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Application of SVM and LDA Models in Eye Image-Based Cataract Detection System

Finis Hermanto Laia[1], Progresif Buulolo[2]

[1,2)]Program Studi lmu Komputer, Universitas Nias Raya, Nias Selatan, Indonesia

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Abstract

The eye is a visual organ that functions to capture light and convert it into signals that are processed by the brain to form visual perception. Cataracts are a condition in which the eye lens becomes cloudy, blocking light from entering, and causing visual impairment. Early detection of cataracts is essential to prevent or slow down vision loss. In this study, the performance optimization of the Support Vector Machine (SVM) and Linear Discriminant Analysis (LDA) algorithms was carried out in detecting cataracts from eye images using digital image processing techniques. Digital image processing is used to improve image quality, extract information, and perform classification with machine learning. LDA is used as a dimensionality reduction technique to improve classification efficiency, while SVM is used to find the optimal hyperplane that separates data with high accuracy. Several studies have combined LDA and SVM in the classification process to improve system performance. The results showed that SVM was superior to LDA in terms of accuracy, recall, and F1-score. The highest accuracy of SVM reached 95.98%, while LDA was only 90.20%. Both algorithms have 100% precision, but SVM recall is higher (92.0%) than LDA (79.3%). The F1-score of SVM is also better (90.9%) than LDA (84.0%), indicating an optimal balance between precision and recall. Thus, SVM is more recommended for cataract detection than LDA due to its higher accuracy and recall, while LDA is more suitable for classification tasks with lower complexity.

Corresponding Author:

Finis Hermanto Laia,
Program Studi Ilmu Komputer,
Universitas Nias Raya,
Jalan Pramuka, Nari-Nari, Kel. Pasar Telukdalam, Kab. Nias Selatan, 22865, Indonesia.
Email : finishermanto@gmail.com

1. Introduction

The eye is an organ of sight that functions to capture light and convert it into signals that are processed by the brain to form visual perception (Abbasov, 2019; Gregory, 2015; Zhang, 2019). Cataracts are a condition in which the lens of the eye becomes cloudy, blocking light from entering and causing visual impairment (Munteanu et al., 2024; Suh & Kane, 2019). Machine learning algorithms have become very popular and continue to be widely studied. Support Vector Machine (SVM) is one of the techniques of machine learning classification algorithms that has supervised learning properties that work by finding the optimal hyperplane (decision boundary) that separates the distance between classes, generalization and stable classification accuracy (Boateng et al., 2020; Pisner & Schnyer, 2020). Linear Discriminant Analysis (LDA) is a dimensional reduction technique that is carried out for the pattern classification stage and machine learning applications (Choubey et al., 2020). LDA is used to obtain image features and provide a larger distance between classes, while the distance between training data in a class becomes smaller (Ghojogh & Crowley, 2019; Zhao et al., 2024; Zhu et al., 2022). Early detection of eye disease is very important, especially for individuals who have a history of eye disease in the family of people over 60 years of age or less than 60 years depending on the eye disease experienced by each individual. Detecting eye disease early is essential to prevent or slow the progression of vision loss and blindness.

Digital image processing is a computational engineering process to improve the quality of digital images, extracting information from the eye lens that can be used in identifying cataract classification. Images from a mathematical perspective are continuous functions of light intensity in a 2-dimensional plane f(x, y), with x and y being spatial coordinates and amplitude f in the companion coordinates (x, y) which are interpreted as the intensity or degree of gray of the image at a point (Kumar et al., 2019). In the era of increasingly advanced technology in the health sector including the use of medical equipment and information technology can improve the quality and efficiency of health services such as digital image processing used in MRI, CT scans, and image-based disease detection, including cataract detection from eye images using machine learning algorithms (Tong et al., 2020). Machine learning algorithms have been applied to solve various problems and are widely used in the field of science. In its implementation, there are various algorithms that can be used for classification tasks, including Support Vector Machine (SVM) and Convolutional Neural Network (CNN) (Chaganti et al., 2020; Hasan et al., 2019).

