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PAPER

An Efficient System for Diagnosis of Human Blindness Using Image-Processing and Machine-Learning Methods

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ABSTRACT

The two main causes of blindness are diabetes and glaucoma. Routine diagnosis of blindness is based on the conventional robust mass-screening method. However, despite being cost-effective, this method has some problems as a human eye-disease detection method because there are many types of eye disease that are similar or that result in no visual changes in the eye image. These issues make it highly difficult to recognize blindness and control it. Moreover, the color of the macula of the spot can be very close to that of the affected macula in a variety of eye diseases, which suggests that the color of the macula spot can indicate various possibilities, rather than one. This paper discusses the shortcomings of current blindness-screening and monitoring systems and presents a feature-based blindness diagnosis approach using digital eye fundus images for the purpose of automated diagnosis of eye disorders, considering three conditions: healthy eye, diabetic retinopathy (DR), and glaucoma. As such, this paper develops a computer-aided diagnosis (CAD) method for automated detection of human blindness. The proposed approach integrates Gabor filter features, statistical features, colored features, morphological features, and local binary pattern features, then compares them with features drawn from a standard dataset of 1580 fundus images. Several classification techniques were applied to the extracted-features neural network (NN), support vector machine (SVM), naïve bias (NB). SVM classifiers show the most promising accuracy. They achieved 93.3% over the other classifiers.

KEYWORDS

glaucoma, diabetes, machine learning, naïve bias, NN, SVM, diabetic retinopathy, fundus images

1 INTRODUCTION

The contemporary human lifestyle is thought to be one of the main causes of numerous health disorders, such as diabetes mellitus, which can impair functioning of critical human body organs, such as the kidneys, heart, and eyes. Prolonged diabetes can lead to eye disorders and diseases, including Diabetic Retinopathy (DR), Diabetic Maculopathy (DM), and glaucoma [1]. These eye diseases are the leading

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causes of blindness worldwide. Their early detection can save people's vision. In the human eyes, the retina is made up of sensorineural tissue that converts the optical pictures to electrical impulses that our brain can interpret. The most frequent disorders that may cause blindness in the elderly are glaucoma and DR [2]. Glaucoma affects 4.7% of people who are older than 75 years, and more than 4 million people in the United States have it. According to the American Diabetic Retinopathy Association (ADRA), more than 12% of the people, in general, and more than 80% of patients with diabetes up to 20 years old develop new cases of blindness [3]. Diabetes, though its effects vary by place, is a significant cause of mortality worldwide. With the mortality risks associated with the COVID-19 pandemic excluded, about 6.7 million adults aged 20 to 79 years perished in 2021 as a result of diabetes. Globally, it was estimated that 537 million adults between the ages of 20 and 79 years—about 10.5% of all adults worldwide will have diabetes. According to predictions, the total number of people in the world within this age group who will have diabetes will rise to 643 million (11.3% of the world's population) by 2030 and 783 million people (12.2%) by 2045 [4], [5].

Digital fundus imaging is one of the fundamental diagnostic techniques that are frequently employed to detect DR, DM, and glaucoma. Disease-related and disease-specific features can be traced in the fundus image, and based on these features, a conclusion can be drawn about the ocular health of the patient [6]. Hence, image processing is performed on digital fundus images to assess the health of the eye. Mass screening of individuals can be a solution for early detection and diagnosis of these eye diseases. In many parts of the world, especially developing countries, screening of people in rural areas for eye diseases is inadequate due to the limited financial resources and numbers of clinicians working outside urban centers. Therefore, there is a pressing need to develop efficient screening methods that can successfully diagnose these eye diseases in the absence of ophthalmologists.

The eyes are considered the most valuable sense organ in the human body since they enable us to visualize the beautiful and lively world around us. Saving the vision of individuals is invaluable. Once patients with vision problems are identified, they must be examined by an ophthalmologist. This is, actually, the motivating factor for the development of a computer-aided diagnosis (CAD) technique that can help in mass screening of people, especially patients who show signs of or are at risk for these eye diseases. This screening has the valuable, practical implication of saving the eyesight of many diabetic patients. It has been the fundamental motive for researchers to work on development of eye-disease screening and monitoring systems based on CAD techniques [7]. In fact, CAD using digital fundus images can be a very useful tool for eye-disease diagnosis, as it is safe, quick, accurate, and economical [8]. This diagnostic means can even be used without the presence of ophthalmologists.

In recent years, no element of ophthalmology has been as scientifically and clinically blessed as retina research. Retinal illnesses are ever attracting attention, as impairment of the retina is one of the primary causes of serious vision loss and blindness on a global scale [9]. The ophthalmoscope is used to look into the eye using a very high-intensity light in order to detect changes that occur in the retina or other changes in the eye, as well as high blood pressure and other pathological conditions that may appear during the examination [10]. It provides the physician with a three-dimensional view of the eye, and ophthalmoscopy provides her/him with of the eye with amplified focal points. But the process is a time–consuming, and the process that is neither effective for the physician, nor for the patient. In addition, the diagnostic error rate concomitant to this diagnostic procedure is high.

Nowadays, one of the most important diagnostic tools for DR and glaucoma is photography of the eye fundus. The diagnostic system proposed in this study, Heidelberg retinal tomography, uses feature extraction to extract the most meaningful features from the eye fundus images to detect glaucoma and DR disorders. The method is both more cost effective method and accurate than digital eye fundus imaging. Moreover, the machine learning (ML) and computational approaches are cost-effective approaches that are readily integrated into medical systems and easily implemented. The classifier can discriminate effectively between healthy and unhealthy fundi of patients' eyes [11], [12]. The main advantages of the proposed method for computer-aided eye-disease screening, diagnosis, and monitoring system are:

- Very accurate results if huge test data are available;
- Ability to test very large numbers of patients in a relatively short time.

