acharya, E. Y. K. Ng, and J. S. Suri, Image modelling of human eye. Artech House, MA, USA, 2008a, April.

[79] T. Walter, J. C. Klein, P. Massin, and A. Erginay, “A contribution of image processing to the diagnosis of diabetic retinopathy— detection of exudates in color fundus images of the human retina,” IEEE Trans. Med. Imaging. Vol. 21, pp. 1236–1243, 2002.

[80] M. Petrou, and C. Petrou, Image Processing the Fundamentals. Singapore: Wiley, second edition ed., 2010.

[81] J. Meier, R. Bock, G. Michelson, L.G. Ny´ul, J. Hornegger, Effects of preprocessing eye fundus images on appearance based glaucoma classification. In: Procceedings of International Conference on Computer Analysis of Images and Patterns. 2007. (accepted for publication).

[82] M. Lester, D. Garway-Heath, H. Lemij, Optic Nerve Head and Retinal Nerve Fibre Analysis. European Glaucoma Society. 2005.

[83] S. Sri Abirami and et all.,” Glaucoma Images Classification Using Fuzzy Min-Max Neural Network Based On Data-Core,” International Journal of Science and Modern Engineering (IJISME) ISSN: 2319-6386, Volume-1, Issue-7, June 2013.

[84] R. McIntyre and et all. , “Toward Glaucoma Classification with Moment Methods,” Proceedings of the First Canadian Conference on Computer and Robot Vision, IEEE, 2004.

[85] H. Yuji and et all., “Vertical Cup-to-disk ratio measurement for diagnosis of glaucoma fundus images,” Medical Imaging 2010: Computer-Aided Diagnosis, vol. 7624,SPEI,2010.

[85] J. Hornegger, H. Niemann, R. Risack, “Appearance-based object recognition using optimal feature transforms,” Pattern Recogn, vol. 2, no. 33, pp. 209–224, 2000.

[86] A. Jain, F. Farrokhnia, “Unsupervised texture segmentation using Gabor filters. In: Proceedings of IEEE International Conference on Systems, Man and Cybernetics,” pp. 14–19, 1990. IEEE Computer Society Press, Los Alamitos.

[87] H. N. jung, and et all. ,“Detection of Glaucoma Progression by Assessment of Segmented Macular Thickness Data Obtained Using Spectral Domain Optical Coherence Tomography” Investigative Ophthalmology & Visual Science, Vol. 53, No. 7, June 2012.

[88] H. Chih-Yin, and et all., “An atomatic fundus image analysis system for clinical diagnosis of glaucoma,” International Conference on Complex, Intelligent, and Software Intensive Systems, IEEE, 2011.

[89] K. Nouri-Mahdavi, R. Zarei, & J. Caprioli, "Influence of visual field testing frequency on detection of glaucoma progression with trend analyses," Archives of ophthalmology vol. 129, no. 12, pp. 1521-1527, 2011.

[907] R. Bock, J. Meier, L. G. Nyul, J. Hornegger, and G. Michelson, (2010) "Glaucoma risk index: Automated glaucoma detection from color fundus images," Medical Image Analysis vol. 14, no. 3, pp. 471 – 481.

[91] Y. Jin and et all., "Automated Optic Nerve Analysis for Diagnostic Support in Glaucoma," 8th IEEE Symposium on Computer-Based Medical Systems, IEEE, 2005.

[92] A. Hoover, V. Kouznetsova, and M. Goldbaum, "Locating blood vessels in retinal images by piecewise threshold probing of a matched filter response," IEEE Transaction on Medical Imaging, vol. 19, pp. 203–210, March 2000.

[93] L. Zhang, Q. Li, J. You, and D. Zhang, "A modified matched filter with double sided thresholding for screening proliferative diabetic retinopathy," IEEE Transactions on Information Technology in Biomedicine, vol. 13, pp. 528–534, July 2009.

[94] Y. Hatanaka, T. Nakagawa, Y. Hayashi, T. Hara, and H. Fujita, "Improvement of automated detection method of haemorrhages in fundus images," (Vancouver, British Columbia, Canada), pp. 5429–5432, EMBS, IEEE, August 2008.

[95] S. Nirmala, S. Dandapat, and P. Bora, "Wavelet weighted blood vessel distortion measure for retinal images," Biomedical Signal Processing and Control, vol. 5, pp. 282–291, July 2010.

