Glaucoma Detection Using Retinal Nerve Fiber Layer Texture Features

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The retinal nerve fiber layer (RNFL) is one of the most affected parts of the eye retina by glaucoma disease. Progression of this disease results in RNFL texture changes and can be observed from the fundus images and RNFL thickness; thus, the glaucoma is one of the ocular diseases contributing to most of the blindness worldwide. There are increasing demands for medical image–based computer-aided diagnosis system based on fundus image for glaucoma detection. Thus, the RNFL thickness changes can be assessed by optical coherence tomography. However, an examination using the optical coherence tomography device is rather expensive and still not widely available in resource-poor countries. On the other hand, a fundus camera is a fundamental diagnostic device and can be used for diagnosing other diseases. In this article, we introduce glaucoma detection using fundus images. This algorithm uses texture analysis based on co-occurrence matrix and Tamara features. The texture measures are extracted from the RNFL segmented part. The method was tested on a set of 158 images composed of 118 healthy retina images and 40 glaucomatous images and achieved an area under the curve of 93% and accuracy of 89.5%.

Computer-aided diagnosis, the way to automate the detection process for glaucoma disease, attracts extensive attention from clinicians and researchers. Therefore, if glaucoma is diagnosed early enough, it can be properly managed to prevent major loss of vision. Glaucoma is most common cause of permanent blindness worldwide; there is no cure for glaucoma, but medication can be used to prevent vision loss. In the case of glaucoma in which the visual field test result and intraocular pressure assessment are not reliable, the visual field measurement is usually carried out using a static perimeter, which is difficult for different diseases, for example, advanced age-related macular degeneration, and it needs patient corporation to follow the instruction and the intraocular pressure not sensitive because, in some types of glaucoma, the pressure is normal, which is called normal tension glaucoma. The best way to detect glaucoma is optic nerve head (ONH), and the imaging modalities used (optical coherence tomography [OCT], Heidelberg retina tomography) are expensive. Then, it is necessary to search for other methods that will enable to determine the glaucoma disease. One such method is the analysis of digital fundus images of the eye fundus via taken fundus camera device. Features extraction techniques in fundus images are classified based on the type of features. The types of features are divided into 2 groups, namely, morphological and nonmorphological. The morphological features based on optic disc and optic cup segmentation then calculate features such as retinal nerve fiber layer (RNFL), Cup to Disc Ratio, per-papillary atrophy (PPA), and Inferior, Superior, Nasal, Temporal rule.

Nonmorphological features are whole image features without segmentation such as color, shape, and texture, the types of features that are captured from the whole image. This article is a combination of the 2 methods by segmenting the RNFL part and extracting the texture features from the specific part.

The use of texture features extraction was performed by Kavya and Padmaja, which detects glaucoma using ONH texture, which is the region that consists the optic cup and optic disc. The features are extracted from the ONH fundus image by using Hough transformation and k-means for segmentation. From the segmented ONH part, the different texture features used are gray level co-occurrence matrix (GLCM) and Markov random field. Thus, the structural changes take place in ONH; the texture and the intensity values also change. These features are used to classify the fundus images as normal and glaucoma. The obtained results have approximately 94% accuracy in segmentation using Hough transformation, 84% for segmentation using k-means clustering, and approximately 86% for classification using support vector machine classifier. In another research done by Oh et al., they proposed a fully automatic method for detecting various forms and widths of RNFL defects in color fundus images. Fundus photography is the most common screening tool to detect RNFL defects in various optic neuropathies. However, the detection of...
RNFL defects by using fundus photographs depends on the experience of the examiner, and early defects may be missed because of the low contrast of the RNFL. Therefore, they developed a simple and efficient algorithm to assist the ophthalmologist in the detection of RNFL defects. The strength of the proposed algorithm is that it can accurately differentiate very narrow defects in early-stage glaucoma to nonglaucomatous optic neuropathy involving the papilla macular bundle. Thus, no previous studies have described specific methods for detecting RNFL defects with various forms and widths in fundus images. Their results showed that the proposed algorithm was successful, with a sensitivity of 90% for glaucoma and 100% for papilla macular bundle defects in nonglaucomatous optic neuropathies.