Some researchers generally combine the application of SVM with LDA. Where LDA is used as one of the Feature Reduction methods to reduce complexity in SVM. However, some researchers such as have used LDA as a fairly good image processing method with good computing time in image recognition. Conducting research on which method is better between High Dimensional Features and Low Dimensional Features and obtaining results that which method is better depends on the size of the existing dataset and also the size of the training data and testing data used. This is also the same as research on the use of the Linear Discriminant Analysis method for face recognition by comparing the amount of training data and research by Bansal (2022) on the effect of training dataset size on the performance of Support Vector Machine and Discision Tree. It is interesting to observe how the performance optimization between SVM and LDA in detecting cataract and normal eye image diseases, especially with the percentage of data and the percentage of training data and testing data. Recognition of digital image eye diseases is converted from rgb to grayscale then the preprocessing stage, segmentation, feature extraction and identification of eye disease detection and which is the highest accuracy result of the two machine algorithms. Therefore, researchers in this study are interested in optimizing the performance of the LDA and SVM algorithms in early detection of cataracts, especially related to the percentage of datasets and also the percentage of training data and testing data.

2. Research Methodolgy

Research Design

In this study, the second performance optimization of the identification algorithm on normal cataract eye images and those affected by cataract eye disease was carried out. This study will produce the highest accuracy results in recognizing the identification of an image from the highest accuracy results detected as normal eye images and cataract eyes, when implementing both LDA and SVM algorithms. The following figure shows the general flow of the research methodology Figure 1.

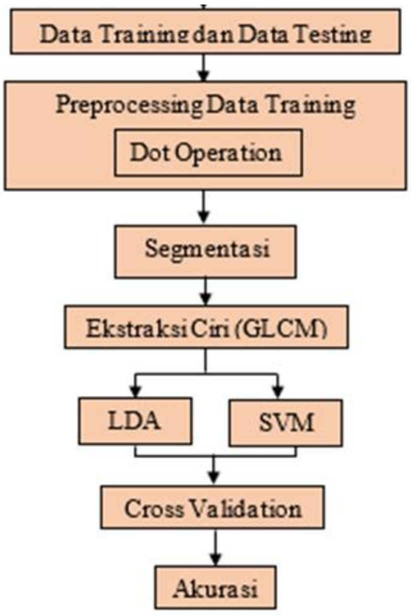

Figure 1 . Research Methodology

A. Data Collection

The data used in this study are secondary data sourced from the largest collection of open source computer vision datasets that can be found on the website address kaggle.com Cataract Eye Image Dataset, the author collected with 150 training data and 150 testing data images including, cataract eye disease classes and normal eyes. The following image shows a sample of one image dataset containing cataract eye disease and normal eyes

Figure 2. Cataract Eye and Normal Eye Image

The complete data can be seen in table 1 of variations in creating training and testing data as follows:

Table 1. Percentage of Training Data and Testing Data

No	Dataset Variations	Training Data	Data Testing	Total
1.	50% : 500%	150 images	150 images	300 images
2.	60% : 40%	180 images	120 images	

B. Training Data Preprocessing

The image preprocessing stage in processing is image quality improvement (Image Enhancement) consisting of dot operations and special operations and the resize process is carried out to standardize the size of the same data set. The image is improved in image quality to one of the dot operations with the histogram Equalization technique. The following grayscale image has been improved in quality to the Intensity Adjustment Image image shown in figure 3. dataset preprocessing stage:

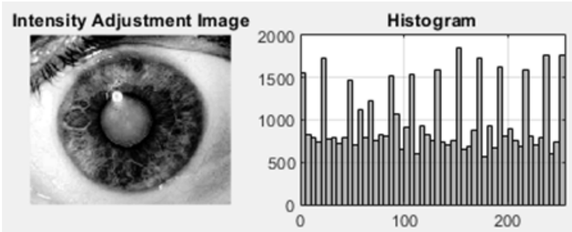

Figure 3. (a) Adjustment Image (b) Histogram

In figure 3 Image quality improvement from grayscale to Intensity Adjustment Image (Histogram) aims to increase the difference between pixel intensity values in the image and help to facilitate the differentiation of objects in the image such as reducing noise, increasing feature visibility, for the Identification process. At this stage the pixel intensity value in the image is changed to a higher intensity value so that objects in the image are more visible and the segmentation process becomes easier.