[96] A. Dey, S.K. Bandyopadhyay, "Automated glaucoma detection using support vector machine classification method," J Adv Med Med Res 1–12, 2016.

[97] X. Chen, Y. Xu, S. Yan, D.W.K. Wong, T.Y. Wong, J. Liu, "Automatic feature learning for glaucoma detection based on deep learning," In: International conference on medical image computing and computer-assisted intervention. Springer, Cham, pp. 669–677, 2015.

[98] H. Fu et al., "Segmentation and Quantification for Angle-Closure Glaucoma Assessment in Anterior Segment OCT," in IEEE Transactions on Medical Imaging, vol. 36, no. 9, Sept. 2017, pp. 1930–1938.

[99] Y.-C. Tham, X. Li, T. Y. Wong, H. A. Quigley, T. Aung, and C.-Y. Cheng, ''Global prevalence of glaucoma and projections of glaucoma burden through 2040: A systematic review and meta-analysis,'' Ophthalmology, vol. 121, no. 11, pp. 2081–2090, 2014.

[100] S. Maheshwari, V. Kanhangad, R. B. Pachori, S. V. Bhandary, U. R. Acharya, Automated glaucoma diagnosis using bit-plane slicing and local binary pattern techniques, Comput. Biol. Med., vol. 105, pp. 72–80, 2019.

[101] S. Masood, M. Sharif, M. Raza, M. Yasmin, M. Iqbal, M. Younus Javed, "Glaucoma disease: A survey," Curr. Med. Imaging, vol. 11, pp. 272–283, 2015.

[102] F. Cabitza, R. Rasoini, G.F. Gensini, "Unintended consequences of machine learning in medicine," JAMA. Vol. 318, no. 6, pp. 517–8, 2017.

[103] D. Komura, S. Ishikawa, "Machine learning methods for histopathological image analysis," Comput Struct Biotechnol J. vol. 16, pp. 34–4, 2018.

[104] Z. Burgansky-Eliash, G. Wollstein, T. Chu, J. D. Ramsey, C. Glymour, R. J. Noecker, & J. S, Schuman, "Optical coherence tomography machine learning classifiers for glaucoma detection: a preliminary study." Investigative ophthalmology & visual science, vol. 46, no. 11 pp. 4147-4152, 2005.

[105] A. Dey, & S. K. Bandyopadhyay, "Automated glaucoma detection using support vector machine classification method," British Journal of Medicine and Medical Research vol. 11, no. 12 pp. 1, 2016.

[106] C. W. Wu, H. Y. Chen, J. Y. Chen, & C. H. Lee, "Glaucoma detection using support vector machine method based on spectralis oct," Diagnostics vol. 12, no. 2, pp. 391, 2022.

[107] D. K. Agrawal, B. S. Kirar, & R. B. Pachori, "Automated glaucoma detection using quasi-bivariate variational mode decomposition from fundus images," IET Image Processing vol. 13, no. 13, pp. 2401-2408, 2019.

[108] B. S. Kirar, & D. K. Agrawal, "Current research on glaucoma detection using compact variational mode decomposition from fundus images," International Journal of Intelligent Engineering and Systems, vol. 12, no. 3, pp. 1-10, 2019.

[109] U. Raghavendra, S. V. Bhandary, A. Gudigar, & U. R. Acharya, "Novel expert system for glaucoma identification using non-parametric spatial envelope energy spectrum with fundus images," Biocybernetics and Biomedical Engineering vol. 38, no. 1, pp. 170-180, 2018.

[110] R. Sharma, P. Sircar, R. B. Pachori, S. V. Bhandary, & U. R. Acharya, "Automated glaucoma detection using center slice of higher order statistics," Journal of Mechanics in Medicine and Biology, vol. 19, no. 01, pp. 1940011, 2019.

[111] P. V. Rao, R. Gayathri, and R. Sunitha. "A novel approach for design and analysis of diabetic retinopathy glaucoma detection using cup to disk ration and ANN," Procedia Materials Science, vol. 10, pp. 446-454, 2015.

[112] T. Yoshida, A. Iwase, H. Hirasawa, H. Murata, C. Mayama, M. Araie, & R. Asaoka, "Discriminating between glaucoma and normal eyes using optical coherence tomography and the 'Random Forests' classifier," PloS one vol. 9, no. 8, pp. e106117, 2014.

[113] L. Abdel-Hamid, "Glaucoma detection from retinal images using statistical and textural wavelet features," Journal of digital imaging, vol. 33, no. 1, pp. 151-158, 2020.

