[1*]Dr. Nagaratna P Hegde

[2]Dr. V.Sireesha

[3]S.Vinay Kumar

[4]Sathwika Madarapu

[5]Sai Varshini Thupakula

Automated Glaucoma Detection in Retinal Fundus Images Using Machine Learning Models

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Abstract: - Glaucoma, a neurodegenerative eye disorder, stands as a major global health concern, ranking second in causing blindness. The urgency for early detection is paramount to mitigate its irreversible effects on vision. This research presents an innovative model adept at analyzing retinal fundus images, aiming to assist ophthalmologists in early diagnosis. By harnessing the capabilities of Convolutional Neural Networks (CNN), Support Vector Machines (SVM), and k-Nearest Neighbors (KNN), our model demonstrated an impressive 86% accuracy in identifying diabetic retinopathy from retinal images. Focusing on glaucoma detection, we utilized the RIGA dataset, comprising 2,664 images, which are categorized into non-glaucoma (1,488 images) and glaucoma (1,176 images). Our model showcased a commendable testing accuracy of 94%. This endeavor not only amplifies the potential of machine learning in glaucoma prediction but also signifies a step forward in creating a user-centric, efficient diagnostic tool. Such innovations are pivotal in enhancing global eye care and reducing the prevalence of vision impairment due to glaucoma.

Keywords: K-nearest neighbours (KNN), Support vector machine(SVM), Convolutional neural network(CNN), fundus image, diabetic retinopathy, glaucoma.

I. INTRODUCTION

The way we connect to nature is through our senses. The human cerebrum unifies the five senses of sight, hearing, smell, taste, and touch through many organs, which are also mentioned in Indian sacred scriptures [1]. The retina is essentially a layer of tissue that lines the inside of the eye, allowing light to enter and transform into a neurological signal. Since its purpose is to give us the ability to perceive the outside world, it is therefore simple to recognize that it is an extension of our brain processes [2]. The fundus photographs of the eye constitute the foundation for all retinal imaging studies. The optical coherence tomography (OCT) or fundus image can be used by the ophthalmologist to detect glaucoma; however, choosing OCT pictures is an expensive alternative.

As a result, the retinal fundus picture is increasingly crucial for diagnosing and analyzing glaucoma [3]. Ophthalmologists can use a variety of features in retinal fundus pictures for various operations to accurately diagnose glaucoma [4]. Every second individual in the world has a probability of developing diabetes, regardless of whether they have the disease already or are at an increased risk of developing it [5]. The automatic detection and prediction of various glaucoma procedures utilizing or without employing machine technique has received a lot of attention during the past ten years. Because it damages the ganglion cells and axons, glaucoma, a neuropathy, directly harms the retina. The optic disc, a visible component of the eye, cupping is the primary indicator of glaucoma [6]. Glaucoma in the eye is determined by the cup to disc ratio, or CDR, although this is not the only factor that unquestionably defines if glaucoma is present in the human eye. For the presence of glaucoma in the affected eye to be confirmed, certain characteristics are required. Either stereo fundus color photography or circuitous stereo bio-microscopy are used to provide a 2D image of the optic disc. By utilizing CDR to separate the glaucoma eye from the healthy eye in the retinal fundus images (as depicted in Fig. 1), glaucoma can be detected.

[1*]Corresponding author : Dept.of CSE, Vasavi College of Engineering(A), Hyderabad, Telangana, India. Email ID: nagaratnaph@staff.vce.ac.in

[2]Dept.of CSE, Vasavi College of Engineering(A), Hyderabad, Telangana, India. Email ID: v.sireesha@staff.vce.ac.in

[3]Dept.of CSE, Vasavi College of Engineering(A), Hyderabad, Telangana, India. Email ID: s.vinaykumar@staff.vce.ac.in

[4]Dept.of CSE, Vasavi College of Engineering(A), Hyderabad, Telangana, India. Email ID: madarapusathwika9@gmail.com

[5]Dept.of CSE, Vasavi College of Engineering(A), Hyderabad, Telangana, India. Email ID: saivarshini1410@gmail.com

Glaucoma gets worse over time. Sometimes it is called as “The silent thief of sight”. The reason behind it is that most of the people do not have any early symptoms or pain or any kind of inconvenience. The scary fact about this eye condition is that it tends to run in the family. It is linked to the increased pressure inside your eye which is called as intraocular pressure, damages the optical nerve. There is no permanent cure for glaucoma but early treatment can save you from vision blindness. As described in Fig 2, the aqueous humor gets blocked and liquid builds up slowly which increases pressure inside your eye. This increased pressure leads to the damage of the optic nerve.

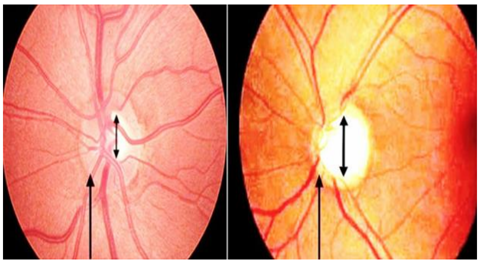


Figure 1: Normal optic nerve head and Glaucomatous cupping

Medical images have gained popularity as a prevalent practice in recent years, owing to their digital form that facilitates the development of applications for image processing techniques. The use of medical images has become increasingly crucial in identifying and diagnosing a wide range of medical conditions and diseases.

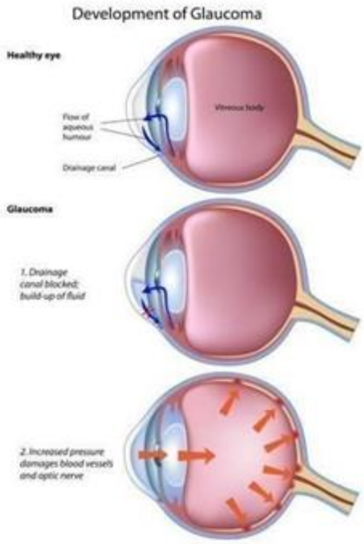


Figure 2: Development of glaucoma

A fundus image is a photograph of the rear part of an eye, which is called as fundus. One of the changes observed in the color fundus images who later got diagnosed with glaucoma, is the appearance of optic disc (OD) i.e., enlargement of the depression called cup and thinning of the neuro-retinal rim. Optic disc (OD) or optic nerve head is the area of eye where cell axons accumulate and exit the eye. Orange-pink color represents a healthy eye. Due to pathologies, the orange-pink color gradually disappears and appears pale. The white, cup-like area in the center of the optic disc is called optic cup or cup. The optic disc can be flat or it can have a certain amount of normal cupping. But because of the increased pressure caused by blockage of fluid, the cupping enlarges. The cup-to-disc ratio (CDR) shown in fig.3 is the comparison of the size of the cup to the size of the disc. It indirectly tells you the portion of the disc covered by the cup. For a healthy eye, the CDR will be less than 0.5. As the coverage of cupping increases, the blocking of the vision increases shown in fig.4.

