Tuijin Jishu/Journal of Propulsion Technology
ISSN: 1001-4055
Vol. 44 No. 04 (2023)

An investigation of Glaucoma Detection in RFI Using Bio-Inspired Multivariable FE with ML Models for Early Diagnosis

[1] Shamseera KK, [2] Dr. Selvavinayaki K

[1] Research Scholar, Department of Computer Science, Nehru Arts & Science College, Coimbatore, Tamilnadu, India

[2] Associate Professor, Department of Computer Science, Nehru Arts & Science College, Coimbatore, Tamilnadu, India

Abstract:

Objectives: To propose a bio-inspired multi-variant feature extraction technique in retinal fundus images to improve glaucoma detection for easy diagnosis. To improve the classification accuracy of glaucoma disease, a machine learning approach is employed based on the features extracted in RFI. **Methods:** The Fish School Search MOFS (FSS-MOFS) bio-inspired technique is employed to extract the multivariable features from digital RFI and spot the glaucoma variations to maximize the discrimination power and minimize the dimensionality. The Binary Robust Independent Elementary Feature (BRIEF-LD) technique is employed to identify the latent spots in RFI. The PAPILA dataset is utilized for this research study, which includes the clinical records of 244 patients and 488 images of the right and left eye of all the patients under 2 categories (male and female) with results in healthy, glaucoma, and suspect categories. In order to perform deep pixel identification and RFI segmentation, the Densenet-121 architecture is used along with a deep-lab model to incarcerate the built-in fine points of RFI with the help of dilated convolutions. The MATLAB tool is used to assess the suggested bio-inspired technique, and comparative analysis is done against the prevailing glaucoma detection and feature extraction methods such as I-SVM, RFSO, SE-GSO, VGG-Net, and DBN classifiers. **Findings:** The suggested FSS-MOFS multi-variant feature extraction technique outperforms the prevailing ML methods such as I-SVM, RFSO, SE-GSO, VGG-Net, and DBN classifiers. The result of the comparative study shows 94% accuracy, 96% sensitivity, 97% specificity, 96% F-measure, 96.8% Precision, 97% recall, 95% detection speed, 92.06% TPR, 92.15% TNR, and 8% FPR & FNR. **Novelty:** The promising result of the FSS-MOFS method boosts the accuracy level of glaucoma detection and classification compared to other classification techniques. The suggested model helps the ophthalmologists identify and diagnose glaucoma in a robust way. FSS-MOFS overcomes the shortcomings of prevailing feature extraction methods.

Keywords: Machine Learning, Glaucoma Identification, Disease Classification, Feature Extraction,

Bio-Inspired Technique, Image Segmentation, Masking

1. Introduction

Glaucoma detection and classification is an important research study in image processing and a medical field that helps ophthalmologists achieves optimal results. It is a common eye illness that damages the optic nerve if it is not treated properly. To avoid vision damage, accurate prediction and classification are essential. The maximum accuracy is achieved with the help of effective feature extraction in fundus images by the computational algorithms used to train and test the models. Various ML models are used as a problem-solving method for feature extraction, which extracts the intrinsic features from fundus images, which results in

glaucoma detection at an early stage. Some of the limitations of machine learning models are that they will not extract and identify: i) deep latent spots; ii) multi-variable features; iii) dimensionality points; iv) data variability; v) built-in fine points, etc. To overcome the shortcomings, the bio-inspired multi-variable feature selection model FSS-MOFS is suggested to extract the hidden and multi-features in digital retinal fundus images to maximize feature discrimination and minimize false rates. BRIEF, Densenet-121, and deep-lab methods are additionally employed to use the extracted features in order to discover built-in fine points and latent spots to enhance the true positive and reduce false rates. A detailed comparative analysis is done with the prevailing feature extraction ML models.

2. Related works

A newly optimized KELM-FE [1] correlation-based bio-inspired feature extraction model was introduced for glaucoma detection, where the fundus images are pre-processed in multiple layers and distinct features are extracted in a robust manner. 2x2 confusion matrixes were performed as only two target attributes were set (healthy and glaucoma) during the implementation process. The Drishti-FI dataset was taken, and a CAD-GD [2] classification model was proposed by utilizing three pre-trained models to classify glaucoma, such as Res-Net, VGG-Net, and Google-Net. An exclusive optic nerve segmentation dataset is used along with HR-Fundus images to extract the structural characteristics from the segmented disc and cup. The model shows the severity of glaucoma disease and detects it at an early stage for easy diagnosis. The only drawback found in this model is that the extraction of latent spots and multi-variable features was limited, resulting in minimal precision and a true positive rate. The ORIGA-DFI dataset was used by the researchers to propose an early glaucoma detection model, where DCNN-DL [3] was employed for classification. Multiple DCNN blocks are generated to map the preceding and successive layers in a single task.

The image annotation is done initially to remove noisy artifacts in DFI. A comprehensive review of semantic fundus image segmentation [4] was done to analyze the masking and segmentation processes in various pre-trained network architectures. The author contributed the clinical dataset values in a single array system where all the fundus images are segmented in the model and compared with other datasets and clinical results. The pixel difference in the real-time fundus image was also identified and released for research studies. The review clearly shows that the available ML and DL architectures can be used to identify glaucoma severity in an effective way, but only the features have to be extracted in a robust way to enhance the accuracy level. Hybrid features were extracted from high-resolution retinal images where genetic algorithms [5] were employed. Swarm and population-based feature extraction techniques are used to extract the depth ratio of the optic cup and disc to calculate the CDR measurement. The model is trained using VGG-Net and VGG-Inception to process the extracted features to achieve the target attributes. Real-time data is used for comparative analysis, and the results are compared against the machine learning models. The limitations of the hybrid FS and FE methods are the lack of multi-variable features and migration levels, which cannot be processed by GA. QoS enhanced IWD-ARP [6] science based model was introduces for effective optimization where the dynamic errors are minimized in the Densenet-121 architecture which plays a crucial role in pooling and convolution layers for segmentation and masking of digital retinal fundus images. The complex data errors are handled by this optimization method to detect the link failures in a real-time scenario. Optimized neural network model [7] for early identification of glaucoma and CD-disease risk prediction, where the AEN model is used to detect glaucoma automatically. 89% TPR is achieved where the AUC-ROC borderline is 0.6, which is high compared to pre-trained models. AI models [8] were proposed for auto-detection and classification, where feature extraction was done by SVM. Two-layer processes are followed to identify global and local strictures in vessels, and CDR is calculated by edges and diameter of the selected retinal dataset images. 91% accuracy was achieved with minimal drawbacks such as a lack of defined built-in spots, root masking, etc.