[114] S. Vimal, Y. H. Robinson, M. Kaliappan, K. Vijayalakshmi, & S. Seo, "A method of progression detection for glaucoma using K-means and the GLCM algorithm toward smart medical prediction." The Journal of Supercomputing, vol. 77, no. 10, pp. 11894-11910, 2021.

[115] J. Ayub, J. Ahmad, J. Muhammad, L. Aziz, S. Ayub, U. Akram, & I. Basit, "Glaucoma detection through optic disc and cup segmentation using K-mean clustering." In 2016 international conference on computing, electronic and electrical engineering (ICE Cube), pp. 143-147. IEEE, 2016.

[116] S. C. Shetty, & P. Gutte, "A novel approach for glaucoma detection using fractal analysis," In 2018 International Conference on Wireless Communications, Signal Processing and Networking (WiSPNET), pp. 1-4. IEEE, 2018.

[117] V. Mahalakshmi, and S. Karthikeyan, "Clustering based optic disc and optic cup segmentation for glaucoma detection." International Journal of Innovative Research in Computer and Communication Engineering, vol. 2, no. 4, pp. 3756-3761, 2014.

[118] N. Kowsalya, A. Kalyani, C. Jasmine Chalcedony, R. Sivakumar, M. Janani, and V. Rajinikanth. "An approach to extract optic-disc from retinal image using K-means clustering." In 2018 Fourth International Conference on Biosignals, Images and Instrumentation (ICBSII), pp. 206-212. IEEE, 2018.

[119] N. Kavya, and K. V. Padmaja, "Glaucoma detection using texture features extraction," In 2017 51st Asilomar Conference on Signals, Systems, and Computers, pp. 1471-1475. IEEE, 2017.

[120] C. B. Anusorn, W. Kongprawechnon, T. Kondo, S. Sintuwong, & K. Tungpimolrut, "Image processing techniques for glaucoma detection using the cup-to-disc ratio," Science & Technology Asia, pp. 22-34, 2013.

[121] A. S. V. de Carvalho Junior, E. D. Carvalho, A. O. de Carvalho Filho, A. D. de Sousa, , A. C. Silva, & M. Gattass, "Automatic methods for diagnosis of glaucoma using texture descriptors based on phylogenetic diversity," Computers & Electrical Engineering, vol. 71, pp. 102-114, 2018.

[122] S. Kavitha, and K. Duraiswamy, "An efficient decision support system for detection of glaucoma in fundus images using ANFIS," International Journal of Advances in Engineering & Technology, vol. 2, no. 1, pp. 227, 2012.

[123] T. R. Kausu, V. P. Gopi, K. A. Wahid, W. Doma, & S. I. Niwas, "Combination of clinical and multiresolution features for glaucoma detection and its classification using fundus images," Biocybernetics and Biomedical Engineering, vol. 38, no. 2, pp. 329-341, 2018.

[124] M. Norouzifard, A.A. Dehkordi, M. N. Dehkordi, H. Gholamhosseini, & R. Klette, "Unsupervised optic cup and optic disk segmentation for glaucoma detection by icica." In 2018 15th International Symposium on Pervasive Systems, Algorithms and Networks (I-SPAN), pp. 209-214. IEEE, 2018.

[125] T. R. Babu, S. Devi, and R. Venkatesh, "Optic nerve head segmentation using fundus images and optical coherence tomography images for glaucoma detection," Biomedical Papers, vol. 159, no. 4, pp. 607-615, 2015.

[126] A. A. G. Elseid, & A. O. Hamza, "Glaucoma detection using retinal nerve fiber layer texture features." Journal of Clinical Engineering, vol. 44, no. 4, pp. 180-185, 2019.

[127] S. Maheshwari, R. B. Pachori, V. Kanhangad, S. V. Bhandary, & U. R. Acharya, "Iterative variational mode decomposition based automated detection of glaucoma using fundus images," Computers in biology and medicine, vol. 88, pp. 142-149, 2017.

[128] C. Raja and N. Gangatharan, “Optimal hyper analytic wavelet transform for glaucoma detection in fundal retinal images,” J Electr Eng Technol., vol. 10, no. 4, pp. 1899-1909, 2015.

[129] R. Kolar, and J. Jan, “Detection of glaucomatous eye via color fundus images using fractal dimensions,” Radio Eng., vol. 17, no. 3, pp. 109– 114, 2008.

