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*Research Article*

# Effectiveness of Feature Extraction by PCA-Based Detection and Naive Bayes Classifier for Glaucoma Images

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After cataract, glaucoma is one of the second leading retinal diseases in the world. This paper presents the methodology to detect the glaucoma using principal component analysis. The images are involved in dilation as a preprocessing, enhancement using the contrast limited adaptive histogram equalization method, and followed by the extraction of features using principal component analysis. The extracted features are classified using support vector machine, Naive Bayes, and K-nearest neighbor classifiers. Comparing with other classifiers, the Naive Bayes provides high accuracy of 95% which demonstrates the effectiveness of the feature extraction and the classifier.

## 1. Introduction

Glaucoma is the second-leading cause of blindness in the U.S. The prevalence of glaucoma in the world is 60.5 million in 2015, and by 2030, it is expected to increase up to 10 percentages of world population [1]. The high prevalence of undetected glaucoma in the society contributes to the high rate of blindness among the Indian people [2]. A physical eye examination technique can occasionally result in incorrect diagnosis. Automated and accurate diagnosis of retinal disease helps to prevent the loss of vision. A thorough eye examination for the detection of glaucoma involves tonometry, ophthalmoscopy, perimetry, gonioscopy, and pachymetry. Utilizing the right automated decision tools while imaging the retina improves the early detection of glaucoma and prevents visual loss. The brightest section within retinal fundus image is where the optic nerve exits the retina and to the brain, which is called the optic disc. To prevent vision loss, the optic disc region must be examined for the existence of glaucoma at an early stage. The nerve that transmits data from the eye to the nerve is called the optic nerve. When the optic nerve gets damaged, glaucoma occurs. Early on, there are no symptoms, but if a proper diagnosis is not made, vision loss sets in. The greater than usual pressure in the eye, which occasionally accompanies glaucoma, is referred to as ocular hypertension.

Initial enhancements are made to the input retinal images to improve their quality. The feature extraction technique has an impact on analyses on the detection and classification of glaucoma utilizing retinal images. Glaucoma progression is identified using morphological and nonmorphological elements. Glaucoma detection using CDR feature was performed by Xu et al. [3], Muramatsu et al. [4], Joshi et al. [5], and Yin et al. [6]. On the other hand, the categorization of the retina structures is not a characteristic of the nonmorphological features. The published investigations have demonstrated that morphological parameters like colour, pixel intensity, histogram, and texture are not used to detect glaucoma. A system based on hybrid feature extraction from fundus images using higher order spectra, trace transform, and support vector machine classifier was proposed by Muthu Rama Krishnan and Faust [7]. Celina Rani George [8] suggested methodology to classify glaucoma using wavelet-based energy features and neural network. Wang et al. [9] have introduced recognition of facial features using contourlet and support vector machine. Zhang et al. [10] segmented the blood vessels using Gabor filter bank and textons. Shiny Christobel and Joshan Athanesious, [11] suggested that the fractal dimension (FD) of the image feature could be used as a parameter in detection of glaucoma. The features are the useful information that can be extracted from the retinal images without preprocessing which has an accuracy of 84%. The images are classified and detected using neural networks, NB, K-NN, and SVM classifiers.

This paper is organized as follows: section 2 deals with the overall methodology that includes preprocessing of the input retinal fundus image followed by enhancement using contrast limited adaptive histogram equalization then implementation of principal component analysis (PCA) and classification of normal and glaucomatous images. The section 3 deals with simulation results and performance measures in section 4 followed by conclusion in section 5. The proposed methodology to classify the healthy and glaucomatous image using PCA is shown in the Figure 1.

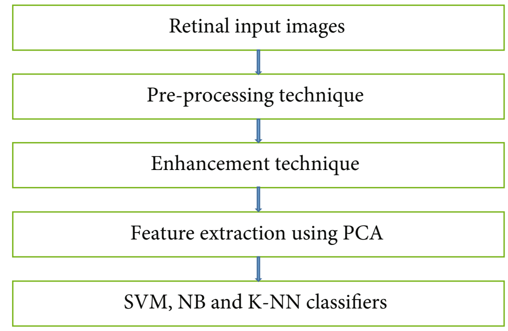


Figure 1: Work flow of Glaucoma detection.

