

COMPUTER-AIDED SCREENING AND DIAGNOSIS SYSTEM FOR GLAUCOMA CLASSIFICATION USING DEEP LEARNING

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ABSTRACT

Vision is a fundamental human sense, facilitated primarily by the eyes. However, the eye is vulnerable to damage, often resulting in vision loss due to injuries or diseases such as glaucoma. While early detection and accurate identification of glaucoma are crucial for preventing vision impairment, existing research has primarily focused on general glaucoma detection rather than differentiating between its various types. Leveraging advancements in imaging technology, this paper explores the utilization of computer vision and image processing techniques for near-instant diagnosis of different types of glaucoma. Specifically, we propose a method utilizing multi-layer perceptron and particle swarm optimization (PSO) to classify different varieties of glaucoma. However, our experimental results indicate accuracies in the proposed mechanism's ability to detect glaucoma subtypes effectively.

Keywords: *Glaucoma, Deep Learning, Multi-Layer Perceptron, Optimization*

1. INTRODUCTION

Sense organs are essential components of the human body, enabling individuals to perceive and interact with the physical world through touch, taste, sight, sound, and smell. Among these senses, vision, facilitated by the eye, plays a pivotal role in providing individuals with a comprehensive understanding of their surroundings. The eye functions akin to a pin-hole camera, where light initially enters through the cornea, a transparent layer covering two-thirds of the human portion of the eye's surface. The iris, acting as the variable pupil, regulates the amount of light entering the eye, akin to the aperture of a camera lens. Subsequently, light passes through the lens onto the retina, creating an inverted image of the object being observed. This image is then transmitted to the brain via neurons, where it is corrected to produce an upright visual perception [9].

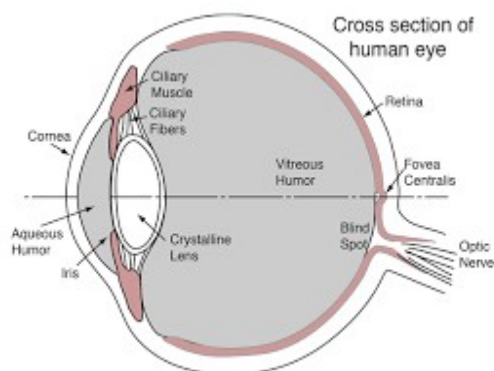
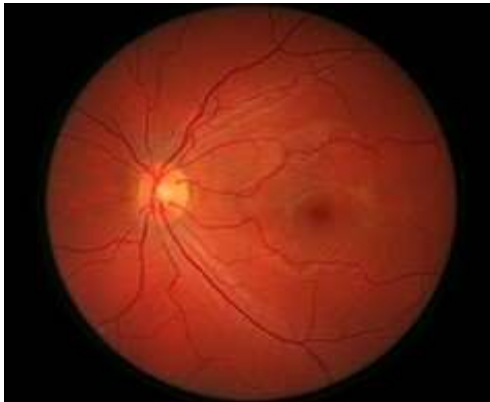
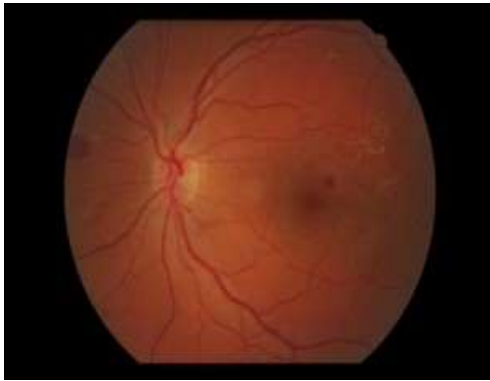


