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Diagnosis of Eye Diseases like Glaucoma, Cataract and Diabetic Retinopathy using Illumination Surgical Keratoscope (ISK) and Hierarchical Fuzzy Expert System (HFES)

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Abstract: Glaucoma, Cataract, and Diabetic Retinopathy are ocular conditions characterized by shared symptoms such as elevated eye pressure, optic nerve damage, and potential vision loss. Untreated, these ailments can lead to blindness, particularly affecting peripheral vision. Timely detection of these eye diseases necessitates regular and often expensive checkups, posing a challenge in terms of cost and time. This study introduces a novel approach, employing a Hierarchical Fuzzy-based decision system, to address Glaucoma, Cataract, and Diabetic Retinopathy at their initial stages. Additionally, a cost-effective Surgical Illuminating Keratoscope is proposed to tackle issues related to irregular corneal curvature, cataract surgeries, and Penetrating Keratoplasty. The Hierarchical Fuzzy rule-based system aids medical practitioners in delivering accurate results by taking into account the patients' symptoms. Comprehensive testing of the Hierarchical Fuzzy system and the practicality of the Keratoscope were conducted in collaboration with ophthalmologists. The results, with accuracy, sensitivity, and specificity rates of 93%, 94%, and 92% correspondingly, demonstrate the precision and utility of these systems. Notably, this technique proves to be efficient and incurs low computational costs.

Keywords: *Hierarchical Fuzzy expert system, Graphical User Interface, Cornea, Glaucoma, Cataract, Diabetic Retinopathy, Surgical Illuminating Keratoscope.*

1. Introduction

The diagnostic assessment of medical conditions presents a significant challenge in contemporary society, necessitating the application of engineering methodologies to access crucial data. Recent advancements in engineering for medical, coupled with the implementation of strategical artificial intelligence [1], offer promising solutions. In the context of glaucoma, a primary factor contributing to the disease is the persistent failure of retinal nerve fiber layers due to increased intraocular pressure within the eyes. Detecting glaucoma in its early stages proves challenging, and various methods, such as Tonometry, Ophthalmoscopy, and Pachymetry, have been employed for this purpose. However, these approaches are characterized by their high cost, time-consuming nature, and the requirement for specialized skills [2].

Cataracts are directly associated with the lens of the eye. When clusters of proteins accumulate on the lens, it impedes the passage of incoming light, affecting vision. On the other hand, diabetic eye disorder results from abnormal glucose levels in the bloodstream, which manifest in the eye's membrane, specifically the retina [26]. This condition can lead to the bulging or sealing of blood vessels, preventing the normal flow of blood. In some cases, irregular blood vessels may develop on the retina's surface, posing a threat to vision loss [27]. Diabetic eye disease is categorized into two types: proliferative diabetic retinopathy (PDR) and non-proliferative diabetic retinopathy (NPDR) [28].

The significance of the Hierarchical Fuzzy system lies in its ability to transform ambiguous and complex information into easily understandable patterns, utilizing human knowledge and acting as a guiding principle with a set of linguistic elements [4]. This study introduces a proactive framework employing the Hierarchical Fuzzy system to identify Glaucoma, Cataract, and Diabetic Retinopathy based on their associated symptoms. Using eight sets of informational parameters (indicators), a Hierarchical Fuzzy interference system is established. This rule-based Hierarchical Fuzzy framework incorporates medical expert knowledge to interpret patients' symptoms, generating specific preferences in line with predefined standards.

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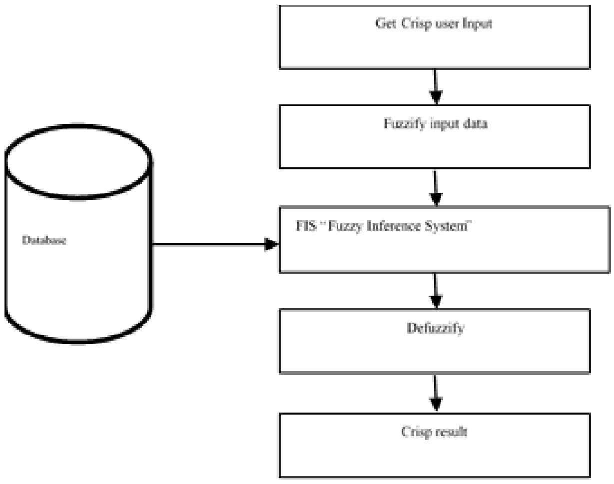

Fig. 1- Hierarchical "Fuzzy Expert System" [5]

For diagnosing glaucoma, a comprehensive set of eight factors is taken into account, with the cornea being a particularly expensive element to detect. To address this challenge, a Surgical Illuminating Keratoscope is employed as a hardware device. This innovative tool effectively addresses issues related to the irregular curvature of the lens and cornea, providing a cost-effective solution. The Surgical Illuminating Keratoscope proves to be an accurate method for diagnosing and managing "Corneal Refractive errors", as well as facilitating "Corneal Relaxing Incisions" [6].