The main disadvantage of this approach to testing and diagnosis is that artificial intelligence (AI) may miss many features that are not searched for, which could give the patient a false sense of safety and reassurance.

This paper presents a highly accurate CAD system for eye-disease screening, diagnosis, and monitoring that is capable of properly determining the health condition of the eye in a timely and dependable manner. This system helps individuals in underdeveloped nations with inadequate resources by diagnosing ocular disorders (e.g., glaucoma and DR) and diabetic hypertension, with the hope that early detection of these health conditions can help in avoiding vision loss and blindness. Furthermore, the proposed system can help ophthalmologists in quick detection and diagnosis of ophthalmic diseases. This, in turn, will improve performance of their health-care facilities by making them more productive and the diagnosis outcomes more accurate.

2 THEORETICAL BACKGROUND

Digital imaging has left an everlasting imprint on nearly every field, including medicine and engineering. Early detection of eye disorders is crucial in various vision-threatening illnesses such as cataracts, in general, and diabetes mellitus cataracts and diabetic retinopathy, in particular, which can cause blindness for young people Retinal image analysis has emerged as an important disease-screening tool in modern ophthalmology [13] over the past two decades. The advent of inexpensive cameras for taking direct images of the retina, known as fundus photography, has allowed for straightforward, noninvasive examination of the eye for many eye diseases [14], in which retinal imaging has progressed rapidly over the last two decades. The advent of inexpensive cameras for taking direct images of the retina, known as fundus photography, allowed for straightforward, non-invasive examination of the eye for many eye diseases [15].

2.1 Human eye anatomy

The human eye consists of many parts that are sensitive and easily damaged by disease, especially diabetes mellitus. The rod and cone cells in the retina enable light perception and vision, including color discrimination and depth perception [16]. Figure 1 shows structure of the human eye and highlights its major components.

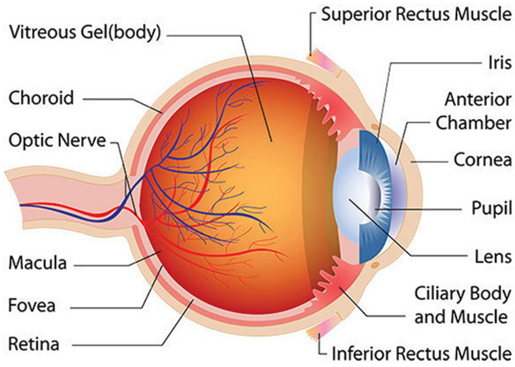

Fig. 1. Structure of the human eye

The computer-aided eye-disease screening and diagnosis system proposed in this study focuses on extraction of the blood vessels and retina as regions of interest (ROI) for detection and classification of human eye impairments such as glaucoma and DR [17].

2.2 Eye glaucoma

Glaucoma is a group of diseases of the optic nerve that may cause blindness. In order to maintain a healthy eye pressure of 16 mm Hg, the eye continually generates aqueous fluid. The main type of glaucoma is open-angle glaucoma, which blocks drainage channels in the eye and creates pressure due to eye fluid accumulation. This pressure will harm the optic nerve, which transports all information from the eye to the brain for processing [18]. Glaucoma initially contributes to the loss of peripheral or side vision, and the result can be like looking through a funnel or a narrow tunnel. The consequence of this *tunnel vision* is that it becomes difficult for one to walk without colliding with things that are off to one side, close behind, or at foot level.

Glaucoma is a particularly dangerous eye disease since most people do not show any symptoms or early warning signs at the start of glaucoma. Glaucoma is sometimes referred to as the “stealth sight robber” [19]. Glaucoma can be treated; however, it is not curable. It causes irreversible damage to the optic nerve. Lowering the pressure in the eye will assist in prevention of additional optic nerve injury and loss of peripheral vision. People with glaucoma can live productive and enjoyable lives if they undergo early diagnosis, receive proper and continuous treatment, and have access to special poor-vision and vision-rehabilitation programs. An eye pressure check (tonometry) for glaucoma should be part of the individual’s yearly thorough eye checkup, starting from as early an age as 35 years. Furthermore, a visual field test may reveal peripheral vision loss before one perceives it [20].

2.3 Diabetic retinopathy

Diabetic retinopathy is the leading cause of blindness in individuals aged 20 to 74 years. More than half of the patients with type 1 diabetes develop retinopathy during the first two decades of diabetes. According to the *Wisconsin Epidemiologic Review of Diabetic Retinopathy*, around 3.6% of patients with type 1 diabetes and 1.6% of patients with type 2 diabetes have retinopathy and are legally blind.

Additionally, nearly 86% of the blindness in a younger-onset population was due to DR. In an older-onset group, when other eye problems were absent, one-third of the instances of legal blindness was attributable to DR [21]. Diabetic retinopathy progresses from mild non-proliferative defects, characterized by increased vascular permeability, to moderate, then extreme non-proliferative diabetic-retinopathy (NPDR) that develops into proliferative diabetic retinopathy (PDR), which is distinguished by the formation of new blood vessels in the retina to the posterior surface of the vitreous. Macular edema, which is characterized by a thickening of the retina caused by leaky blood vessels, can progress to retinopathy at any time. These changes can be accelerated by pregnancy, puberty, blood glucose management, hypertension, or cataract surgery [22]. Glycemic regulation is the protective measure for type 2 diabetic people who have been diagnosed as having diabetic retinopathy. The United Kingdom Prospective Diabetes Research (UKPDS) has shown that enhanced glucose regulation decreases the risk of developing nephropathy and that retinopathy can reduce the likelihood for neuropathy. In patients undergoing intensive treatment versus traditional therapy, the average incidence of microvascular complications decreased by 25% [23].

