

HFESISK: Hierarchical Expert-Fuzzy System and Illumination Surgical Keratoscope based diagnosis of diseases of eye: Diabetic Retinopathy, Glaucoma and Cataract

Virat Rehani1, Research Scholar Department of CSE CT University, Ludhiana
Dr. Yogesh Kumar2, Department of Electronics and Communication, CT University, Ludhiana

Abstract: Glaucoma, Cataract, and Diabetic Retinopathy are eye diseases with similar indicators vis-a-vis high pressure on the eye, optic nerve damage, and seldom vision loss. Loss of sight may occur if the patient is not treated, it affects the bordering visualization. Diagnosis of ocular diseases at the initial state necessitates consistent check-ups which is time consuming as well as too expensive. This research work suggests a Hierarchical Fuzzy decision system which is built for analyzing and treating Diabetic Retinopathy, Glaucoma & Cataracts at very early state along with a very price-effective procedure room illumination Keratoscope which can be installed for handling the case of uneven corneal curvature, surgery for cataract & even Full-thickness corneal graft. The hierarchical Fuzzy-rule mechanism proposed in this research assists the medicinal experts in the diagnosis of the result with precision given the patient's symptoms. All the tests were done on the proposed system and even the testing of feasibility of the Keratoscope were undertaken under the supervision of an eye care specialist and were scribed to be accurate and beneficial, evaluating accuracy to 93%, sensitivity to 94% and specificity to 92 %. This technique is effective and has a small cost of computation.

Keywords: *Corneal Examination, Glaucoma, Cataracts, Diabetic Retinopathy, Hierarchical Fuzzy-based training system, User-friendly Graphical Interface, Surgical Illuminating Keratoscope.*

INTRODUCTION

The healing investigation of any disease/disorder is a foremost issue in this era that requires engineering methods for accessing the data, with advancement in the field of therapeutic engineering and other regulator structures that have developed by the arrangement of artificial intelligence methods [1]. This substitute technique has rendered a pulsating exploration which includes Artificial Neural Networks, Genetic Algorithms, and Hierarchical Fuzzy Logic. All these approaches are expected to provide important data beginning from one to further type and address the life-threatening issues. The maximum reachable strategy that provides support and help to medicinal experts in the recognition of the disease is an augmentation of the medical sustainable detection system [1].

The vital cause of occurrence of glaucoma is the inflexible failure of retina Nerve fiber sections due to the increased the pressure exerted by the fluid (aqueous humor) inside the eye. Changes in the volume of retinal nerve filaments alter the signals transmitted to the brain, affecting how images are perceived. These signals are interpreted as objects by the brain. Damage to these nerve filaments can result in the formation of spots and blind spots, leading to visual impairment. [2]. Glaucoma is difficult to diagnose in early stages. The supplementary ways for detecting Glaucoma are Pachymetry, Tonometry, and Ophthalmoscopy etc. It is undisputable that these systems are costly, wearisome and requires Great competencies [2]. Glaucomatous conditions are typically classified into two main categories: open-angle and closed-angle glaucoma. Open-angle glaucoma involves the iris and cornea, often referred to as wide-angle glaucoma. This underscores the importance for experts to have access to a system that offers both precision and affordability for early detection of glaucoma.

Cataract is directly related to lens. When clumps of protein are present on a lens then lens cannot able to pass the incoming light from itself. This causes blurriness in the front of a human eye. This process is reversible.

The diabetic eye condition arises from irregular glucose levels in the bloodstream, manifesting in the retinal membrane of the eye. It is a leading cause of complete vision loss in many countries. Diabetic Retinopathy (DR) occurs when elevated glucose levels damage the small blood vessels responsible for supplying nutrients and oxygen to the retinal tissue layer [26]. These blood vessels can either swell or become blocked, impeding the flow of blood. In some cases, abnormal blood vessels may develop on the surface of the retina, leading to vision loss. There are two recognized categories of diabetic eye conditions: proliferative diabetic retinopathy (PDR) and non-proliferative diabetic retinopathy (NPDR) [28].

The practical application of Hierarchical Fuzzy logic has proven beneficial across a range of applications. A particularly valuable technique involves experts transforming undecided, complex information into a more easily understandable human rational form, using suitable methods to incorporate human input. This process results in a Hierarchical Fuzzy management directive comprised of linguistic components [4]. This paper introduces an expert system utilizing the Hierarchical Fuzzy framework for the recognition of eye diseases such as Glaucoma, Cataract, and Diabetic Retinopathy based on comprehensive test results. The specific assessment is conducted by utilizing a carefully curated statistical dataset that consists of six distinct patterns. Through logical expert analysis, Hierarchical Fuzzy rules are formulated to serve as a decision-making tool. The healthcare industry, leveraging artificial intelligence, has transitioned effectively from theoretical examination applications to real-world tasks. Considering the complexities involved in diagnosing Glaucoma, Cataract, and Diabetic Retinopathy, the adoption of a Hierarchical Fuzzy logic system is crucial. To assess accuracy levels, clinical center datasets prove to be highly valuable. Utilizing eight system input parameters (symptoms), a Hierarchical Fuzzy inference system is developed. This inference system, based on Hierarchical Fuzzy instructions, leverages medical experts' knowledge to interpret patients' symptoms and incorporate them as input parameter values.

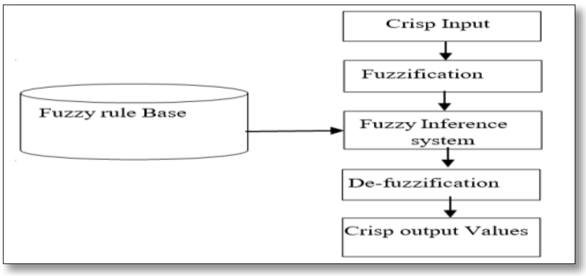

Fig 1.0- Hierarchical Expert-Fuzzy System [5]

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In the diagnosis of glaucoma, eight parameters have been identified, with the cornea being a crucial aspect. However, detecting abnormalities in the cornea can be costly. Hence, the Surgical Illuminating Keratoscope is employed. This device, also known as a Keratoscope, effectively addresses the challenge of detecting irregular curvature of the lens and cornea in a cost-effective manner. It serves as a precise technique for diagnosing and managing corneal refractive faults and administering corneal reducing incisions. [6].

Fig 1.1- Surgery Illumination Keratoscope [6]

The Surgery Illumination Keratoscope is utilized for diagnosing Astigmatism, a condition characterized by an irregular curvature of the cornea. The cornea, which is the clear outer layer covering the iris and pupil of the eye, as well as the outline of the lens, plays a crucial role. Both the cornea and lens are adjacent and curved uniformly in all directions. Together, they focus incident light rays onto the retina at the back of the eye [6]. Corneal astigmatism occurs when the cornea has an irregular curvature. Similarly, when the lens of the eye is irregularly shaped, it also results in astigmatism. Any form of astigmatism can cause blurred or unclear vision, whether myopic (nearsighted) or hypermetropic (farsighted).