Fig 2. Illuminating Surgical Keratoscope [6]

The deployment of a "Surgical Illuminating Keratoscope" serves the purpose of identifying Astigmatism, which stands as the primary cause for the irregular curvature of the cornea. The cornea acts as a clear, encompassing dome covering the eye's iris and pupil, or alternatively, the outline of the eye lens. Under normal conditions, the cornea and lens possess a smooth and uniformly curved surface in all directions, aiding in focusing light rays sharply onto the retina at the back of the eye [6].

Once the "Intraocular Lens" (IOL) is in place, the coaxial illumination is either reduced or turned off, allowing the reflections from the IOL to become visible. The reflections of the cornea's curvature become more pronounced, particularly highlighting any astigmatism present. The sharpest section (the shorter cross-section of the speckled mires) correlates with the pre-marked surgical areas. Reflection of the IOL might seem bigger, lighter, and exhibit variations in color [6].

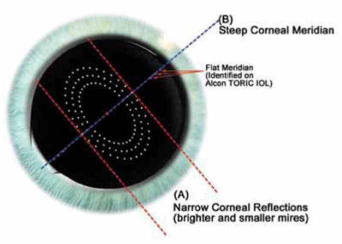

Fig. 3. Reflection of Astigmatic Cornea [6]

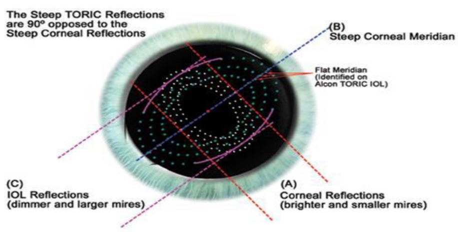

Fig. 4. Reflection of Toric IOL [6]

The fine reflections from cornea depicted in the image undergo reorientation with distinct meridian marks (B). To execute this procedure effectively, instruct the patient to focus on a LED that blinks, while ensuring that the scope positioned at 90^0 angle relative to the visual axis of patient. This precise alignment enhances the accuracy of the results obtained during the examination.

2. Relevant Work

A diverse range of heuristic studies has been conducted, shedding light on the activation and formation of medical expert schemas.

I. **Illuminating Surgical Keratoscope**

Wang J. et al. (1988) introduced a qualitative method called Photo keratoscopy for evaluating corneal shape. They highlighted that the 2-D information provided by the Keratoscope figure is insufficient for an explicit reconstruction of the “3-D corneal surface”. The authors proposed an algorithmic approach involving a set of non-linear equations to more accurately depict the geometric and optical relationships. These equations were numerically interpreted using the Newton-Raphson method. Testing on two ellipsoid models (ellipse=0.5 and ellipse =0.75) demonstrated a significant decrease in max errors (at the outermost ring) from around 8% (ellipse =0.5) and 12% (ellipse =0.75) using the existing method to less than 2% using the novel method [7].

Vijfvinkel G et al. (1988) introduced a qualitative “keratometer” that offers direct information about the entire corneal outline [8]. Corbett M et al. (1994) concluded with an accurate reconstruction of the cornea using the “2-step profile method”. This method involved comparing the diameters of individual Keratoscope mires reflected from the cornea with those from spheres for calibrating [9].

Carvalho L et al. (1999) proposed a numerical theory for a “surgical keratometer”, which is computer-based and designed to measure the middle region (3mm to 4mm) of the cornea’s surface. This approach yielded precise results for corneal shape, with a mean deviation of .05mm for the radius of curvature, .24 diopters for power, and 5^0 for cylinder measurement [10].