## 2. Proposed Methodology

The retinal image is initially preprocessed using one of the morphological operations called dilation, and then the image is enhanced using CLAHE method. The features are extracted using PCA. The extracted features are given as input to the SVM, Naive Bayes, and K-NN classifier for identifying the normal and glaucomatous images. From the classifier results, the performance measure of each classifier is calculated and compared with other classifiers.

*2.1. Retinal Images.* Glaucoma diagnosis is the most efficient method in the detection of blindness. The glaucoma images are obtained from STARE database, and the healthy images are obtained from MESSIDOR database.

*2.2. Preprocessing.* The preprocessing technique is an important step in detection of a disease which deletes the unwanted distortions and increases the image qualities like noise brightness, sharpness, and contrast. The erosion is one of the morphological operations that remove pixels to the boundaries of an image. The erosion is the process of finding the minimum value. The erosion uses a structuring element to process an image. The structuring element is a binary matrix with a center pixel in which it has a center pixel value as 1. The shape of the structuring element or a matrix can be disk, square, etc. [12]. Any one of the pixels in the structuring element interacts with an input image, the value obtained is 1, else it is zero.

*2.3. Enhancement Using CLAHE.* After preprocessing, the image is enhanced using contrast limited adaptive histogram equalization method. The CLAHE method increases the quality of an image. The CLAHE operates on tiny parts of an image called tiles rather than the entire image. By using CLAHE, the addition of noise in an image is removed. The output image is slightly brighter than the original image.

*2.4. Feature Extraction Using PCA.* The features are extracted using principal component analysis (PCA), and the features are given as input to SVM, Naive Bayes, and K-NN classifier. The features extracted from the retinal images are mean, variance, standard deviation, energy, kurtosis, and skewness [13].

The principal component analysis (PCA) is a mathematical procedure. It is used to convert a set of observations of correlated variables into a set of values of linearly uncorrelated variables using orthogonal transformations. These are called as principal components. PCA is sensitive to the relative scaling of the original variables. The PCA has very less loss of information.

*2.5. Classifiers.* The extracted features from the enhanced images are given to three classifiers, namely, SVM, NB, and K-NN. The three classifiers undergo two processes: training and testing. The extracted features from images are given as an input to the classifiers which detects the images to be glaucoma or normal images.

## 3. Simulation Results

The input glaucoma image is the retinal image taken from MESSIDOR database. The input image can be healthy and glaucoma. The healthy and the glaucoma images are preprocessed using dilation and CLAHE method [14]. Then, the features are extracted using PCA, and the extracted feature-like are mean, variance, standard deviation, energy, kurtosis, and skewness. For each subdetails are classified by three classifiers, namely, SVM, NB, and K-NN classifiers. The simulation results for PCA are using dilation and CLAHE method. The Figure 2 is the input glaucoma image obtained from MESSIDOR database. Since the CLAHE does not execute, the RGB image is converted into a gray scale image [15]. The Figure 3 is the gray scale image.

The erosion image is shown in Figure 4 in which the pixels of the input image are decreased.

The enhanced image using CLAHE method is shown in Figure 5. The input image contains noise and unwanted distortions. So, it has to be removed. The CLAHE method

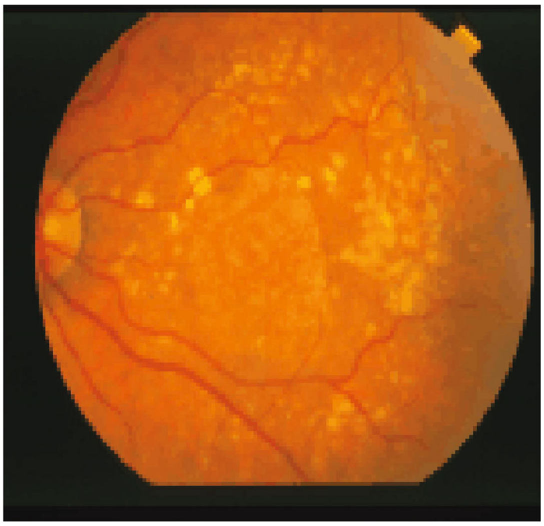

Figure 2: Glaucoma image.