Disordered intraocular lens (IOL) is a very uncommon, but severe complication in which the intraocular lens changes from its usual location in the eye. In patients who lose their vision or they suffer some damage to adjoining ocular structures, surgery is suggestively important in management of IOL dislocation. Most common symptoms for surgery are reduced visual acuity, monocular diplopia and even halos [6].

Fig 1.2- Reflection of Astigmatic Cornea [6]

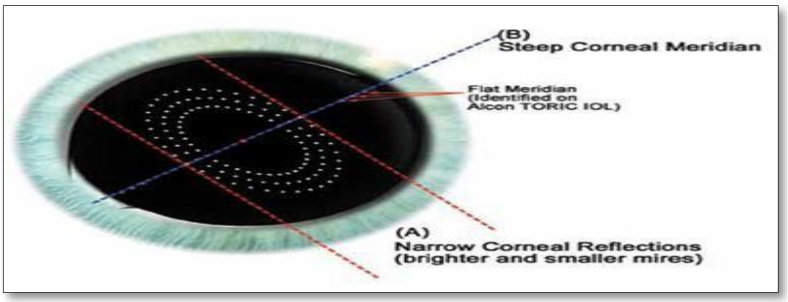
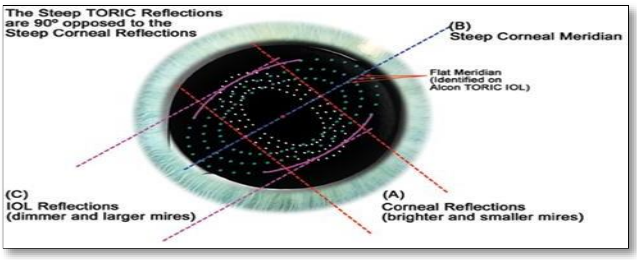


Fig 1.3- Reflection of Toric IOL [6]



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The faint corneal reflections depicted in the image will be realigned with acute apex marks (identified as B). During this process, the patient is instructed to focus on blinking. It is crucial that the LED and the scope are positioned at a 90-degree angle with respect to the patient's visual axis to ensure precise results.

RELEVANT WORK

Considerable heuristic knowledge-based work has been conducted, showcasing the operation and framework of medical expert systems.

1. Illuminating Surgical Keratoscope

Wang J. et al. (1988) have suggested a qualitative way of illuminating keratoscopy for evaluation of corneal shape. The knowledge of 2-Dimensional Keratoscopy is insufficient to reconstruct 3-Dimensional corneal surface recognizably. The assumptions that are taken for analysis leads to erroneous results. The author concluded that the algorithmic instructions, involving the interpretation of a series of non-linear calculations to accurately represent symmetrical and visual connections, yielded significant improvements. These equations can be statistically understood using the Newton-Raphson method. Through the analysis of two ellipsoid models (with eccentricities of 0.5 and 0.75), it was observed that the maximum inaccuracies (occurring in the outer-most ring) were reduced from approximately 8% (for e=0.5) and 12% (for e=0.75) using the current method to below 2% with the new method [7]. Vijfvinkel G et. al. (1988) have put forth a proposal of a qualitative keratometer that makes available direct information with respect to the shape of cornea. Additionally, he noted that any external source of light results in corneal placid reflections, which originate from the inner wall of the device [8]. Corbett M et. al. (1994) elucidated the purpose of topography and traced the evolution of topographic techniques from keratometry to photo-keratoscopy, culminating in video-keratoscopy. He also highlighted the advantages and limitations of these methods. Corbett concluded that precise reconstruction of the central cornea was attained through the 2-step profile technique. He suggested comparing the diameters of separate Keratoscope images reflected from the cornea with those reflected from calibration spheres for enhanced accuracy [9]. Carvalho et al. (1999) proposed a quantitative theory for the surgical keratometer, outlining a computer-based solution for measuring the central region (3-4mm) of the corneal surface. They suggested utilizing a high-density fiber optic illuminated on a ring-shaped base, termed a placid disc, to focus on the cornea. Reflected images from this setup are then captured by a charge-coupled camera, positioned atop Zeus's microscope. This setup promises precise results, with a mean deviation of 0.05mm for the radius of curvature, 0.24 diopter for power, and 5 degrees for cylinder measurement [10].

2. Glaucoma

Ulieru et al. (2000) introduced a Neuro-Hierarchical Expert-Fuzzy System designed to diagnose and detect Glaucoma in its early stages. The authors also introduced a Hierarchical Fuzzy IF-THEN rule-base for classifying three variants of glaucoma: Open-angle glaucoma, narrow-angle, and Pigmentary glaucoma, along with providing insights into clinical

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examination procedures. Author concludes that the unique Neuro-Hierarchical Fuzzy system proposed by their team mitigates many health risks and reduces unnecessary procedures, consequently lowering the overall cost of diagnosis [11]. Varachiu et al. (2002) proposed utilizing Computer Intelligence methods, including three algorithms: Hierarchical Fuzzy Logic, Neural Networks, and Genetic algorithms, to construct an intelligent system capable of analyzing and predicting glaucoma. They then correlated the rules generated by these algorithms with clinical results. Author concluded that the distinct Hierarchical Fuzzy rules closely resembled the clinical results, suggesting their effectiveness in predicting and diagnosing glaucoma [12]. Inoue et al. (2005) proposed an approach involving the systematic investigation and robust processing of data to analyze the size of the optic disk (OD) region and the cup-to-disc (C/D) ratio. They demonstrated that this method was effective, although they noted some challenges such as the unpredictability of veins within the optic disk. The authors suggested that despite these complexities, the new device holds promise for analyzing patients' conditions for glaucoma [13]. Cheng et al. (2010) discuss a comprehensive evaluation of RetCam images for adapting close to/open distinctive nomenclature. The authors propose several concepts, including aspect recognition and arc recognition, to characterize Open angle glaucoma and narrow angle glaucoma. They also revisit clinical literature and outcomes in their study [14]. Xu Y. Et al. (2012) familiarized digital image processing and analysis which were primarily based on mechanism that amended into frontier and confidential Anterior Chamber Angle (ACA), with respect to multi-scaled HOG highpoints [15]. Krishnan M et al. (2012) have suggested a unique Intuitionist Hierarchical Fuzzy Set (IFS) based technique. They deployed IFS to segregate optic disc from fundus images of retina. Krishnan split the ocular disc using Otsu, A-IFSH, Gradient Vector Flow-snake methods for segmentation to select optimum schematic. This method was applied on 100 images which included 31 DR, 30 healthy and 39 glaucomatous eye images. The suggested IFS segmentation technique was able to achieve the F-score of 0.92 with 93.4 % accuracy in contrast to the work of other two segmentation Approaches [16].