C. Segmentation

At the segmentation stage of separating objects or features in the image, the pixel intensity value in the image is converted into a threshold with a threshold value of (128) with the aim of dividing the image that is categorized into objects and backgrounds before being converted from thresholding images to binary images. Binary images are produced from the thresholding process to facilitate the segmentation process. Binary images have two contrasting colors, so that objects in the image are easier to separate from the background. The following are the results of cataract eye images from the conversion of thresholding image values to binary can be seen in the following image

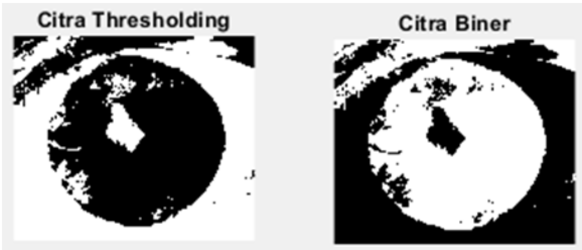

Figure 4. Thresholding Image Conversion to Binary

D. Gray Level Co-occurrence Matrix (GLCM) Feature Extraction

The process of feature extraction or taking features from an image object, the results are as input values for the next stage of the classification process. The results of feature extraction used in this study are using texture feature extraction (GLCM) based on contrast, correlation and energy values, to distinguish objects with certain textures, the contrast value can be used to distinguish objects with smooth and rough textures and the correlation value distinguishes textures that have regular and irregular directions in the pattern, while the energy value distinguishes objects with repetitive and non-repetitive textures from objects in an area.

Ciri Tekstur	Nila
Contrast	0.042281
Correlation	0.91546
Energy	0.45956

Figure 5. GLCM Feature Extraction

The following are the results of the GLCM texture feature extraction. The percentage of training data and testing data of 300 images can be seen in the table below, splitting the results of the feature values in GLCM:

Table 2. GLCM Texture Feature Extraction

No .	File Name	Contrast	Correlation	Energy
		Testing Data		
1.	'cataract1.jpg'	0.042281	0.91546	0.45956
2.	'cataract2.jpg'	0.35421	0.97702	0.65626
130.	'cataract130.jpg'	0.27252	0.87622	0.76542
150.	'cataract150.jpg'	0.19782	0.24311	0.42311
		Training Data		
1.	'normal1.jpg'	0.87252	0.87622	0.76542
2.	'normal2.jpg'	0.09788	0.24311	0.42311
149.	'normal149.jpg'	0.042281	0.92546	0.45956
150.	'normal150.jpg'	0.35421	0.87702	0.15626

In table 2 the results of texture feature extraction using Gray Level Co-occurrence Matrix (GLCM) on two data sets, training data and testing data. glcm is used to analyze texture in images by examining the spatial relationship between pixel intensities. In the testing data, a similar pattern can be seen. The image 'noraml149.jpg' has a lower contrast value and a higher correlation value compared to the image 'katark2.jpg'. The results obtained are used to train a classification model to distinguish between cataract and normal eye images based on GLCM texture feature extraction.

3. Results and Discussion

Implementation of test software and performance evaluation of research conducted using the Matlab programming language for identification of cataract and normal eye diseases. The application of algorithms using LDA and SVM in this study varies the percentage that has been set with the training data dataset and test data.

A. Matlab Application Gui Result View

For model optimization of the two algorithms that have been built, the first step is to input cataract eye images from the test data. Furthermore, the image goes through a preprocessing stage to improve its quality before segmentation. After that, the image texture features are extracted using the GLCM method with contrast, correlation, and energy parameters. The next step is to identify the image using the lda and svm methods. The following are the test results on one of the cataract eye images.