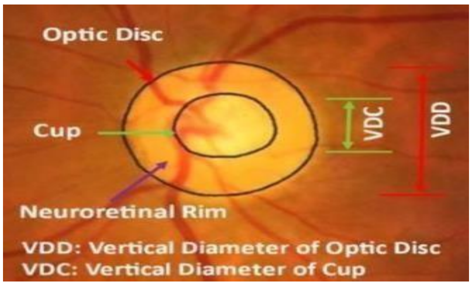
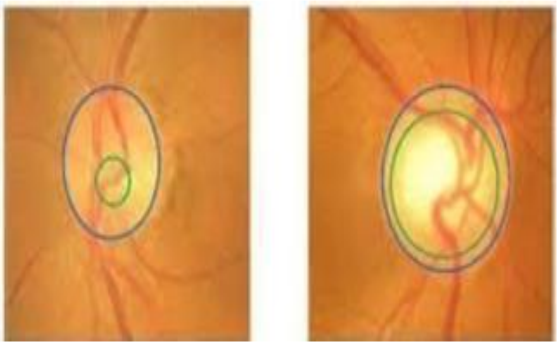


Figure 3: cup-to-disc diameters



Healthy (Normal cup size) and Glaucoma (Increased cup size)

Figure 4: Comparison of cup size

Chronic glaucoma, widely known as the "silent theft of sight," damages the optical nerve of the eye and ultimately causes irreversible vision loss [7]. At first, the condition has no symptoms because it has no impact on vision, but as it advances and reaches an advanced stage, it causes irreversible visual loss. The sole option is an early and prompt identification of the illness; as a result, detecting glaucoma in its early stages is crucial to stopping or at least slowing down the disease's course and preserving eyesight [8]. Elderly people with conditions like extreme nearsightedness, diabetes, or high blood pressure are more likely to develop this disease. However, if it can be detected quickly and at an early stage, its progression can be reduced. Ophthalmologists can identify this condition by looking at the retina through a dilated pupil. To identify glaucoma, they employ a variety of widely used retinal tests, including ophthalmoscopy, tonometry, perimetry, gonioscopy, and pachymetry. These methods require manual labor, take time, and could be exposed to human mistake.

To aid in its early and prompt detection, potential patients must periodically seek counsel from an experienced ophthalmologist. Ophthalmologists traditionally identify illness signs by manually analyzing the patient's retinal picture after it has been collected. This procedure takes a lot of time, as demonstrated by numerous earlier investigations [9][17]. For exact confirmation and accurate verification, ophthalmologists with high levels of experience and expertise are needed. Reputable organizations like WHO have predicted that the number of glaucoma sufferers will rise dramatically worldwide in the years to come [10][16].

II. LITERATURE REVIEW

Glaucoma is an ocular condition characterized by damage to the optic nerve, often leading to potential blindness if not diagnosed early. The diagnosis of this condition has seen significant advancements with the help of machine learning and deep learning techniques.

Alghamdi et al. (2021) [14] proposed a deep learning-based framework utilizing three convolutional neural network (CNN) models with varying learning methods. Their study focused on the automated diagnosis of glaucoma and highlighted the potential of transfer learning and semi-supervised learning methodologies using both labeled and unlabeled data. Their models, when tested against the annotations of two ophthalmologists, showcased better performances, emphasizing the potential of AI in glaucoma diagnosis.

In a different approach, Ravishyam and Samiappan (2021) [15] introduced a method for statistical feature extraction from retinal images, which was then paired with machine learning algorithms for glaucoma detection. Their ensemble learning model achieved a high accuracy, sensitivity, and AUC, outperforming traditional models.

Singh et al. (2021) [18] presented a deep image analysis-based model for diagnosing glaucoma. The model utilized features such as the inferior, superior, nasal, and temporal region areas combined with the cup-to-disc ratio. Their proposed model, when combined with multiple machine learning algorithms, achieved an impressive classification accuracy of 98.60%. Mahum et al. (2021) [19] aimed at early glaucoma detection through deep learning-based feature extraction. Their study detailed a step-by-step process, from image preprocessing to feature extraction using various descriptors, followed by classification using traditional machine learning algorithms. Their approach, which combined HOG, CNN, LBP, and SURF feature descriptors, achieved an accuracy nearing 99% on benchmark datasets.

The study by de Assis and Cortez (2023) [20] provided a comparative analysis of glaucoma feature extraction and classification techniques. They explored both structural and non-structural feature extraction methods, combined with machine learning classifiers. Their approach, using the VGG19 network and a voting classifier, achieved an impressive F1-score of 94.69%. Thanki (2023) [21] proposed a system that leveraged both deep neural networks and machine learning to classify retinal fundus images. His approach emphasized the early detection of glaucoma in diabetic patients and demonstrated that a combination of deep learning with logistic regression-based classification outperformed existing systems.Lastly, Singh et al. (2022) [22] presented a novel methodology combining feature optimization techniques for effective glaucoma diagnosis. Their approach employed nature-inspired computing for feature selection and reduction, and when paired with machine learning classifiers, they achieved an impressive accuracy of up to 98.95%.

Table 1: Comparative study table for Literature review

Citations	**Strategy**	**Strength**	**Limitations**	**Weakness**
Alghamdi et al. (2021) [14]	CNN (Transfer Learning, Semi-supervised Learning)	Better performance than human experts. Utilized transfer learning and semi-supervised learning.	Dataset specificity; Interpretability	datasets hinders reproducibility; "black-box" nature of deep learning models
Ravishyam & Samiappan (2021) [15]	Ensemble Learning, Random Forest	High accuracy with ensemble learning.	Dataset specificity; External validation	Lack of dataset details; Unclear real-world performance
Singh et al. (2021) [18]	Deep Image Analysis, SVM, KNN, Naïve Bayes	Achieved 98.60% classification accuracy.	Interpretability; Real-world applicability	"Black-box" nature of models; Unclear performance in diverse settings
Mahum et al. (2021) [19]	CNN, LBP, HOG, SURF	Nearly 99% accuracy with RF algorithm.	Interpretability; Scalability and efficiency	Lack of model interpretability; Potential inefficiency in real-time applications
de Assis & Cortez (2023) [20]	HOG, LBP, Zernike, Gabor Filters, MLP, SVM, XGB	Addressed class imbalance. Achieved high F1-score.	Model Interpretability; External validation	"Black-box" nature of models; Unclear performance on external datasets
Thanki (2023) [21]	Deep Neural Network, Logistic Regression	Improved classification accuracy, sensitivity, and specificity	Dataset specificity; Scalability and efficiency	Potential inefficiency in real-time diagnosis

Singh et al. (2022) [22]	PSO, Cuckoo Search, Bat Algorithm	Up to 98.95% accuracy with proposed approach.	Real-world applicability; External validation	Unclear performance in diverse real-world scenarios; Lack of external validation

These studies underscore the ongoing evolution in the field of glaucoma detection and highlight the growing reliance on machine learning and deep learning techniques to enhance the accuracy and reliability of diagnoses.