Padmanaban K. (2013) in their work showcased a Hierarchical Fuzzy C mean clustering method. This Hierarchical Fuzzy C mean clustering method was set out for the identification of an optic disc in a color fundus image. Padmanaban put his technique for separating the green channel from the RGB palette and used a median filter to remove the noise from the image with the extraction of ROI. The authors concluded that to locate the optic disc, the system proposed by them increases efficiency [17]. Elshazly et al. (2014) addressed the challenge of early-stage detection of primary open-angle glaucoma (POAG). The author conducted a study in which a classifier was constructed by integrating principal component analysis using the rotation forest tree (ROT) method. Three primary methods were compared: decision tree (DT), Hierarchical Fuzzy logic, and neural network (NN). The study concluded that ROT achieved high accuracy in most tests, leading to near-perfect results and facilitating early detection of glaucoma [18].

Agarwal et al. (2015) introduced an adaptive system that integrates key image parameters such as infer, variance, and deviation to analyze the surrounding optic circle and optic disc from fundus images. The authors also addressed concerns regarding scientific database compatibility. Their framework demonstrated favorable results, achieving an accuracy of 90 % [19]. Aloudat et al. (2015) explored the potential of utilizing corneal fluid thickness to distinguish between open and closed-angle glaucoma at the initial stage. They conducted a review of final results from patients treated at the Jordanian Governmental health center, specifically Al Ameera Basma Hospital. The patients encompassed a wide range of ages, including elderly individuals, and all presented with acute or primary stage illnesses [20]. Haveesh et al. (2015) proposed methods utilizing a Hierarchical Fuzzy classifier and image processing for glaucoma recognition. The primary selection criterion in this process is the determination of the cup-to-disk ratio (CDR) for glaucoma detection. The main objective of this work was to enhance retinal fundus imaging and incorporate the CDR of acquired images using operational rule-based techniques. The aim was to monitor the disease from its symptoms by deploying a Hierarchical Fuzzy classifier implemented in MATLAB. [21]. Lamani D. et. al. (2015) incorporated some factors collectively along with neuro retinal thickness, intraocular stress and central cornea thickness etc. for diagnosis of glaucoma through medical tools like perimetry, tonometry and pachy-metry [22].

Kumar B. Et al. (2016) brought forward an image processing method to diagnose glaucoma. The researcher deployed definite approaches including HOS, PCA and mixing textures to compare the effects for analyzing accuracy. The result of this approach yielded 86 percent success out of 200 actual photographs for bi-segment classification with SVM [(23) twenty three]. John A. et. al. (2017) recommended a Hierarchical Fuzzy Inference System for diagnosis of Glaucomatous condition. They concluded that result yielded 88 percent accuracy with the help of distinct Hierarchical Fuzzy conclusions and medical expert confirmation [24].

3. Diabetic Retinopathy

Furtado et al. (2017) introduced a method for fragmenting Eye Fundus Images (EFI) in Diabetic Retinopathy using Density Clustering. The author stressed the significance of segmenting regions with potential abrasions to highlight and classify them, as well as to determine the severity of Diabetic Retinopathy. Density clustering methods were deemed essential for isolating individual abrasions and were recommended to be used in conjunction with operational techniques for feature extraction, removal of vascular trees, and classification. The study concluded that combining Simple Linear Iterative Clustering (SLIC) with Density-based spatial clustering of applications with noise (DBSCAN) resulted in better segregation of the lesions [29].

Bhatia et al. (2016) concentrated on disease recognition by employing a collaborative approach of machine learning classification algorithms. They utilized parameters derived from various retinal image processing algorithms, including lesion-specific features such as microaneurysms and exudates, as well as characteristics like the diameter of the optic disk, AM/FM, and image level attributes such as pre-screening and quality assessment. The decision-making process for predicting diabetic retinopathy was conducted through an alternative deployment of Naive Bayes, Random Forest, decision tree, AdaBoost, and SVM algorithms [26]. Dhanasekaran R., et. al. [2016] suggested Gaussian Mixture Model (GMM) classifier for cataloging the input retinal images as normal or abnormal images. They were able to achieve an accuracy of 97.78 % [30]. Gupta et al. (2016) proposed an algorithm centered on analyzing fundus images of the human eye, particularly focusing on blood vessels in the retinal fundus image for the detection of Diabetic Retinopathy (DR). They achieved improved results with reduced calculation time by employing morphological supervision along with Gaussian channel processing [31]. Kusakunniran et al. (2016) introduced a logic for the automated analysis of retinal image quality and the identification of fragments of hard exudates. They conducted characteristic analysis using contrast histograms. The segmentation of the optic disk (OD) and hard exudates fragments relied on recursive selection thresholding and the seize cut technique. Kusakunniran concluded that their method achieved over 90 % accuracy [32]. Labhade J. et al. (2016) presented soft computing methods (Gaussian Naive Bayes, Support-Vector-Machine, Gradient boost, Random-Forests) for detecting DR with distinctive precision. The author concludes that the SVM classifier yields 88 percent precision while Gradient boost and random forests give 83 % precision [33]. Paing M. et al. (2016) projected a method for detecting and classifying DR by means of ANN. The author was able to detect lesions like exudates, blood vessels and micro-aneurysms from the input images and then gotten dynamic features and categorization through an ANN classifier. Author concludes that the accuracy, sensitivity and precision of the system were 96, 95, 95 % respectively [34]. Zohora S. et al. (2016) studied various preset methods deploying various algorithms that lead to improved performance for detection of exudates. Author established that midst a variety of approaches used, fuzzy-c (clustering techniques) is able to detect the exudates more precisely as compared to other methods mentioned for exudates detection [35].

Ibraheem et al. (2015) developed a taxonomy for Diabetic Retinopathy (DR) classification, dividing it into categories such as hemorrhages, microaneurysms, and exudates using fundus images. They extracted numerous parameters, including discrepancy, entropy, mean of the pre-processed images, and standard deviation, to characterize the image content and infer the presence of diabetic retinopathy. The authors concluded that the precision of this taxonomy could significantly enhance results, and employing image processing methods could alleviate the workload of ophthalmologists [36]. Sangwan S. et. al. (2015) propose taxonomy for proliferative DR, Non-proliferative DR and healthy eye with the precision of about 92.6 percent. Author concludes SVM as a logical construct for detection of diseases caused by diabetes [37]. Gandhi M., et al. [2015] premeditated the level of severity that was measured by detection os the position of the exudates from affected region with reference to macula (for macular degeneration). The JSEG segmentation algorithm flawlessly used Localization the existence of exudates. In term of computational and homogeneity of an image it is quite efficient with given color pattern that results in an imposing method [38].