[130] S. L. Baxter, C. Marks, T. T. Kuo, L. Ohno-Machado, & R. N. Weinreb, "Machine learning-based predictive modeling of surgical intervention in glaucoma using systemic data from electronic health records," American journal of ophthalmology, vol. 208, pp. 30-40, 2019.

[131] K. Sugimoto, H. Murata, H. Hirasawa, M. Aihara, C. Mayama, & R. Asaoka, "Cross-sectional study: Does combining optical coherence tomography measurements using the ‘Random Forest’decision tree classifier improve the prediction of the presence of perimetric deterioration in glaucoma suspects?." BMJ open, vol. 3, no. 10, pp. e003114, 2013.

[132] K. Sugimoto, H. Murata, H. Hirasawa, M. Aihara, C. Mayama, & R. Asaoka, "Predicting eyes at risk for rapid glaucoma progression based on an initial visual field test using machine learning," PloS one, vol. 16, no. 4, pp. e0249856, 2021.

[133] K. Nouri-Mahdavi, V. Mohammadzadeh, A. Rabiolo, K. Edalati, J. Caprioli, & S. Yousefi, "Prediction of visual field progression from OCT structural measures in moderate to advanced glaucoma," American Journal of Ophthalmology, vol. 226, pp. 172-181, 2021.

[134] M. S. Eswari, & S. Balamurali, "An intelligent machine learning support system for glaucoma prediction among diabetic patients," In 2021 International Conference on Advance Computing and Innovative Technologies in Engineering (ICACITE), pp. 447-449. IEEE, 2021.

[135] M. Sharifi, T. Khatibi, M. H. Emamian, S. Sadat, H. Hashemi, & A. Fotouhi, "Development of glaucoma predictive model and risk factors assessment based on supervised models," BioData Mining, vol. 14, no. 1, pp. 1-152021.

[136] M. Zhalechian, M. P. Van Oyen, M. S. Lavieri, C. G. De Moraes, C. A. Girkin, M. A. Fazio, & J. D. Stein, "Augmenting Kalman Filter Machine Learning Models with Data from OCT to Predict Future Visual Field Loss: An Analysis Using Data from the African Descent and Glaucoma Evaluation Study and the Diagnostic Innovation in Glaucoma Study," Ophthalmology Science, vol. 2, no. 1, pp. 100097, 2022.

[137] C. Bowd, I. Lee, M. H. Goldbaum, M. Balasubramanian, F. A. Medeiros, L. M. Zangwill, & R. N. Weinreb, "Predicting glaucomatous progression in glaucoma suspect eyes using relevance vector machine classifiers for combined structural and functional measurements," Investigative ophthalmology & visual science, vol. 53, no. 4, pp. 2382-2389, 2012.

[138] S. Nagesh, A. Moreno, H. Ishikawa, G. Wollstein, J.S. Shuman, & J.M. Rehg, "A spatiotemporal approach to predicting glaucoma progression using a ct-hmm." In Machine Learning for Healthcare Conference, pp. 140-159. PMLR, 2019.

[139] G. G. P. Garcia, K. Nitta, M. S. Lavieri, C. Andrews, X. Liu, E. Lobaza, & J. D. Stein, "Using Kalman filtering to forecast disease trajectory for patients with normal tension glaucoma." American journal of ophthalmology, vol. 199, pp. 111-119, 2019.

[140] M. A. Elfattah, M. I. Waly, M. A. A. Elsoud, A. E. Hassanien, M. F. Tolba, J. Platos, & G. Schaefer, "An improved prediction approach for progression of ocular hypertension to primary open angle Glaucoma," In Proceedings of the Fifth International Conference on Innovations in Bio-Inspired Computing and Applications IBICA 2014, pp. 405-412. Springer, Cham, 2014.

[141] I. A. Jones, M. P. Van Oyen, M. S. Lavieri, C. A. Andrews, & J. D. Stein, "Predicting rapid progression phases in glaucoma using a soft voting ensemble classifier exploiting Kalman filtering," Health Care Management Science, vol. 24, no. 4, pp. 686-701, 2021.

[142] Y. LeCun, Y. Bengio, & G. Hinton, Deep learning. Nature, vol. 521, pp. 436–444, 2015.

[143] Z. Obermeyer, & E. J. Emanuel, "Predicting the future — big data, machine learning, and clinical medicine," N. Engl. J. Med, vol. 375, pp. 1216–1219, 2016.