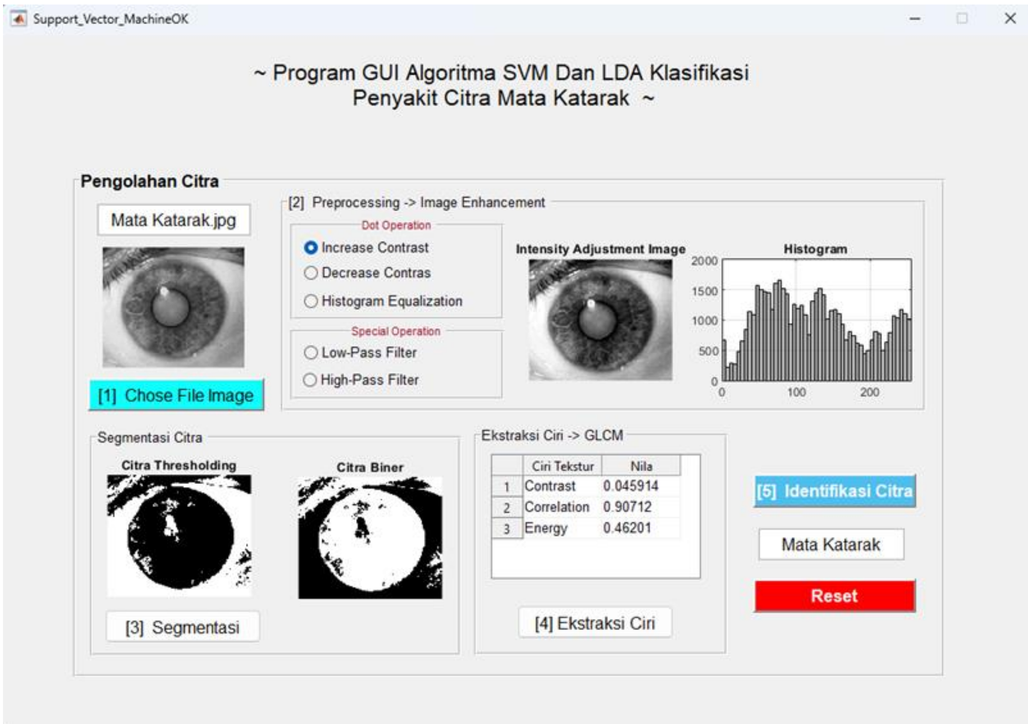

Figure 6. Matlab Application Identification Gui

The test was conducted using test data of 150, 120 images. There are two classes, namely cataract eye class and normal eye class. In the figure, the results of the cataract eye disease image identification. All test images will be compared with the detection results to evaluate the performance of the highest accuracy algorithm.

B. Cross Validation Results

The algorithm used to test the validity of the accuracy results is k = 3 Cross Validation. The dataset is divided into 3 folds, with a total of 270 of the testing data. In each iteration, the selection of the test dataset is carried out according to the fold order. The training process is carried out twice with a percentage of data ratio: 50:50, 60:40. After each training session is completed, testing is carried out immediately to obtain the predicted value. The accuracy level is then calculated as the average of all iterations. The results of the Cross Validation test can be seen in the following table

Table 3. Cross Validation Results K-3

ML Model Types	Iteration To	Testing n-1%	Testing n-2%	Testing n-3%	Average
Support Vector Machine (SVM)	1	88.67	98.0	89.0	91 ,89
	2	85.87	88.0	97.0	90.29
	3	88.78	97.0	88.0	91.26
	Average	87 ,77	94 ,33	91.33	91.14
ML Model Types	Iteration To	Testing n-1%	Testing n-2%	Testing n-3%	Average
	1	80.01	79.55	81.00	80.18

Linear Discriminant Analysis (LDA)	2	78.32	88.59	76.03	80.98
	3	72.33	82.64	92.00	82.32
	Average	76.88	83.59	83.01	81.16

Based on Table 3. the average test results using Linear Discriminant Analysis (LDA) show that the highest prediction was obtained in the 3rd iteration with a test data percentage of 40%, reaching 82.32%. Meanwhile, the lowest average value was found in the 1st iteration with a test data percentage of 50%, which was 80.18%. Overall, the average system prediction accuracy using LDA was 81.16%. While for testing using Support Vector Machine (SVM), the highest average prediction was achieved in the 1st iteration with a test data percentage of 40%, amounting to 91.89%. The lowest accuracy value was found in the 2nd iteration, which was 90.29%. Overall, the average system prediction accuracy using SVM was 91.14%, obtained based on the results of each average of the number of iterations, the following is a comparison graph of the accuracy of the testing data.

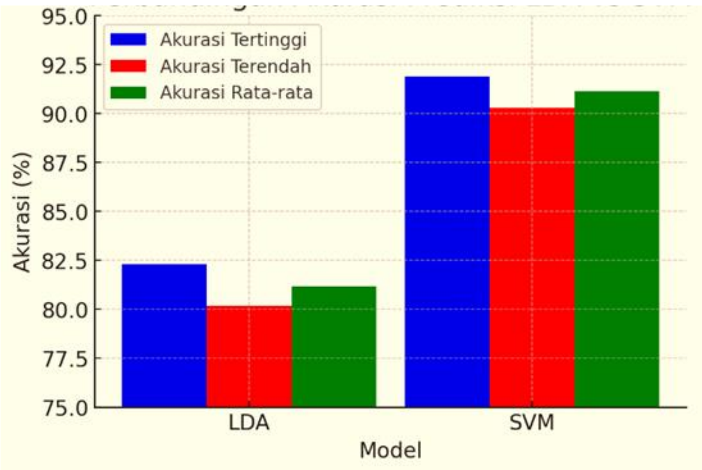

Figure 7. Comparison Graph of Testing Accuracy of K-Fold Cross Method

C. Accuracy Results

The evaluation of the results was carried out using accuracy, precision, recall, and F1-score metrics on training and testing data to measure the effectiveness and performance of both algorithms, in identifying cataract and normal eye images. The following are the accuracy results based on the percentage of test data from the total dataset: The first percentage (50%): 150 test images from 300 total images. The second percentage (40%): 120 test images from a total of 300 images.