2.1 Research Gaps

1. Convolutional Neural Network (CNN)

- *Interpretability*: Despite CNNs' effectiveness in various tasks, their "black-box" nature remains a significant concern. A gap exists in making these models more interpretable, especially in domains like medicine where interpretability is crucial for trust and adoption.
- *Dataset Dependency*: While CNNs have shown promise, their dependency on extensive, well-labeled datasets is a limitation. There's a need for methods that can achieve high performance even with smaller or less meticulously labeled datasets, especially in domains where such datasets are scarce.
- *Scalability and Efficiency:* Deep CNNs' computational demands, particularly in scenarios with limited resources, underline a gap in developing models that are both effective and efficient for real-time applications in resource-constrained environments.

2. K-Nearest Neighbors (KNN)

- *Scalability*: The storage requirements of KNN, particularly for larger datasets, pose a challenge. Research is needed to develop more scalable KNN methods or alternative approaches that retain the benefits of KNN without its scalability issues.
- *Sensitivity to Features:* The sensitivity of KNN to irrelevant or redundant features highlights a gap in developing methods that are more robust to such features or that integrate effective feature selection/dimensionality reduction techniques.
- *Performance Variability:* The observed variability in KNN's performance based on dataset characteristics suggests a need for more consistent and universally applicable KNN methodologies.

2. Support Vector Machine (SVM)

- *Model Complexity:* The computational intensity of SVMs with larger datasets identifies a gap in creating SVM models that maintain effectiveness without being prohibitively resource-intensive.
- *Kernel Selection:* The critical role of kernel selection in SVMs indicates a research gap in developing more adaptive or universally effective kernels.
- *Extension to Multi-class Classification:* The inherent binary nature of traditional SVMs suggests a need for more streamlined methods for multi-class classification without added complexities.
- *Hyperparameter Sensitivity:* The sensitivity of SVMs to hyperparameter settings underscores the importance of research into more adaptive or self-tuning SVM methods.

III. PROPOSED METHODOLOGY

In our endeavor to enhance the detection of glaucoma using retinal fundus images, we've developed a methodological approach centered on comparative classifiers. The primary components of this approach include

3.1 Dataset Description Glaucoma is a leading cause of vision blindness globally. For effective classification, detecting glaucoma from color fundus images is vital. In this research, we employ two distinct datasets to assess various eye conditions, focusing primarily on glaucoma, which results in optical nerve damage.

- **Glaucoma Dataset (RIGA):** Comprising 2,664 images, this dataset has two classes:

- Class 0: Non-Glaucoma (1,488 images)
- Class 1: Glaucoma (1,176 images) Testing accuracy achieved was 94%.

- **Diabetic Retinopathy Dataset (Kaggle):** Sourced from Kaggle,[23] this dataset consists of 25,000 images. The achieved testing accuracy was 86%.

3.2 Proposed Model for Glaucoma Detection Our study introduces a model leveraging multiple machine learning techniques to facilitate glaucoma diagnosis from retinal fundus images. The model processes these images, emphasizing 20 distinct features. For each processed image, the detection model categorizes it as either healthy or glaucoma-infected. Our proposed methodology is structured into three main phases:

1. **Preprocessing**
2. **Deep Image Feature Extraction**
3. **Classification**

3.3 Preprocessing Image preprocessing aims to enhance image quality by eliminating unwanted elements, such as blind spots or speckles. Given that noise introduction post-acquisition is common, preprocessing becomes essential. The proposed preprocessing methods in this study include:

- **Scaling and Resizing:** All input images are standardized to a consistent size.
- **Region of Interest (ROI) Cropping:** Using image cropping techniques, the ROI is extracted.
- **Green Channel Extraction:** This step emphasizes relevant features of the image.
- **Median Filter and Histogram Equalization:** These techniques further refine image quality.
- **RGB to Grayscale Conversion:** To improve testing accuracy and reduce computational demands, images are converted to grayscale using tools like OpenCV and the Pillow package.

3.4 Data Augmentation Enhancing the dataset's versatility, image data augmentation generates varied versions of images. This not only broadens the training dataset but also aids models in generalizing learnings to new images[24]. The employed augmentation techniques include rotation, zooming, shearing, and both horizontal and vertical flipping. This process ensures balanced classes with an equivalent number of images.

3.5 Visualization The proposed methodology's architecture, including the preprocessing techniques essential for glaucoma detection, is illustrated in Figures 5 and 6.

