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Research Article

Feature Extraction and Classification of Retinal Images Using Sobel Segmentation and Linear SVC

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Abstract:
Eye diseases such as Diabetic Retinopathy, Cataract, and Glaucoma are significant causes of visual impairment and blindness worldwide. Early detection and accurate diagnosis are crucial for effective treatment and management of these conditions. This study aimed to develop a machine learning model for the automated classification of retinal images into four categories: Normal, Diabetic Retinopathy, Cataract, and Glaucoma. The dataset, sourced from Kaggle, comprised approximately 1000 images per class, which were pre-processed using Sobel segmentation to enhance relevant features. Hu Moments were employed for feature extraction due to their invariance to scale, rotation, and translation. The classification was performed using a Linear Support Vector Classifier (SVC), and the model's performance was evaluated through 5-fold cross-validation. The average performance metrics were 44.34% for accuracy, 48.26% for precision, 44.34% for recall, and 41.76% for F1-score. These results indicate that while Sobel segmentation and Hu Moments effectively highlight and capture essential features of retinal images, the Linear SVC classifier's performance is moderate, suggesting the need for more advanced classifiers. The study's findings contribute to the ongoing research in automated eye disease diagnosis by demonstrating the strengths and limitations of classical image processing and machine learning techniques. Future research should focus on exploring more sophisticated models, such as convolutional neural networks, and addressing dataset imbalances to enhance classification accuracy and reliability. This study underscores the potential for automated diagnostic tools in clinical settings but also highlights the necessity for further optimization to achieve practical applicability.

Keywords: Retinal Image Classification, Sobel Segmentation, Hu Moments, Linear SVC, Eye Disease Diagnosis.

Dataset link: https://www.kaggle.com/datasets/gunavenkatdoddi/eye-diseases-classification

1. Introduction

Eye diseases such as Diabetic Retinopathy, Cataract, and Glaucoma are significant contributors to visual impairment and blindness globally. Early detection and treatment are crucial for preventing permanent vision loss and managing these conditions effectively [1]. With advancements in medical imaging and machine learning, there is a growing interest in automating the classification of retinal images to aid in the diagnosis of these diseases. This research leverages a publicly available dataset from Kaggle, comprising retinal images categorized into Normal, Diabetic Retinopathy, Cataract, and Glaucoma, to develop a robust classification model. The dataset, sourced from various repositories like IDRiD and HRF, provides a comprehensive collection of retinal images essential for training and evaluating machine learning models.

Despite the availability of advanced diagnostic tools, manual examination of retinal images remains time-consuming and subject to human error. Automated classification systems can significantly reduce the burden on

healthcare professionals and improve diagnostic accuracy. However, developing a reliable model for classifying retinal images is challenging due to the variability in image quality and the subtle differences between disease classes. This research aims to address these challenges by implementing an effective pre-processing [2] and feature extraction pipeline, followed by a robust classification algorithm. The goal is to create a model that can accurately classify retinal images into their respective disease categories, thereby facilitating early detection and treatment. The primary objective of this research is to develop a machine learning model for the classification of eye diseases using retinal images. To achieve this, the study will focus on several key tasks: pre-processing retinal images using Sobel segmentation to enhance the relevant features, extracting meaningful features from the segmented images using Hu Moments, implementing a Linear Support Vector Classifier (SVC) to classify the images into Normal, Diabetic Retinopathy, Cataract, and Glaucoma categories, and evaluating the model's performance using standard metrics such as accuracy, precision, recall, and F1-score [3]. By accomplishing these objectives, the research aims to contribute a reliable and efficient tool for the automated classification of retinal images

This research is guided by several questions and hypotheses. Firstly, can Sobel segmentation and Hu Moments feature extraction effectively pre-process retinal images for disease classification? Secondly, how well does the Linear SVC perform in classifying eye diseases from retinal images? The hypothesis is that the combination of Sobel segmentation and Hu Moments will enhance the discriminative features of the images, thereby improving the classification accuracy of the Linear SVC. Additionally, the study hypothesizes that the model will achieve high precision, recall, and F1-score, making it a reliable tool for clinical use. The scope of this research includes the use of a specific dataset from Kaggle, which contains approximately 1000 images per class for Normal, Diabetic Retinopathy, Cataract, and Glaucoma. The dataset will be split into training and testing sets in an 80-20 ratio. The research focuses on applying Sobel segmentation for image pre-processing and Hu Moments for feature extraction [4], [5], followed by classification using Linear SVC [3]. One limitation of the study is the potential imbalance in the dataset, which may affect the model's performance. Additionally, the research is confined to the chosen pre-processing and feature extraction techniques and does not explore other potential methods that might further improve classification accuracy [6], [7].