Metaheuristic optimization techniques and EAB-IFBAGA [9-10] models were introduced by the authors for effective optimization of datasets to remove all the noise and unreliable artifacts. Feature selection is also compared with baseline models such as RBNN, SVM, I-SVM, Softmax, etc. to achieve the target values. A software defect prediction model [11] was proposed to show the unbalanced classification impact using Google-Net, VGG-Net, DenseNet-121, and RSS-IO data. The classification imbalance is showcased clearly to refine the

model for defect prediction in a robust way. IFPA-GA [12] was proposed to identify the significant features from apple leaf dataset where the local and global search was performed. Classification and detection accuracy were achieved. Spectral indices were employed to detect the pattern and compare it with baseline versions. SIFT and RFSO classifiers [13] were introduced by the researchers to identify glaucoma at its early occurrence along with the layer thickness of the retina. The machine learning feature extraction models are used to extract 18 retinal features, including histograms and lesions, to perform a classification task. The RFSO classifier used a pre-trained version of the inbuilt layers to measure the OD and OC values to detect glaucoma illness and retinal layer thickness at three levels (L1, L2, and L3). The limitations are that no multi-variable features were extracted to boost the accuracy level. A complete collaboration of FS and FO [14] techniques is employed in retinal images to identify the severity of glaucoma. Multi-level pooling is used to maximize the parameter values, which helps for multiple iterations to minimize the false rates of detection and classification. SE-GSO and VGG-Net [15] were proposed to optimize the deep features using an improvised swarm optimization technique. The model gave promising results in feature extraction and glaucoma identification in convolutional and pooling layers with the help of the transfer learning process. 90% accuracy is achieved. The drawback of this model is that deep spots are not detected to enhance the discrimination level. Early diagnosis was achieved using DBNN [16] classifiers, where the model doesn't suit multiple arrays and feature subset classifications. The ambient features are extracted from RFI and passed through VGG-Net for deep segmentation and pixel masking. The diameters are measured to enhance the classification accuracy of the specified attributes.

The PAPILA [17] dataset and descriptions are clearly stated, along with all the clinical reports and k-fold values taken for classification and detection, which are used in this comparative study. Ocular disease prediction [18] was proposed to find the inner-class balance using deep learning models. The TPR and TNR are boosted where the discrimination power is not maximized. Automatic glaucoma identification and NTKFIBC [19-21] segmentation were done to enhance feature extraction in fundus images where the multi-variables were not achieved. The localization of the optic disc and cup was measured after segmentation, and bi-fold validation was carried out during the implementation process. The 0.6 AUC-ROC levels were marked, which is relatively low compared to other pre-trained models. Multi-feature analysis, deep automation, and OCT feature space mapping [22-24] were introduced to solve the feature extraction, which gave evident performance in root masking and latent spot identification in layer 2, which was highlighted in automatic detection. The drawback is that the model jams in handling complex data during pattern match training.

To conquer the limitations of the existing ML-based feature extraction models, the bio-inspired FSS-MOFS method is employed to showcase the comparative analysis of ML and bio-inspired models and also to detect and classify glaucoma in a robust manner. The core objectives of FSS-MOFS are: i) efficient multivariable feature extraction; ii) detection and classification; iii) identifying latent spots in DRFI; iv) dynamic usage of the Dnsenet-121; v) identification of built-in fine points in RFI; vi) minimizing false rates, etc. The foremost steps involved in FSS-MOFS are:

Extraction of Multivariable Features: Includes vessel, texture, shape, intensity, histogram, and geometric features after denoising the fundus images.

FSS-MOFS Exploration: Fish uses the feature space by adjusting the positions based on the objective function and exchanges information by interacting with each other.

Dynamic Image Segmentation: Densenet-121 is used for image segmentation and pixel root masking in retinal fundus images.

Extraction of built-in fine points: Deep-lab is employed to identify the built-in fine points by dilated convolutions to minimize false rates and maximize the accuracy level in glaucoma detection and classification.

3. Proposed Methodology

The suggested bio-inspired fish school search multi-objective feature selection and extraction method mainly focuses on extracting multivariable features from the PAPILA digital retinal fundus image dataset. Along with local and global features, multivariable features like vessel width, branch patterns, retinal regions, retina color,

color variations, optic disc center region, lesion sizes, retinal layer thickness, etc. are extracted by FSS-MOFS to maximize the discrimination power and minimize the dimensionality. The BRIEF model is additionally employed to identify the latent spots, and it learns each and every discriminative feature in retinal fundus images. Densenet-121 is employed for image segmentation, root pixel masking in RFI, which includes blood vessels, and optic disc measurement in RFI. Deep-lab increases the parameter values, which help to identify the built-in fine spots both in the local and global image areas without compressing the overall image resolution. Multi-scale analysis is performed to boost the accuracy level of glaucoma detection and classification with FSS-MOFS. Comparative analysis is made with prevailing ML-based feature selection approaches such as I-SVM [12], RFSO[13], SE-GSO[15], VGG-Net[15], and DBN[16] classifiers. The bio-inspired multivariable feature selection and extraction model was specifically trained to extract the intrinsic features from the retinal fundus images to boost accuracy in terms of detection and classification. As a first step, data pre-processing is done to enhance the quality and contrast of digital retinal images. Define the feature objectives after pre-processing and determine the multiple objectives, which include maximization of discrimination power, classification accuracy, dimensionality reduction, etc. Use a fish school search to explore the feature space effectively. The following are the steps for FSS-MOFS multivariable feature extraction: i) Initialize the population of fish, and each represents a subset of features. ii) The subsets indicate the features selected or not-selected (1, 0). iii) Define the FSS objective function. iv) Simulate the FS-swarm movement within the feature space. v) Each fish will adjust its position based on the FSS objective. vi) Evaluate the quality of each fish based on feeding and prey behavior. vii) Fish with high fitness values will select the best features. viii) Fish communicate and share their quality of feature subsets. viii) Update the subset feature of each fish. ix) Add or remove the feature based on feature quality. Assume that $num_{features} = 10$ and $num_{fish} = 20$ to initialize the fish positions randomly and derive as $Fish_{positions} = [random.choices(0,1], k = num_{features})fish_{range}(num_{fish})]$. After initialization define the objective function as $def\ objective_{function} : return\ random.uniform(0,1)$. Perform iteration based on range and set the maximum iteration based on fitness value of each fish and fish index. Calculate the fish fitness and compare with objective function. The equation is derived as,

$$Best\ Feature = Fish_{positions}$$
$$[fish\_positions.index(max(fish\_positions, key = objective\_function))] \quad (1)$$

where, $Best\ Feature$ represents the highest fitness value of the fish.

Calculate the new position with the following equation,

$$NewFish_{positions} = Current_{Position}[i] + Individual_{Move} + Social_{Move} \quad (2)$$

where, the position remains within the bounds (0, 1).