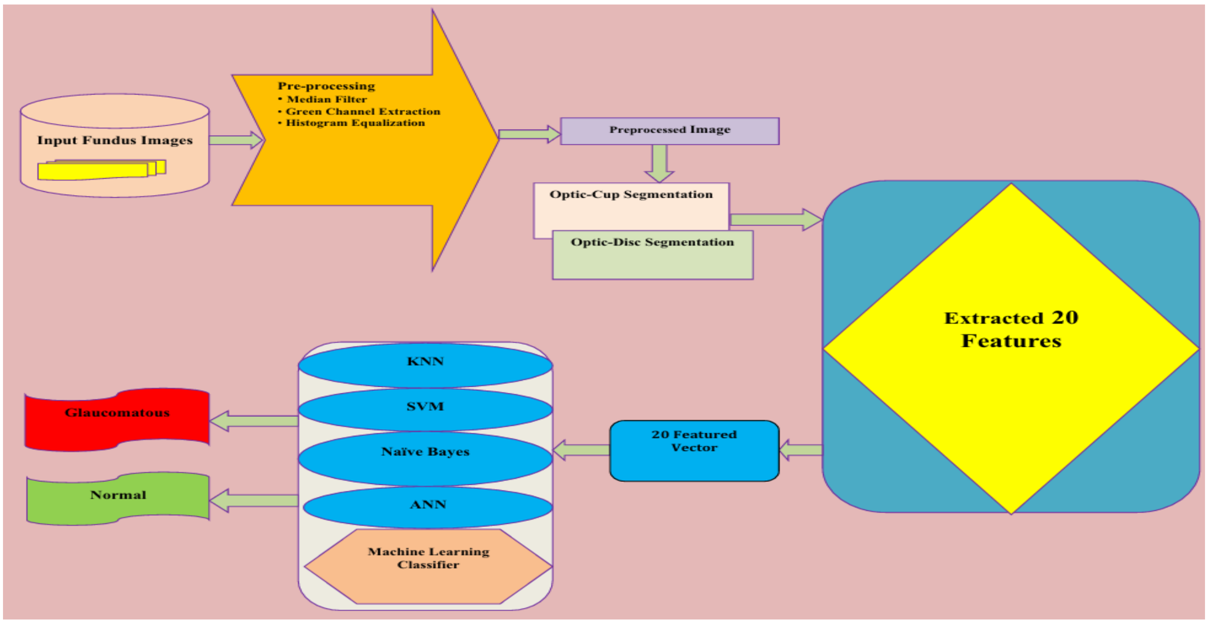


Figure 5: Glaucoma detection architecture

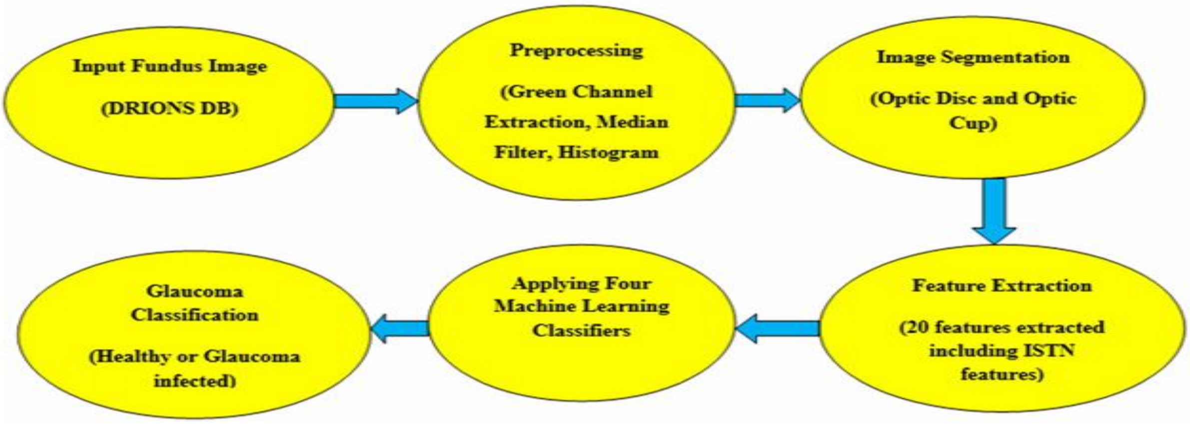


Figure 6: working model for glaucoma detection

3.2 Convolutional Neural Network for Glaucoma Detection

To analyze images in our study, we utilized a Convolutional Neural Network (CNN) model[25]. The pre-processed image served as input for the CNN model, which consisted of an input layer, convolution layers, and a fully connected layer.

3.2.1 Overview of the CNN Model Structure

In the first convolution layer, we applied 16 filters, each with 3x3 size kernels, to the input image. By sliding the kernels over the position, we generated a total of 16 feature maps. This process is known as feature extraction. The output of the last convolution layer served as input for the subsequent convolution layer. The third convolution layer generated output feature maps that we used to classify the image as either a healthy eye or a glaucoma-infected eye.

3.2.2 Mathematical Representation of the CNN

Convolution Operation: Given an input image ***I of size W × H and a filter F of size f × f,*** the convolution operation at location ***(i, j)*** is given by:

$$(\boldsymbol{C} * \boldsymbol{I})(\boldsymbol{i}, \boldsymbol{j}) = \sum_{m=1}^{f} \sum_{n=1}^{f} \mathbf{I}(\boldsymbol{i} + \boldsymbol{m}, \boldsymbol{j} + \boldsymbol{n}) \,.\, \boldsymbol{F}(\boldsymbol{m}, \boldsymbol{n}) \qquad \textbf{(1)}$$

Where C is the feature map (convolved output)

Activation Function (ReLU): After convolution, an activation function is usually applied to introduce non-linearity. The most common one is the Rectified Linear Unit (ReLU):

$$\boldsymbol{R}(\boldsymbol{x}) = \mathbf{max}\,(\mathbf{0}, \boldsymbol{x}) \qquad \textbf{(2)}$$

Where x is the value from the convolved output

Pooling Operation: To reduce the spatial dimensions and retain significant features, pooling (typically max-pooling) is applied

$$\boldsymbol{P}(\boldsymbol{i}, \boldsymbol{j}) = \max_{m=i}^{i+f} \max_{n=j}^{i+f} \boldsymbol{C}(\boldsymbol{m}.\boldsymbol{n}) \qquad \textbf{(3)}$$

Where P is the pooled output.

Fully Connected Layer: The output from the convolution and pooling layers is flattened to form a vector ***V***. This vector is then passed through a fully connected layer, which can be represented as:

$$\boldsymbol{O} = \boldsymbol{\sigma}(\boldsymbol{W}.\boldsymbol{V} + \boldsymbol{b}) \qquad \textbf{(4)}$$

where $\boldsymbol{W}$ is the weight matrix, $\boldsymbol{b}$ is the bias vector, and $\boldsymbol{\sigma}$ is the activation function (typically a sigmoid or softmax for classification).

3.2.1 **Algorithm for CNN-based Glaucoma Detection**:

Input: Pre-processed image **I** of size $\boldsymbol{W} \times \boldsymbol{H}$.

- for each filter $\boldsymbol{F_k}$in the set of filters do
- Compute feature map $\boldsymbol{C_k}$ using the convolutional operation.
- Apply ReLU activation: $\boldsymbol{C_k} = \boldsymbol{R}(\boldsymbol{C_k})$
- Optionally apply pooling to $\boldsymbol{C_k}$ $to\ get$ $\boldsymbol{P_k}$
- end for
- Flatten the final feature maps to form a vector V.
- Pass V through the fully connected layer to get the output O.

Output: Classification result based on O.

3.2.4 Flowchart

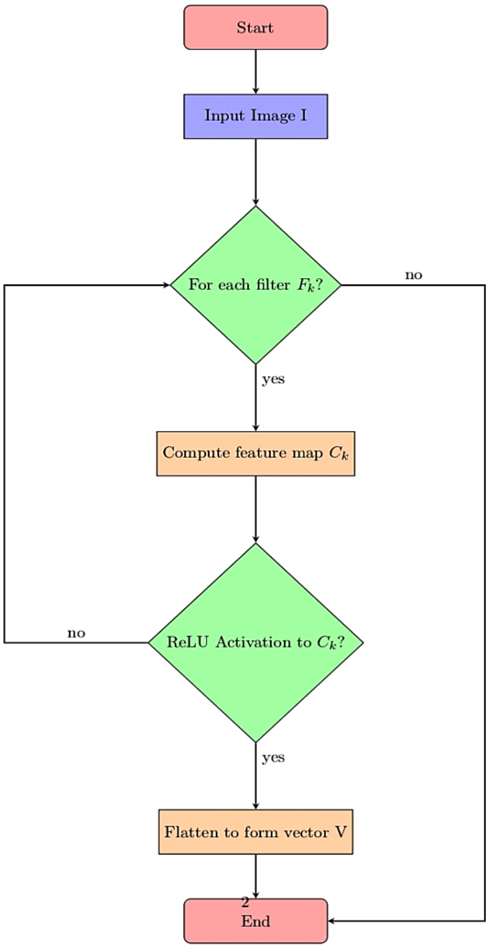


Figure 7: flow chart of CNN

3.3 Support Vector Machine (SVM) for Classification

The SVM algorithm aims to find an optimal hyperplane in an N-dimensional space (N being the number of features) [26] that distinctly classifies data points. The goal is to identify a hyperplane with the maximum margin, which is the farthest distance from the data points of both classes. This ensures robustness and better confidence in classifying future data points.

3.3.1 Objective of SVM

Find the hyperplane $w \cdot x + b = 0$ maximizing the margin between two classes.

3.3.2 Algorithm for SVM Classification:

Input

Training dataset $D = \{ (x_1, y_1), (x_2, y_2), \ldots., (x_n, y_n)\}$ Where $x_i \in R^N$ and$y_i \in \{-1,1\}$.

