Glaucoma Identification on Retinal Fundus Image Using Random Forest Method

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ABSTRACT
Glaucoma is a disease caused by a buildup of fluid in the eye that can increase intraocular pressure and cause vision loss. This disease cannot be cured, therefore early detection is very important to prevent total vision loss in sufferers. To reduce the errors of observation and diagnosis from doctors, applied computer vision to detect glaucoma in retinal fundus images. The retinal fundus image is first cropped to remove unnecessary parts, then the color image captured by the fundus camera is converted into a grayscale image. The gray scale image will be extracted using the Gray Level Co-occurrence Matrix (GLCM) method. The extracted features will be processed to create a classification model using the Random Forest method which will determine whether the image identified is normal or glaucoma. A series of experiments were conducted on the comparison of training data and testing data, as well as the number of decision trees. Experiments were also conducted on the size of the image cropping and changes in the value of the distance variable in the GCLM feature extraction process. The results of the experiment on an image size of 720x720 pixels and a distance value of 2, obtained a model with an accuracy of 81%, precision 79% and recall 88% in a data comparison of 80:20, and the number of trees as much as 50. The results show that the more number of decision trees does not increase the number of decision trees. accuracy value significantly.

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1. INTRODUCTION

Glaucoma is an eye disease that is the second most common cause of blindness after cataracts. Unlike the case with cataracts, blindness caused by glaucoma is permanent or irreversible. It is due to fluid accumulation in the eye, where the fluid can increase intraocular pressure that damages the optic nerve in the brain and causes vision loss [1].

The most worrying things about glaucoma are there are no significant symptoms and it can only be detected at the most advanced stage. There are no cures for glaucoma, but it can be treated to reduce the damage the disease can cause. Therefore, early detection is necessary to prevent total vision loss in patients [2]. Approximately 50% of patients with glaucoma in developing countries are undiagnosed and not under medical treatment. About half started seeing a doctor in the following years, meaning that in some patients, glaucoma is undetectable and progresses rapidly [3].

There are several ways of detecting glaucoma, such as visual field tests and measurement of intraocular pressure (IOP), but these methods are not specific enough to diagnose glaucoma. One effective way is directly observe the optic nerve condition in the eye. The optic nerve condition observation requires rare and expensive special tools, such as Optical Coherence Tomography (OCT) and Heidelberg Retinal

Tomography (HRT). However, there is a cheaper and easier way, and it is by observing the condition of the retinal surface captured using a two-dimensional fundus camera [4].

In general, ophthalmologists will detect the presence of glaucoma by directly observing the surface of the eye retina and the characteristics that indicate the symptoms of glaucoma. The most visible feature of this disease is the comparison of the optical cup and optical disc in the eye. Generally, the size of the optical disc in glaucoma patients tends to be larger than in normal eyes due to growing intraocular pressure. Other signs of this disease are that the eye lens tends to look cloudy even though it is not as clouded as a cataract patient [5], and the appearance of Peripapillary atrophy (PPA) around the optic nerve is caused by thinning of the retinal layer [6].

Manual identification by doctors takes longer time and bigger error possibilities in observations that can lead to inaccurate diagnostic results [7]. Therefore, to overcome errors in observing retinal fundus images, one can build a classification system to help detect glaucoma signs more effectively.

Computer vision is part of artificial intelligence in which the development of algorithms is to automatically and visually extract features from an object. More simply, computer vision tries to imitate the way humans work in seeing [8]. It is widely developed to help human labor, in which case it is to extract information from an image [9].

A particular method is needed to extract the required features and find information from an image. Gray Level Co-occurrence Matrix (GLCM) is a texture feature extraction method that analyzes how often the combination of pixels and neighboring pixels is in an image [10]. GLCM is widely used because of its popularity, usability, and ease of computing [11]. The GLCM method can extract 14 features, but these features do not stand alone [12]. The combination of features with the best performance extracted to analyze an image includes contrast, correlation, energy, and homogeneity [13].