This research makes several important contributions to the field of medical imaging and machine learning. It provides a comprehensive methodology for the automated classification of eye diseases using retinal images, incorporating effective pre-processing and feature extraction techniques. The study also demonstrates the feasibility of using Linear SVC for this classification task, presenting a detailed evaluation of the model's performance. By addressing the challenges associated with the variability in retinal image quality and the subtle differences between disease classes, this research offers a valuable tool for early diagnosis and treatment planning. Furthermore, the findings can serve as a foundation for future studies exploring more advanced models and additional image features to enhance classification accuracy.

2. Method

This research adopts a supervised learning approach to classify retinal images into four categories: Normal, Diabetic Retinopathy, Cataract, and Glaucoma. The methodology involves several key steps: image pre-processing, feature extraction, model training, and evaluation. The images are pre-processed using Sobel segmentation to highlight the edges and structures in the retinal images [8], [9]. For feature extraction, Hu Moments are utilized [5], which capture the shape characteristics of the segmented images. The classification is performed using a Linear Support Vector Classifier (SVC) [10]. The performance of the model is evaluated using metrics such as accuracy, precision, recall, and F1-score. The full research methodology is graphically outlined in **Figure 1**.

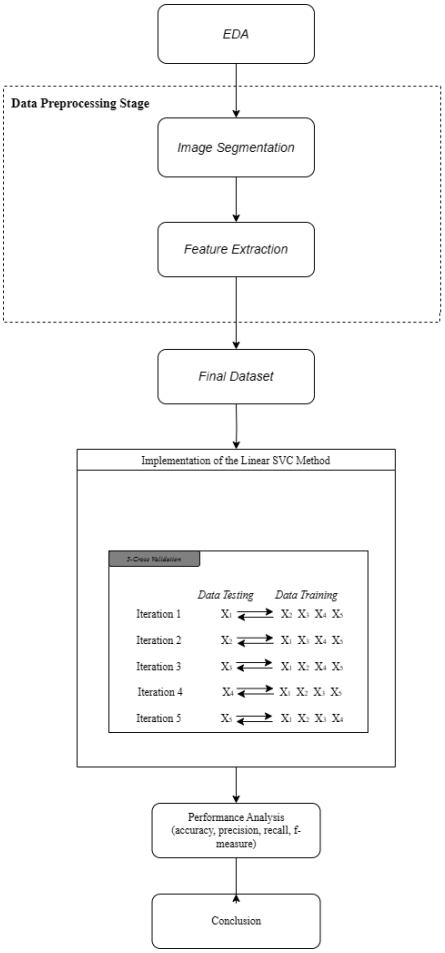

Figure 1: Procedure for Assessing a Linear SVC

Sample or Data Selection:

The dataset used in this study is obtained from Kaggle and consists of approximately 1000 images for each class: Normal, Diabetic Retinopathy, Cataract, and Glaucoma. The images are collected from various sources, including IDRiD, Oculur recognition, and HRF. The dataset is split into training and testing sets in an 80-20 ratio to ensure that the model is trained on a diverse set of images and tested on unseen data to evaluate its generalization capability.