III. THE PROPOSED METHOD

This segment holds the concerns in constructing the wide-range Hierarchical Fuzzy system for constructing the structure. The Hierarchical Fuzzy frame is a mechanism that is based on the Hierarchical Fuzzy set scheme. It substitutes a fuzzified explanation of the current state of the patient and prompts a Hierarchical Fuzzy relationship with an explicit objective to develop the

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Hierarchical Fuzzy interpretation i.e. to infer unresolved explanation and the competence of the simplified and significant solution. Hierarchical Fuzzy-based evaluation techniques work on the fundamental concept of if (antecedent)-then (consequence) approach to sketch inference. Therefore, a Hierarchy-based Fuzzy structure permits a simple pathway for inputting the correct values. The considered Hierarchical Fuzzy set works in affiliation to membership function and which my lie between a range of 0-1. A Hierarchy fuzzy set has no existing advantage and has a hierarchical fuzzy intermediate. The tmp (trapezoidal membership plot) is a chore with quadruple parameters a, b, c, d. In this "a and d" signify feet of quad with degree 0 and "b and c" signifies shoulders of the trapezoid of degree 1.

IV. METHODOLOGY

Fig 2- illustrates the design of the expert device, incorporating twenty-three inputs as input variables, including Intraocular pressure (IOP), Rim to disc ratio (RDR), field of vision, corneal thickness, angle, visual acuity, cup to disc ratio (CDR), lens, and others. These inputs are utilized to determine the fitness rating of a parameter. After selecting the input variables, the next step involves fuzzifying the factors, which entails organizing the Hierarchical Fuzzy sets for all input variables and assessing the variance of their fitting to the Hierarchical Fuzzy set. The Hierarchical Fuzzy rule-base enables the expert system to provide nearly accurate results. Important signs and symptoms for evaluating the illness are derived from available main medical treatment evaluations. Figure 2 outlines the methodology for the proposed tool, which leverages Hierarchical Fuzzy Inference System (FIS) and Graphical User Interface (GUI), powerful tools provided by MATLAB, to propose a Hierarchical Fuzzy decision framework. The training of the Hierarchical Fuzzy inference system is conducted through the FIS editor, another robust tool provided by MATLAB. Figure 3 presents a straightforward and rational depiction illustrating the weight of all input parameters (8 input parameter values) on the left-hand side and the output on the right-hand side. However, the number of inputs may be limited by the available memory of the machine.

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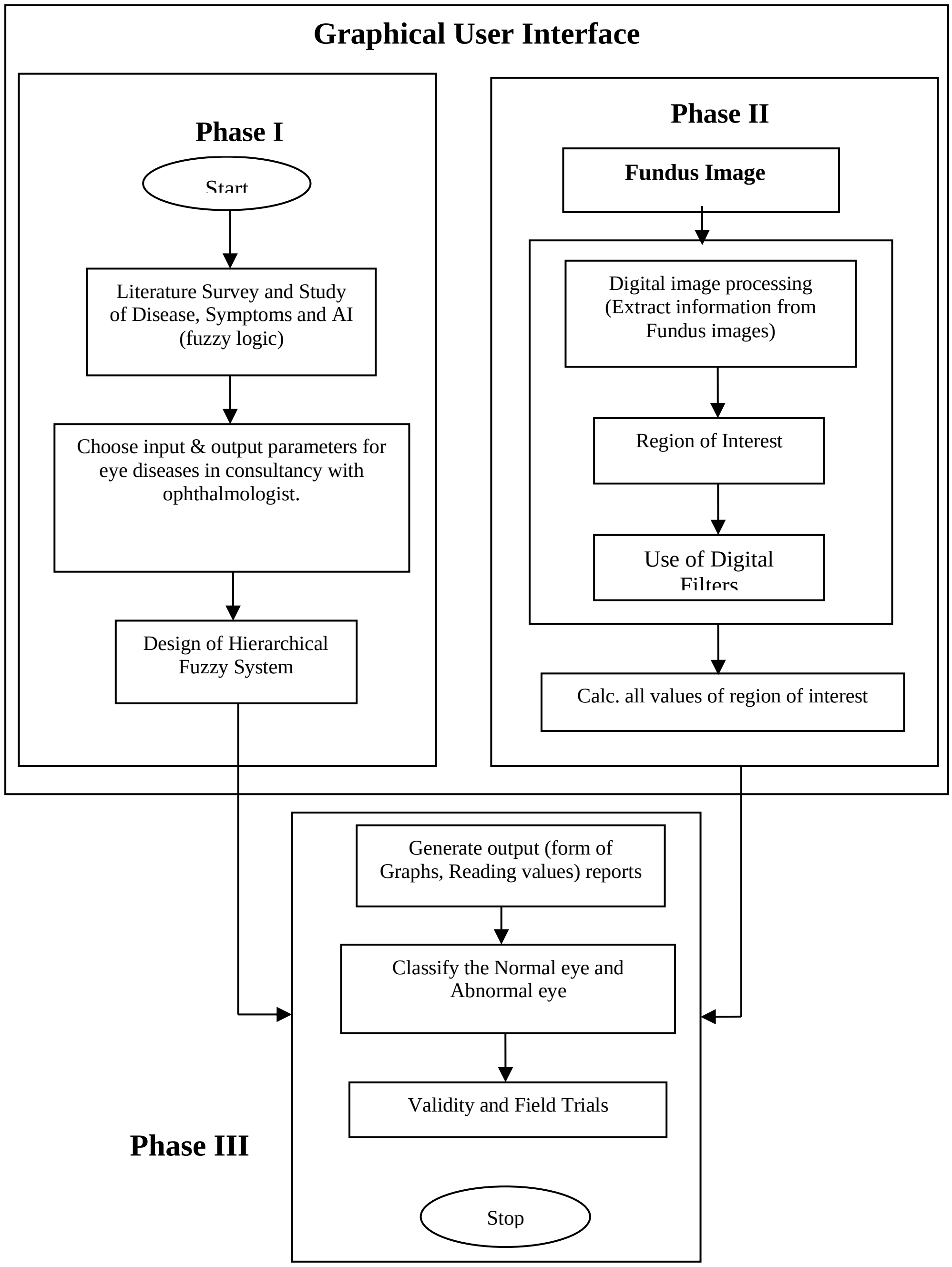

Fig 2- Flow chart of Methodology

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Total (23) twenty three input variables are accustomed for planning the design of this expert system. These input variables include Intraocular pressure, Cup-to-disc ratio, Rim-to-disc ratio, View field, corneal Thickness, View Acuity, size of Lens and Angle etc. These inputs are deployed for prediction of the health of a person's eye. The Hierarchical Fuzzy sets and their corresponding range have to be determined for every input variable.