Meanwhile, the method used to detect glaucoma was the Random Forest classification method, which is one of the homogeneous ensemble methods with a decision tree as the base classifier [14]. This method consists of several predetermined decision trees and generates each model randomly at each node using training data [15]. Random forest is widely used in classification applications due to its advantages in dealing with large amounts of data, can handle many variables without deletion, and has an accuracy that tends to be greater than the standard decision tree method [16].

The researcher hopes this study could provide solutions to problems faced by the community and medical personnel in the early detection of glaucoma. Thus, with the development of this glaucoma detection system, it can reduce the number of blindness due to delays in handling glaucoma patients.

2. RESEARCH METHOD

The researcher chose Random Forest as the classification method proposed in this study. The classification model was made using a dataset called RIM-ONE with a total of 159 data, consisting of 74 glaucoma images and 85 normal images. The conduction of this study was by going through a series of processes, such as image preprocessing, image feature extraction, classification, and model evaluation. Figure 1 below shows the framework model of the proposed method.

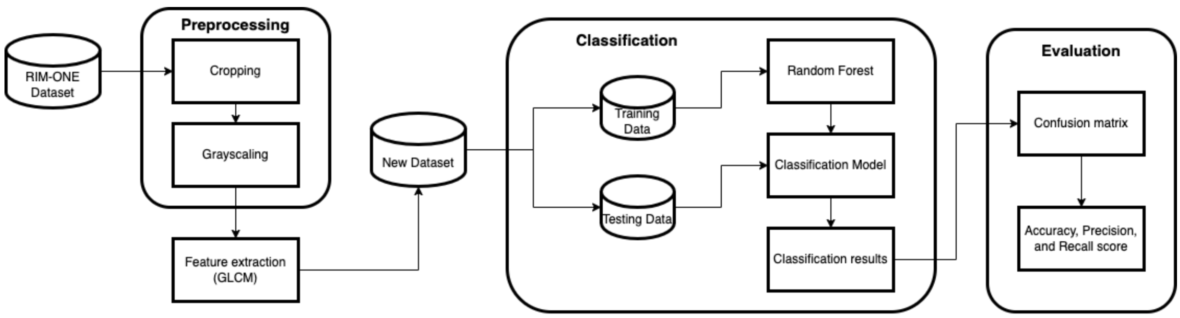

Figure 1. The proposed model framework

In Figure 1, the first step is to prepare the dataset. In this study, the researcher used a dataset called RIM-ONE consisting of 159 retinal fundus images divided into two classes, namely 74 glaucoma images and 85 normal images. The dataset was pre-processed, namely through a cropping process. This process aims to remove the unnecessary parts of the image, with the image cropping size of 364x378 pixels. The second process was changing the colored image into a gray image (gray scaling). There were changes in the image data for the researcher could conduct the feature extraction process using the Gray Level Co-occurrence Matrix (GLCM) method.

After image pre-processing, the following process was image texture feature extraction using the GLCM method. There are four features extracted, namely:

1. Correlation is the calculation result representing a linear relationship of the degree of a grayscale image, where the result of this calculation is between -1 to 1 [17]. The correlation calculation formula is shown in equation 1.

$$COR = \sum_{i=0}^{n-1}\sum_{j=0}^{n-1}\frac{G(i,j)[(i-\mu_x)(j-\mu_y)]}{\sigma_x\sigma_y} \dots\dots\dots\dots\dots\dots (1)$$

2. Contrast is a feature representing the differences in colour levels or grey scales that appear in an image [17]. The contrast is zero if the neighbouring pixels have the same value. The formula for calculating contrast is shown in equation 2.

$$CON = \sum_{i=0}^{n-1}\sum_{j=0}^{n-1} G(i,j)(i-j)^2 \dots\dots\dots\dots\dots\dots (2)$$

3. Homogeneity is a feature the similarity of variation and image intensity. Homogeneity has high value if all pixels have the same value [17]. The homogeneity calculation formula is shown in equation 3.

