Cataract Detection in Retinal Fundus Image Using Gray Level Co-occurrence Matrix and K-Nearest Neighbor

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ABSTRACT

Cataract is one of the visual impairments that can lead to blindness if not detected and treated early. Cataract detection still takes a long time and is very objective based on the decision of the ophthalmologist. This is one of the reasons for conducting an automatic screening process based on fundus image analysis. This study was made as decision support for an ophthalmologist in determining whether someone has cataracts or not. There are three main stages in this research, namely preprocessing, feature extraction, and classification. Preprocessing perform by converting the image to grayscale and changing the image size so that the image is easier to process. The second stage is feature extraction by applying Gray Level Co-occurrence Matrix to extract contrast, correlation, energy, and homogeneity features. And the last stage is classification using k-nearest neighbors based on the features that have been obtained from the previous stage. The highest accuracy results obtained are 80% with $k = 5$, which indicates the proposed method can detect cataracts well.

Keywords: *Cataract, Fundus image, GLCM, KNN.*

1. INTRODUCTION

One of the main causes of visual impairment and blindness apart from uncorrected refractive errors is cataract. Cataract is a vision disorder caused by cloudiness or opacity in the lens of the eye so that it blocks the reception of light by the lens of the eye [1]. According to World Health Organization, approximately 94 million of the 1 billion cases of visual impairment are caused by cataracts [2]. Currently, cataract detection only relies on the ability of an ophthalmologist so that the decision is very objective and takes a long time. One way to identify cataracts is by screening the fundus image. This screening can help to detect cataracts early so that the risk of blindness can be minimized.

Several studies have been done previously in identifying this disease. Mas Andam Syarifah et al. [3] conducted a study to classify cataracts using Convolutional Neural Network (CNN). Another study was also conducted by Yanyan Dong et.al. [4]. In this study, apart from classifying images into normal and non-normal, they also classified cataracts into four classes: normal, slight, medium, and severe. The classification process is carried out using Support Vector Machine (SVM) and Softmax classifier by performing feature extraction before.

This study focused on cataract classification using retinal fundus images by emphasizing the feature differences between normal and cataract images. Normal images tend to have clearer features, such as blood vessels and optic disks than cataract images. The feature will be extracted using GLCM. After feature extraction, the classification process using KNN is carried out. Automatic cataract detection is expected to help ophthalmologists in determining patients with cataracts more accurately and quickly.

2. METHODS

The proposed method involves three main steps, (1) preprocessing, (2) feature extraction, and (3) classification that shown in figure 1.

Figure 1 Proposed Method.

2.1 Preprocessing

The first step in this study was preprocessing to prepare the images. Preprocessing was done by converting the RGB image to grayscale so that it is easier to process. The reason why use grayscale is to reduces computational requirements. The conversion process of RGB to grayscale images is performed by adding up the pixel values of the Red (R), Green (G), and Blue (B) channels and then dividing by three as the average of the pixel values of the entire image. The equation for converting RGB to grayscale is shown in equation (1). In addition, the resizing process as a part of preprocessing was carried out to equalize the image size to 480 x 640 pixels.

$$grayscale = \frac{R+G+B}{3} \tag{1}$$

2.2 Feature Extraction

The features used in this study are the texture features obtained using the co-occurrence matrix. The texture feature is chosen based on the characteristics of the object under study by assuming that the texture of the cataract image will be different from the texture of the normal image [5].

In this stage, feature extraction was performed to obtain characteristics or information from objects in the image that you want to recognize/ distinguish from other objects. Gray Level Co-occurrence Matrix (GLCM) extracts texture features using four values: contrast, correlation, energy, and homogeneity [6]. GLCM method is a second-order statistical-based feature extraction method. This method overcomes the shortcomings of first-order feature extraction for image texture recognition with better texture recognition.

Contrast is a feature that represents differences in color levels or grayscale that appears in an image. The value of the contrast is equal to zero if the neighbor pixels have the same value. Contrast can be shown in equation (2).

$$Con = \sum_i \sum_j (i-j)^2 p_d(i,j) \tag{2}$$

Correlation is a representation of the linear relationship to the degree of the grayscale image. The correlation value ranges from -1 to 1. Correlation can be shown in equation (3), where μi is the average of row elements in matrix $p(i,j)$, μj is the average of column elements in matrix $p(i,j)$, σi and σj are the standard deviations of the row and column elements in the $p(i,j)$ matrix respectively.

$$Cor = \sum_i \sum_j \frac{(i-\mu i)(j-\mu j)p_{(i,j)}}{\sigma i \sigma j} \tag{3}$$

Energy represents a measure of uniformity in the image. The higher the image similarity, the higher the energy value shown in equation (4)

$$Energy = \sum_{i,j} p_2^d(i,j) \tag{4}$$

Homogeneity represents the size of the similarity value of the variation of the intensity of the image. If all pixel values have a uniform value, then homogeneity has the maximum value. The formula of homogeneity is shown in equation (5).

$$Hom = \sum_i \sum_j \frac{p_d(i,j)}{1+|i-j|} \tag{5}$$

where *i and j* indicate row index and column index of matrix $p_d(i,j)$ respectively and $p_d(i,j)$ is the normalized matrix of matrix co-occurrence.