Odstrcilika et al. introduced a novel approach to capture these variations using computer-aided analysis of the RNFL textural appearance in standard and easily available color fundus images. The proposed algorithm was built based on the Gaussian Markov random fields and local binary patterns features, together with various regression models for prediction of the RNFL thickness. The algorithm describes the changes in RNFL texture, by reflecting variations in the RNFL thickness. The method was tested on 16 healthy and 8 glaucomatous eyes. The results achieved significant correlation (normal = 0.72 ± 0.14; P = 0.05, glaucomatous = 0.58 ± 0.10; P = 0.05) between the results of the predicted output and the RNFL thickness measured by OCT, which is the standard glaucoma assessment device. The evaluation achieved good results to measure possible RNFL thinning.

Therefore, those studies provide an expert system for real-time fundus image analysis, which gives an opportunity to improve the image interpretation. The proposed system will improve the diagnosis of glaucoma with another method, and therefore, it will minimize the missed detection rate and help in early diagnosis and treatment, which can significantly improve the chance of managing glaucoma disease.

Materials and Methods

Data were acquired from an open Retinal Image Database for Optic Nerve Evaluation (RIM-ONE), which contains 169 ONH images, where the images are divided as follows: normal, 118 images; early glaucoma, 12 images; moderate glaucoma, 14 images; deep glaucoma, 14 images; and ocular hypertension, 11 images. In this study, the RIM-ONE...
The proposed algorithm provides an automated glaucoma detection computer-aided system used for early diagnosis of glaucoma with high accuracy. The algorithm takes a preprocessed fundus image and segments the optic disc followed by RNFL part extraction and extracting texture features and classifying them. The results are used to classify the images as glaucoma and healthy cases. Figure 2 illustrates the complete methodology.

Preprocessing Step
Image preprocessing steps are as follows: resizing the image to 256 \times 256 pixels so that it has the specified number of rows and column to reduce computational time and denoising stage by median filters (5 \times 5) by Elseid et al.\(^7\). Before any procedures are made, red channel has been extracted because it appears as a good boundary and has fewer blood vessels, which affects the segmentation accuracy as to facilitate intensity analysis, as shown in Figure 3.

Optic Disc Segmentation
The optic disc segmentation algorithm was developed and tested in the RIM-ONE public database. The proposed method by Ahmed et al.\(^8\) can be divided into 4 steps. The first step is vessel removal to obtain accurate segmentation, and it was done by morphological operation. The second step is applying thresholding level of 180 to segment disc region from the red channel, which appears to best contrast the disc region; after that, in the third step, the boundary was smoothed and cleared from unconnected object, and binary image obtained at the final step circle image was constructed based on the radius and center of the detected region to minimize segmentation errors resulting from the main blood vessels and PPA surrounding the optic disc, using the formula and the result shown in Figure 4:

\[(x-h)^2 + (y-k)^2 = r^2\]  \hspace{1cm} (1)

where \(r\) = the radius from segmented object, and \(h, k\) = the center from segmented.

RNFL Region-of-Interest Extraction Step
The RNFL is the area surrounding the disc for the region of interest determined based on mathematical method to subtract the whole image from the disc area, by the formula:

\[\text{RNFL} = \text{ROI image} - \text{OD}\]  \hspace{1cm} (2)

where the ROI image represents the ONH part, and OD is the optic disc after circle reconstruction step. The results are shown in Figure 5.

The OD and RNFL are used for the third step, which is feature extraction and selection, and the final step is the classification.

Texture feature Extraction Step
Many methods can be used to describe the main features of the textures such as directionality, smoothness, coarseness, and regularity. Gray-level co-occurrence matrices measure is one of the most important measures that can

![Preprocessing Step](image1)

![Optic Disc Segmentation](image2)
be used to describe the texture. In this research, 2 techniques are used to describe the RNFL.