3.1 Data Attainment, Acquisition and Data Pre-Processing (PAPILA)

This FSS-MOFS bio-inspired multivariable feature selection study uses PAPILA datasets for implementation and comparative analysis. The datasets include expert results with clinical records of 488 retinal fundus images of 244 patients in 2 categories (male and female). The contour image segmentation pixel dimension is 2576x1934 for both the left and right eyes. The clinical reports of three target attributes were given, such as healthy eye (0), glaucoma eye (1), and suspect glaucoma (2). The resulting data is used for comparative analysis, and RFI is used for the implementation and processing of feature extraction.

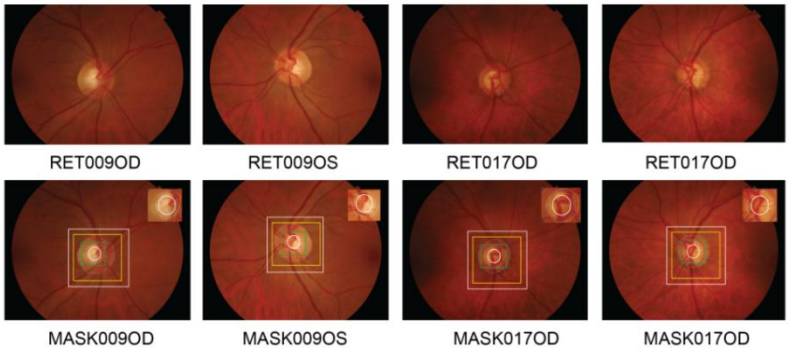

Figure 1: Retinal Fundus Images of #9 and #17 (OD/OS) / Normal: 1st Row, Pixel & Root Masking: 2nd Row

Table 1 shows the sample values of the PAPILA datasets, which have the details of 18 patients under 2 categories with 3 target results. During the study, 75% of RFI data were used for training and validation, and 25% were used for testing purposes. Figure 1 shows the image segmentation and pixel masking of 2 patients.

Table 1: PAPILA RFI Dataset (Samples of 18 Patients with OD/OS)

P-ID	Age	Eye Type	Gen	D-Values	Refractive Defect			Lens/ Crystalline
					D1	D2	AM	
#027	78	OD	1	0	0.25	-1.25	30	1
#028	26	OD	0	0	-2.25	-0.25	177	1
#029	41	OD	1	0	-1.25	-0.25	180	1
#027	26	OS	1	1	-0.5	-2	85	1
#028	26	OS	0	0	-1.5	-0.5	5	1
#029	41	OS	1	0	-1.25	0	0	1
#004	79	OD	1	1	1.5	-1.75	85	0
#005	72	OD	1	1	-0.75	-1.25	101	1
#010	70	OD	1	1	2.25	-1.5	105	0
#004	58	OS	1	1	1.5	-2.5	85	1
#005	89	OS	1	1	-0.5	-2	100	1
#010	72	OS	1	1	2.5	-1	70	0
#002	47	OD	0	2	0.75	-1.75	90	0
#006	69	OD	0	2	1	-1.5	95	0
#007	22	OD	1	2	-0.25	0	0	0
#002	47	OS	0	2	-0.5	-1.5	88	0
#006	69	OS	0	2	1	-1.5	85	0
#007	22	OS	1	2	-0.25	-0.5	0	0

(18/244 images are displayed as samples)

3.2 OD, OC and CDR Measurement and OR BRIEF technique

The BRIEF-LD latent descriptor is used to discover the latent spots and intensity patterns in the PAPILA RFI. BRIEF-LD represents the distinctiveness of the RFI patch by generating the digital vector images. For semantic segmentation, Densenet-121 is employed. Annotate or label the RFI to define the ROI and to mark the boundaries of structures, which include OD and lesions. Fine-tune the network and perform RFI segmentation, which generates binary masks and highlights the ROI. Later, it automatically removes the minor artifacts and fills the gaps, if any, to ensure accurate segmentation for better visualization of the masked image to identify the eye condition based on the target objective. The precise features extracted by Densenet-121 within the segmented disc and cup regions, such as area, centroid, mean, standard deviation, and latent spots like vessel values, layer thickness, etc., are recorded by BRIEF. The diameter of the cup and disc is calculated by using the below equation,

$$\textbf{\textit{Cup to Disc Ratio}}\ (\textbf{\textit{CDR}}) = \frac{\textbf{\textit{Cup Diameteer}}}{\textbf{\textit{Disc Diameter}}}\ (\textbf{\textit{for every image}}) \qquad \textbf{(3)}$$

Based on the CDR values measured, the target attributes are achieved. Various threshold levels give different outputs depending on the number of iterations. The crucial part is data augmentation for accurate measurement of CDR, which includes rotation, width shift, height shift, zoom, shear, channel, and horizontal shift. Densenet-121 bifurcates the input digital RFI into multiple feature maps with convolution and pooling layers. Various dense blocks are used until accuracy is achieved. To enhance efficiency, 3x3 convolutional bottleneck layers are used. Some of the major features extracted for CDR measurements are MAL, EN, ED, ECC, and AOE. During implementation, new hyper parameters are added and optimized to improve the growth rate of feature extraction. The sample parameter preparation is that if the sample size is 30, the number of iterations may go up to 15 with a dimension value of 3. A 3x3 confusion matrix is used to find the actual, glaucoma, and suspect cases.

3.3 FSS-MOFS with DenseNet-121 Architecture Diagram

The features extracted through FSS-MOFS are passed to the segmentation and classification stage using Densenet-121. The multilayer consists of two levels that deal with activation and dropouts. The architecture shows the detailed digital RFI segmentation process, followed by convolution and pooling of features to predict the accuracy level.