Figure 1: Human Eye Cross-Section

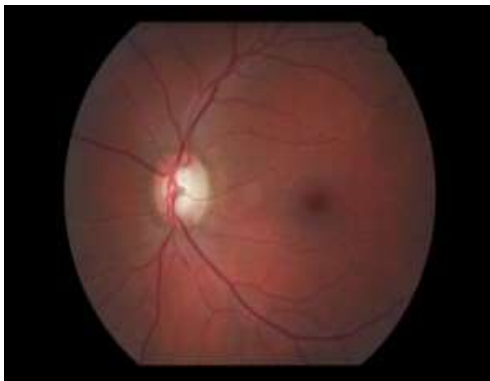
An image of the human eye is displayed in Figure 1. Computational diagnosis, integrating computational methods and learning capabilities, has revolutionized medical data processing, particularly in the context of eye diseases such as glaucoma and diabetic retinopathy. Glaucoma, characterized by optic nerve damage, stands as the second-leading cause of global blindness [11], while diabetic retinopathy, resulting from diabetes-induced retinal damage [12], ranks among the top five causes of blindness worldwide.



(a) Healthy retina



(b) Diabetic retina



(c) Glaucoma retina

Figure 2: Comparisons Of The Retina At Various Stages Of Health

These diseases primarily affect the retina, making early diagnosis crucial for preventing irreversible vision loss. They each display unique changes in their onset, thus making the diagnoses at early stages possible. While there is no permanent cure for both, there is a chance of preventing permanent damage by early diagnosis.

Due to computer imaging techniques, the procedure for diagnosis is non-invasive, i.e., the patient isn't operated upon or has any blood tests conducted at an early stage.

Getting an image of the retina has been made easy due to two main imaging techniques, *Fundus Photography* and *Optical coherence tomography (OCT)*. Fundus photography can be defined as a process where a 2-D representation of the retinal tissues is obtained using reflected light being projected onto a plane. The image intensity changes with the reflected light's intensity [6]. OCT on the other hand obtains results by showing the differences in the refractive indices of various tissue surfaces and measuring the depth of the distance traversed by the backpropagation of light, diagnosis plays a very important role. While physicians with their knowledge and experience can make accurate diagnoses, they may or may not be equipped to handle more than one case at once. This causes unintended delay which is not the best thing for a patient. By the use of tools of computer vision and machine learning techniques, computer scientists are trying to improve the speed of diagnosis. This thesis aims to bridge the gap between the image processing and diagnosis part by developing an algorithm that will not only process the image to show the traits of diseases clearly but will also classify them into two separate categories.

This paper focuses primarily on various types of glaucoma diseases, including open-angle and angle-closure glaucoma, secondary glaucoma, and pigmentary glaucoma. Accurate diagnosis of these conditions is critical for effective treatment and improved patient outcomes. Leveraging multi-layer perceptron and particle swarm optimization-based methods, the proposed algorithm aims to detect and classify glaucoma accurately, paving the way for more efficient diagnosis and management of these sight-threatening conditions.

1.1 Significance of Glaucoma Diagnosis

The conceptualization and theoretical basis of our work revolve around addressing the ongoing challenge of glaucoma diagnosis, which remains a significant problem in ophthalmology and public health. Despite advancements in medical imaging and diagnostic techniques, glaucoma

continues to be a leading cause of irreversible blindness worldwide. This persistent issue stems from several factors:

1. **Silent Progression:** Glaucoma often progresses silently, with patients experiencing no symptoms until irreversible damage has occurred to the optic nerve. This delayed onset of symptoms makes early detection crucial for effective management and prevention of vision loss.
2. **Lack of Awareness:** Many individuals are unaware of their risk for glaucoma or the importance of regular eye examinations. As a result, a significant portion of the population remains undiagnosed until the disease has reached advanced stages.
3. **Complex Diagnosis:** Glaucoma diagnosis typically involves a combination of intraocular pressure measurement, optic nerve assessment, and visual field testing. Interpreting these diagnostic tests accurately requires specialized training and expertise, posing challenges in regions with limited access to eye care specialists.
4. **Variability in Disease Presentation:** Glaucoma encompasses a spectrum of diseases with varying presentations, including open-angle glaucoma, angle-closure glaucoma, and secondary glaucoma. Each subtype may manifest differently and require tailored diagnostic approaches.
5. **Limited Resources:** In many parts of the world, especially in low-resource settings, access to advanced diagnostic equipment and trained healthcare professionals is limited. This exacerbates disparities in glaucoma detection and management, leading to higher rates of undiagnosed and untreated cases.