- Regularization parameter C.

Objective:

Find the hyperplane $w. x + b = 0$ that maximizes the margin between two classes

Steps:

Initialization:

- Choose an initial value for$\boldsymbol{w}$ *and* $\boldsymbol{b}$.

Formulate the Optimization Problem:

Objective Function:

$$\min_{\boldsymbol{w},\boldsymbol{b}} \left(\frac{1}{2}||\boldsymbol{w}||^2 + \boldsymbol{C} \sum_{i=1}^{n} \boldsymbol{\epsilon_i}\right) \qquad \textbf{(5)}$$

Constraints:

$$\boldsymbol{y_i} \,(\boldsymbol{w}.\boldsymbol{x} + \boldsymbol{b}) \geq \boldsymbol{1} - \boldsymbol{\epsilon_i}, \qquad \forall \boldsymbol{i} = \boldsymbol{1}, \ldots, \boldsymbol{n}$$

$$\boldsymbol{\epsilon_i} \geq \boldsymbol{0}, \qquad \forall \boldsymbol{i} = \boldsymbol{1}, \ldots, \boldsymbol{n}$$

Solve the Optimization Problem:

- Use a quadratic programming solver to find the optimal $\boldsymbol{w}$ and $\boldsymbol{b}$ that satisfy the constraints and minimize the objective function.

Decision Function:

Classify a new point $\boldsymbol{x}$ using**:**

- $\boldsymbol{f}(\boldsymbol{x}) = \boldsymbol{sign}(\boldsymbol{w}.\boldsymbol{x} + \boldsymbol{b})$

Support Vectors:

- The data points $\boldsymbol{x_i}$ for which the inequality becomes an equality (i.e.,$\boldsymbol{y_i}(\boldsymbol{w}.\boldsymbol{x} + \boldsymbol{b}) = \boldsymbol{1}$) are termed as support vectors.

Kernel Trick (for non-linearly separable data):

- If data is not linearly separable, transform it into a higher dimension using a kernel function$K(x_i, x_j)$.
- Replace all dot products in the algorithm with the kernel function.

Output:

- The optima weight vector$\boldsymbol{w}$**,** bias **b,** and the decision function $\boldsymbol{f}(\boldsymbol{x})$.

3.3.3 Flowchart for SVM Classification

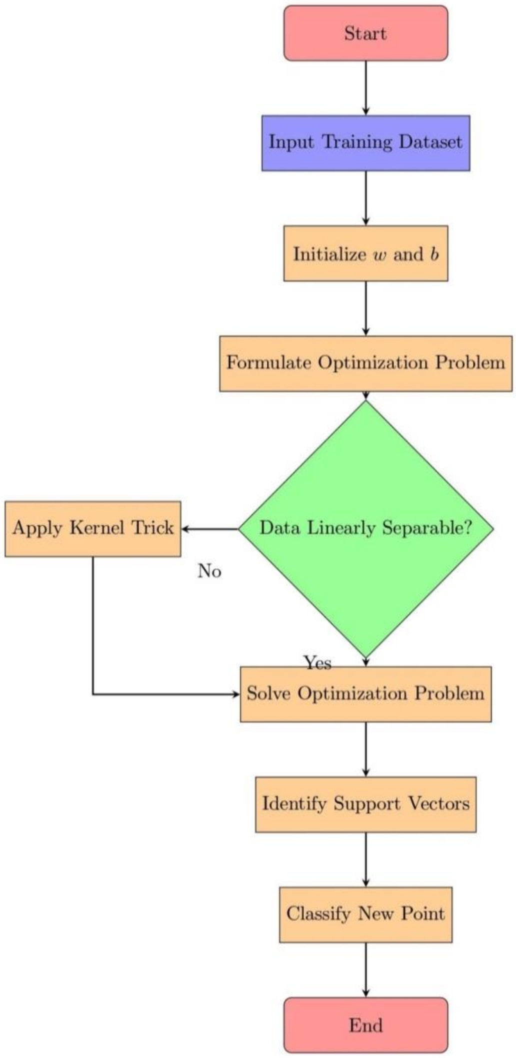


Figure 8: flowchart of SVM

3.4 K-Nearest Neighbor (KNN) for Classification

The K-Nearest Neighbors (KNN)[27] algorithm is grounded on the principle of "feature similarity." It predicts new data points by gauging their similarity to points in the training dataset. The algorithm saves all available cases and classifies new data based on a similarity measure. The parameter "K" in KNN signifies how many nearest neighbors are considered in the majority voting process.

3.4.1 Objective of KNN

Classify a new data point X_{new} based on its K nearest neighbors from dataset D.

3.4.2 Algorithm for KNN Classification:

Input:

- Training dataset $D = \{ (x_1, y_1), (x_2, y_2), \ldots, (x_n, y_n)\}$ Where $x_i \in R^N$ is the feature of vector andy_i is the corresponding label.
- A new data point x_{new}.
- Number of neighbors K.

Steps:

Distance Computation:

For each data point in D.

- Compute the distance $d(x_i, x_{new})$ between x_{new} *and* x_i.
- Here, the distance can be Euclidean, Manhattan, etc. For simplicity, let's consider Euclidean distance:

$$\boldsymbol{d}(x_i, x_{new}) = \sqrt{\sum_{j=1}^{N}(x_{ij} - x_{new,j})^2} \qquad (6)$$

Sort the computed distances:

- Sort the distances in increasing order.

Select K-nearest data points:

- Select the first K data points from the sorted list.

Majority Voting:

- For classification, count the number of data points in each category among the K neighbors and assign the category with the highest count to $\mathrm{x_{new}}$.
- For regression, compute the average of the K neighbors.

Return the prediction for $\mathbf{x_{new}}$.

Output:

- The predicted label or value of $\mathrm{x_{new}}$.