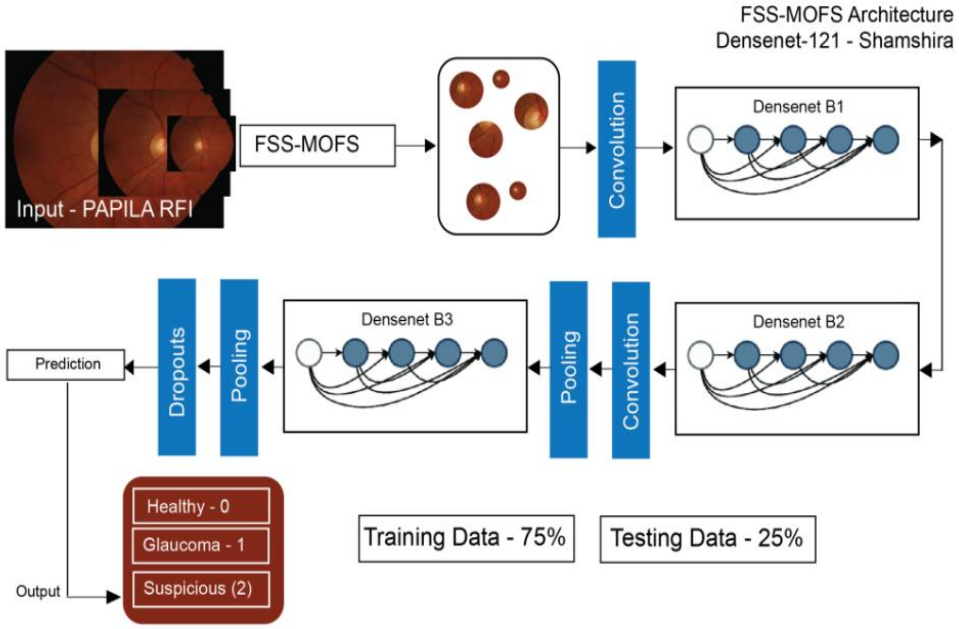

Figure 2: Densenet-121 Architecture

3.4 RFI segmentation using Densenet-121 & Deep-Lab

Segmentation using two-level layers with Densenet-121 and Deep-Lab to process the image into dilated convolutions to identify the finest built-in points and learn the retinal fluid from the provided annotations The segmentation consists of binary masks that identify the p-values of the corresponding PAPILA RFI, and the regions are highlighted to boost the accuracy level based on the features extracted by FSS-MOFS. The basic layer thickness level was also calculated to find the CDR accurately. The following are the major steps of Densenet-121 for segmentation and prediction.

- FSS-MOFS Pre-processing and Model Selection
- Densenet-121 and Deep-Lab model configuration for masking and segmentation
- Data splitting, labeling, and annotation before the training
- Feature validation and testing based on FSS-MOFS prediction
- Prediction of target values after 3 layers and functional points

3.5 Uniqueness in Bio-Inspired Feature Extraction compared to ML models

The FSS-MOFS multi-variable bio-inspired feature extraction model for efficient glaucoma detection is derived from the biological process of the fish swarm, which offers unique advantages like fostering adaptability and parallelism compared to the machine learning FSE process. Bio-inspired techniques combine both local and global searches, which enables efficient feature exploration that maximizes discrimination power and minimizes dimensionality. Multi-objective optimization is excelled at in FSS-MOFS to reduce dimensionality and overfitting. It captures complex features into a simple form, which is highly challenging for ML models due to its versatility. As FSS-MOFS is domain-independent, it can be combined with any architecture to perform any number of iterations based on the features extracted. The limitations are that, based on the nature of the data, the model works effectively.

FSS-MOFS bio-inspired process

1. **Input:** MATLAB settings with PAPILA RFI Dataset which has 488 Images
2. **Begin**:
3. Load PAPILA fundus retinal image $retinaldata.papila$
4. Perform pre processing
   for image in dataset:
   normalized_RFI image = normalize(N) denoised_RFI image = denoise(DN)
   resized_RFI image = resize(RI)
   preprocessed_RFI images.append(resized_RFI image)
   return preprocessed_RFI images

Extract Feature $objective\_function(feature\_subset)$

5. **Initialize FSS Parameters** $Features, Fish, Iterations, Search\ Space, Learning\ Rate$
6. **Initialize Fish Positions** fish_school = [random.sample(search_space, random.randint(1, num_features)) for _ in range(num_fish)]
7. **Calculate Fitness** fitness_1 = objective_function_1(fish)
8. Latent Spots selection with **BRIEF** $keypoints, descriptors = BRIEF(Segmented_{Spots})$
9. Segment and Prediction using Densenet-121
10. Glaucoma Assessment using segmented layered results by $CDR\ Measurement$
11. Generate **prediction (0,1,2) and Output:** Prediction of target values
12. **End**

3.6 Comparative Analysis using MATLAB R2021a

The suggested FSS-MOS bio-inspired feature extraction, glaucoma detection & classifier is compared against the prevailing ML based models such as I-SVM [12], RFSO[13], SE-GSO[15], VGG-Net[15], and DBN[16] classifiers. MATLAB R2020a tool is used for comparative analysis and the performance is measured and portrayed. MATLAB ensures dynamic processing of digital retinal fundus images and segments the RFI in a simple manner. Also it helps to train and test the ML glaucoma detection models with the available toolsets. The FSS-MOS tested with the help of PAPILA-DRFI clinical dataset. The following are the performance metrics used to assess the machine learning models in terms of feature extraction, detection and classification. The bio-inspired FE models and ML models are compared and the results are compared.

Sensitivity and Specificity: Sensitivity measures all positive instances out of actual positive detections by FSS-MOS, and specificity measures the negative instances out of actual negative detections.

Accuracy: Shows the accuracy in overall glaucoma detection and classification. Here, FSS-MOS measures the ratio of accurate classifications out of the total testing datasets.

$$\boldsymbol{GDC_{Accuracy}} = \frac{(TPR+TNR)}{(TPR+TNR+FPR+FNR)} \times 100 \quad (4)$$

$$\boldsymbol{GDC_{Sensitivity}} = \frac{TPR}{(TPR+FNR)} \times 100 \quad (5)$$

$$\boldsymbol{GDC_{Specificity}} = \frac{TNR}{(TNR+FPR)} \times 100 \quad (6)$$

Precision & Recall: Precision measures the +ve prediction value by FSS-MOFS out of total testing datasets and estimates the accuracy level, while recall calculates the TPR values in each iteration.

$$\boldsymbol{GDC_{Precision}} = \frac{TPR}{(TPR+FPR)} \times 100 \quad (7)$$

$$\boldsymbol{GDC_{Recall}} = \frac{TPR}{(TPR+FNR)} \times 100 \quad (8)$$

F-Measure: It assesses the balance between the precision and recall classification tasks of FSS-MOFS. It deals with imbalanced datasets during execution.

$$\boldsymbol{GDC_{FScore}} = \frac{2*(Precision\ *Recall\ )}{(Precision\ +Recall\ )} \quad (9)$$

TPR & TNR and FPR & FNR: Measures the +ve and -ve predictions of glaucoma cases identified by the bio-inspired FSS-MOFS models. It shows the prediction values during all iterations of FSS-MOFS, which are compared with ML methods.

$$\boldsymbol{MCC} = \frac{T_1}{\sqrt{T_2 \times T_3 \times T_4 \times T_5}} \times 100 \quad (10)$$

where, $\boldsymbol{GDC}$ *denotes Glaucoma Detection & Classification* and the above performance evaluation equation is derived as, $T_1 = (TPR \times TNR - FPR \times FNR)$, $T_2 = (TPR + FPR)$, $T_3 = (TPR + FNR)$, $T_4 = (TNR + FPR)$, and $T_5 = (TNR + FNR)$.