2. Glaucoma

A “Neuro-Hierarchical Fuzzy Expert System” for the diagnosing and early stage detection of Glaucoma was proposed by Ulieru M. et al. (2000). The deduction was drawn by the authors that the defined Neuro-Hierarchical Fuzzy System” reduces health risks and unnecessary procedures, leading to a decrease in the overall cost of diagnosis [11]. “Computational intelligence strategies”, including Hierarchical FL, NN, and GAs, were introduced by Varachiu N. et al. (2002) to develop an intelligent system for the identification and prediction of glaucoma [12].

Discriminatory analyses and threshold processing to calculate the range of the optic disk (OD) and the circle cup zone (C/D ratio) were proposed by Inoue N. et al. (2005). The methodology was found to work effectively, suggesting that new devices are viable for examining patient conditions for glaucoma [13]. A radiant configuration for the assessment of “Ret-Cam images” for personalized near/open characteristic taxonomy was introduced by Cheng J. et al. (2010), followed by a retrospective review of clinical catalogs and results [14].

Image processing and analysis-based ML were utilized by Xu Y. et al. (2012) to frontier and classify the “Anterior Chamber Angle” (ACA), employing multi-scale “HOG features” [15]. An original “Intuitionist Hierarchical Fuzzy Set” (IFS) premise-based method for dividing the optic disc of retinal fundus images was proposed by Krishnan M et al. (2012). The IFS segmentation method achieved an F-score of .92 with 93.4% precision matched to other segmentation methods [16].

A “Hierarchical Fuzzy c-mean clustering” method was presented by Padmanaban K (2013) to detect the optic disc in color-fundus images, enhancing the efficiency of optic disc localization [17]. The early recognition of “Primary Open-Angle Glaucoma” (POAG) was addressed by Elshazly H et al. (2014), concluding that “Recognition of Optic disc and cup and Thickness” (ROT) achieved high classification precision, enabling accurate and early detection of glaucoma [18].

An “Adaptive Thresholding Method” combining image features like mean, variance, and standard deviation to locate the optic circle and optic disc from fundus images was introduced by Agarwal A. et al. (2015). The framework yielded promising results with 90% accuracy [19]. A “Haar filter” was implemented by Aloudat M. et al. (2015) to segregate “open and closed-angled glaucoma” by assessing the thickness of fluid in the cornea [20].

A system employing a “Hierarchical Fuzzy classifier and image processing” to distinguish glaucoma was proposed by Haveesh G. et al. (2015). The primary objective of this method was to determine “Cup-to-Disc Ratio” (CDR) and subsequently classify glaucoma based on the calculated CDR [21]. Lamani D. et al. (2015) examined glaucoma using various parameters “neuro-retinal thickness, including central cornea thickness, and intraocular pressure”, with clinical tools like Peri, Pachy and Tonometry [22].

An image processing approach to detect glaucoma was introduced by Kumar B. et al. (2016), utilizing techniques such as “PCA, HOS, and texture blending”. The outcome of this approach achieved more than 85% success rate from 200 actual images for a 2-phase classification with SVM [23]. A Hierarchical Fuzzy expert system (FIS) for diagnosing Glaucoma as of normal and Glaucomatous eyes was proposed by John A et al. (2017). The results showed above 87% accuracy by comparing Hierarchical Fuzzy outcomes with clinical findings [24].

3. Diabetic Retinopathy

In 2017, “Segmentation by Density Clustering of Fundus Images” (EFI) for Diabetic Retinopathy was introduced by Furtado P. et al. The authors found that combining “Simple Linear Iterative Clustering” (SLIC) and

"Density-based Spatial Cluster of Applications with Noise" (DbSC-AN) proved to be more effective in isolating exudates [29]. In 2016, Bhatia K. et al. proposed methods such as "Artificial Neural Networks" (ANN) and "Support Vector Machines" (SVM) for detecting and classifying Diabetic Retinopathy [26].

Dhanasekaran R. et al. presented work on a "Gaussian Mixture model" (GM-m) classifier in 2016, categorizing input retina pictures as normal or anomalous [30]. Gupta V. et al. (2016) developed an algorithm focusing on human retina images to recognize blood vessels to detect "Diabetic Retinopathy" (DR) [31]. Also in 2016, Kusakunniran W. et al. proposed a logic for the automated assessment of retina image quality and the segmentation of hard exudates, achieving an accuracy rate of 90% [32].