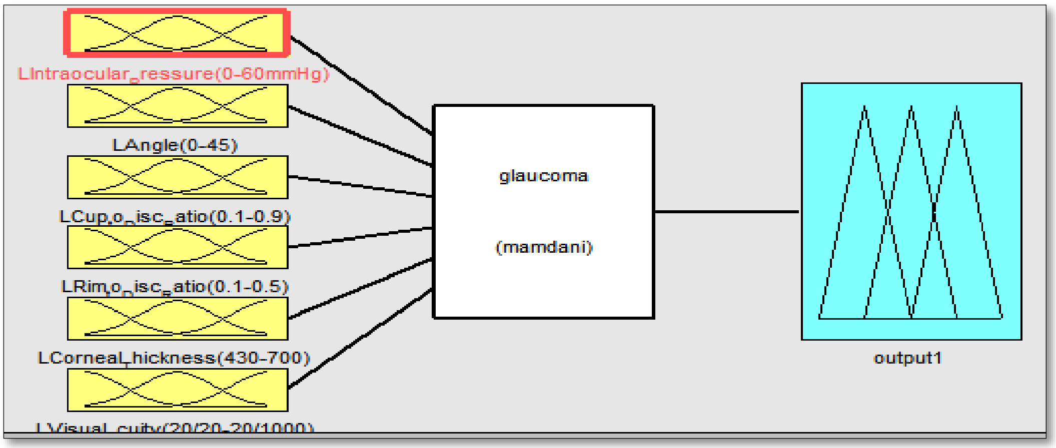

Fig 3- FIS Editor of MATLAB with 8 inputs & 1 output

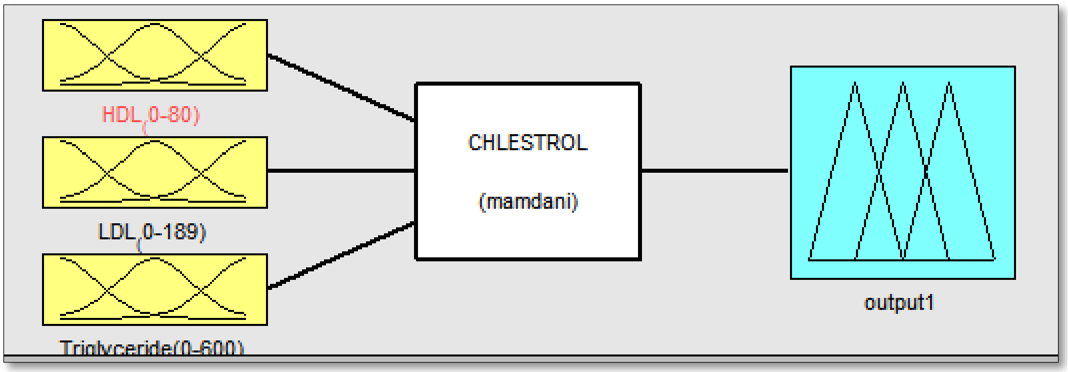

Fig 4- Cholestrol

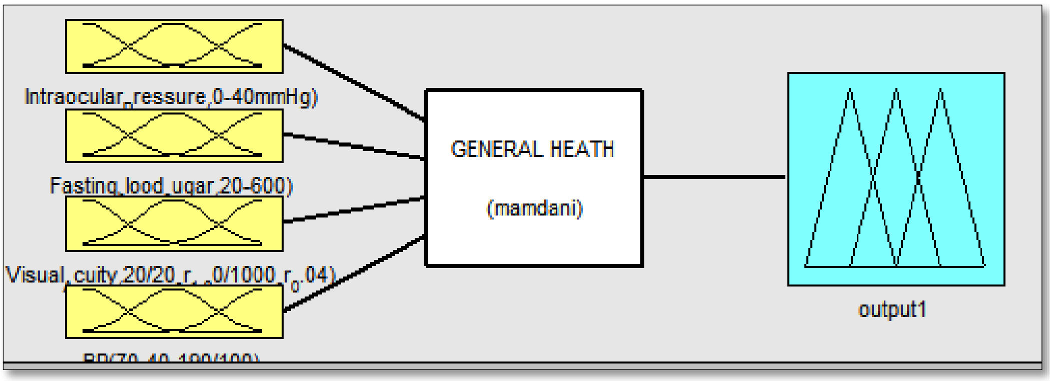

Fig 5- General Health

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A. Membership Function

All relationship functions are interconnected with each variable. The relationship functions depicted here provide a clear outline of the membership functions. These membership functions are utilized for editing rules and validating all relationship functions within the interconnected Hierarchical Fuzzy inference system. This collaborative approach encompasses both input and output parameters, facilitating comprehensive analysis and decision-making processes.