By highlighting the ongoing significance of glaucoma as a real and pervasive problem, our study aims to offer meaningful insights and solutions. Through the development of automated glaucoma identification mechanisms leveraging cutting-edge technologies such as deep learning and optimization techniques, we seek to address critical gaps in current diagnostic capabilities. By providing accurate and efficient methods for early detection and classification of glaucoma, our work strives to empower healthcare professionals and improve patient outcomes worldwide.

The hypothesis for the study could be Utilizing Deep Learning-Based Multi-Layer

Perceptron (MLP) with Particle Swarm Optimization (PSO) for Accurate Glaucoma Identification in Retinal Images.

The outcomes of the research align well with the initial goals of developing an automated mechanism for glaucoma identification using deep learning techniques. The proposed algorithm, based on a multi-layer perceptron (MLP) and particle swarm optimization (PSO), demonstrates promising results in accurately classifying different types of glaucoma diseases. By achieving better performance compared to existing literature methods, the study successfully addresses the need for more effective and efficient diagnostic tools in ophthalmology.

Comparison with current state-of-the-art solutions presented in the literature highlights several strengths of the proposed algorithm. While previous studies have utilized various techniques such as deep convolutional neural networks (CNNs), clustering algorithms, and level-set procedures for glaucoma detection, the combination of MLP and PSO in this research offers distinct advantages. The accuracy and efficiency of the proposed mechanism in classifying glaucoma diseases demonstrate its potential to outperform traditional approaches. Additionally, the use of different datasets and validation techniques ensures robustness and generalizability of the results.

2. LITERATURE WORK

W. K. Wong et al. [1] have proposed a strategy to consequently identify CDR utilizing level-set procedures to infer limits of the Optic Cup and plate for fundus pictures of the eye, using introductory shapes utilizing force examination of the retinal picture. This is a key part of the ARGALI framework created by them for finding glaucoma chances. They have handled 104 retinal pictures that were prepared and have determined CDR esteem. The proposed strategy gives 96% certainty of getting results inside a scope of ± 0.2 , which is inside the inconsistency for physically evaluated CDR values. They have not utilized preparing datasets for approval of the strategy. Along these lines, the precision of the model has not been confirmed.

Arturo Aquino et al [2]. have utilized two free systems to identify Optic disks in retinal pictures. They have utilized a freely accessible MESSIDOR database comprising 1200 pictures. The Optic Disk has been found utilizing round estimation acquired through morphological activity, edge recognition, and roundabout Hough change. The precision rate has been 86% for the recognition of the optical disk in the pictures.

U R Acharya et al. [3] have utilized Higher Order Spectra (HOS) highlights and surfaces from fundus pictures for the location of glaucoma. They have analyzed glaucoma utilizing RNFL thickness of the retinal pictures. They have utilized SVM, innocent Bayesian, successive insignificant streamlining, and irregular backwoods classifiers for diagnosing glaucoma. They have accomplished 91% precision.

K. Chiranjeevi et al. [4] have proposed a calculation that identifies highlights from ultrasound pictures of the eye utilizing the fundus. They have built up a calculation that naturally distinguishes clinical highlights in ultrasound pictures of the eyes utilizing order and division systems. They have utilized multiscale calculation to decrease dot clamor in the pictures, as dot commotion corrupts the visual nature of the picture. The calculation functioned admirably in 97% of situations where highlights were effectively extricated in the prepared picture. Notwithstanding, the structured calculation fizzled for a couple of pictures, where more commotion was available.

N. Anil Kumar et al. [5] have proposed a calculation that centers around programmed identification and deciding the specific area of the zenith purpose of the front load locale. The investigation has been done for productive point estimation from ultra-sound pictures of the eye. They have concentrated on the count of Angle Open Distance and built up a calculation dependent on dynamic forms. The investigation needs expressing, the clinical parameters that have been thought about. It additionally doesn't refer to the dataset of retinal pictures taken for

picture preparation. They have not tended to the issue of commotion evacuation in this paper.