Soft computing techniques for DR detection were introduced by Labhade J. et al. in 2016, showing varying precision. The "SVM classifier" demonstrated precision more than 87%, while "Gradient Boost and Random Forests" achieved 83% [33]. In the same year, Paing M. et al. presented a system for detection and classification of DR using Artificial Neural Networks (ANN). The system exhibited sensitivity of 95%, precision 95%, and accuracy 96% [34].

Zohora S. et al. concluded in 2016 that amid various methods used, "fuzzy-c" (clustering techniques) performed more precise exudate recognition compared to other methods [35]. In 2015, Ibraheem S. proposed the nomenclature of DR into "microaneurysms, hemorrhages, and exudates" using fundus pictures. The author concluded that classification accuracy can be amended, and image handling techniques can simplify the responsibilities of ophthalmologists [36].

In the same year, Sangwan S. proposed the organization of "Non-proliferative-DR, Proliferative-DR, and Normal eye" with a precision of 92.6 percent. The research concluded that "Support Vector Machine" (SVM) is a logical classifier for detecting diseases caused by diabetes [37]. Also in 2015, Gandhi M. et al. designed a severity level measurement by detecting the position of the exudates-affected region with respect to the macula. The existence of exudates was effectively localized using the JSEG segmentation algorithm [38].

3. Proposed Scheme

The Hierarchical Fuzzy skeletal construct is rooted in Hierarchical Fuzzy Set principles, where a un-crisp portrayal of the patient's present state is obtained, and Hierarchical Fuzzy relations are brought about. The primary objective is to ensure that the patient's condition is depicted with maximum opaqueness. The recognized HF set, with regard to its membership function, is defined by the extent of adherence to its specific membership, typically within the range of (0 and 1). A contemporaneous value is absent in a HF set, and an intermediate level of fuzziness is inherent. The tetragonal association plot is a configuration with four variables—specifically, a, b, c, and d—where a and d represent the base of the quad with a membership of 0^0, while b and c denote the shoulders of the trapezoid with a membership of 1^0.

4. Methodology

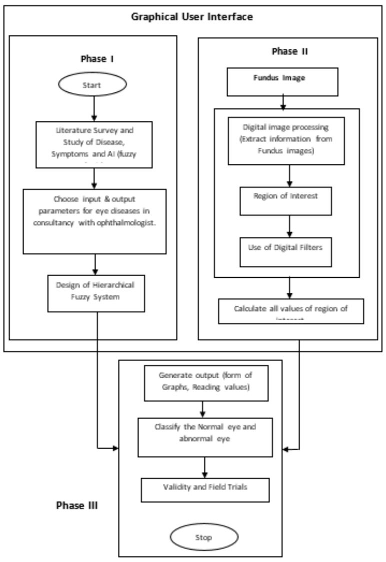

Fig.5. Methodology for Implementing the Proposed System

Fig. 5 illustrates the methodology for implementing the proposed system, depicting the design of the professional gadget deploying 23 inputs. The process involves selecting the input variables, followed by the fuzzification of these factors. The Hierarchical-Fuzzy Rule-Base enables experts to simulate ongoing symptoms and assists in developing rules to yield a nearly accurate conclusion. Fig. 6 outlines the steps in the proposed system's methodology.

The “Hierarchical FIS” and “GUI” of MATLAB serve as powerful tools for establishing a robust Hierarchical Fuzzy decision-making structure. The training phase for the “Hierarchical FIS” is conducted through the FIS-editor, another robust tool in the MATLAB environment. Fig. 7 provides a clear and logical representation, denoting all inputs (8) on the left and the corresponding output on the right side. It is important to note that the number of inputs may be constrained by the available memory of the computing system.

i. *Inputs*

The expert system is designed with a total of twenty-three inputs, encompassing parameters such as "Cup to Disc Ratio (CDR)," "Rim to Disc Ratio (RDR)," "Visual Field," "Intra-ocular Pressure (IOP)," "Lens Size," "Corneal Thickness," "Visual Acuity," and "Angle," among others. These inputs collectively contribute to predicting the health status of a visitor. In the development process, developers are required to create a specific Hierarchical Fuzzy set for each input variable, defining the corresponding range for all Hierarchical Fuzzy sets associated with these inputs. This ensures a comprehensive and nuanced representation of the diverse factors influencing the health assessment within the expert system.