4. Results and Discussions

This chapter deals with the comparative results of the machine learning and bio-inspired Fish School Search MOFS method, which is used for efficient feature extraction in digital RFI to enhance glaucoma detection and classification for easy diagnosis. The FSS-MOFS is compared against the prevailing machine learning-based feature selection and extraction methods such as I-SVM [12], RFSO[13], SE-GSO[15], VGG-Net[15], and DBN[16] classifiers.

The bio-inspired feature extraction method shows promising results in terms of identifying deep latent spots and extracting multivariable features in retinal images such as vascular, texture, motion, optic disc and cup, lesion, histogram, topological features, etc., which boosts the classification accuracy. The findings and discussions

shown in Figure 3-8 are in the form of a MATLAB graph plotted with an X-axis and a Y-axis.

4.1 Sensitivity and Specificity Analysis

Figure 3 shows the sensitivity and specificity performance analysis of the bio-inspired multivariable model FSS-MOFS. Due to the extraction of intrinsic features in digital RFI, the level of positive and negative predictions is identified correctly. FSS-MOFS is compared against the prevailing ML-based methods such as I-SVM [12], RFSO [13], SE-GSO [15], VGG-Net [15], and DBN [16] classifiers. As effectual pre-processing is done in the PAPILA retinal dataset, and contour image values are taken for analysis and comparison. The bio-inspired method outperforms with evident results compared to baseline versions. 96% sensitivity and 97% specificity are achieved, which is relatively higher than ML techniques.

Table 2: Sensitivity and Specificity analysis

Metrics	I-SVM [12]	RFSO[13]	SE-GSO[15]	VGG-Net[15]	DBN[16]	**FSS-MOFS (Bioinspired)**
Sensitivity	70.30	76.70	80.95	86.71	89.76	**96**
Specificity	71.15	78.34	82.37	88.97	90.05	**97**

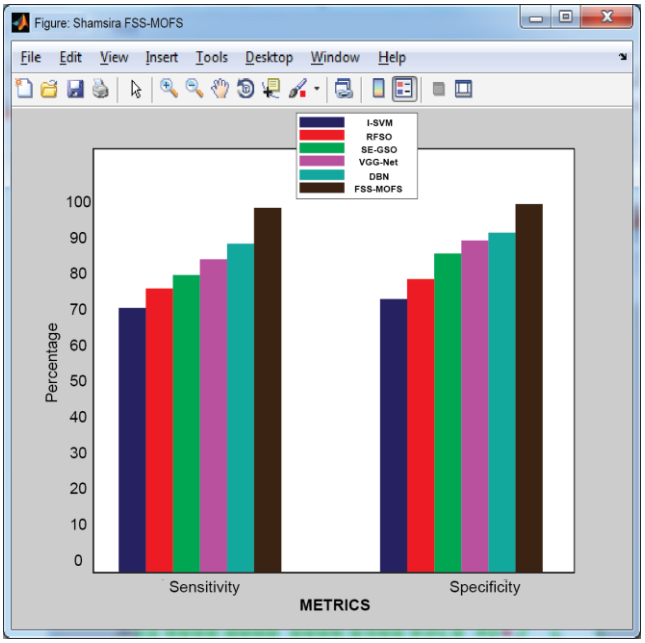

Figure 3: Comparative Analysis Graph of S&S

4.2 Accuracy Analysis

Detection and Classification accuracy of the FSS-MOFS and ML models are compared, and the result analysis is presented in Figure 4. The deep-lab model extracts all the built-in fine points with dilated convolutions from the contour image clinical dataset to boost the accuracy level. Image segmentation and pixel masking is done by using the Densenet-121 architecture, where the image root analysis is performed. FSS-MOFS shows promising results of 94% accuracy, which is comparatively higher than the existing ML classifier methods as histogram features were used. The multivariable feature extraction is the unique advantage of FSS-MOFS to outperform in all performance metrics.

Table 3: Accuracy analysis

Metrics	I-SVM [12]	RFSO[13]	SE-GSO[15]	VGG-Net[15]	DBN[16]	FSS-MOFS (Bioinspired)
Accuracy (It-1)	71.32	76.15	81.08	85.16	89.17	**91**
Accuracy (It-N)	74.15	80.20	85.25	88.19	90.16	**94**

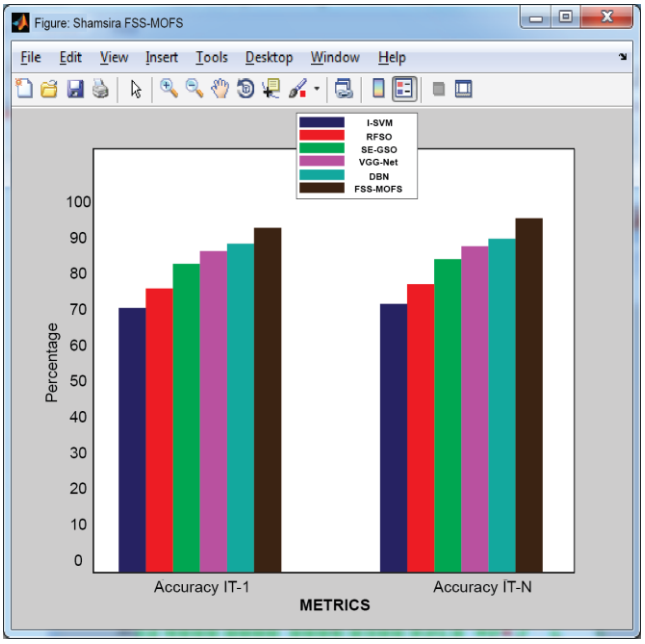

Figure 4: Comparative Analysis Graph of Classification Accuracy

4.3 Detection Speed Analysis

Figure 5 portrays the glaucoma detection speed of the FSS-MOFS bio-inspired method. The segmentation masking and level 0 masking are done as part of pre-processing to remove the noise in retinal datasets. Once the noise is removed, the time taken to detect the +ve and -ve predictions is less compared to other models. As the robust independent elementary feature is used to extract the latent spots in RFI, the speed of detection is improved to 95%, which is only 16 seconds for 100 iterations. During the comprehensive evaluation, the bio-inspired FSS-MOFS showed remarkable output compared to other detection and classification models. During the last iteration, the detection speed was recorded at 9.3 seconds, which is very imperative.