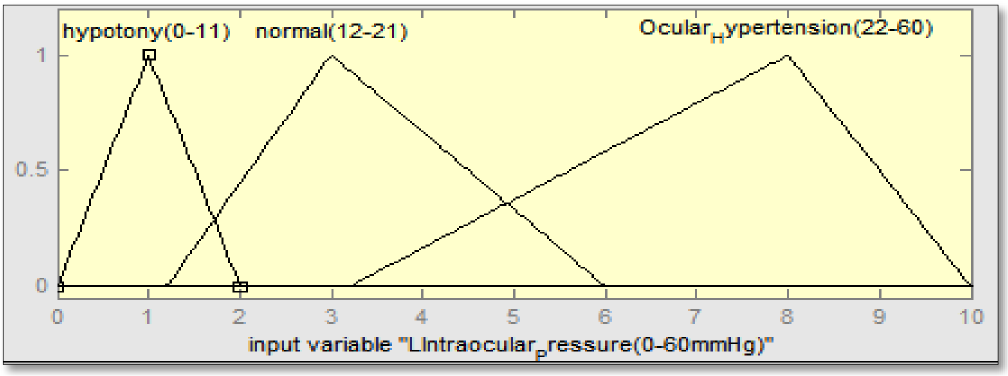

Fig 6- Mf plot-IOP

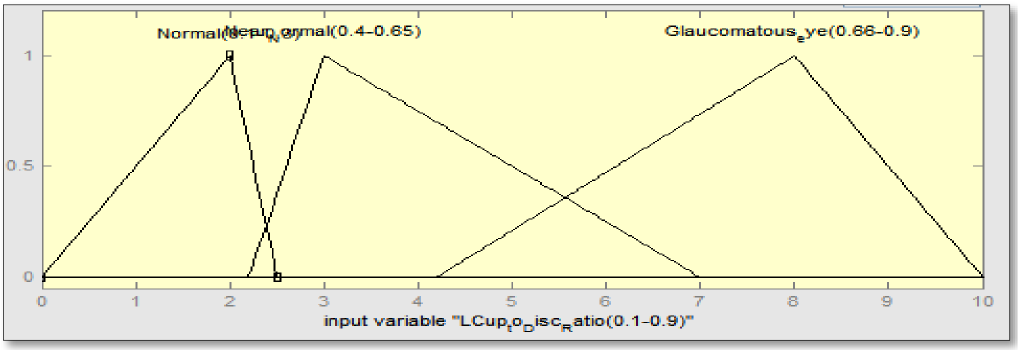

Fig 7- Mf plot-C to D ratio

The method involves the union of rules, where the membership functions of all constructed rules for evaluation are merged into a single Hierarchical Fuzzy set. During development, multiple rules are combined into a Hierarchical Fuzzy set for each construction variable. The Mamdani model is utilized as the inference method. Table 1 demonstrates the range of membership function parameters alongside the input variables.

B. Output

The proposed Hierarchical Fuzzy Inference System (FIS) offers below mentioned output for identifying Glaucoma and Cataract:

1. Normal eye (0-3)
2. Glaucoma, Cataract and Diabetic Retinopathy (3.1-5.3) Mild condition.
3. Glaucoma, Cataract and Diabetic Retinopathy (5.4-7.6) Moderate condition.
4. Glaucoma, Cataract and Diabetic Retinopathy (7.7-10) Severe condition.

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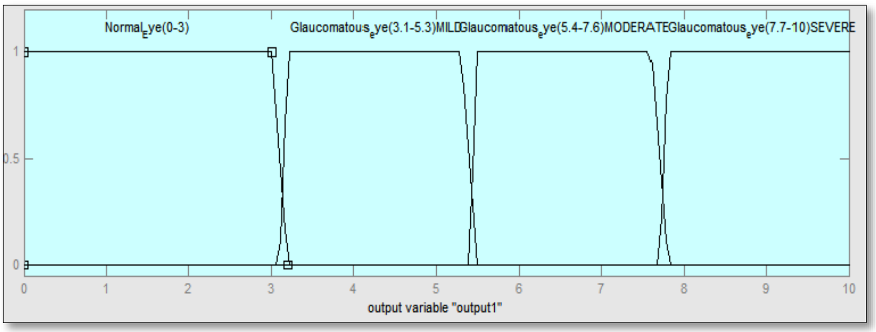

Fig 8- Membership Plot-Output

Sr.No.	Input variables	Membership Functions	Ranges
1	Intraocular pressure	Hypotony	[0 1 2]
		Normal	[1.2 3 6]
		Ocular hypertension	[3.2 8 10]
2	Angle	Extremely Narrow	[0 1 1.8]
		Narrow	[1.2 2 6]
		Wide open angle	[2.2 8 10]
3	Cup to disc ratio	Normal	[0 2 2.5]
		Near Normal	[2.2 3 7]
		Glaucomatous eye	[4.2 8 10]
4	Rim to disc ratio	Normal	[0 2 5]
		High Glaucomatous	[2.2 6 7]
		Severe Glaucomatous	[6.2 8 10]
5	Corneal thickness	Thick	[0 3 3.8]
		Average	[3.2 4 7]
		Very Thin	[4.2 8 10]
6	Visual Acuity	Normal	[0 3 5]
		Moderate Low Vision	[3.2 6 8]
		Severe Low Vision	[6.2 9 10]

Table 1. Range of Mf parameters and Input variables

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4.3 THE RULE EDITOR

To describe the Rule Editor, it is used for viewing or modifying the rules of a fuzzy system. For defining the rules, the input and output variables of our FIS and their corresponding membership functions must be specified. The Fuzzy Logic Designing GUI consists of many interactive interfaces to create a fuzzy inference system (FIS), including the Rule Editor.

Number of Rules = $M^{i[(23)\text{ twenty three}]}$

Where M ➔ Mf and I ➔ I/P parameters

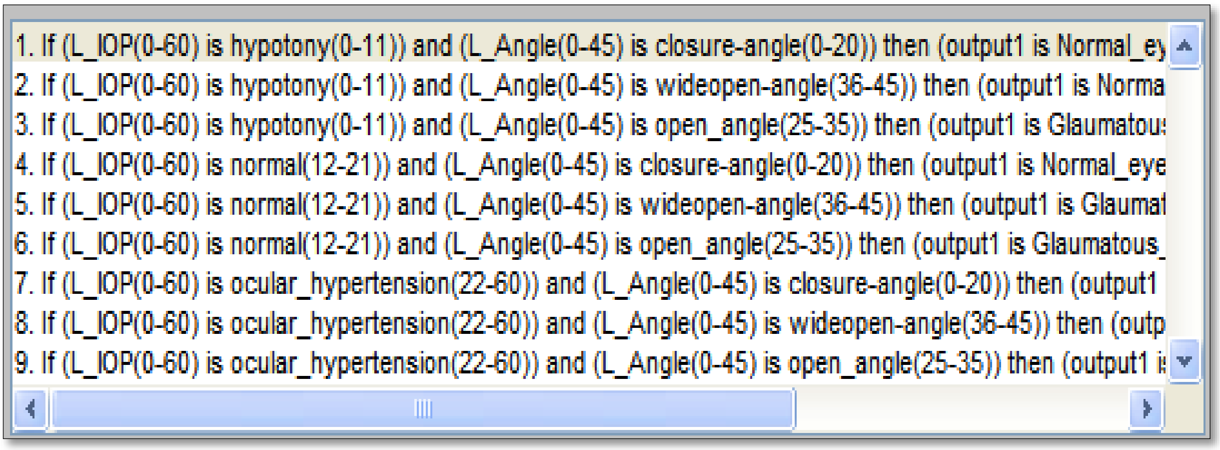

Fig 9- GUI Rule-Editor

C. Fuzzification-Defuzzification

In the next section of the Hierarchical Expert-Fuzzy System, we encounter the process of Fuzzification. This procedure involves mapping a hard evaluation of an input to a degree of membership in several Hierarchical Fuzzy linguistic variables. Defuzzification, on the other hand, is the opposite process of Fuzzification. Therefore, a crisp inference output scheme is referred to as the Defuzzification method.

V. INVESTIGATIONAL OUTCOMES

A. Rule Viewer

The Rule Viewer is utilized to present a blueprint of the entire fuzzy inference procedure. It is constructed based on the fuzzy inference diagram described here. In a single figure window, there are 10 small plots accumulated. The top three minor plots characterize the antecedent and consequent of the 1st rule. Each rule is represented by a row of plots, with each column representing a variable. Figure 10 illustrates the Rule Viewer of the projected system. It displays the result of the entire Hierarchical Fuzzy system. At the left plane at the top, we observe a value of 5.95 (defuzzified values), indicating that the person is normal.