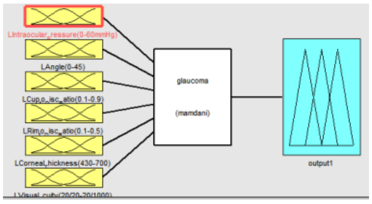

Fig. 6. FIS-Editor (8 I/P and 1 O/P)

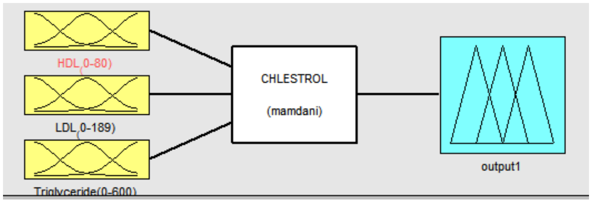

Fig. 7. Cholestrol (HDL, LDL, Tryglyceride)

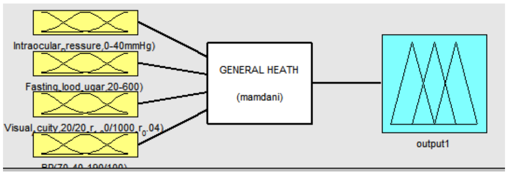

Fig. 8. General-Health (IOP, Sugar (Fasting), Visual Acuity, BP)

B) Output

The projected “Hierarchical Fuzzy inference system” (FIS) delivers subsequent outputs to detect Glaucoma and Cataract: 1. Healthy eye (0-3) 2. Glaucoma affected eye, Cataract affected eye and Diabetic Retinopathy affected eye (3.1-5.3) Mild 3. Glaucoma affected eye, Cataract affected eye and Diabetic Retinopathy affected eye (5.4-7.6) Moderate 4. Glaucoma affected eye, Cataract affected eye and Diabetic Retinopathy affected eye (7.7-10) Severe

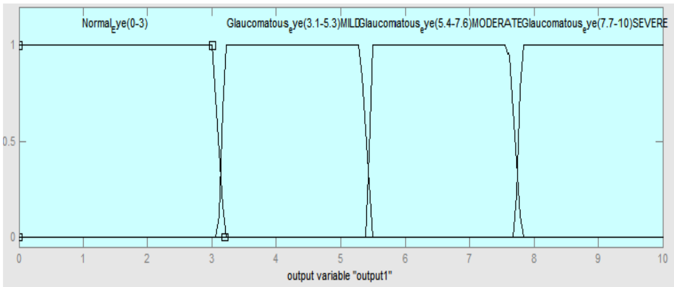

Fig. 9. Membership Plot (O/P)

C) Membership Function

Each variable is associated with its respective association functions. The relationship functions for the parameters are outlined below, providing a clear representation of the membership functions. These membership functions play a crucial role in refining rules and serve as confirmation for all relationship functions within the integrated Hierarchical-FIS. This collaborative process encompasses both input and output factors, facilitating a comprehensive adjustment of the system's rules, based on the membership functions.

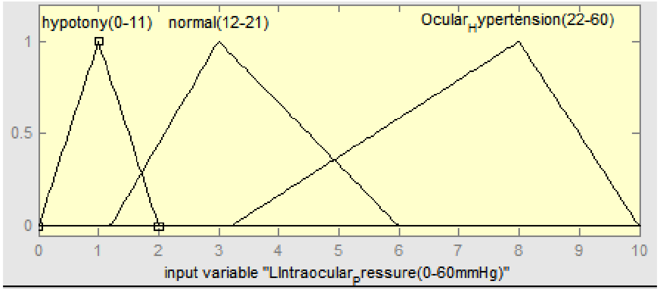

Fig. 10. MF for IOP

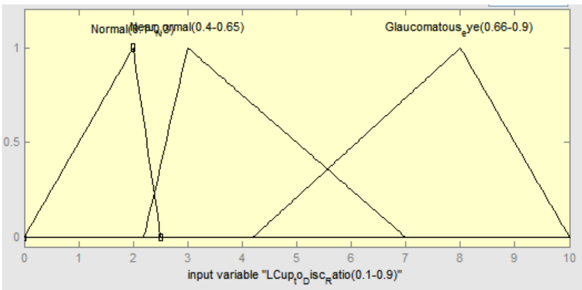

Fig. 11. MF for Cup to disc ratio

This represents the process of consolidating rules. The membership functions from all previously clipped rules during rule evaluation are employed and amalgamated into a unified Hierarchical Fuzzy set. Table 1.0 displays the assortments of membership function for the inputs.