Table 4: Glaucoma Detection Speed Analysis

Metrics	I-SVM [12]	RFSO[13]	SE-GSO[15]	VGG-Net[15]	DBN[16]	FSS-MOFS (Bioinspired)
Speed (It-1)	72.62	77.24	82.38	86.46	90.47	**92.90**
Speed (It-N)	75.45	81.50	86.55	89.49	91.46	**95.03**

4.4 TPR and TNR Analysis

TPR and TNR performance and comparative analysis are done under different threshold values set during execution, and the results are shown in Figure 6. The FSS-MOFS-MOFS bio-inspired model is compared with the prevailing ML techniques such as I-SVM [12], RFSO [13], SE-GSO [15], VGG-Net [15], and DBN [16] classifiers. As the model uses the Densenett-121 architecture, it helps to learn the feature during the training and reduce overfitting to generate the labeled data. It understands the image regions, particularly after segmentation, to compare the original data to the trained data. 92.06% TPR and 92.15% TNR are achieved, which is comparatively higher than the other ML models for feature extraction, detection, and classification.

Table 5: TPR & TNR Analysis

Metrics	I-SVM [12]	RFSO[13]	SE-GSO[15]	VGG-Net[15]	DBN[16]	**FSS-MOFS (Bioinspired)**
TPR	65.15	70.06	75.70	80.19	86.48	**92.06**
TNR	68.90	74.53	78.40	82.37	89.61	**92.15**

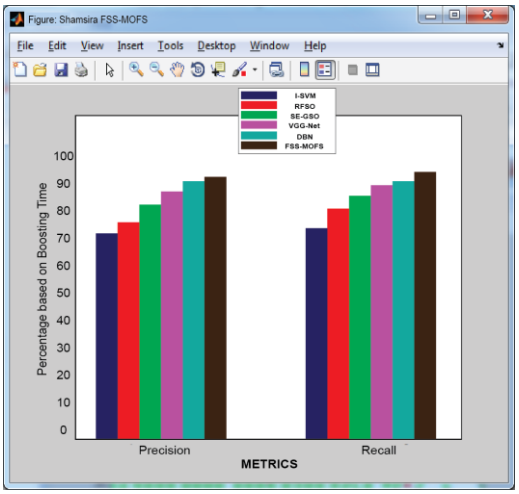

Figure 5: Comparative Analysis Graph of Detection Speed

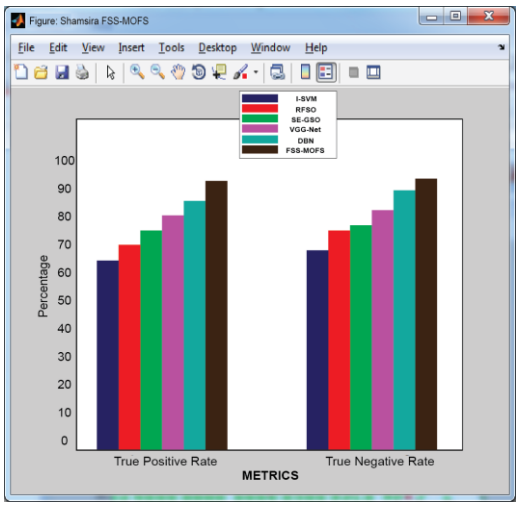

Figure 6: Comparative Analysis Graph of TPR & TNR

4.5 Precision and Recall Analysis

Figure 7 presents a detailed analysis of the performance of FSS-MOFS bio-inspired and other ML models in terms of precision and recall. The modified feature extraction from digital RFI for efficient glaucoma detection works on extracting the intrinsic multivariable features, which helps the model, detect and classify the glaucoma in a robust manner. The outcome of positive predicted values and TPR is measured. It measures the ability of FSS-MOFS to correctly detect glaucoma without any false classification as non-glaucoma. 96.8% precision and 97% recall are achieved, which is higher than other ML models.

Table 6: Precision & Recall Analysis

Metrics	I-SVM [12]	RFSO[13]	SE-GSO[15]	VGG-Net[15]	DBN[16]	**FSS-MOFS (Bioinspired)**
Precision	65.10	71.24	83.15	87.40	90.68	**96.8**
Recall	64.05	70.29	84.52	88.50	91.36	**97**

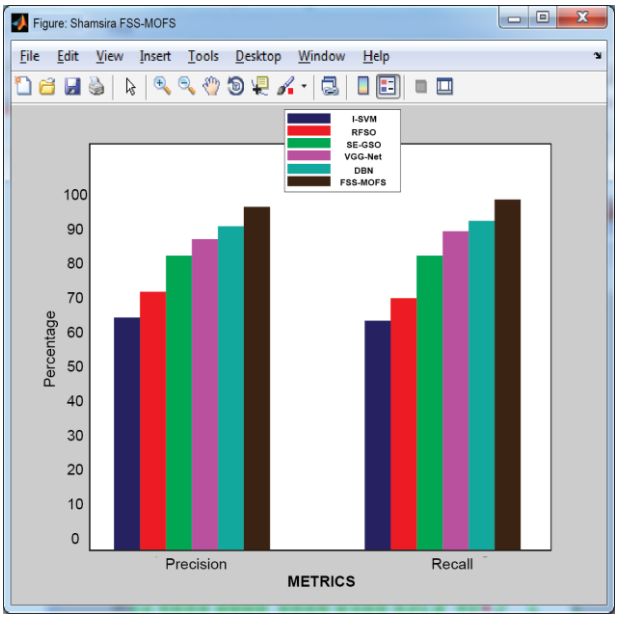

Figure 7: Comparative Analysis Graph of P & R

4.6 F-Score Analysis

Figure 8 demonstrates the f-measure analysis of FSS-MOFS and compares it with the baseline machine learning models such as I-SVM [12], RFSO[13], SE-GSO[15], VGG-Net[15], and DBN[16] classifiers. The comparative results are portrayed with values in Table 8. The OD-Disc and OC-Cup edges are measured as part of glaucoma detection; the latent spots are identified and compared with the trained retinal RFI to assess their performance. The process of Densenet-121 and deep-lab with dilated convolutions extracts all the overall intrinsic and built-in spots in the digital RFI to balance the +ve and -ve predictions. 96% f-measure is achieved, which is higher than other ML models.