Dehghani et al. [6] have utilized DRIVE and STARE databases, which are open information bases accessible for retinal pictures. They have utilized histogram to portion Optic Disk. The limit esteem has been set to $\frac{1}{2}$ of the most extreme edge acquired for the picture. The testing size for the framework has been 40 pictures and 81 pictures separately. Exactness accomplished is 91.36% and 98.9%. Running time for the calculation is 27.6 seconds which is very high contrasted with the little dataset.

J. Cheng et al. [7] have determined CDR for the determination of glaucoma. They have sectioned Optic Disk and Optic Cup utilizing histogram and focus encompass insights strategy. To effectively fragment Optic Cup, they have applied area data. They have a covering mistake of 9.5% and 24.1% in the Optic Disk and Optic Cup division. Superpixel characterization has been utilized for glaucoma screening. The precision accomplished is 85.9%.

Jyotika Pruthi et al. [8] have utilized an anisotropic dispersion channel for commotion expulsion, and OTSU thresholding on the dataset comprising of 20 retinal pictures (10 typical and 10 glaucoma). Edge recognition has been completed utilizing the Canny technique and estimation of CDR has been finished by extraction of veins utilizing picture impainting. The conclusion of Glaucoma has been completed utilizing SVM, ANFIS, and Back Propagation Neural Network. They have gotten exactness for SVM, ANFIS, and Neural Network as 98.12%, 97.77%, and 97.35% individually. The figured CDR shows proximity when contrasted with HRT and Ophthalmologist.

Chaline Burana et al. [9] have identified glaucoma utilizing CDR from the retinal pictures. They have utilized a level set technique for the discovery of an Optic Disk. Identification of Optic Cup has been done utilizing shading segment investigation and limit level set strategies. The oval fitting strategy has been utilized for reshaping the Optic Disk and Cup. The dataset

comprises of 44 retinal pictures (28 were typical and 16 were glaucoma). They have accomplished a precision of 89%.

G. Jayanthi et al. [10] have utilized a dynamic form model for the optic Disk division cup. The highlights removed for analysis of glaucoma is CDR. They have applied shading picture division by introducing window size, piece profundity, and hues for division. K-implies calculation has been applied for grouping pixels in a removed component space. They have accomplished an exactness esteem of 0.9, a review estimation of 0.966, and F-Score of 0.9323. For the Optic Disk and for the Optic Cup division they have accomplished an accuracy estimation of 0.9, review estimation of 0.94732, and F-score estimation of 0.9218. The examination needs to reference the dataset utilized for the investigation, which is significant in any therapeutic research.

Darsana S, and Rahul M Nair [11] proposed a veiling technique for the computation of visual parameters, for example, RDR and ISNT Ratio and confirmation of the ISNT Rule. The division of fundus picture highlight has been finished by ISNT quadrants utilizing the cluster centroid technique. They have built up a novel technique for concealing of picture.

Eleesa Jacob et al. [12] have completed the division of Region of Interest (ROI) utilizing average hub. Superpixel grouping and histogram have been utilized for the division of the Optic Disk and Cup. They have utilized CDR to analyze glaucoma in the patient. They have utilized unwavering quality scores, which are created by them, to quantify the achievement pace of the Optic Disk and Cup division.

Neeraj Sharma et.al [13] segmented and detected optic discs using K-means clustering. Initially, the extracted green plane of the fundus image is pre-processed using spatial average filtering. Then, K-means clustering is used to segment the pre-processed image into clusters. Cluster with maximum intensity is filtered out using connected component segments optic disc from the cluster-based segmented image. The

overall efficiency in optic disc detection achieves 83.4% as its performance.

Juneja et.al [14] proposed a method for segmentation of the Optic Disk and the Optic Cup from retinal fundus pictures utilizing mechanized methodology dependent on a Deep Convolutional Neural Network design named Glaucoma Network (G-Net). This calculation comprises of two neural systems working related to accomplish correctness of 95.8% and 93.0% on OD and OC divisions individually. The engineering can be changed and applied to other restorative pictures for a large group of uses.