Table 1.0. Assortments of membership function for the inputs.

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]

4.3 Rule developer (editor)

The depiction of the structure's appearance is termed a fact list, which is editable using the rule developer/editor. The rule editor includes a sizable editable text field designed for both displaying and composing rules. Additionally, the rule editor incorporates a variety of widely recognized landmark constants found within the F-I-S editor. This is inclusive of the menu bar and the membership function editor located along the status line. Total Rules = MI [23] Where M is Membership functions and I is Input parameters

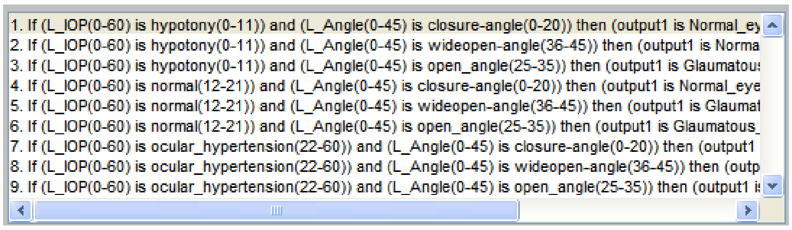

Fig. 12. Rule Developer/Editor

D) Fuzzify and Defuzzify

The subsequent stage in the Hierarchical FES includes undergoing Fuzzification. This process involves having a clear evaluation of an input mapped into relational degree across various "Hierarchical Fuzzy linguistic variables". In contrast, to Defuzzify, the inverse of to Fuzzify, is employed to determine the crisp inference output by evaluating its input significance.

5. Results of Experiment

A) Rule (Standard) Viewer

The Rule (standard) viewer is employed to scrutinize the "Hierarchical Fuzzy inference system". This tool reveals comprehensive information about the entire Hierarchical Fuzzy inference process. In Fig. 13, the Rule Viewer of the proposed organization is presented, showcasing the outcomes of the entire Hierarchical Fuzzy logic based system. On the top left plane, the value of 5.95 (de-fuzzified) indicates that the individual with healthy eye.

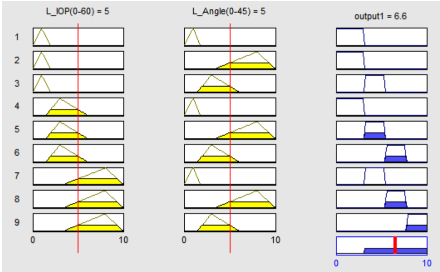

Fig. 13. Rule Viewer

B) Surface (Landscape) Viewer

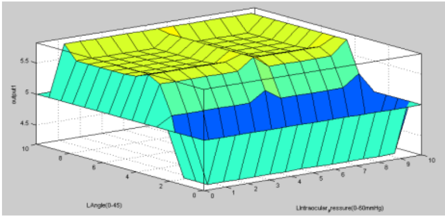

Fig. 14. 3-D Surface (landscape) View of IOP v/s Angle

To assess the dependence of one of the outputs on one or two inputs, the Surface Viewer is employed. For the "Hierarchical Fuzzy Inference System" (FIS), it generates and constructs an output surface's plot. It generates a three-dimensional surface from two input variables and one production variable of an FIS. Fig.14 displays the Surface (landscape) View of IOP v/s Angle. The input is represented in blue and the output is represented in yellow.

C) Graphical User Interface (GUI)

The GUI for human-computer interaction with MATLAB graphic objects is facilitated by MATLAB's GUI (Graphical User Interface). Two types of MATLAB files, namely M-file and fig-file, are generated by GUIDE (Graphical User Interface Development Environment). With the M-file editor, code can be added to the callbacks to implement the desired functions. Figures 15, 16, and 17 showcase the GUI for the projected system.