Table 7: F-Score Analysis

Metrics	I-SVM [12]	RFSO[13]	SE-GSO[15]	VGG-Net[15]	DBN[16]	FSS-MOFS (Bioinspired)
F-Measure (It-1)	60.19	67.89	74.56	80.67	87.13	**93.05**
F-Measure (It-N)	64.56	71.65	79.17	84.81	91.47	**96.35**

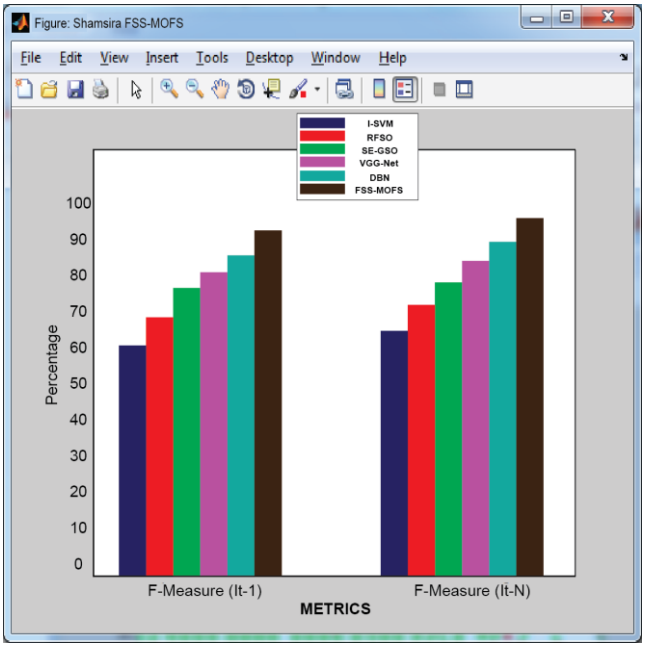

Figure 8: Comparative Analysis Graph of F-Score

4.7 FPR & FNR Analysis

Figure 9 represents the FPR and FNR analysis of the bio-inspired model and is compared against the prevailing machine learning feature extraction techniques. As the model works with improved pixel segmentation, the cup boundary detection is enhanced, which minimizes the error rate in both FPR and FNR directions. FSS-MOFS aligns with the specific goal of glaucoma detection and classification, where the deep-lab provides the interpretable image segmentation that maps and highlights the region identified as glaucoma disease. The false alarm rate is reduced to 7.80% FNR and 8.16% FPR, which is comparatively better than other ML models such as I-SVM [12], RFSO[13], SE-GSO[15], VGG-Net[15], and DBN[16] classifiers.

Table 8: FPR & FNR Analysis

Metrics	I-SVM [12]	RFSO[13]	SE-GSO[15]	VGG-Net[15]	DBN[16]	FSS-MOFS (Bioinspired)
FPR	38.17	32.68	27.75	20.35	16.54	**8.16**
FNR	37.34	31.27	26.89	19.71	15.43	**7.80**

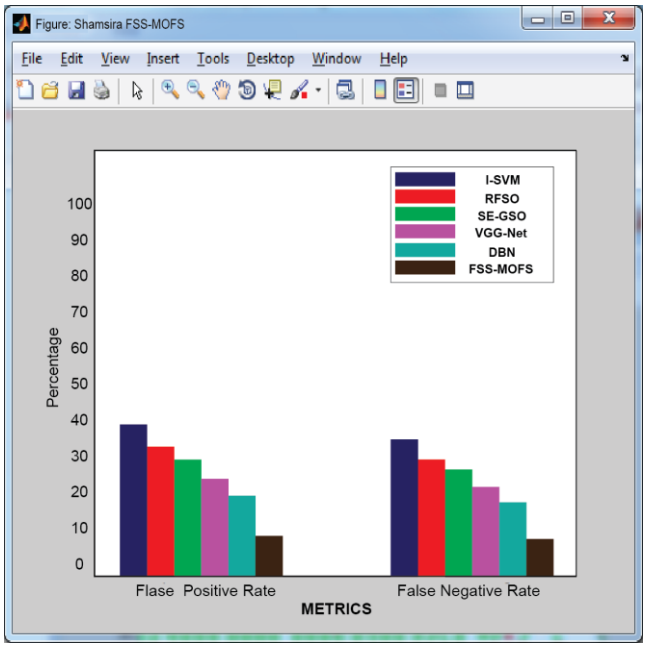

Figure 9: Comparative Analysis Graph of FPR & FNR

5. Conclusion

The suggested bio-inspired Fish School Search MOFS (FSS-MOFS) multivariable feature extraction technique is used in retinal fundus images for efficient glaucoma detection and classification with the help of machine learning models. Various ML models are studied and compared to analyze the performance of the bio-inspired feature extraction method. The unique FSS-MOFS method extracts all the multivariable features from the retinal images by reducing the dimensionality. The PAPILA retinal digital fundus images dataset was used for this research study, which has proven clinical results by experts. The dataset includes the details of 244 patients and 488 images (male and female categories) with three target attributes, such as healthy, glaucoma, and suspect. 75% of the data is used for training and validation and 25% for testing purposes. The BRIEF-LD method is employed to recognize the latent anatomical spots, which helps boost the accuracy level. The deep-lab learning model and Densenet-121 architecture are used for pixel masking and image segmentation to constantly measure the CDR, optic edges and curves.

FSS-MOFS with ML shows evident results with 94% accuracy and 8% false rates. As the model to incarcerate all the built-in fine points of RFI with dilated convolutions and outperforms the existing methods such as I-SVM, RFSO, SE-GSO, VGG-Net, and DBN classifiers with the results of 96% sensitivity, 97% specificity, 96% F-measure, 96.8% precision, 97% recall, 95% detection speed, 92.06% TPR, and 92.15% TNR. The limitations are: i) result deviation when there is noise in RFI; ii) complex pre-processing, which includes normalization, restoration, optimization, and identification of global spots in noisy RFI, etc. To make the system work in real-time, updated clinical values are required for implementation, which is hard to get. This method may be enhanced further with feature extraction in animated images, multi-modal data, and batch normalizations.

References

[1] Kishore Balasubramanian, Ananthamoorthy N.P. Correlation-based feature selection using bio-inspired algorithms and optimized KELM classifier for glaucoma diagnosis, *Applied Soft Computing*, 2022, 128, 109432. Available From: https://doi.org/10.1016/j.asoc.2022.109432

[2] M.B. Sudhan, M. Sinthuja, S. Pravinth Raja, J. Amutharaj, G. Charlyn Pushpa Latha, S. Sheeba Rachel, T. Anitha, T. Rajendran, Yosef Asrat Waji. Segmentation and Classification of Glaucoma Using U-Net

with Deep Learning Model, *Journal of Healthcare Engineering*, 2022, 1601354, 1-10. Available From: https://doi.org/10.1155/2022/1601354

[3] P. Anilkumar, P. Venugopal. Research Contribution and Comprehensive Review towards the Semantic Segmentation of Aerial Images Using Deep Learning Techniques, *Security and Communication Networks*, 2022, 6010912, 1-31. Available From: https://doi.org/10.1155/2022/6010912

[4] Tamim N, Elshrkawey M, Nassar H. Accurate Diagnosis of Diabetic Retinopathy and Glaucoma Using Retinal Fundus Images Based on Hybrid Features and Genetic Algorithm. *Applied Sciences*, 2021, 11(13), 6178. Available From: https://doi.org/10.3390/app11136178

[5] Nithyanandh S and Jaiganesh V. Quality of service enabled intelligent water drop algorithm based routing protocol for dynamic link failure detection in wireless sensor network. *Indian Journal of Science and Technology*, 2020, 13(16), 1641-1647. Available From: https://doi.org/10.17485/IJST/v13i16.19