**GLCM method:** A method used to calculate spatial relationship of pixels is the gray level, also known as the gray-level spatial dependence matrix, by characterizing the texture of an image by calculating how often pairs of pixel with specific values and in a specified spatial relationship occur in an image, creating a GLCM, and then extracting statistical measures, which are autocorrelation, contrast, correlation, cluster prominence, homogeneity, cluster shade, difference variance, dissimilarity, energy, entropy, maximum probability, sum of squares, sum average, sum variance, sum entropy, difference entropy, information measure of correlation, inverse difference, inverse difference normalized, and inverse difference moment normalized. Below are examples of GLCM features equations.

**Tamara method:** A method used to calculate coarseness, contrast, and directionality features for digital fundus image:

<table>
<thead>
<tr>
<th>Energy Feature</th>
<th>Entropy Feature</th>
</tr>
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<tbody>
<tr>
<td>[ \text{Energy} = \sum_{i,j=0}^{N-1} \left( \frac{\rho_y}{\sigma_i^2} \right) ]</td>
<td>[ \text{Entropy} = \sum_{i,j=0}^{N-1} -\ln \left( \frac{\rho_y}{\sigma_i^2} \right) ]</td>
</tr>
<tr>
<td>Contrast Feature</td>
<td>Homogeneity Feature</td>
</tr>
<tr>
<td>[ \text{Contrast} = \sum_{i,j=0}^{N-1} \left( \frac{\rho_y}{\sigma_i^2} \right)^2 ]</td>
<td>[ \text{Homogeneity} = \sum_{i,j=0}^{N-1} \left( \frac{\rho_y}{\sigma_i^2} \right)^4 ]</td>
</tr>
<tr>
<td>Correlation Feature</td>
<td>Shade feature</td>
</tr>
<tr>
<td>[ \text{Correlation} = \sum_{i,j=0}^{N-1} \left( \frac{\rho_y}{\sigma_i^2} \right) ]</td>
<td>[ \text{Shade} = \text{sgn}(A) A^{1/3} ]</td>
</tr>
<tr>
<td>Prominence Feature</td>
<td></td>
</tr>
<tr>
<td>[ \text{Prominence} = \text{sgn}(B) B^{1/4} ]</td>
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- **Coarseness:** The most fundamental texture feature, which is a direct relationship to scale and repetition rates. It aims to identify the largest size at which a texture exists; even a smaller microtexture exists.

\[ A_k(x,y) = \sum_{i=x-2^{k-1}-1}^{x+2^{k-1}-1} \sum_{j=y-2^{k-1}-1}^{y+2^{k-1}-1} f(i,j)/2^{2k} \]  

- **Contrast** is a statistical distribution of the pixel intensity obtained.

\[ F_{\text{con}} = \frac{0}{\alpha_4^{1/4}} \]  

\[ F_{\text{dir}} = \sum_p \sum_{\theta \in \Theta_p} (\theta - \theta_0) 2 H_D(\theta) \]  

**Feature Selection Step**

Feature selection is the process of selecting a subset of relevant features for use in model construction.

The objective of this step is 3-fold: improving the prediction performance of the predictors, providing faster and more cost-effective predictors, and providing a better understanding of the underlying process that generated the data.

In this article, sequential feature selection method was applied to the 25 texture features and results in 1 feature, which was used to classify the fundus images to glaucoma and healthy cases.

**Classification Step**

Many classification techniques are used such as support vector machine (SVM), k-nearest neighbor (KNN), and ensembles, which use multiple learning algorithms to obtain better predictive performance than could be obtained from any of the constituent learning algorithms alone. To get more model accuracy, ensemble learning is used to improve machine learning results by combining several models that ensembles RUS Boost, an excellent technique for learning from imbalanced data (1 class outnumbers other classes by a large proportion), where synthetic minority oversampling technique (SMOTE) algorithm is used to create artificial data based on feature space (rather than data space) similarities from minority samples. Therefore, it generates a random set of minority class observations to shift the classifier learning bias toward minority class, to generate artificial data, using bootstrapping and the same k-nearest technique used before.