2.3 K-NN Classification

Classification will be carried out using the *k*-nearest neighbor algorithm. The input in this process were features that have been extracted including contrast, correlation, energy, and homogeneity in the previous stage. The first stage for the classification process was to determine the parameters of the number of *k* nearest neighbors. After that, the distance between the testing data and the entire training data was calculated using the Euclidean distance, as shown in equation (6). The distance obtained then sorted and taken as much as *k* data based on the smallest distance. After that, the majority class of the top *k* data will be used as classes from the test data.

$$D_{ij} = \sqrt{\sum_{k=1}^{n} (i-j)^2} \tag{6}$$

In equation (5), D_{ij} is the Euclidean distance between *i* and *j*, where *i* is the parameters of testing data, and the parameters of training data are symbolized as *j*.

2.4 Performance Measure

The classification results will be evaluated by calculating the system's accuracy shown in equation (7). Evaluation will be carried out on several combinations of training data and testing data using different amounts of *k*.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{7}$$

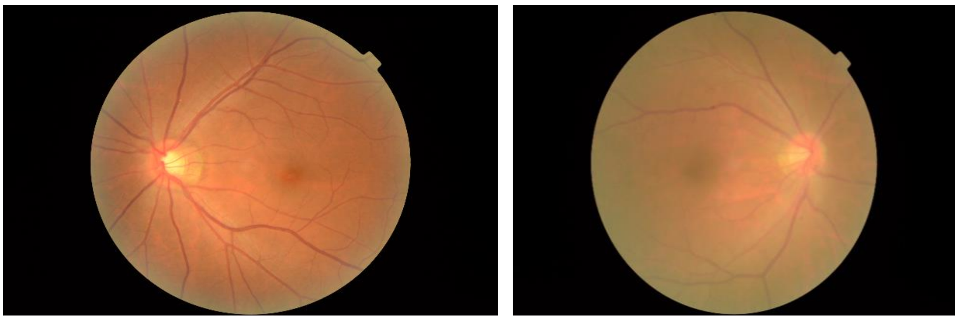
where True Positive (TP) is the number of data that classified as normal class according to predicted class and actual class, False Positive (FP) is the number of data that classified as normal by system but categorized as cataract on the actual class, False Negative (FN) is the number of data that classified as cataract according to predicted class but categorized as normal on actual class, and True Negative (TN) is the number of data that classified as cataract on predicted class and also categorized as cataract on actual class [7].

3. RESULTS AND DISCUSSION

The data used in this study were taken from the Kaggle dataset [8]. The total number of images was 200, with normal images consisting of 100 data, while cataracts had as many as 100 data. Sample of retinal fundus image for normal and cataract is shown in figure 1. Based on the Kaggle dataset, the normal image consists of 300 pieces of data. However, to avoid imbalanced data, the number of normal data is equated with cataract data. Partition of training and testing data is selected randomly. The classification process using k-nearest neighbor is carried out five times using different amounts of training and testing data to see the effect of the amount of data on the accuracy rate. The classification results obtained are shown in table 1. The testing process was performed by finding the accuracy value based on equation (6) with various combinations of the amount of training data and testing data as well as several *k* values.

Table 1. Cataract classification results

Training Data	Testing Data	Accuracy (%)			
		k=3	*k=5*	*k=7*	*k=9*
100	100	52	51	52	57
120	80	50	48.75	57.5	52.25
140	60	56.7	50	48.3	50
160	40	52.5	57.5	47.5	50
180	20	60	**80**	70	65



a) normal b) cataract

Figure 2 Retinal fundus image.

obtained using training data and testing data, respectively 180 and 20 data. In addition, the value of *k* also affects the classification results. This study evaluated with four different *k* values, namely 3, 5, 7, and 9. Odd *k* values were used to avoid majority voting with the same value considering the number of classes there were 2 (even). The most optimal *k* value was at *k*=5, with the accuracy value was 80%.

		Actual Class	
		Normal	Cataract
Predicted Class	Normal	7	3
	Cataract	1	9

Figure 3 Confusion matrix.

The confusion matrix shows the classification result using 20 testing data in Figure 3. There are still classification errors in this study, three data for normal class and one data for cataract class. This is because some images have almost the same features as normal and cataract images, making them difficult to distinguish. This research is expected to get a better result if it uses more data so that in the training process, using texture features can better differentiate between normal and cataract images.

4. CONCLUSION

In this study, there are three main steps to classify cataract and normal images, such as preprocessing, feature extraction, and classification. The highest accuracy value was 80% using 180 training data and 20 testing data, with the optimum value of *k* = 5 indicates that the proposed method can classify well. For further research can use a combination of Gray Level Co-occurrence Matrix (GLCM) and Local Binary Pattern (LBP) for feature extraction and use classification methods other than KNN, such as CNN, decision tree, and Naive Bayes.

AUTHORS' CONTRIBUTIONS

All authors discuss the concept and research design. Nahya Nur: data analysis, proofreading, and help to draft the manuscript. Sugiarto Cokrowibowo: conducting literature study and article writing. Rosalina Konde: data acquisition and visualization results. All authors read and approved the final manuscript

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