[6] Muthu, S.P.V., Devadoss, A.K.V. Genetically optimized neural network for early detection of glaucoma and cardiovascular disease risk prediction. *Traitement du Signal*, 2023, 40 (4), 1641-1651. Available From: https://doi.org/10.18280/ts.400432

[7] Lauren J. Coan, Bryan M. Williams, Venkatesh Krishna Adithya, Swati Upadhyaya, Ala Alkafri, Silvester Czanner, Rengaraj Venkatesh, Colin E. Willoughby, Srinivasan Kavitha, Gabriela Czanner, Automatic detection of glaucoma via fundus imaging and artificial intelligence: A review, *Survey of Ophthalmology*, 2023, 68 (1), 2023, 17-41. Available From: https://doi.org/10.1016/j.survophthal.2022.08.005

[8] Kaur, S., Kumar, Y., Koul, A. A Systematic Review on Metaheuristic Optimization Techniques for Feature Selections in Disease Diagnosis: Open Issues and Challenges. *Archives of Computational Methods in Engineering*, 2023, 30, 1863–1895. Available From: https://doi.org/10.1007/s11831-022-09853-1

[9] Nithyanandh S, Omprakash S, Megala D, Karthikeyan MP. Energy Aware Adaptive Sleep Scheduling and Secured Data Transmission Protocol to enhance QoS in IoT Networks using Improvised Firefly Bio-Inspired Algorithm (EAP-IFBA). *Indian Journal of Science and Technology*, 2023, 16(34), 2753-2766. Available From: https://doi.org/10.17485/IJST/v16i34.1706

[10] Eldho KJ. Impact of Unbalanced Classification on the Performance of Software Defect Prediction Models. *Indian Journal of Science and Technology*, 2022, 15(6), 237-242. Available From: https://doi.org/10.17485/IJST/v15i6.2193

[11] Donu V Jose, Santhi K. (2022) Early Detection and Classification of Apple Leaf Diseases by utilizing IFPA Genetic Algorithm with MC-SVM, SVI and Deep Learning Methods. *Indian Journal of Science and Technology*, 15(29), 1440-1450. Available From: https://doi.org/10.17485/IJST/v15i29.1235

[12] Shubham Joshi, B. Partibane, Wesam Atef Hatamleh, Hussam Tarazi, Chandra Shekhar Yadav, Daniel Krah. Glaucoma Detection Using Image Processing and Supervised Learning for Classification, *Journal of Healthcare Engineering*, 2022, 2988262, 1-12. Available From: https://doi.org/10.1155/2022/2988262

[13] Sheeba Jeya Sophia, S., Diwakaran, S. Effective recognition of glaucoma using SIFT and RFSO classifier. *Multimedia Tools and Applications*, 2023, 17 (1), 1-20. Available From: https://doi.org/10.1007/s11042-023-17109-8

[14] Law Kumar Singh, Munish Khanna, Shankar Thawkar, Rekha Singh, Collaboration of features optimization techniques for the effective diagnosis of glaucoma in retinal fundus images, *Advances in Engineering Software*, 2022, 173, 103283. Available From: https://doi.org/10.1016/j.advengsoft.2022.103283

[15] Balasubramanian, Kishore & K, Ramya & Devi, Gayathri. Improved swarm optimization of deep features for glaucoma classification using SEGSO and VGG Net. *Biomedical Signal Processing and*

Control, 2022, 77. Available From: https://doi.org/10.1016/j.bspc.2022.103845

[16] Ajesh, F. & Ravi, R. & G, Rajakumar. Early diagnosis of glaucoma using multi-feature analysis and DBN based classification, *Journal of Ambient Intelligence and Humanized Computing*, 2021, 12. Available From: https://doi.org/10.1007/s12652-020-01771-z

[17] Kovalyk, O., Morales-Sanchez, J., Verdu-Monedero, R. PAPILA: Dataset with fundus images and clinical data of both eyes of the same patient for glaucoma assessment. *Scientific Data*, 2022, 9, 291. Available From: https://doi.org/10.1038/s41597-022-01388-1

[18] MdShakib Khan, NafisaTafshir, KaziNabiulAlam, AbdurRabDhruba, Mohammad Monirujjaman Khan, Amani AbdulrahmanAlbraikan, Faris A. Almalki, Deep Learning for Ocular Disease Recognition: An Inner-Class Balance, *Computational Intelligence and Neuroscience*, 2022, 5007111, 1-12. Available From: https://doi.org/10.1155/2022/5007111

[19] Nawaz, M, Nazir, T, Javed, A, Tariq, U, Yong, H.-S, Khan, M.A, Cha, J. An Efficient Deep Learning Approach to Automatic Glaucoma Detection Using Optic Disc and Optic Cup Localization. *Sensors*, 2022, *22*, 434. Available From: https://doi.org/10.3390/s22020434

[20] Raja, P.M.S., Sumithra, R.P., Ramanan, K. Glaucoma Detection with Fundus Images Based on NTKFIBC-IS Segmentation. In: Gunjan, V.K., Zurada, J.M. Proceedings of the 2nd International Conference on Recent Trends in Machine Learning, IoT, Smart Cities and Applications. *Springer Lecture Notes in Networks and Systems*, 2022, 237. Available From: https://doi.org/10.1007/978-981-16-6407-6_14

[21] Zedan, M. J. M., Zulkifley, M. A., Ibrahim, A. A., Moubark, A. M., Kamari, N. A. M., &Abdani, S. R. Automated Glaucoma Screening and Diagnosis Based on Retinal Fundus Images Using Deep Learning Approaches: A Comprehensive Review. *Diagnostics*, 2023, 13(13). 2180. Available From: https://doi.org/10.3390/diagnostics13132180

[22] Akter, N., Fletcher, J., Perry, S. *et al.* Glaucoma diagnosis using multi-feature analysis and a deep learning technique. *Science Repprts, 2022*, 12, 8064. Available From: https://doi.org/10.1038/s41598-022-12147-y

[23] Shoukat, Ayesha, Shahzad Akbar, Syed Ale Hassan, Sajid Iqbal, AbidMehmood, and QaziMudassarIlyas. Automatic Diagnosis of Glaucoma from Retinal Images Using Deep Learning Approach. Diagnostics, 2023, 13(10), 1738. Available From: https://doi.org/10.3390/diagnostics13101738

[24] Divya Jyothi Gaddipati and Jayanthi Sivaswamy. Glaucoma Assessment from Fundus Images with Fundus to OCT Feature Space Mapping. *ACM Transactions on Computing Healthcare*, 2021, 3(1), 1-15. Available From: https://doi.org/10.1145/3470979