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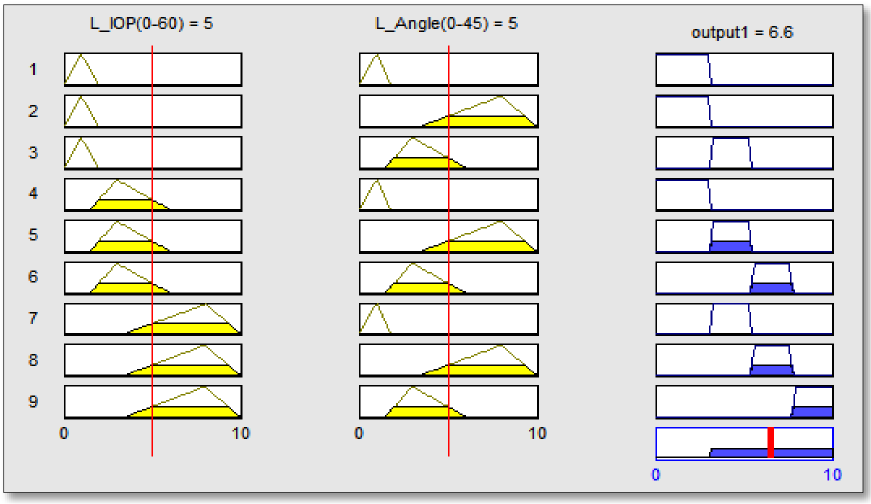

Fig 10- GUI Rule-Viewer

B. Surface View

After opening the Surface Viewer, we encounter a 2-dimensional curve representing the mapping from service quality to tip amount. In this 1-input 1-output scenario, the entire mapping is displayed in a single plot. Systems with 2 inputs and 1 output work similarly, generating 3-dimensional plots that MATLAB can efficiently handle. The Surface Viewer's distinct ability for cases with 2 (or more) inputs and 1 output is that we can manipulate the axes to obtain different 3-dimensional views of the data. Figure 11 displays the surface plot of disease between two symptoms: (1) angle and (2) intraocular pressure. The graph clearly illustrates that when the angle ranges between 0-10 and intraocular pressure ranges from 0-10, the disease is predicted. Input is depicted in blue color, while output is shown in yellow color.

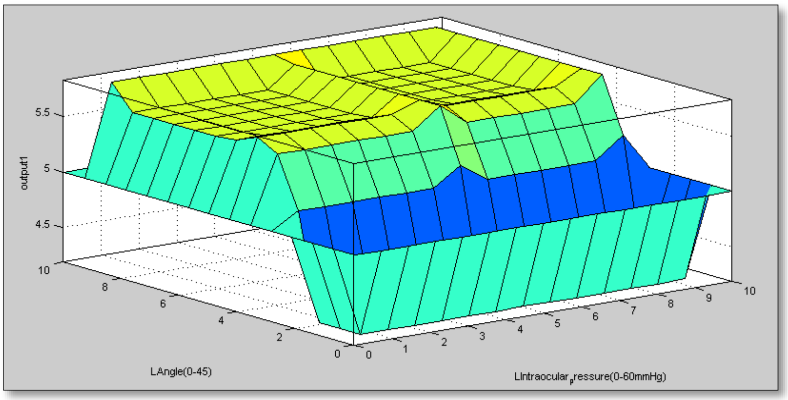

Fig 11- A 3-D Surface View between Intra Ocular Pressure and Angle

C. Graphical User Interface

The MATLAB Graphical User Interface (GUI) serves as an essential tool for controlling information from MATLAB graphic objects in a human-computer interface. GUIDE generates two forms of MATLAB files: one for MATLAB edge-figures and another for M-files. The M-file contains code for initializing the GUI and provides support for the graphical user interface responses, enabling interactive elements for the user. The M-file editor allows you to add code

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to the GUI to complete its functions. Figures 12, 13, and 14 showcase the GUI for the projected system, providing a visual representation of the interface design and functionality.