$$HOM = \sum_{i=0}^{n-1}\sum_{j=0}^{n-1}\frac{G(i,j)}{1+(i-j)^2} \dots\dots\dots\dots\dots\dots (3)$$

4. Energy is the calculation result representing the gray intensity variation amount in an image [17]. The energy calculation formula is shown in equation 4.

$$ENR = \sum_{i=0}^{n-1}\sum_{j=0}^{n-1} G(i,j)^2 \dots\dots\dots\dots\dots\dots (4)$$

The angles used were 0, 45, 90, and 135, with a distance of one. In total, there were 16 features extracted in one image data. The extraction results will be stored and become a new dataset ready for the classification process.

The training data group will be used to create a classification model using the random forest method, with the following stages:

1. Determine the total of k Decision Trees
2. Random bootstrapping data train
3. Make a decision tree for k times, with the following process:
   a. Determine the attribute for the split based on the information gain value from the root node to the leaf node.
   b. Conduct the entropy calculation. The entropy calculation formula is shown in equation 5.

$$\mathrm{Entropy}\ (S) = \sum_{i=1}^{c} -p_i \log_2 p_i \dots\dots\dots\dots\dots\dots (5)$$

   c. Conduct the information gain calculation on each attribute. The information gain calculation formula is shown in equation 6.

$$\mathrm{Gain}\ (A) = \mathrm{Entropy}\ (S) - \sum_{i=1}^{k}\frac{|S_i|}{|S|}\mathrm{Entropy}(S_i) \dots\dots\dots\dots\dots\dots (6)$$

   d. Divide the data based on the threshold value at the node, and re-calculate the gain until it reaches the leaf node

4. Save the decision trees and make them a classification model.
5. Make predictions based on the classification model using data testing
6. Conduct a majority vote for the results of the predictions on each decision tree to determine the final prediction results of the data.

The researcher conducted several experimental scenarios to find the best classification model to detect glaucoma in the classification process. The researcher experimented with training and testing data comparison and the decision trees produced. Comparison of training and testing data tested was 50:50, 70:30, and 80:20, while the number of decision trees tested were 50, 100, 200, 300, 400, 500, 600, 700, 800, 900, and 1000 trees. Thus, there were a total of 33 experimental scenarios conducted.

The last process is the classification model evaluation to determine the performance of the built classification model. In this process, the researcher used a confusion matrix to determine the amount of data tested and the prediction results. Based on this matrix, the researcher calculated the accuracy, precision, and recall values, which will be the reference for measuring the performance of the classification model. The confusion matrix table is shown in Table 1.

Tabel 1. Confusion Matrix

Predictive Class	Actual Class	
	Glaucoma	Normal
Glaucoma	True Positive	False Positive
Normal	False Negative	True Negative

Accuracy is the value that indicates the level of proximity of the actual value and the value of the system's prediction results [18]. The formula for calculating accuracy is shown in equation 7.

$$\text{Accuracy} = \frac{(TP + TN)}{(TP + FP + FN + TN)} \quad (7)$$

Precision is the value that indicates the accuracy between the requested information and the information provided by the system [18]. The formula for calculating precision is shown in equation 8.

$$\text{Precision} = \frac{TP}{TP+FP} \quad (8)$$

Recall is the value that indicates the level of success in retrieving an information [18]. The formula for calculating recall is shown in equation 9.

$$\text{Recall} = \frac{TP}{TP+FN} \quad (9)$$

3. RESULTS AND DISCUSSION

The researcher conducted Model testing on a total of 33 experimental scenarios consisting of training and testing data comparison and the decision trees. The results obtained in this process were the best classification model based on the highest accuracy, precision, and recall values. The comparison of training and testing data was 50:50, and the total of trees of 50 is the best classification model with an accuracy percentage of 64%, a precision of 63%, and a recall of 74%.