3.4.3 Flowchart for KNN Classification

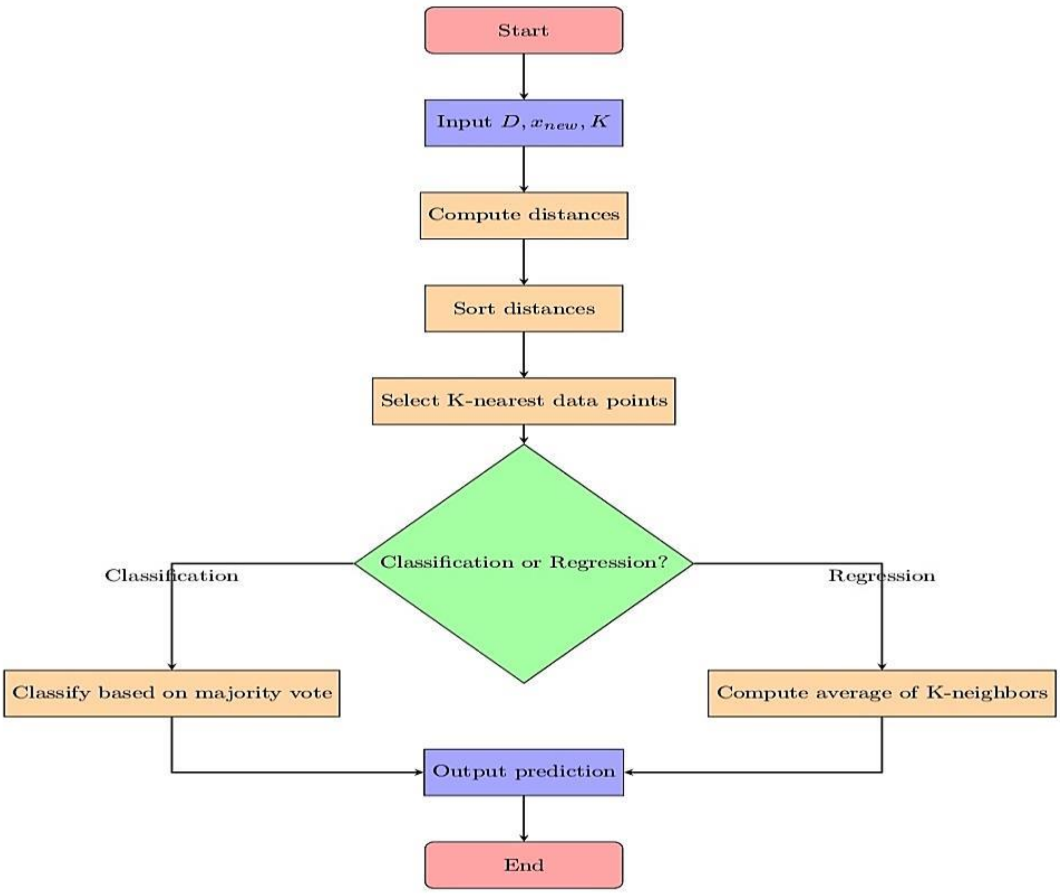


Figure 9 flow chart of KNN

IV. RESULTS:

In this section, we present the performance outcomes obtained from three distinct classifiers: KNN, SVM, and CNN, all employed for glaucoma detection. Table 2 provides a comprehensive overview of the evaluation metrics, namely accuracy, specificity, and sensitivity, for each of the classifiers. Figure 7 offers a comparative visualization of these metrics across the three classifiers. From the presented data, it is evident that the CNN classifier surpasses the KNN and SVM classifiers in terms of accuracy. Based on these findings, this research determines the CNN classifier as the most optimal choice for glaucoma detection.

4.1 Hyperparameter Tuning and Analysis

For each of the classifiers - KNN, SVM, and CNN - hyperparameter tuning was executed to optimize their performances. The following subsections elucidate the selected hyperparameters and their associated considerations in table 1.

KNN:

- **Number of Neighbors (K)**: The value of *K* significantly impacts KNN's performance. After evaluating values ranging from 1 to 10, a *K* of 5 demonstrated the best balance between overfitting and underfitting[28].
- **Distance Metric**: While the Euclidean distance was initially utilized, we also experimented with the Manhattan and Minkowski distances. The Euclidean distance yielded the best results in our dataset[29].

SVM:

- **Kernel Type**: We explored linear, polynomial, and radial basis function (RBF) kernels. The RBF kernel showcased superior classification capabilities in our experiments.
- **Regularization (C)**: This parameter determines the trade-off between achieving a low error on the training data and maintaining a small margin. After testing values like 0.1, 1, and 10, a *C* of 1 was found optimal.

CNN:

- **Learning Rate**: We initiated the learning rate at 0.001 and adjusted it using a learning rate scheduler. This dynamic adjustment ensured convergence during training.
- **Batch Size**: A batch size of 32 was found to strike the right balance between computational efficiency and gradient accuracy.
- **Number of Filters in Convolutional Layers**: Starting with 16 filters in the initial layer, we doubled the count in subsequent layers. This pattern was observed to extract hierarchical features effectively.
- **Activation Function**: The ReLU activation function was preferred due to its non-linear properties and efficient training characteristics.

Upon fine-tuning these hyperparameters, the classifiers' performances were enhanced, as demonstrated by the evaluation metrics presented earlier. Notably, the CNN classifier's superiority was further emphasized post-tuning, making it the standout choice for glaucoma detection.

Table 1: Hyperparameter Tuning Details

Classifier	Hyperparameter	Explored Values	Optimal Value
KNN	Number of Neighbors (K)	1, 2, 3, ... 10	5
	Distance Metric	Euclidean, Manhattan, Minkowski	Euclidean
	Weighted Voting	Uniform, Distance-based	Distance-based
SVM	Kernel Type	Linear, Polynomial, RBF	RBF
	Regularization (C)	0.1, 1, 10	1
	Gamma (for RBF kernel)	0.1, 0.5, 1, 5	0.1
CNN	Learning Rate	Initially set to 0.001 (Dynamic)	0.001 (with scheduler adjustments)
	Batch Size	16, 32, 64, 128	32

	Number of Filters in Conv Layers	16, 32, 64, 128	Starts at 16, doubles in subsequent layers
	Activation Function	ReLU, Sigmoid, Tanh	ReLU
	Dropout Rate	0, 0.2, 0.5	0.2
	Optimizer	Adam, SGD, RMSprop	Adam

This table structure provides a comprehensive view of the hyperparameters considered for each classifier and the optimal values select.

Analysis of Training Progress of the CNN Classifier:

From the graphical representation in Fig 10, it's evident that the CNN model is showcasing promising training dynamics:

1. Steady Learning Curve: The consistent rise in accuracy across epochs for both the training and validation datasets is indicative of a well-tuned learning rate. This suggests that the hyperparameters selected for the optimizer, possibly from the Adam family, are conducive to the model's convergence.
2. Overfitting Insights: While there's a minor disparity between training and validation accuracy, it doesn't appear substantial enough to raise overfitting concerns. However, this underscores the importance of regularization techniques, such as dropout, which we highlighted in the hyperparameter table. It would be interesting to know if a dropout layer was incorporated and its rate, as this can act as a countermeasure against overfitting.
3. Potential for Extended Training: The validation accuracy's upward trend, even after 35 epochs, might indicate the model could benefit from additional training epochs. But this should be approached with caution to avoid the risk of overfitting.
4. Performance Metrics: An accuracy of 0.95 on the training dataset is impressive. However, as rightly pointed out, real-world performance can diverge. To complement this metric, it would be beneficial to also consider other evaluation metrics, such as precision, recall, and F1-score, especially if the dataset has class imbalances