2.4 Eye fundus tomography

Fundus photography is a method of photographing the fundus, that is, the back of the eye. Fundus photography employs specialized fundus cameras that consist of a complex microscope linked to a flash-enabled camera. The central optic nerve macula, and peripheral retina are the primary structures seen on a fundus image. As seen in Figure 2, fundus photography can be performed using colored filters or specific dyes such as fluorescein and indocyanine green [24].

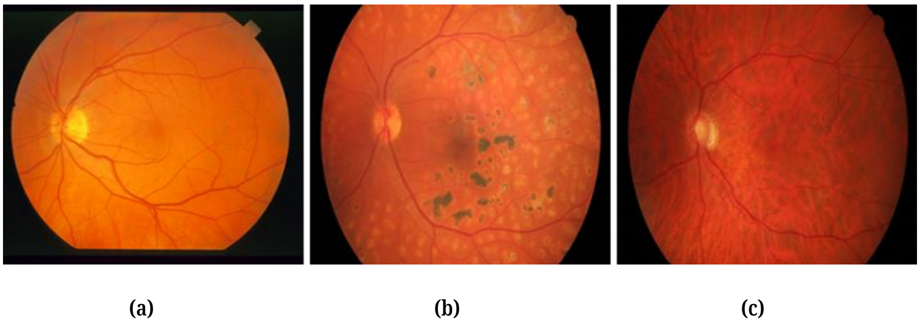

Fig. 2. Eye fundus tomography (a) healthy eye, (b) eye with DR, and (c) eye with glaucoma

Over the last century, fundus photography technology and models have grown and changed greatly. However, because the fundus photography equipment is complicated and difficult to construct to clinical standards, there are only few manufacturers of this equipment [25].

3 RELATED WORK

Human eye-disease detection by combining state-of-the-art image-processing techniques and AI methods provides highly valuable information for discovering eye disorders and treating them. It makes diagnosis of impairment and assessment of the spread of some eye diseases easy, affordable, and accurate. A literature review found the following advances.

A system has been developed by Malik et al. [26] to detect and classify human eye diseases using ML that employs the patient's health record as the source of data. This system depends solely on data taken from the historic medical records of the patients without imaging and image processing. The data are then processed by using different ML methods (neural network, random forest, naive Bayes, and decision tree). Assessment of the performance of this system found an eye-impairment diagnostic accuracy of 93.5%, outpacing all other systems presented in the literature [27]. Harini and Sheela proposed human-eye DR detection based on hand-craft feature extraction. Their proposed method uses the fuzzy c-means (FCM) algorithm besides morphological image processing for ROI detection and feature extraction. In addition, the method applies image preprocessing, which includes the processes of contrast adjustment, Contrast Limited Adaptive Histogram Equalization (CLAHE), picture scaling, and extraction of the gray and green channels from a color fundus image. The accuracy of classification achieved by employing the Support Vector Machine (SVM) classifier with specified features was 92.67% [20].

Literature reviewing machine learning for diagnosis of eye diseases has considered the feasibility of developing a completely automated system for human eye diagnosis. For instance, Harini and Sheela researchers [28] proposed a dual ML system for diagnosing human eyes. Recently, a novel technique based on image processing and AI fulfilled the performance standards for detecting DR in fundus images and produced a classification accuracy of 98.80% [22]. Furthermore, Civit-Masot et al. [29] presented a loss-less generative adversarial network (DR-LL GAN) for production of high-resolution fundus images that can be customized to incorporate random grading and lesion information. The high incidence rates of the diabetes disease explain why research has been paying diabetic-related eye disorders and their detection high attention in the recent years. The human eye diseases are a major problem in the contemporary life. As illustrated in Table 1 summarizes three of these studies.

Table 1. Comparison of eye-imaging studies in terms of the method and data employed and the classification accuracy produced

Ref	Technique	Datasets and Numbers of Images	Accuracy
[14]	SVM	510 eye fundus images	93%
	ANN		91%
[24]	Inception-v3	1,500 eye fundus images	92%
	Eighteen-layer CNN		91%
[28]	ResNet50	500 eye fundus images taken from three different datasets	90%

Review of the published literature found that most of the previous studies support employment of more than one method for easier and more accurate detection and monitoring of the human eye diseases. The present study attempts to find a system that can detect and classify human eye disease using eye fundus images because early detection of human eye diseases reduces the eye health risk which the humans can face. Review of the published literature unfolded that most of the relating previous studies support employment of more than one method for easier and more accurate detection and monitoring of the human eye diseases.

4 OVERALL SYSTEM

This section explains the structure and steps of the eye-disease detection and diagnosis system proposed in this paper. The system is intended to enhance the eye health classification accuracy and allow for early detection of diseases of the retina using eye fundus images. By doing so, wrong classification of the eye disorders is reduced and the probability for patient healing and recovery is increased. The proposed system proposed should help ophthalmologists to make correct eye-disease classification using a simple and easy-to-use graphical user interface (GUI) that allows for loading the fundus images to provide fast and accurate classification. The main elements of this system and the key image-processing steps it performs are presented in Figure 3.