3.1. Cropping Measurement

The researcher conducted further experiments on changes in image size and variable distance values in the feature extraction process to find the best model with higher accuracy, precision, and recall values. The researcher first experimented by changing the cropping image size to be larger, where the initial cropping image size was 354x378 pixels to 720x720 pixels. Figure 2 below shows the changes in the image size.

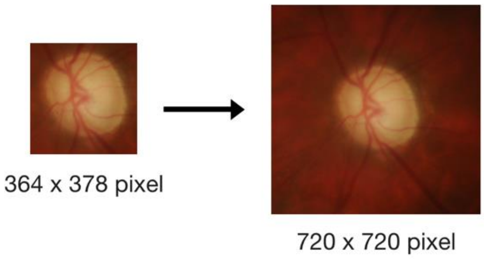

Figure 2. Image cropping size change

The results obtained were of higher accuracy than the previous experiment, which was 67%, precision of 67%, and recall with 72% in the training and testing data comparison of 70:30 with a total of 400 trees. Table 2 below shows the experimental results.

Table 2. Image cropping size experiment results

Split data	Total of trees	Accuracy (%)	Precision (%)	*Recall* (%)
50 : 50	50	55	57	55
	100	52	55	57
	200	54	56	57
	300	54	56	57
	400	50	52	52
	500	48	50	59
	600	50	52	52
	700	49	51	50
	800	49	51	50
	900	51	54	52
	1000	48	50	50
70 : 30	50	60	60	72
	100	65	64	72
	200	65	65	68
	300	65	64	72
	400	**67**	**67**	**72**
	500	65	64	72
	600	62	63	68
	700	60	62	64
	800	62	64	64
	900	65	65	68
	1000	67	67	72
80 : 20	50	56	57	71
	100	53	55	71
	200	62	62	76
	300	59	60	71
	400	62	62	76
	500	62	62	76
	600	59	60	71
	700	62	62	76
	800	59	60	71
	900	62	62	76
	1000	62	62	76

3.2. Distance Value

The researcher conducted the second experiment by changing the value of the distance variable in the feature extraction process, which was 2. The researcher obtained a higher value with 81% accuracy, 79% precision, and recall with 88% in data comparison of 80:20 with a total of 50 trees. Each distance or neighboring distance produced a different level of accuracy with the GLCM matrix value and a distinct texture characteristics value [19]. Based on the test results, the distance value obtained the best results at d=2 with an accuracy percentage of 81% and produced better feature extraction.

Table 3. Distance value experiment results

Split data	Total of trees	Accuracy (%)	Precision (%)	Recall (%)
50 : 50	50	59	69	69
	100	62	61	79
	200	59	58	79
	300	61	61	74
	400	57	58	71
	500	57	58	71
	600	60	59	81
	700	59	58	79
	800	62	61	79
	900	59	58	74
	1000	57	58	71
70 : 30	50	62	61	80
	100	67	66	76
	200	65	62	80
	300	60	59	76
	400	62	61	76
	500	65	63	76
	600	65	62	80
	700	65	62	80
	800	62	61	80
	900	67	65	80
	1000	65	62	80
80 : 20	**50**	**81**	**79**	**88**
	100	69	78	76
	200	72	70	82
	300	72	70	82
	400	69	68	76
	500	72	70	82
	600	69	67	82
	700	69	67	82
	800	69	67	82
	900	72	70	82
	1000	72	70	82

4. CONCLUSION

The researcher conducted glaucoma identification in retinal fundus images using the Random Forest method through preprocessing stages consisting of image cropping and gray scaling, followed by extracting texture features from images using the Gray Level Co-occurrence Matrix (GLCM) method. The feature extraction results will be processed to create a classification model using the Random Forest method. There were several experimental scenarios to find the best model to detect glaucoma, including the split data comparison and the decision trees. The researcher conducted further experiments by changing the cropping size of the image by 720x720 pixels and the distance value in GLCM by 2. From the results, the researcher obtained 81% accuracy, 79% precision, and 88% recall at a data split ratio of 80:20 with 50 trees. More trees do not guarantee a better classification model performance and higher accuracy value.

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