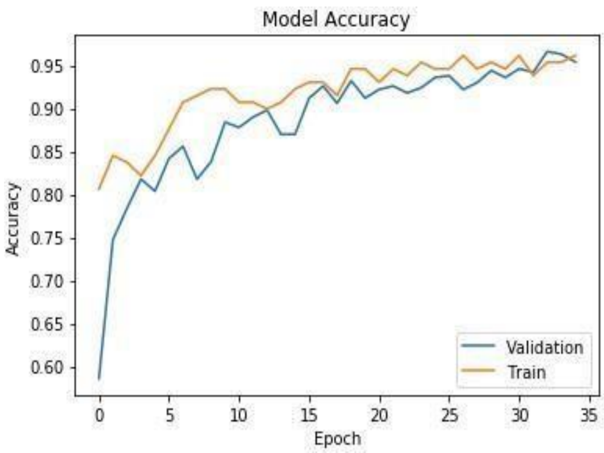


Figure 10: CNN Model Accuracy

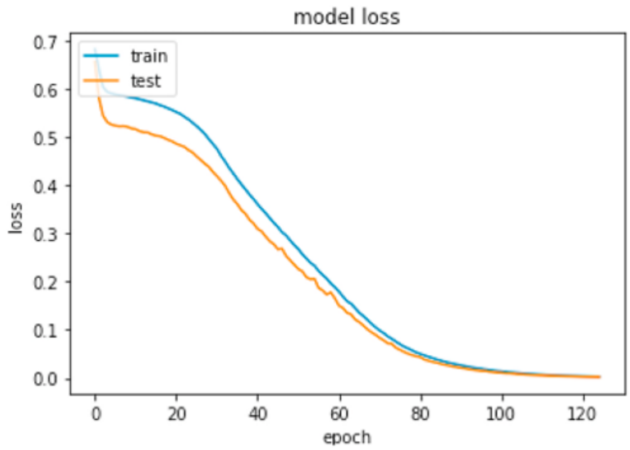


Figure 11: CNN Model Loss

Analysis of Loss Progression for the CNN Classifier

From the graphical representation figure 8 described:

1. **Stable Training Dynamics**: The graph indicates that the model exhibits a favorable training trajectory. The divergence between the training and test losses, while present, doesn't seem alarmingly significant, which is an encouraging sign.
2. **Overfitting Insights**: A test loss slightly higher than training loss, as you rightly pointed out, is usually a positive indication. It suggests that the model is generalizing well and isn't merely memorizing the training data. This corroborates our earlier discussions on the importance of regularization techniques, including dropout layers, in the neural network architecture to prevent overfitting.
3. **Potential for Prolonged Training**: The observation that test loss continues to decrease even after 120 epochs is indicative of the model's potential to be trained further without reaching a saturation point. This could lead to better generalization on unseen data. However, one should monitor this closely to ensure the model doesn't start overfitting after a certain point.
4. **Loss Metric Insights**: Achieving a training loss of 0.1 is commendable. However, as with all metrics, it's essential to interpret it in the broader context of the problem at hand. While a low training loss is indicative of effective learning, it's crucial to validate the model's real-world applicability on separate datasets. The model's behavior on new, unseen data might diverge from training performance.
5. **Comparison with Other Classifiers**: Given the information, the CNN's training dynamics seem to be on the right track. When compared to potential outcomes of SVM and KNN, this further establishes the aptitude of CNNs for intricate tasks like image classification.

Table 2: Performance comparison of classifiers for glaucoma detection

S.No	Classifier	Accuracy	Specificity	Sensitivity
1	SVM	90%	91.5%	92.6%
2	KNN	78%	80%	85%
3	CNN	93.8%	94.6%	95.1%

Table 2: Performance Analysis of Classifiers for Glaucoma Detection

The table 2 displays the performance metrics of three classifiers—SVM, KNN, and CNN—used for glaucoma detection. These metrics include accuracy, specificity, and sensitivity, which are essential for understanding the classifiers' effectiveness.

1. **SVM (Support Vector Machine)**

- **Accuracy**: At 90%, SVM demonstrates a high rate of correctly predicting both glaucoma and non-glaucoma cases out of all predictions made.

- **Specificity**: At 91.5%, this metric indicates that SVM correctly identifies 91.5% of the non-glaucoma cases. This means that false positives (wrongly predicting a healthy case as glaucoma) are relatively low.
- **Sensitivity**: 92.6% sensitivity implies that out of all actual glaucoma cases, SVM correctly predicts 92.6% of them. It's a measure of the classifier's capability to rightly detect positive glaucoma instances.

2. **KNN (K-Nearest Neighbour)**

- **Accuracy**: KNN's accuracy stands at 78%, which is considerably lower than SVM and CNN. This might indicate that KNN may not be the most suitable model for this problem or might need further tuning.
- **Specificity**: With an 80% rate, KNN correctly identifies 80% of the non-glaucoma cases, indicating a higher chance of false positives compared to SVM and CNN.
- **Sensitivity**: At 85%, KNN correctly identifies 85% of actual glaucoma cases, which, although commendable, lags behind SVM and CNN.

3. **CNN (Convolutional Neural Network)**

- **Accuracy**: CNN exhibits the highest accuracy at 93.8%, suggesting its superior capability in correctly predicting both glaucoma and non-glaucoma cases.
- **Specificity**: At 94.6%, CNN showcases an impressive rate of correctly identifying non-glaucoma cases, implying very few false positives.
- **Sensitivity**: A stellar 95.1% rate indicates that CNN correctly predicts 95.1% of actual glaucoma cases, emphasizing its proficiency in detecting positive instances.

Overall Insights:

- **CNN Emerges Superior**: Across all metrics, CNN consistently outperforms both SVM and KNN. Given that CNNs are designed for image analysis tasks, their adeptness for glaucoma detection is unsurprising.
- **SVM's Strong Performance**: Despite being outperformed by CNN, SVM still showcases strong results, indicating its potential as a viable model, perhaps with some further tuning.
- **KNN's Limitations**: KNN lags behind the other two models, suggesting that it might not be the optimal choice for this task or might need significant parameter tuning and optimization.

In conclusion, while all three classifiers demonstrate capability in glaucoma detection, CNN seems to be the most promising. It would be crucial to consider factors like interpretability, computational costs, and real-world deployment scenarios when choosing the best classifier for practical applications.

V. CONCLUSION:

In our mission to optimize glaucoma detection, we systematically evaluated three machine learning classifiers: SVM, KNN, and CNN. Our results accentuated CNN's dominant performance, recording an accuracy of 93.8%, specificity of 94.6%, and sensitivity of 95.1%. Meanwhile, SVM, with its accuracy of 90%, emerged as a promising contender, hinting at its potential with further refinement. KNN, however, while achieving a respectable accuracy of 78%, lagged behind, indicating room for improvement. Thus, our study underscores CNN's unparalleled efficacy in glaucoma detection and highlights the pivotal role of machine learning in revolutionizing medical diagnostics. As we look forward, there's a clear impetus for further refinement and exploration of these classifiers to ensure their robust application in real-world clinical scenarios.