[144] A. Bordes, X. Glorot, J. Weston, et al. "Joint learning of words and meaning representations for open-text semantic parsing," in: Proceedings of the AISTATS, 2012.

[145] D.C. Ciresan, U. Meier, J. Schmidhuber, "Transfer learning for Latin and Chinese characters with deep neural networks," in: Proceedings of the IJCNN, 2012.

[146] J.S.J. Ren, L. Xu, "On vectorization of deep convolutional neural networks for vision tasks," in: Proceedings of the AAAI, 2015.

[147] T. Mikolov, I. Sutskever, K. Chen, et al., "Distributed representations of words and phrases and their compositionality," in: Proceedings of the NIPS, 2013.

[148] D. Ciresan, U. Meier, J. Schmidhuber, "Multi-column deep neural networks for image classification," in: Proceedings of the CVPR, 2012.

[149] A. Krizhevsky, I. Sutskever, G.E. Hinton, "Imagenet classification with deep convolutional neural networks," in: Proceedings of the NIPS, 2012.

[150] L. Deng, "A tutorial survey of architectures, algorithms, and applications for deep learning, APSIPA Trans," Signal Inf. Process. Vol. 3 pp. e2, 2014.

[151] C. Szegedy, W. Liu, Y. Jia, P. Sermanet, S. Reed, D. Anguelov, D. Erhan, V. Vanhoucke, and A. Rabinovich, "Going deeper with convolutions," in Proceedings of the IEEE conference on computer vision and pattern recognition, pp. 1–9, 2015.

[152] C. Szegedy, V. Vanhoucke, S. Ioffe, J. Shlens, and Z. Wojna, "Rethinking the inception architecture for computer vision," in Proceedings of the IEEE conference on computer vision and pattern recognition, pp. 2818–2826, 2016.

[153] K. Simonyan and A. Zisserman, "Very deep convolutional networks for large-scale image recognition," arXiv preprint arXiv:1409.1556, 2014.

[154] S. Targ, D. Almeida, and K. Lyman, "Resnet in resnet: Generalizing residual architectures," arXiv preprint arXiv:1603.08029, 2016.

[155] G. Huang, Z. Liu, L. Van Der Maaten, and K. Q. Weinberger, "Densely connected convolutional networks," in Proceedings of the IEEE conference on computer vision and pattern recognition, pp. 4700–4708, 2017.

[156] B. Al-Bander, W. Al-Nuaimy, M. A. Al-Taee, & Y. Zheng, "Automated glaucoma diagnosis using deep learning approach," In 2017 14th International Multi-Conference on Systems, Signals & Devices (SSD), pp. 207-210. IEEE, 2017.

[157] X. Chen, Y. Xu, S. Yan, D. W. K. Wong, T. Y. Wong, & J. Liu, "Automatic feature learning for glaucoma detection based on deep learning." In International conference on medical image computing and computer-assisted intervention, pp. 669-677. Springer, Cham, 2015.

[158] S. Serte, & A. Serener, "A generalized deep learning model for glaucoma detection." In 2019 3rd International symposium on multidisciplinary studies and innovative technologies (ISMSIT), pp. 1-5. IEEE, 2019.

[159] S. Yu, D. Xiao, S. Frost, & Y. Kanagasingam, "Robust optic disc and cup segmentation with deep learning for glaucoma detection," Computerized Medical Imaging and Graphics, vol. 74, 61-71, 2019.

[160] M. Christopher, K. Nakahara, C. Bowd, J. A. Proudfoot, A. Belghith, M. H. Goldbaum, & L. M. Zangwill, "Effects of study population, labeling and training on glaucoma detection using deep learning algorithms," Translational vision science & technology, vol. 9, no. 2, pp. 27-27, 2020.

[161] Y. Chai, H. Liu, & J. Xu, "Glaucoma diagnosis based on both hidden features and domain knowledge through deep learning models," Knowledge-Based Systems, vol. 161, pp. 147-156, 2018.

[162] W. Liao, B. Zou, R. Zhao, Y. Chen, Z. He, & M. Zhou, "Clinical interpretable deep learning model for glaucoma diagnosis," IEEE journal of biomedical and health informatics, vol. 24, no. 5, pp.1405-1412, 2019.

[163] M. Nawaz, T. Nazir, A. Javed, U. Tariq, H. S. Yong, M. A. Khan, & J. Cha, "An efficient deep learning approach to automatic glaucoma detection using optic disc and optic cup localization," Sensors vol. 22, no. 2, pp. 434, 2022.