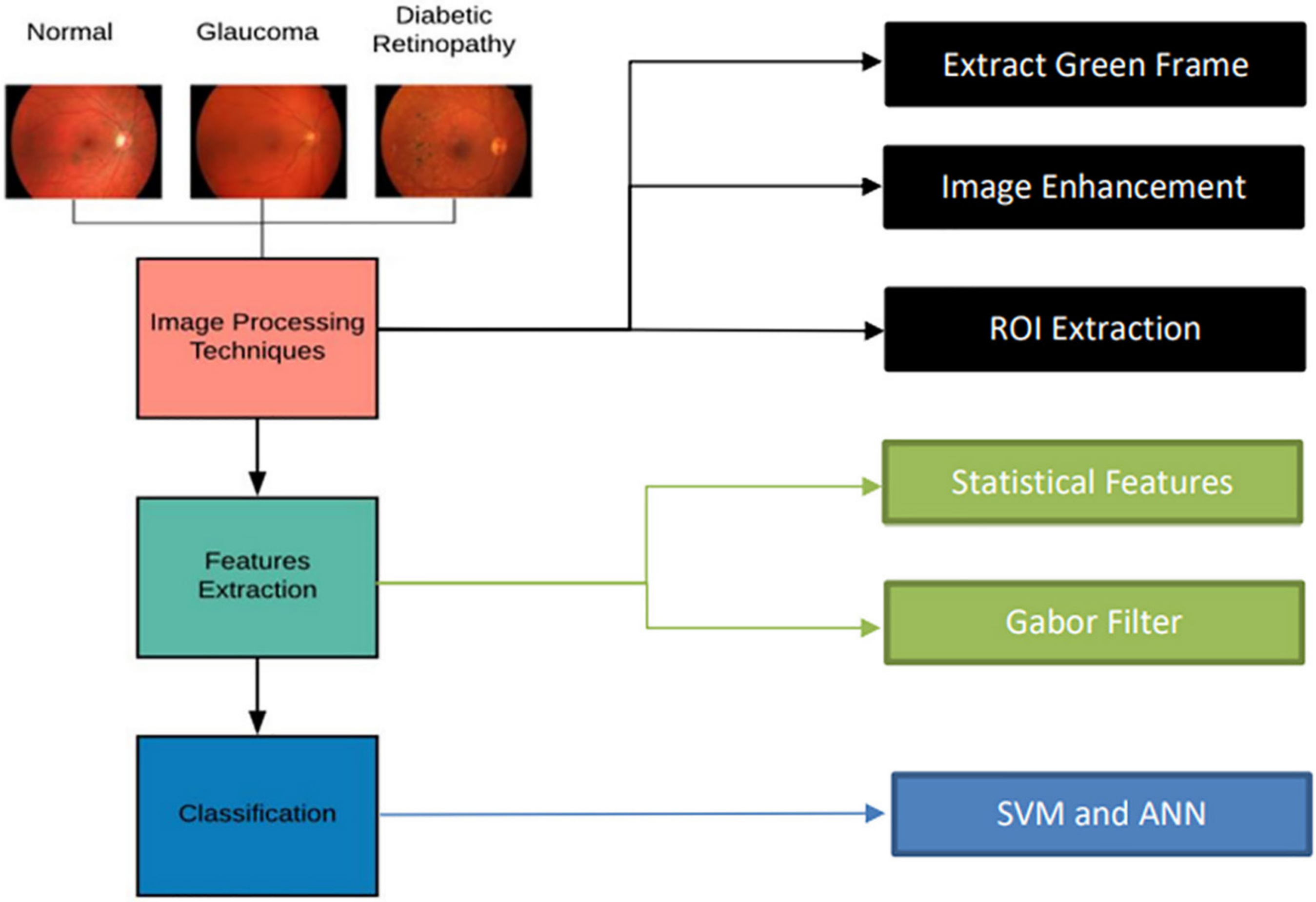

Fig. 3. Structure and steps of the proposed eye-disorder detection system

5 DESIGN AND IMPLEMENTATION

This section describes processes and operation of the proposed system and the interactions that occur between the software system and the user in order for her/him to inspect the human eye by using fundus images. The user-system relationship is typically shown as a series of events using a sequence diagram (Figure 4). Such representations illustrate what happens during each process and what is presented to the user.