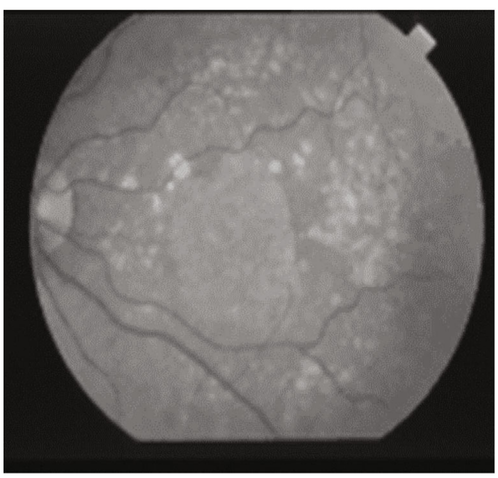

Figure 3: Gray scale image.

operates in smaller regions called tiles rather than operating in the entire image [16, 17].

The extracted features are classified using three classifiers, namely, SVM, NB, and K-NN classifiers. From the extracted features, all the three classifiers are trained with 160 healthy and 160 glaucoma images. The remaining 40 healthy and 40 glaucoma images are tested. Among 40 healthy and glaucoma images, the SVM detected 38 healthy and 37 glaucoma images correctly [18, 19]. The NB classifiers detect 38 healthy and 39 glaucoma images correctly. The K-NN classifier detects 33 healthy and 35 glaucoma images correctly. The Table 1 shows the classification results for PCA using dilation and CLAHE method [20, 21].

## 4. Performance Measures

To identify that the proposed method detects to be accurate, the four parameters are calculated. The performances of the classifiers are measured using three parameters like accuracy, sensitivity, and specificity. From the output produced by the classifiers, a number of true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN) are counted [22, 23].

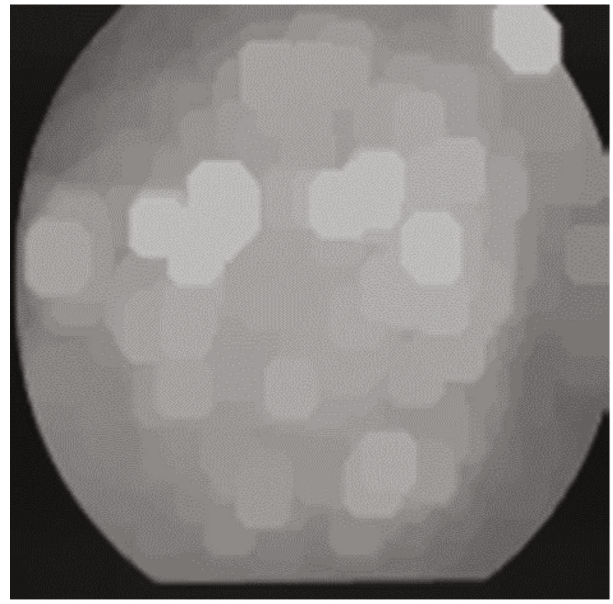

Figure 4: Erosion image.

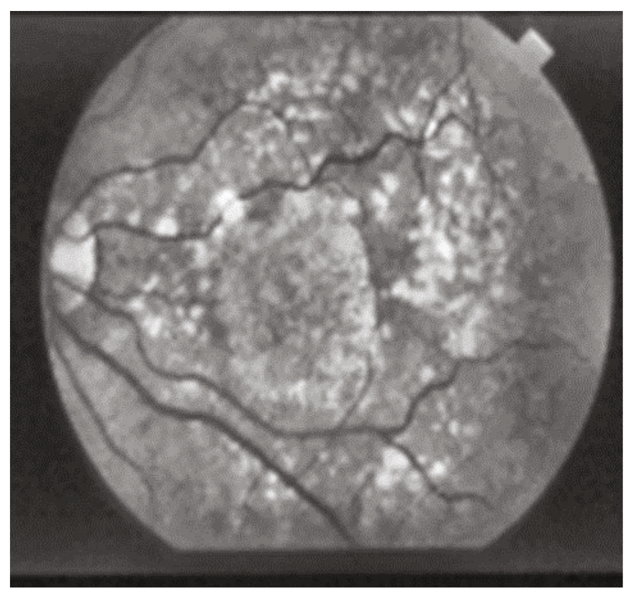

Figure 5: Enhanced image.