3. PROPOSED MECHANISM

The proposed work focuses on two kinds of images and those contain different kinds of glaucoma deceases. This paper prime focuses on different varieties of glaucoma deceases. Glaucoma comes in different formats open-angle and angle-closure glaucoma: Secondary Glaucoma, and Pigmentary Glaucoma...etc. Diagnosing accurately gives promising treatment and more better cure. To make these different types of glaucoma diseases we need multiple classes, and use multi-layer perceptron and PSO-based methods. The proposed mechanism detects glaucoma accurately.

3.1 Multi-Layer Perceptron

MLP is a network that is composed of three different layers input, hidden, and output layers. In MLP no restriction on the number of hidden layers. The input layer takes the input weights and supplies the inputs to the hidden layer, the hidden layer processes the inputs and gives the outputs to the output layer. The associations between the layers are called loads W , which are ordinarily characterized somewhere in the range of 0 and 1. The yield estimation of every neuron in each layer is determined in two phases as beneath.

In the principal arrangement, the weighted summation of the information esteems is determined as underneath:

$$\forall l \in \{1, 2, \dots, j\}, h_l = \sum_{i=1}^m W_{il} I_i + \beta_l \quad (1)$$

Where I_i is the information variable i , W_{il} is the association weight among I_i and the shrouded neuron l , m is the all-out number of sources of info and β_l is the inclination of the i^{th} concealed neuron. In the subsequent stage, the yield estimation of every neuron in the shrouded layer is determined dependent on a weighted summation utilizing an actuation work, for example, the sigmoid initiation work, to outline the shrouded layer to yield esteems. That is,

$$\forall l \in \{1, 2, \dots, j\}, H_l = \text{sigmoid}(h_l) = \frac{1}{1 + e^{-h_l}} \quad (2)$$

The output of the mechanism finally is calculated as below:

$$\forall k \in \{1, 2, \dots, n\}, o_k = \sum_{l=1}^j W_{lk} H_l + \beta_k \quad (3)$$

$$\forall k \in \{1, 2, \dots, n\}, O_k = \text{sigmoid}(o_k) = \frac{1}{1 + e^{-o_k}} \quad (4)$$

where W_{lk} is the linking weight between the i^{th} hidden neuron and the k^{th} output neuron. β_k is the bias of the k^{th} hidden neuron.

3.2 Particle Swarm Optimization

PSO [16] is a swarm of keen systems roused by fowls rushing. As a populace-based developmental procedure, every molecule of PSO looks through the area space with position and speed data and jam the best position. Every molecule improves itself by keeping track of two ideal arrangements found by the molecule swarm. PSO is a procedure that advanced from displaying the conduct of gatherings of social creatures, such as rushing winged animals and tutoring fish. The instinct behind this strategy is that particles freely investigate the pursuit space and speak with each other to recognize the most ideal arrangement — that is, the most ideal pursuit space area. PSO is a moderately straightforward system to execute and doesn't require costly calculations.

Initialize all parameters

While (count of iterations < Max Generations || Stopping criteria)

Evaluate the fitness of particle

For all particles do

Find pbest and pleast

For all dimensions of particles

Do

Update weights and velocity of particles

End for

End for

End while

3.3 Glaucoma detection based on MLP and PSO

MLP-based PSO for Glaucoma detection {

Step 1: Initialize PSO parameters

Step 2: Start

Step 3: Training of MLP model with Initial parameters

Step 4: Calculate the fitness function

Step 5: If (fitness values of each particle > gbest and lbest values)

{

Update positions

Update velocity

}

Step-6: If (reaches to the max. number of iterations)

{

{

MLP training is completed

}

```
Else
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```
{
```

```
Go to step-1
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}
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}
```