Table 4. Testing Data Accuracy Results for Both Algorithms

ML Model Types	Percentage Variation	Amount of Testing Data	Accuracy	Precision	Recall	F1-Score
Linear Discriminant Analysis (LDA)	1st	150	90.66%	100%	79.3%	84.0%
	2nd	120	65.78%	100%	80.0%	89.0%
Support Vector Machine (SVM)	1st	150	95.98%	100%	92.0%	90.9%
	2nd	120	78.88%	100%	80.3%	90.0%

In the testing data, the accuracy of the SVM algorithm is higher than LDA in the 1st and 2nd percentage variations, LDA gives results in the 1st percentage variation with an accuracy of 90.20%, precision 100%, recall 79.3%, and F1-Score 84.0%. SVM gives the best results in the 1st percentage variation with an accuracy of 95.98%, precision 100%, recall 92.0%, and F1- Score 9 0.9% where SVM tends to be better. The following is a visualization of the accuracy graph of the data testing process of the two algorithms (LDA and SVM) based on the percentage variation of the data, the following is a graphic image of the two percentage variation testing algorithms.

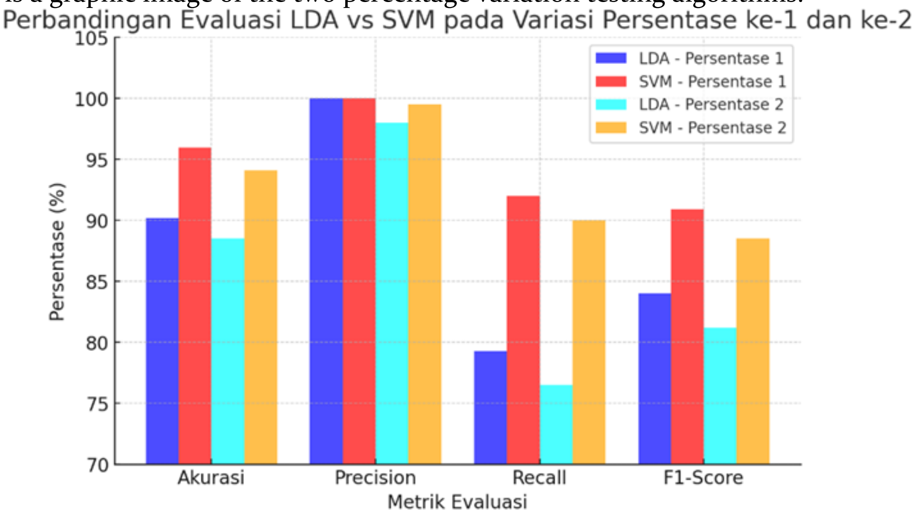

Figure 8. Graph of Percentage Variation of LDA and SVM Testing

The results of the study showed that SVM is more effective in detecting cataract or normal eye images compared to optimizing LDA performance. The results at the stage of the data testing process for the 1st percentage variation (50%), the 2nd percentage variation (40%), LDA performance decreased significantly while SVM remained relatively stable, but with a precision value reaching 100% for both algorithms.

4. Conclusion

From the results of the research on optimizing the performance of the Support Vector Machine (SVM) and Linear Discriminant Analysis (LDA) algorithms in detecting cataracts from eye images as follows:

1. Performance Comparison SVM is superior to LDA in terms of accuracy, recall, and F1-score. The highest accuracy of SVM reaches 95.98%, while LDA is only 90.20%.
2. Precision Both algorithms achieved 100% precision, demonstrating the ability to identify cataract cases without false positives.
3. Recall SVM has a higher recall (92.0%) compared to LDA (79.3%), making it more effective in detecting cataract eye images.
4. The F1-score of SVM (90.9%) is better than LDA (84.0%), indicating a more optimal balance between precision and recall.

Based on the performance optimization results of the evaluation matrix, SVM is better for cataract detection due to its higher accuracy and recall. LDA is more suitable for classification tasks with lower complexity.

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