(i) *TP*. The input glaucoma image is detected as glaucoma by the classifier

(ii) *TN*. The glaucoma image is detected as a healthy image by classifier

(iii) *FP*. The healthy input image is detected as a healthy image by classifier

Table 1: Classification results.

| Classifier | Trained images | Tested images | Detected images |
|---|---|---|---|
| SVM | | | |
| Healthy | | | 38 |
| Glaucoma | | | 37 |
| NB | | | |
| Healthy | 160 | 40 | 38 |
| Glaucoma | | | 39 |
| K-NN | | | |
| Healthy | | | 33 |
| Glaucoma | | | 35 |

Table 2: Performance measures (%).

| Classifiers | Accuracy | Sensitivity | Specificity |
|---|---|---|---|
| SVM | 91.6 | 93.1 | 9.67 |
| NB | 95 | 93.5 | 3.44 |
| K-NN | 80 | 78.1 | 17.8 |

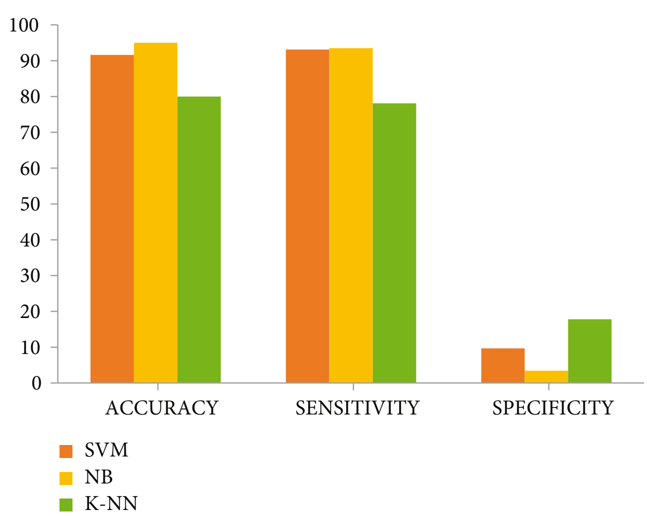


Figure 6: Performance measures' graph.

(iv) *FN*. The healthy input image is detected as a glaucoma image by the classifier

The accuracy, sensitivity, and specificity are calculated by the below formulae;

$$\mathrm{Accuracy}(\%) = \frac{\Sigma\,\mathrm{TP} + \Sigma\,\mathrm{FP}}{\sum \mathrm{TP} + \mathrm{TN} + \mathrm{FP} + \mathrm{FN}},$$
$$\mathrm{Sensitivity}(\%) = \frac{\Sigma\,\mathrm{TP}}{\Sigma\,\mathrm{TP} + \Sigma\,\mathrm{FN}}, \quad (1)$$
$$\mathrm{Specificity}(\%) = \frac{\Sigma\,\mathrm{TN}}{\Sigma\,\mathrm{FP} + \Sigma\,\mathrm{TN}}.$$

The accuracy, sensitivity, and specificity are calculated using their specific formulae, and the performance measures of the three classifiers [24, 25] are tabulated in Table 2.

From the Table 2, the SVM gives the accuracy of 91.6%, sensitivity of 93.1%, and specificity of 9.67 (%). The NB provides 95% accuracy, 93.5% sensitivity, and 3.44% specificity. The K-NN classifier gives 80% accuracy, 78.1% sensitivity, and 17.8% specificity. Comparing the performance measures of the SVM, NB, and K-NN classifiers, the NB classifier gives the highest accuracy of 95% and also less specificity of 3.44% in the detection of retinal image as healthy or glaucoma [26, 27]. The computation time is also less. The elapsed time is 538 seconds. The performance measures' graph is shown in Figure 6.

## 5. Conclusion

This paper presents the PCA feature-based classification for identifying the glaucomatous image. The significance of PCA-based feature extraction is that PCA well describes coefficients like eigenvalues and eigenvectors of the retinal image. The accuracy of glaucoma detection, based on the PCA feature-based classifier, is shown to be better than other transform with NB classifier. Simulation results show that the PCA feature-based classifier performs better with an accuracy of 95%. By using nonlocal means filter as a preprocessing technique and histogram of oriented gradients, contourlet wavelet transform as a feature extraction technique, the accuracy can also be increased.

## Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

## Conflicts of Interest

The authors do not have any type of conflict of interest to declare.

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