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}
```

4. RESULTS & DISCUSSIONS

4.1 Experimental Setup

For experimenting used the hardware of an I5 processor, 4GB RAM, 500GB HDD, and Windows 8 OS. and used the software of Python with ANACONDA navigator. And used libraries Keros, tensorflow, numpy, matplotlib, and python libraries.

4.2 Datasets

ORIGA (-light) ORIGA (an Online Retinal fundus Image database for Glaucoma Analysis and research) means to give clinical ground truth to benchmark division and arrangement calculations. It utilizes a uniquely created instrument to produce manual division for OD and OC. It likewise gives CDR and names to each picture as glaucomatous or solid. This dataset has been utilized as a standard dataset in a portion of the ongoing best-in-class inquiries about glaucoma characterization. The dataset was gathered by the Singapore Eye Research Institute and has 482 sound pictures and 168 glaucomatous pictures.

HRF picture database High-Resolution Fundus (HRF) Image database is given by the Department of Ophthalmology, Friedrich Alexander University Erlangen-Nuremberg, and Germany. It comprises 15 solid pictures, 15 glaucomatous pictures, and 15 pictures with diabetic retinopathy. For each picture, the double highest quality level vessel division is given by a gathering of specialists and clinicians.

OCT and CFI This dataset contains Optical Coherence Tomography (OCT) and Colour Fundus Images according to 50 sound people gathered at the Ophthalmology Department of Feiz Hospital, Isfahan, Iran. As the pictures were taken as a feature of an examination of the correlation of macular OCTs in the right and left eyes of ordinary individuals, it doesn't give any ground truth regarding to division of OD or veins, or OD confinement.

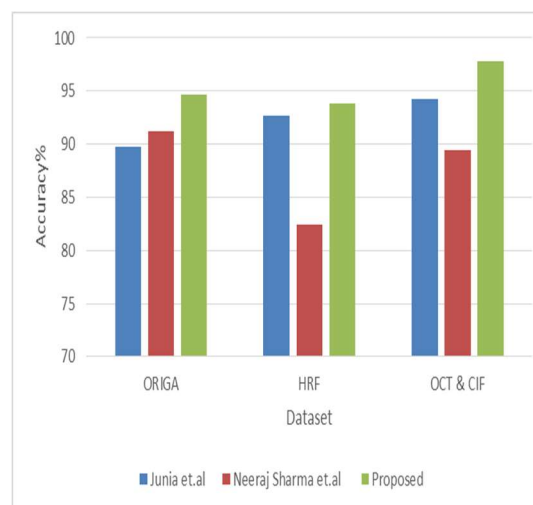


Figure 3: Accuracy

Accuracy represents the exact number of correctly identified by the model to the total number of observations. Figure 3 represents the accuracy comparison of proposed and existing models for different datasets. Considering three different datasets of ORIGA, HRF, and OCT & CIF. Each dataset contains a different number of medical images. We train the model with 75% of input images from every data set and 25% allocated for the model testing. Here proposed mechanism outperformed the state-of-the-art mechanisms.