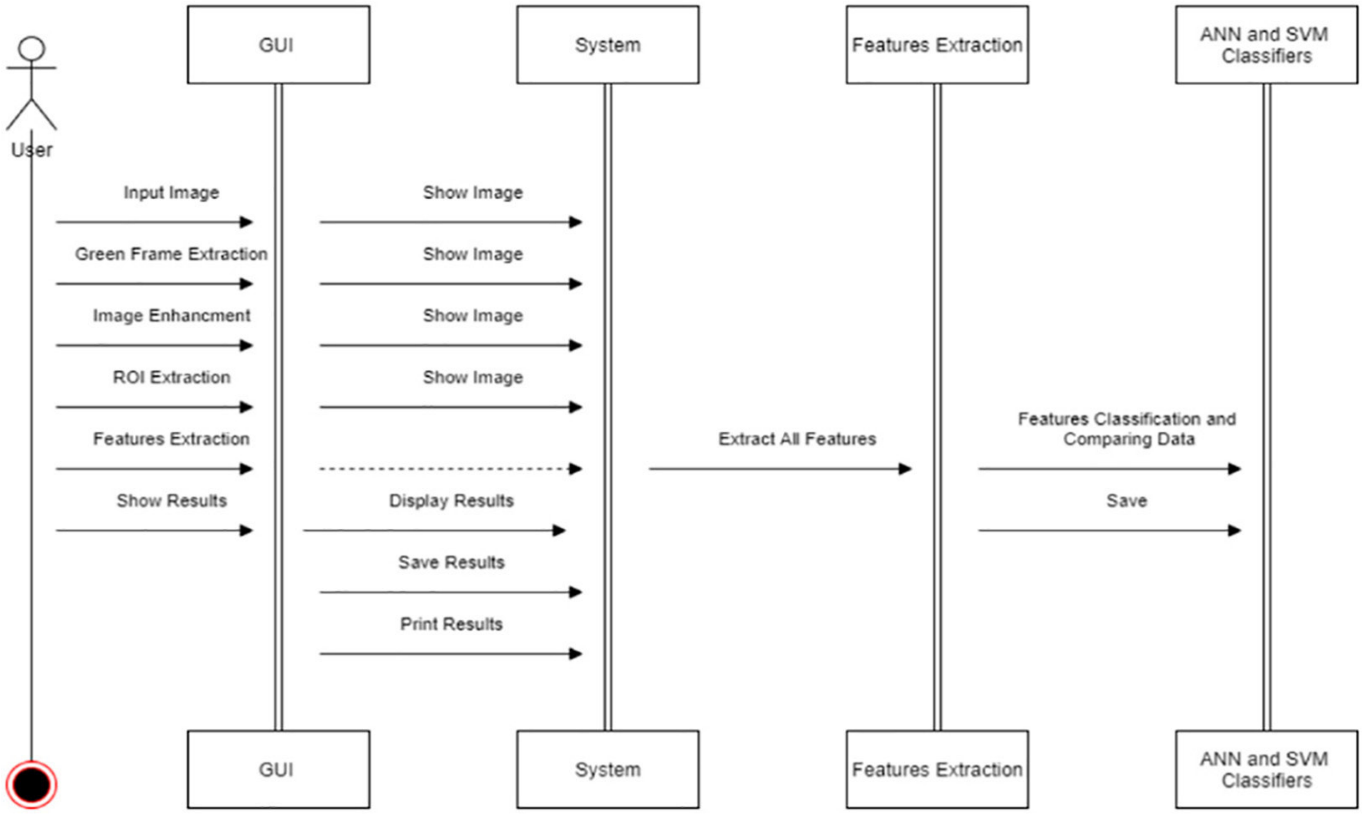

Fig. 4. Procedure for diagnosing human eye disorders using fundus images

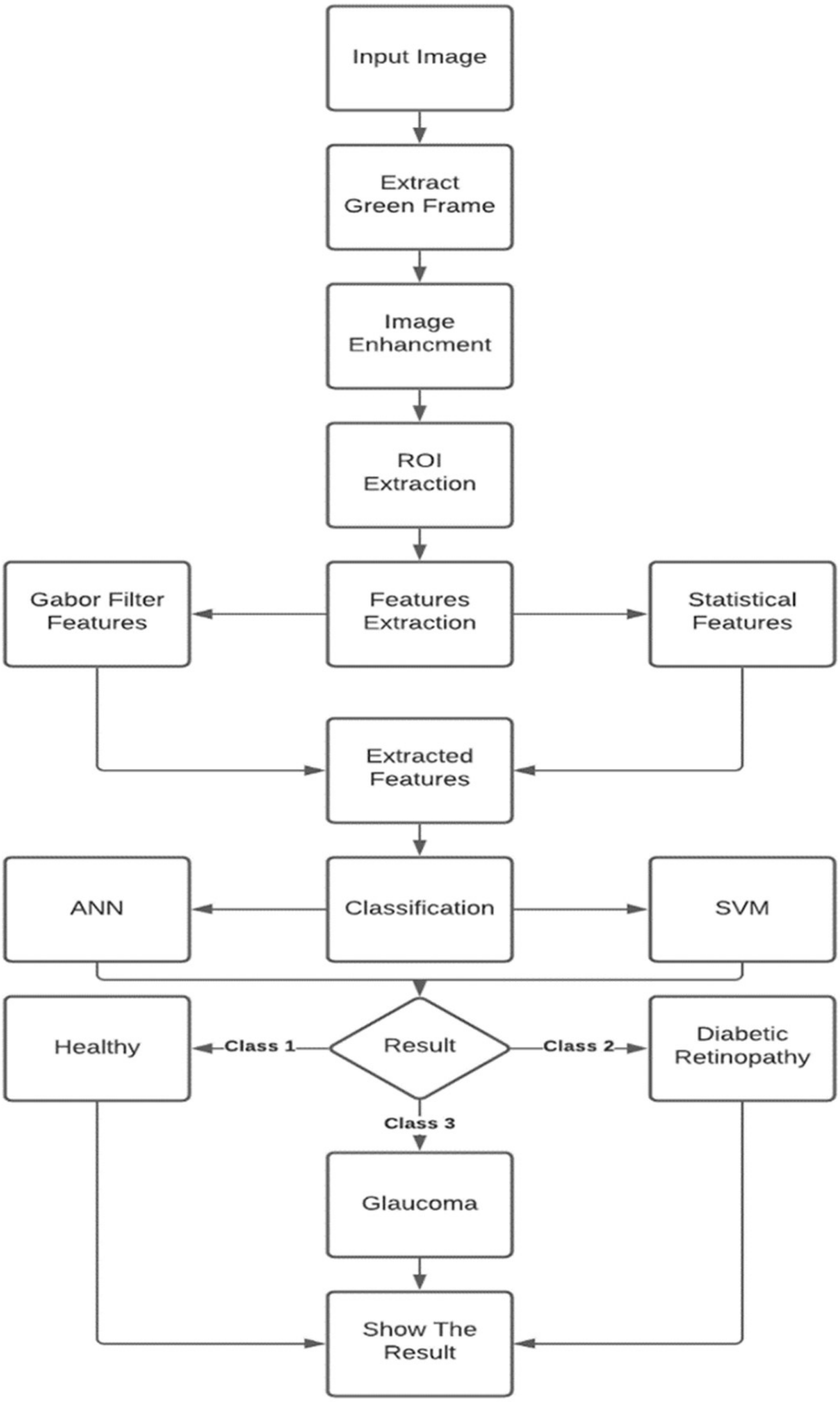

Fig. 5. Flowchart of the stages and processes of eye fundus image analysis according to the proposed system

Figure 5 depicts the stages and steps of eye fundus image analysis and describes how the user can interact with this system on each stage. The analysis processes are also shown. The major steps can be summarized as follows:

Image Insertion: The fundus image is loaded so that it can be detected. The proposed system supports different image formats, such as jpg, png, and tiff.