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REFERENCES

[1] Siamak YG, Michael H, Madhusudhanan B, Tzyy-Ping J, Robert WN,FelipeMA,LindaZM,JeffreyLM,ChristopherGA, Christopher B (2013) Glaucoma progression detection using struc tural retinal nerve fiber layer measurements and functional visual field points. IEEE Trans Biomed Eng 61(4):1143–1154

[2] Cheng J, Liu J, Xu Y, Yin F, Tan NM, Wong WKD, Lee BH, ChengX,GaoX,ZhangZ,WongTY(2017)Methodsandsystems for automatic location of optic structures in an image of an eye, and for automaticretina cup-to-disc ratio computation. USPatent 9:684, 959

[3] Martins J, Cardoso JS, Soares F (2020) Offline computer-aided diagnosis for glaucoma detection using fundus images targeted at mobile devices. Comput Methods Prog Biomed 192:105341

[4] Kourkoutas D, Karanasiou IS, Tsekouras GJ, Moshos M, Iliakis E, Georgopoulos G (2012) Glaucoma risk assessment using a non linear multivariable regression method. Computer Methods Programs Biomed 108(3):31149–31159

[5] Didit Suprihanto, & Retantyo Wardoyo. (2023). Analysis of classification algorithms for Machine Learning using the SPSS Method. *International Journal of Computer Engineering in Research Trends*, *10*(7), 15–21. https://doi.org/10.22362/ijcert.v10i7.859

[6] Ortíz, D., Cubides, M., Suárez, A., Zequera, M., Quiroga, J., Gómez, J. and Arroyo, N., (2010). Support system for the preven tive diagnosis of hypertensive retinopathy. In: Annual International Conference of the IEEE Engineering in Medicine and Biology (pp. 5649-5652). IEEE

[7] SalehMD, EswaranC, MueenA (2011) An automated blood vessel segmentation algorithm using histogram equalization and automatic threshold selection. J Digit Imaging 24(4):564–572

[8] Roodhooft J (2002) Leading causes of blindness worldwide. Bull Society BelgeOphtalmol 283:19–25

[9] Haleem MS, Han L, Van Hemert J, Li B (2013) Automatic extrac tion of retinal features from colour retinal images for glaucoma diagnosis: a review. ComputMedImagingGraph37(7–8):581–596

[10] Abdel-Hamid L (2020) Glaucoma detection from retinal images using statistical and textural wavelet features. J Digit Imaging 33(1):151–158

[11] TuckMW, CrickRP(1992)Screening for glaucoma : age and sex of referrals and confirmed cases in England and Wales. Ophthalmic Physiol Opt 12(4):400–404

[12] George R, Ve Ramesh S (2010) Glaucoma in India: estimated bur den of disease. J Glaucoma 19(6):391–397

[13] Quigley HA, Broman AT(2006) The number of people with glau coma worldwide in 2010 and 2020. Br .J .Ophthalmol 90(3):262 267

[14] Vajaranant TS, Wu S, Torres M, Varma R (2012) A 40-year forecast of the demographic shift in primary open-angle glaucoma in the United States. Invest Ophthalmol Vis Sci 53(5):2464–2466

[15] Alghamdi, M., & Abdel-Mottaleb, M. (2021). A Comparative Study of Deep Learning Models for Diagnosing Glaucoma From Fundus Images. IEEE Access, 9, 23894-23906. https://doi.org/10.1109/ACCESS.2021.3056641

[16] Rakesh, S., Bharadhwaj, A., Sree Harsha, E. (2021). Sign Language Recognition Using Convolutional Neural Network. In: Raj, J.S., Iliyasu, A.M., Bestak, R., Baig, Z.A. (eds) Innovative Data Communication Technologies and Application. Lecture Notes on Data Engineering and Communications Technologies, vol 59. Springer, Singapore. https://doi.org/10.1007/978-981-15-9651-3_58

[17] Ravishyam, D., & Samiappan, D. (2021). Comparative Study of Machine Learning with Novel Feature Extraction and Transfer Learning to Perform Detection of Glaucoma in Fundus Retinal Images. In T.K. Sharma, C.W. Ahn, O.P. Verma, & B.K. Panigrahi (Eds.), Soft Computing: Theories and Applications (Vol. 1381). Springer. https://doi.org/10.1007/978-981-16-1696-9_40

[18] Singh, L.K., Pooja, Garg, H., & et al. (2021). An enhanced deep image model for glaucoma diagnosis using feature-based detection in retinal fundus. Med Biol Eng Comput, 59(3), 333–353. https://doi.org/10.1007/s11517-020-02307-5

[19] Mahum, R., Rehman, S. U., Okon, O. D., Alabrah, A., Meraj, T., & Rauf, H. T. (2021). A Novel Hybrid Approach Based on Deep CNN to Detect Glaucoma Using Fundus Imaging. Electronics, 11(1), 26. https://doi.org/10.3390/electronics11010026

[20] de Assis, D. F., & Cortez, P. C. (2023). A Comparative Analysis of Glaucoma Feature Extraction and Classification Techniques in Fundus Images. Journal of Communication and Information Systems, 38(1), 47–60. https://doi.org/10.14209/jcis.2023.6

[21] Thanki, R. (2023). A deep neural network and machine learning approach for retinal fundus image classification. Healthcare Analytics, 3, 100140. https://doi.org/10.1016/j.health.2023.100140

[22] Singh, L. K., Khanna, M., Thawkar, S., & Singh, R. (2022). Collaboration of features optimization techniques for the effective diagnosis of glaucoma in retinal fundus images. Advances in Engineering Software, 173, 103283. https://doi.org/10.1016/j.advengsoft.2022.103283

[23] Das, D., Biswas, S. K., & Bandyopadhyay, S. (2022). A critical review on diagnosis of diabetic retinopathy using machine learning and deep learning. *Multimedia Tools and Applications*, *81*(18), 25613-25655.

[24] Polishetty Pranay, Mandadi Rahul Reddy, & K Venkatesh Sharma. (2023). Advancing Chronic Kidney Disease Diagnosis: A Predictive Model Using Random Forest Classifier. *International Journal of Computer Engineering in Research Trends*, *10*(10), 1–7. https://doi.org/10.22362/ijcert.v10i10.869

[25] G. Kiran Kumar, D. Malathi Rani, M. Venu Gopalachari, S. Rakesh, Syed Ashraf; Melanoma classification using convolutional neural network. AIP Conf. Procr 2023; 2754 (1): 070019. https://doi.org/10.1063/5.0162544

[26] Hagiwara Y, Koh JEW, Tan JH, Bhandary SV, Laude A, Ciaccio EJ, TongL,AcharyaUR(2018)Computer-aideddiagnosisofglau coma using fundus images: a review. Comput Methods Prog Biomed 165:1–12 48.

[27] Jorge, B., Barrera, D., Caro, MP, Estupinan, AM, Gonzalez-Neira, EM, Perez, N., Carlos, S., Suarez, DR and Torres, MJ, (2018). Dispatch rules in programming of elective surgical procedures: im pact on occupation and opportunity indicators. Health Sciences Magazine

[28] P, P., & J , K. (2023). Effective Predictor Model for Parkinson's Disease Using Machine Learning . *International Journal of Computer Engineering in Research Trends*, *10*(4), 204–209. https://doi.org/10.22362/ijcert.v10i4.27

[29] Robbi Rahim, & Abdul wahid. (2023). Advancements in Plant Disease Detection: Integrating Machine Learning, Image Processing, and Precision Agriculture. *International Journal of Computer Engineering in Research Trends*, *10*(8), 19–25. https://doi.org/10.22362/ijcert.v10i8.860