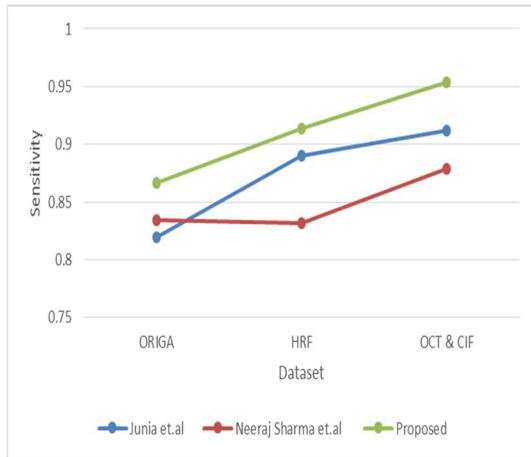


Figure 4: Sensitivity

Sensitivity represents the exact number of correctly identified positive cases by the model to the total number of cases. Figure 4 represents the sensitivity comparison of proposed and existing models for different datasets. Here proposed mechanism outperformed the state-of-the-art mechanisms.

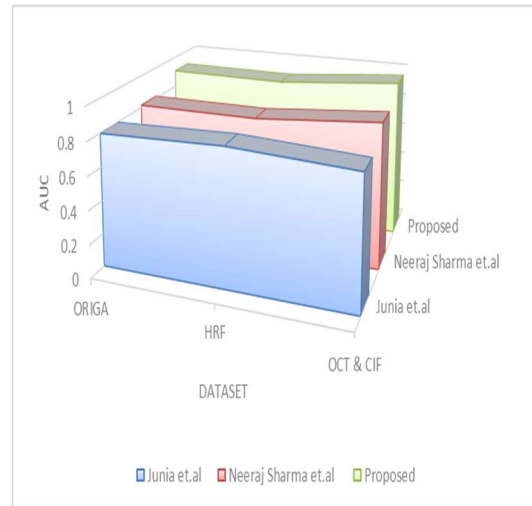


Figure 6: Area under curve (AUC)

The area under curve is used to understand the performance of a classifier in the model. Figure 6 represents the AUC of the proposed and two different state of art mechanisms. Here proposed PSO-based model gives high AUC values. And state of art mechanisms represents the low AUC values. The proposed model outperforms the state of art mechanisms.

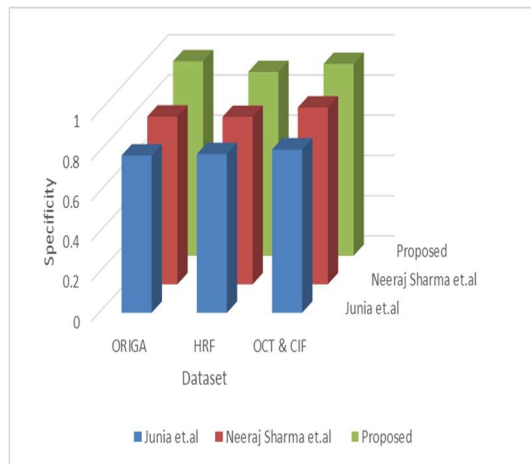


Figure 5: Specificity

Specificity represents the exact number of correctly identified negative cases by the model to the total number of cases. Figure 5 represents the specificity comparison of proposed and existing models for different datasets. Here proposed mechanism outperformed the state-of-the-art mechanisms. It can also handle larger datasets effectively because of PSO.

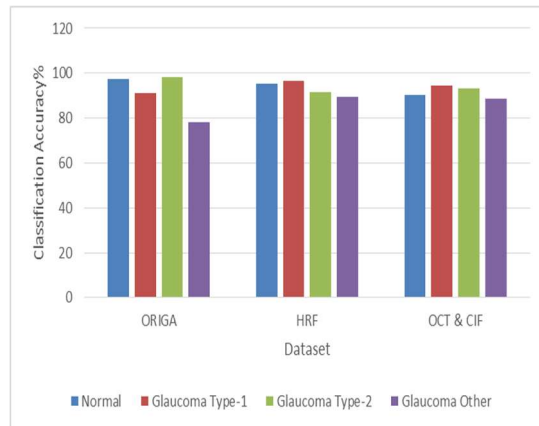


Figure 7: Accuracy percentage of classification of different types of Glaucoma

5. CONCLUSION

In conclusion, this paper has presented an automated mechanism for identifying glaucoma, a leading cause of vision loss worldwide. Leveraging deep learning-based Multi-layer Perceptron (MLP) and Particle Swarm Optimization (PSO), our proposed method

demonstrates improved accuracy in classifying various types of glaucoma datasets. Comparative analysis with state-of-the-art mechanisms from the literature further validates the effectiveness of our approach.

The overarching argument of this work is based on the need for advanced technological solutions to address the challenges posed by glaucoma, a highly prevalent and potentially vision-threatening eye disease. By harnessing the power of deep learning and optimization techniques, we have developed a robust and accurate automated glaucoma identification mechanism. Our study contributes to the ongoing efforts to leverage artificial intelligence for improving medical diagnosis and treatment.

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