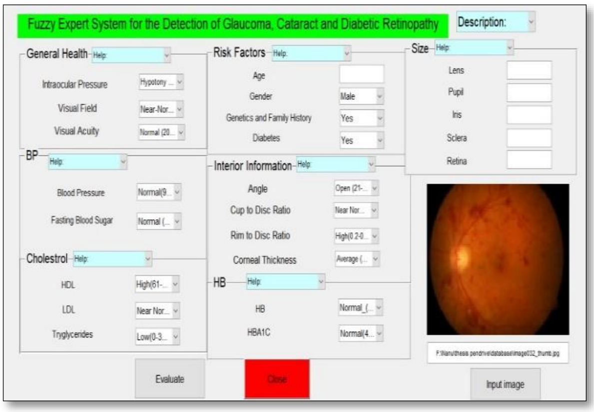

Fig 12- GUI for Detection of Glaucoma with Input Parameters

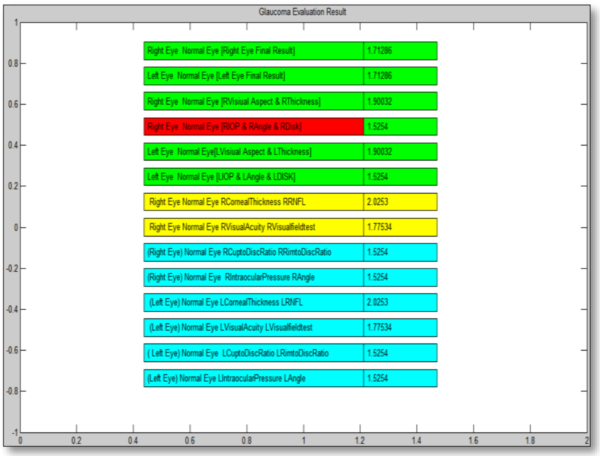

Fig 13- Results of evaluation of Glaucoma

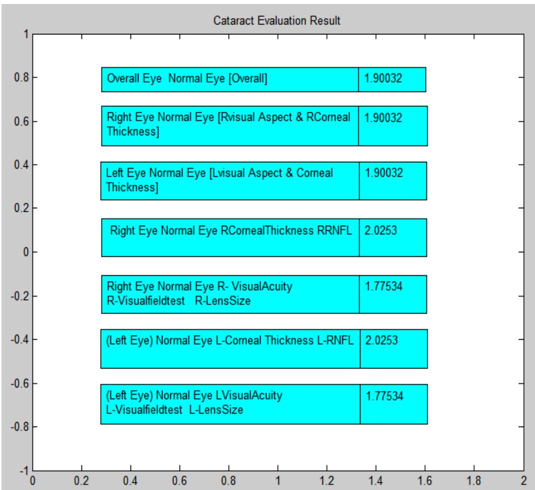

Figure 14. Results of evaluation of Cataract

The proposed technique aims to differentiate between normal and defective eyes using input parameters such as Intraocular Pressure (IOP), Cup to Disc Ratio (CDR), Rim to Disc Ratio (RDR), Angle, Field of Vision, Visual Acuity, Lens Size, and Corneal Thickness. In the Hierarchical Fuzzy Inference System (FIS) designed, a total of 117 rules are defined, out of which 100 rules were arbitrarily selected. Among these 100 rules, 50 are for usual patients and the remaining 50 are for patients with eye ailments. The outputs of the system are then compared with the findings of an ophthalmologist. The results have shown that 97 rules are consistent with the findings of the ophthalmologist. Therefore, the accuracy of the system is evaluated to be 97 percent, indicating its effectiveness in correctly identifying normal and defective eyes based on the input parameters provided. [25].

$$\text{Accuracy} = \frac{\text{No.of correct cases}}{\text{Total No.of Patients}} X100 \qquad (1)$$

$$\text{Accuracy} = \frac{93}{100} X100$$

=93 percent

Sensitivity, in the context described, is defined as the ratio of True Positive cases to the sum of True Positive and False Negative cases. True Positive cases occur when an image with an ailment is correctly identified as such, while False Negative cases occur when an image with an ailment is incorrectly classified as normal. Sensitivity provides a measure of how well a system can correctly detect the presence of an ailment, ensuring that a higher sensitivity value indicates a lower likelihood of missing positive cases. [25].

$$The\ Sensitivity = \frac{\text{True Positive cases(TP)}}{\text{True Positive cases(TP)+False Negative cases(FN)}}\ \text{X } 100 \qquad (2)$$

$$The\ Sensitivity = \frac{47}{47+3}\ X\ 100$$

=0.94 X 100 ➔ 94%

Specificity is defined as the ratio of True Negative cases to the sum of True Negative and False Positive cases. True Negative cases occur when a normal image is correctly classified as normal, while False Positive cases occur when a normal image is incorrectly classified as defective. Specificity provides a measure of how well a system can correctly identify negative cases, ensuring that a higher specificity value indicates a lower likelihood of misclassifying normal images as defective [25].

$$The\ Specificity = \frac{\text{True Negative cases (TN)}}{\text{True Negative cases (TN)+False Positive cases (FP)}} \qquad (3)$$

$$The\ Specificity = \frac{46}{46+4}$$

=92 percent

D. Hardware Implementation

A keratoscope, also referred to as a Placido's disk, is an ophthalmic device which is deployed to analyze the structure of cornea's frontal surface. A sequence of centered coaxial orbit is projected on the cornea and then its reflection is seen by the expert from a small hole in center of the disk like object. A regular-shaped cornea shows equally spaced and symmetric reflection hence inferring normal eye. However the rings seems to be distorted in case of a defective eye.

Fig 15- Use of Surgical Illuminating Keratoscope for examination

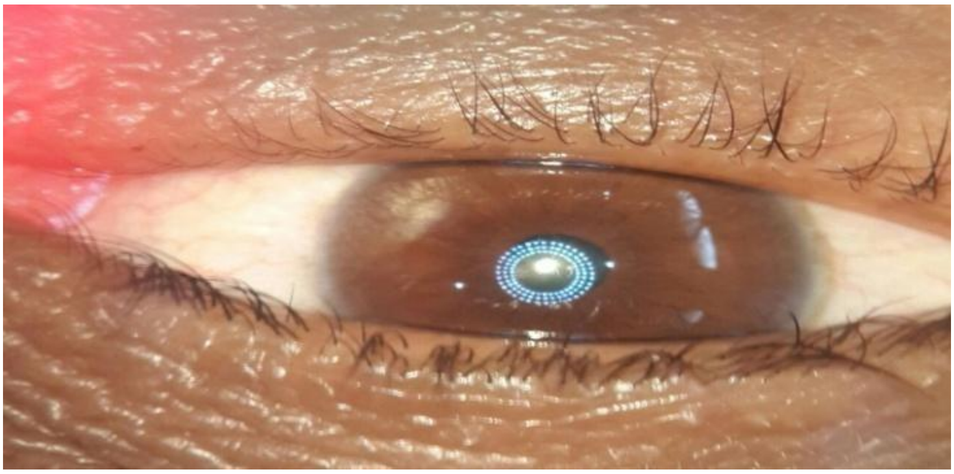

Fig 16- Reflection Image from Surgical Illuminating Keratoscope

VI. CONCLUSION

This work emphasizes the importance of early detection for widespread eye diseases such as Glaucoma, Cataract, and Diabetic Retinopathy. Early identification allows doctors to differentiate between normal eyes and those affected by these conditions, giving them an advantage in treatment. The Surgical Keratoscope is highlighted as a cost-effective tool for detecting irregular corneal curvature, contributing to the proposed solution based on Hierarchical Fuzzy inference for predicting Glaucoma. The system considers unique input parameters crucial for predicting eye ailments and achieves capable results with over 93 percent accuracy when compared with a dataset of 100 patients. It is suggested that the system can be further improved by incorporating additional input parameters. The Surgical Keratoscope is positioned as a cost-effective and efficient solution for various medical settings, from super specialty hospitals to eye clinics. Overall, the presented system is expected to have a significant impact in the future, offering improved diagnosis and treatment for individuals suffering from Glaucoma, Cataract, and Diabetic Retinopathy.

Connotation Statement

The study proposes a simple, early, and cost-effective method for detecting glaucoma and other eye diseases. This approach is expected to be well-received by individuals as it facilitates glaucoma detection through a brief examination, potentially consisting of only two out of eight available tests. Patients can opt to consult an expert if the initial tests suggest a normal eye based on the proposed Hierarchical Expert-Fuzzy System (FIS). Furthermore, the system evaluates the severity level of glaucoma, categorizing it as normal eye, glaucomatous eye, cataract and diabetic retinopathy (mild), moderate, or severe. This research contributes to the field by providing future researchers with insights into the faster detection of glaucoma, which traditionally requires a time-consuming process involving expensive tests. The study incorporates twenty-three parameters, including pachy-metry, gonio-scopy, peri-metry, tono-metry, and ophthalmo-scopy, whereas previous investigations typically utilized only two parameters. By leveraging the proposed Hierarchical Fuzzy interference framework, easier, faster, and more affordable recognition of glaucoma can be achieved.

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