**Results and Discussion**

The performance metrics used for the proposed glaucoma detection method evaluation are sensitivity, specificity,
and accuracy, and the receiver operating characteristic curve. Those values are defined as follows:

\[
\text{Sensitivity} = \frac{TP}{TP + FN} \quad (7)
\]

\[
\text{Specificity} = \frac{TN}{FP + TN} \quad (8)
\]

\[
\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \quad (9)
\]

Sensitivity (SE) is the ratio of glaucoma images that were marked and classified as glaucoma, to all marked images:

\[
SE = \frac{TP}{TP + FN}, \quad \text{from this equation it calculated to be 0.83.}
\]

Specificity (SP) is the ratio of glaucoma images that were marked and classified as healthy, to all marked images:

\[
SP = \frac{TN}{FP + TN} = TNR; \quad \text{from this equation, it was calculated to be 0.92.}
\]

From Figure 6, we can notice that:

- True positive (TP) is the number images detected as glaucoma by an expert and the proposed method.
- True negative (TN) is the number of images detected as normal by an expert and the proposed method.
- False positive (FP) is the number of images detected as normal by an expert but detected as glaucoma by the proposed method.
- False negative (FN) is the number of images detected as glaucoma by an expert but detected as normal by the proposed method.

The values of sensitivity, specificity, and accuracy lie between 0 and 1. Therefore, if the result of the proposed method is accurate, it should be close to 1.

The receiver operating characteristic curve shows TP rate versus FR rate for the currently selected trained classifier. The marker on the plot shows the performance of the currently selected classifier.

The marker shows the values of the FP rate and the TP rate for the currently selected classifier.

The selected feature is the RNFL coarseness. This feature is evaluated by many classifiers such as SVM, KNN, and ensembles bagging classifier and ensembles boosting classifier; the classification result in Figure 6 shows the best result using ensembles RUSBoosted, which has accuracy of 89.5% and area under the curve of 0.93.

The texture features classification errors equal 10.5 explained as follows: in advanced glaucoma or optic atrophy, RNFL defects cannot be detected, because the mean intensity of the RNFL is low in all directions, and a localized lesion is not distinguishable in this effect in the RNFL segmentation. However, in these cases, the pathologic features of disc cupping or atrophy are clearer than RNFL defects and can easily be detected, compared with Morris and Mohammed,\(^{12}\) who used the Binary Robust Independent Elementary Features as a texture feature to detect the glaucoma and achieved an area under the curve of 0.84, and Ali et al,\(^ {13}\) who detected glaucoma by local texture features and achieved 95.1% success rate with a specificity of 92.3% and a sensitivity of 96.4%, which are better than texture features presented in this research because of 2 reasons. The first one is that the database used is small and the texture features extracted from the whole image, therefore the suggested method is better in glaucoma detection.

The MATLAB codes used to extract the Tamara texture features are available for free in MATLAB file exchange side coded by Sornapudi\(^ {14}\) and the GLCM feature coded by Uppuluri\(^ {15}\) (Table).

### Conclusion and Future Work

This article proposed a glaucoma detection algorithm based on the analysis of digital fundus images using RNFL texture feature (coarseness) classified by ensemble RUSBoosted tree classifier. The proposed method achieved an accuracy of 89.5%. The key contribution in this work is that the proposed features are suitable for glaucoma detection with high accuracy.

It is recommended that future work design a complete, integrated, automated system to classify all different types of glaucoma that can be used for follow-up and test different types of features to improve the accuracy and test different classifiers. Different segmentation techniques can be applied to enhance the RNFL segmentation.

### References