Green Frame Extraction: In this step, the green frame only is taken rather than the fully colored image, as the green frame allows the details of the blood vessels to appear perfectly.

Image Enhancement: Different image enhancement processes are applied in this step to improve appearance of the ROI and facilitate the extraction of details.

Region of Interest Extraction: The input image is divided into parts to determine the location(s) of the suspicious areas in it.

Feature Extraction: All relevant features are extracted from the ROI. Commonly, two sorts of features are extracted: (i) statistical features that are taken from the ROI mask and (ii) masked color images and Gabor filter features. After that, the mean, standard deviation, and variance of the masked colored image are calculated.

Statistical Features of the Masked Color Image: Statistical descriptors of the masked color image (Figure 6) are calculated. The descriptors mainly encircle the mean, median, mode, standard deviation, and variance.

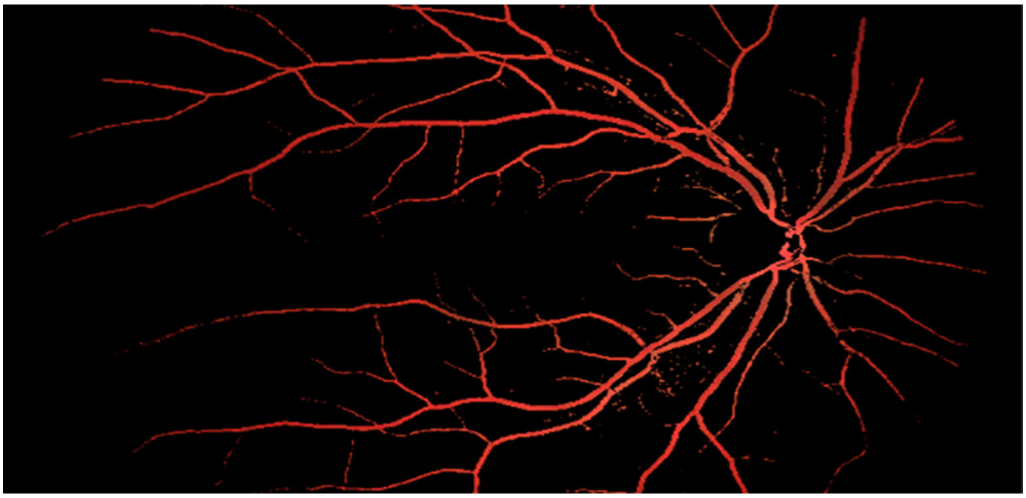

Fig. 6. Masked color image (colored ROI)

- *Mean (μ):* The set of data is determined and the numbers in it are summed. Then, they are divided by the number of data points in the set. The median is the middle number in a collection of data that have been ordered from lowest to highest. The mode is the most common (i.e., frequent) number in the data collection. The mean can be computed using Eq. 1:

$$\mu = \frac{1}{N}\sum_{i=1}^{N} X_i \tag{1}$$

- *Standard Deviation (σ):* In mathematics, the degree of dispersion of a number of values around their mean is the standard deviation. A low standard deviation indicates that the values are close to their mean (also known as the anticipated value), whereas a high standard deviation indicates that the values are widely dispersed around their mean. The formula for σ is given by Eq. 2:

$$\sigma = \sqrt{\frac{\sum_{i=1}^{N}(X_i - \mu)^2}{N}} \tag{2}$$

- *Variance* (S^2)*:* Variance is a measure of dispersion. In probability theory and statistics, it is the expectation of squared deviation of values of a variable from their sample mean or population mean. It reflects how distant from their mean numbers are dispersed. Mathematically, it has the following formula:

$$S^2 = \frac{\sum_{i=1}^{N} (X_i - \mu)^2}{N - 1} \tag{3}$$

- *Local Binary Pattern* (*LBP*) *Features:* The LBP is a visual descriptor of categorization that is widely employed in computer vision and image processing [30]. Thus far, it is the best and most effective spectrum image texture characteristic available. It is frequently used to identify the entire pixels of the whole image by using the threshold method, which is applied to the neighborhood of pixels in the image. The output is treated by LBP as a binary integer [31].

The most essential quality of the LBP method is its tolerance of fluctuations in the monotonic gray level and computational simplicity, which is important in real-world applications because this simplicity enables the method to analyze huge images in real-time [32]. Figure 7 is an illustration of LBP image features.

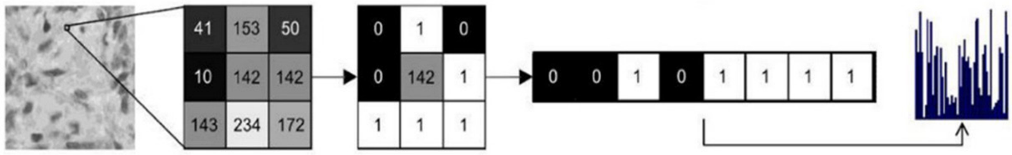

Fig. 7. Local binary pattern features

- *Local Binary Pattern* (*LBP*) *statistical features:* The LBP is a vector that has 19 characteristics, which improves accuracy of the classifier. Often, μ, σ, and S^2 are calculated for each LBP vector of the image.
- *Statistical Features of Gabor Filter:* The Gabor filter is a popular linear filter for image texture analysis. It analyzes content of a specified frequency with a specific direction only in an image. Specifications of orientation and frequency of the Gabor filter are similar to those of the visual system of humans [33], [34]. The Gabor filter creates two important features (magnitude and phase). The μ, σ, and S^2 are calculated as features. The amplitude and phase results of Gabor with a wavelength of 4 and an orientation of 90° are shown in Figure 8.