[164] Q. Abbas, "Glaucoma-deep: detection of glaucoma eye disease on retinal fundus images using deep learning," International Journal of Advanced Computer Science and Applications, vol. 8, no. 6, 2017.

[165] A. Saxena, A. Vyas, L. Parashar, & U. Singh, "A glaucoma detection using convolutional neural network," In 2020 International Conference on Electronics and Sustainable Communication Systems (ICESC), pp. 815-820. IEEE, 2020.

[166] G. Suguna, & R. Lavanya, "Automatic identification of glaucoma using deep learning methods," Proc. 16th World Congr. Med. Health Informat. Precision Healthcare Through Informat.(MEDINFO) vol. 245, 318, 2018.

[167] D. Natarajan, E. Sankaralingam, K. Balraj, & S. Karuppusamy, "A deep learning framework for glaucoma detection based on robust optic disc segmentation and

transfer learning," International Journal of Imaging Systems and Technology, vol. 32, no. 1, pp. 230-2502022.

[168] J. Lee, Y. K. Kim, K. H. Park, & J. W. Jeoung, "Diagnosing glaucoma with spectral-domain optical coherence tomography using deep learning classifier," J Glaucoma, vol. 29, pp. 87–94, 2020.

[169] A. Diaz-Pinto, S. Morales, V. Naranjo, T. Köhler, J. M. Mossi, & A. Navea, "CNNs for automatic glaucoma assessment using fundus images: an extensive validation," Biomedical engineering online, vol. 18, no. 1, pp. 1-19, 2019.M.

[170] M. Juneja, S. Singh, N. Agarwal, S. Bali, S. Gupta, N. Thakur, & P. Jindal, "Automated detection of Glaucoma using deep learning convolution network (G-net)," Multimedia Tools and Applications, vol. 79, no. 21, pp. 15531-15553, 2020.

[171] J. J. Gómez-Valverde, A. Antón, G. Fatti, B. Liefers, A. Herranz, A. Santos, & M. J. Ledesma-Carbayo, "Automatic glaucoma classification using color fundus images based on convolutional neural networks and transfer learning," Biomedical optics express, vol. 10, no. 2, pp. 892-913, 2019.

[172] H. N. Veena, A. Muruganandham, & T. S. Kumaran, "A novel optic disc and optic cup segmentation technique to diagnose glaucoma using deep learning convolutional neural network over retinal fundus images," Journal of King Saud University-Computer and Information Sciences, 2021.

[173] H. Fu, J. Cheng, Y. Xu, C. Zhang, D. W. K. Wong, J. Liu, & X. Cao, "Disc-aware ensemble network for glaucoma screening from fundus image," IEEE transactions on medical imaging, vol. 37, no. 11, pp. 2493-2501, 2018.

[174] S. Gheisari, S. Shariflou, J. Phu, P. J. Kennedy, A. Agar, M. Kalloniatis, & S. M. Golzan, "A combined convolutional and recurrent neural network for enhanced glaucoma detection," Scientific reports, vol. 11, no. 1, 1-11, 2021.

[175] M. B. Sudhan, M. Sinthuja, S. Pravinth Raja, J. Amutharaj, G. Charlyn Pushpa Latha, S. Sheeba Rachel, & Y. A. Waji, "Segmentation and Classification of Glaucoma Using U-Net with Deep Learning Model." Journal of Healthcare Engineering, 2022 (2022).

[176] S. I. Berchuck, S. Mukherjee, & F. A. Medeiros, "Estimating rates of progression and predicting future visual fields in glaucoma using a deep variational autoencoder," Scientific reports, vol. 9, no. 1, pp. 1-122019.

[177] S. Asano, R. Asaoka, H. Murata, Y. Hashimoto, A. Miki, K. Mori, & K. Inoue, "Predicting the central 10 degrees visual field in glaucoma by applying a deep learning algorithm to optical coherence tomography images," Scientific Reports, vol. 11, no. 1, pp. 1-10, 2021.

[178] M. Christopher, C. Bowd, A. Belghith, M. H. Goldbaum, R. N. Weinreb, M. A. Fazio, & L. M. Zangwill, "Deep learning approaches predict glaucomatous visual field damage from OCT optic nerve head en face images and retinal nerve fiber layer thickness maps," Ophthalmology, vol. 127, no. 3, pp. 346-356, 2020.