Fig. 15. Glaucoma Detection GUI with Input Parameters

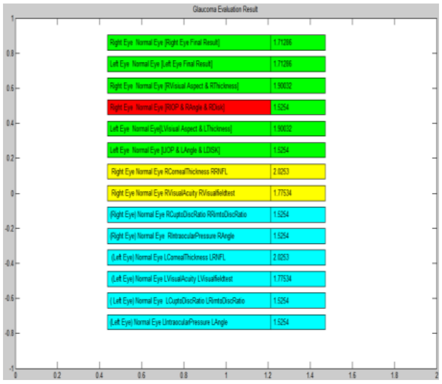

Fig. 16. Glaucoma Evaluation result

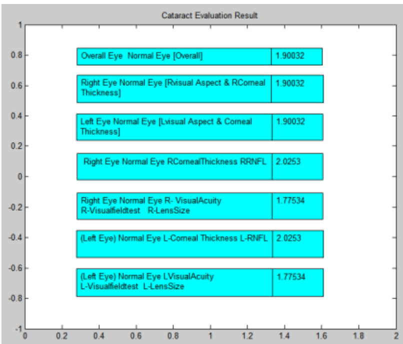

Fig.17. Cataract Evaluation Result

The recognition of a normal eye to an affected eye is represented in the projected method. Within the Hierarchical Fuzzy Inference System (FIS), a total of 117 rules are defined, with 100 rules being randomly selected. Among these, 50 rules correspond to a healthy patient, and the remaining 50 rules relate to an affected patient. The results obtained from these selected rules were then compared with those of a field expert (ophthalmologist). It was found that 97 rules coincide with the results provided by the ophthalmologist. Consequently, the accuracy of the system is determined to be 97% [25].

$$\text{Overall system Accuracy} = \frac{\sum \text{correct Patients}}{\sum \text{Patients}} X\ 100 \quad (1)$$

➔ (93X100)X100 =93%

Sensitivity, also known as True Positive Rate or Recall, is defined as the ratio of True Positives to the sum of True Positives and False Negatives. True Positives occur when a defected image is correctly classified as defected, while False Negatives occur when a defected image is incorrectly classified as normal [25]. Sensitivity is a metric used to evaluate the ability of a classification model to correctly identify positive instances, in this case, defected images.

$$\text{Sensitivity} = \frac{\text{True Positive Cases}}{\text{True Positive Cases} + \text{False Negative Cases}} X\ 100 \quad (2)$$

➔ (47/(47+3))X100 =94%

Specificity is the calculated ratio of True Negative cases to the combined total of True Negative and False Positive cases. True Negative refers to the scenario where a healthy eye image is correctly classified as healthy eye, while False Positives occur when a normal eye image is incorrectly classified as defective [25].

$$\text{Specificity} = \frac{\text{True Negative cases}}{\text{True Negative cases} + \text{False Positivecases}} X\ 100$$

➔ 46/(46+4)X100 ***=92 %***

D) Hardware development

A Keratoscope has been developed to provide unique centration, featuring a flashing fixation target and three concentric rings of illuminating LEDs. These LEDs are arranged at intervals of 100 units. The responsiveness of illumination is controlled by a switch, and this control switch is intended for the secure handling of the surgical Keratoscope. In Figure 18, the illuminating scientific device, Keratoscope, is designed with the objective of accommodating the lens of a surgical microscope with a properly sized mounting ring measuring 48 mm. As shown in Figure 19, bright light in the form of a circle without any irregularities is displayed by the Keratoscope, indicating that the patient is considered normal.

Fig.18. Examination of Cornea using Surgical Illuminating Keratoscope

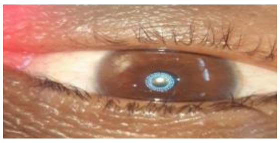

Fig.19. Reflection Image of Surgical Illuminating Keratoscope

6. Conclusion

Glaucoma, Cataract, and Diabetic Retinopathy presently rank as the most prevalent diseases. It is crucial to identify these conditions early on for effective management. The emphasis is on early detection, allowing for the recognition of Normal eyes, Cataract eyes, Glaucomatous eyes, and Diabetic Retinopathy. The application of a surgical Keratoscope serves as an economical and efficient solution for identifying irregular corneal curvature. This study introduces a Hierarchical Fuzzy decision support network for Glaucoma diagnosis. The prediction of Normal eyes, Cataract eyes, and Glaucomatous eyes is facilitated through the proposed Hierarchical Fuzzy interference system. The system's capability to handle various input sources enhances sensitivity during the evaluation phase. Results, compared with a dataset of 100 patients, demonstrate promising accuracy exceeding 93%. The adaptability of this framework can be expanded by incorporating additional inputs. The designed and constructed surgical Keratoscope proves highly effective and valuable, catering not only to super-specialty hospitals but also to small-scale eye clinics due to its cost-effectiveness and purposeful design. Consequently, the future of eye care is expected to witness a significant impact through the adoption of this technology.

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