Fig. 8. Gabor filter

- *Feature Extraction:* In this step, all the features extracted in the previous step are compiled to compare them with the dataset using extracted features, such as NNs, SVM, NB, and SVM classifiers.

- *Classification Using ANN Classifier:* The ANN algorithm is an ML algorithm, which works on determining the weights and biases of artificial neurons that can be used to distinguish and classify the data points. The input data are trained and tested. The features that have been obtained from the image are passed to the ANN classifier to compare them with the trained dataset for classification purposes.
- *Classification Using SVM:* The SVM algorithm is an ML algorithm that is used to discover a hyperplane in a space of *N* features that distinguishes the data points. The input data are trained and tested, and the features that have been extracted from the image are passed to SVM so as to be compared with the trained dataset for classification purposes.
- *Classification:* The *Classify* function takes the outputs of the ANN, NB, or SVM classifier and determines classification based on these features.
- *Healthy Detected:* If the classification results indicate no eye impairments, then the feature is assigned to the *healthy* eye class.
- *Diabetic Retinopathy Detected:* If the classification result uncovers Diabetic Retinopathy (DR) eye impairment, then the corresponding features are allocated to the Diabetic Retinopathy (DR) class.
- *Glaucoma Detected:* If the classification result discloses glaucoma impairment, then the related features are allotted to the *glaucoma* class.
- *Results Printing:* This command allows for printing the classification results.

An illustration of the operation of the eye-disorder detection system proposed in the current study is given in Figure 9.

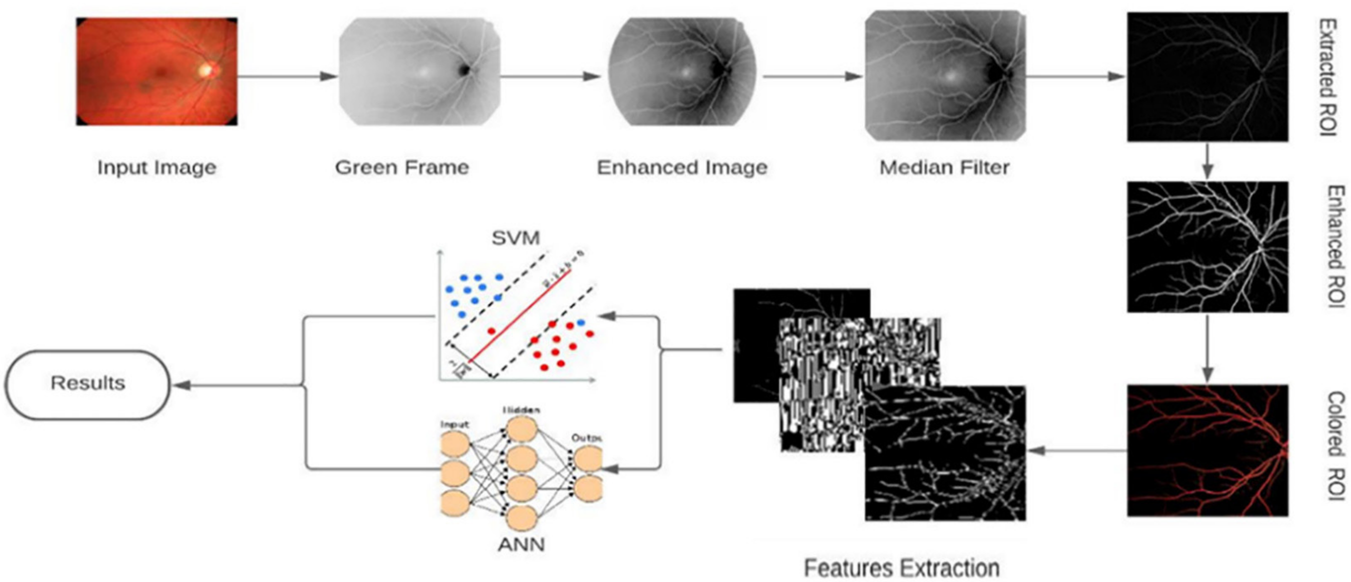

Fig. 9. Operation of the proposed eye-disorder detection system

6 IMPLEMENTATION

In the proposed eye-disorder detection and diagnosis system, the features are classified in a number of steps. The most suitable features for detection of eye disorder are selected. These include statistical features, LBP features, and Gabor filter features. Overall, thirty-one features were needed for successful and accurate eye fundus image classification. Each button in the GUI of the proposed system

(Figure 10) executes a specific command on the image and returns clear, meaningful information to the system user that are easy to understand. A briefing on each button and tab on the GUI of the proposed system follows.

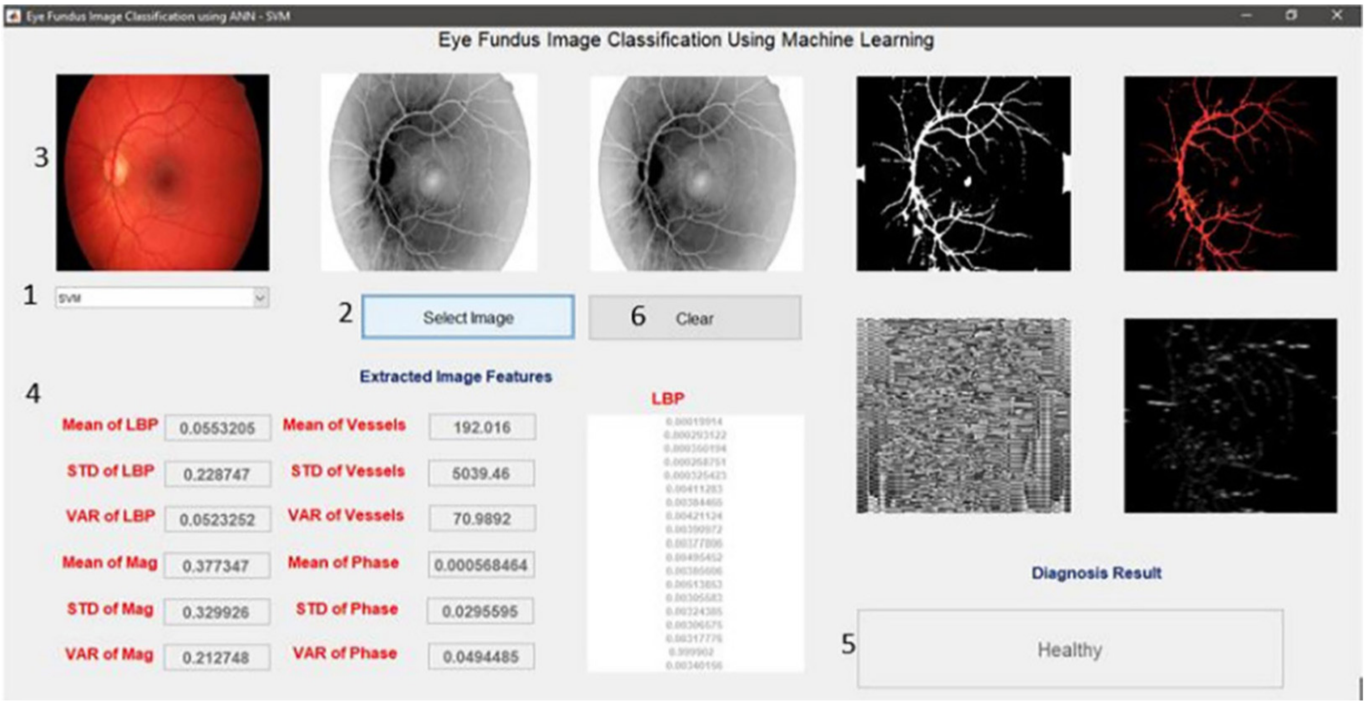

Fig. 10. Graphical user interface of the proposed system

1. **Classifier Selection:** This option enables selection of the classifier (NN, NB, SVM) that one wishes to employ in order to classify the input image using the proposed system.
2. **Input Image Selector (Load Original Image):** The proposed system saves the path of the input image file so that it can be shown to the user on the GUI. It opens a *browse* tab for the user to select the image she/he wishes to view. Once an image is selected, the system loads it, saves its file path, and displays it on the screen.
3. **Processed Images, Extracted ROI, and Final Masked ROI (Images of each Processing Step):** The output image in every step is shown, starting from the original input image and ending with the extracted colored ROI and Gabor filter outputs.
4. **Extracted Feature Values:** This panel shows the values of all extracted features; the statistical colored features, LBP features, statistical LBP features, and Gabor filter statistical features, which will be fed to the selected classifiers.
5. **Classification Results (Diagnosis of the Eye):** This tab allows for showing the results of classification of the input image(s) using the extracted features and selected classifier.
6. **Clear**: This command clears all data and images from the fields of the interface to start over.

7 RESULTS

After running the code, it was noticed that the obtained results are very close to the expected results. This paper used NN, SVM, and NB classifiers and a fundus image dataset consisting of 1580 fundus images. Of the images, 70% were used for training, 10% for validation, and 20% for testing. The overall classification errors were 12.6% in the case of the NN classifier, 6.67% in the case of the SVM classifier, and 13.1% in the case of the NB. The classification accuracy values are very good. The classification accuracy of the NN classifier was 87.83%, and the accuracy results of the NB classifier was 86.87%, whereas that of the SVM classifier was 93.33%. As illustrated in Tables 2–4, the foregoing accuracy and error values suggest that the SVM classifier performs better than the NN and NB.

Table 2. SVM results

Classification Matrix				
Diabetic	354	8	5	96%
Glaucoma	10	346	12	89%
Healthy	7	9	349	95%
Overall accuracy				**93.33%**

Table 3. NB results

Classification Matrix				
Diabetic	302	20	15	89%
Glaucoma	26	320	22	86.95%
Healthy	27	29	309	84.65%
Overall accuracy				**86.87%**

Table 4. NN results

Classification Matrix				
Diabetic	304	28	35	82%
Glaucoma	20	326	12	91.1%
Healthy	17	18	330	90.4%
Overall accuracy				**87.83%**

In general, the classification performance is critical to successful detection and diagnosis of eye impairments. Therefore, the features to extract and the classifier to use should be carefully selected. In this account, the proposed system used ANN, NB, and SVM classifiers, which are very popular classification algorithms. The classification matrix associated values of accuracy of each of these three classifiers in the testing phase.

In conclusion, this paper presents an automated human eye-disorder detection and diagnosis system that can extract different features from the fundus image (Gabor filter, morphological, colored, and local binary image features) and combine them. This system then compares the extracted features with features of images of standard dataset(s). The current study used a standard fundus image dataset that consists of 1580 fundus images. Then it used ANN, NB, and SVM classifiers to categorize the fundus images in three groups based on eye health condition: healthy eyes and eyes with DR or glaucoma. The results of experiments of performance assessment pointed out that the ANN classifier had an overall classification accuracy of 87.83% and a classification error of 12.6%. The overall classification accuracy of the NB classifier was 86.87% with 13.1% classification errors, while the SVM classifier had an overall classification accuracy of 93.33% and a classification error of 6.67%.

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