Data Collection Process

The images in the dataset were collected from publicly available repositories and curated to ensure a balanced representation of each class. The images were pre-processed using Sobel segmentation to enhance the relevant features, such as blood vessels and lesions, which are critical for the diagnosis of eye diseases. Sobel segmentation is performed using the following formula, where G_x and G_y are the gradients in the x and y directions, respectively [9], [11], [12]:

$$\begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix} \times I \quad G_y = \begin{bmatrix} -1 & -2 & -1 \\ 0 & 0 & 0 \\ 1 & 2 & 1 \end{bmatrix} \times I \tag{1}$$

The magnitude of the gradient is then computed as:

$$G = \sqrt{G_x^2 + G_y^2} \tag{2}$$

This highlights the edges and boundaries within the retinal images, which are essential for feature extraction. To illustrate the pre-processing and feature extraction process [13], we present several visualizations. **Figures 2** to **5** shows the result of Sobel segmentation applied to a sample retinal image.

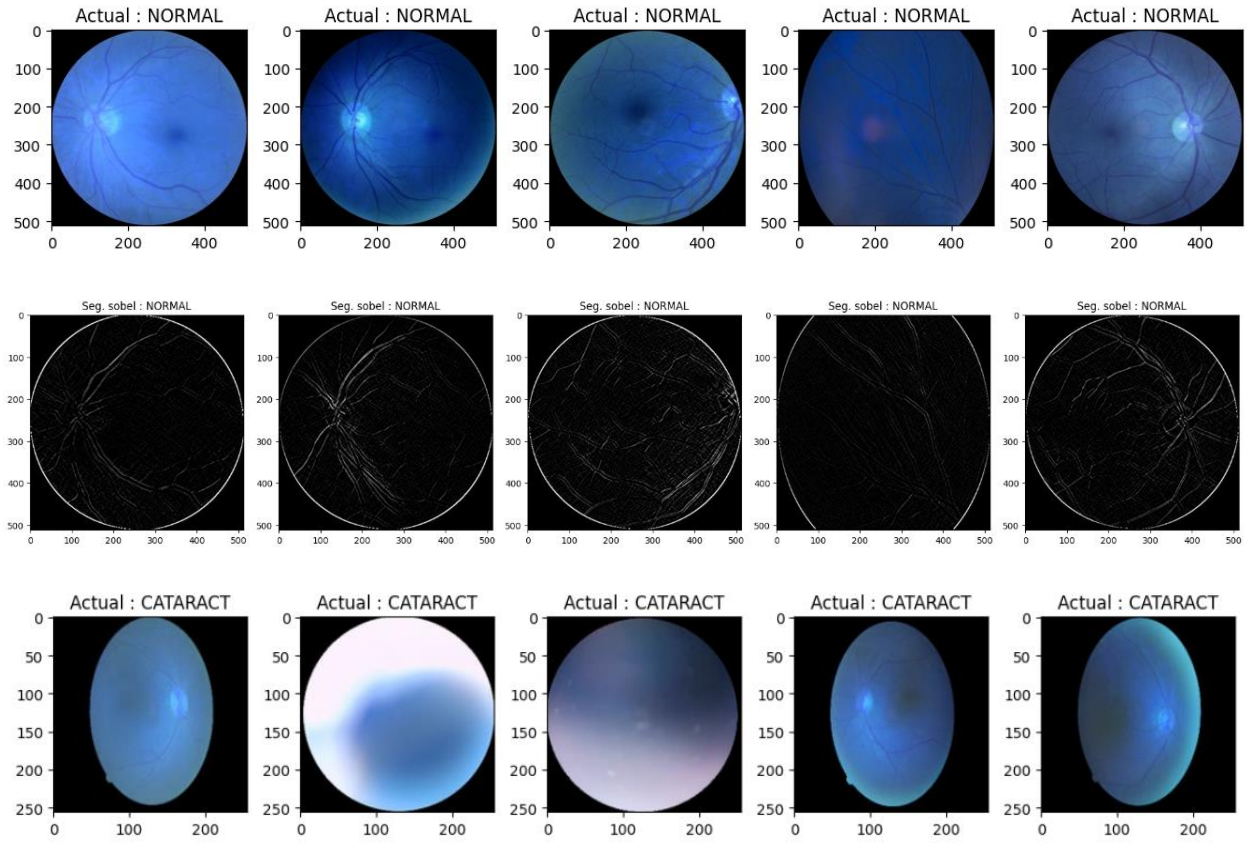

Figure 2: Normal Class

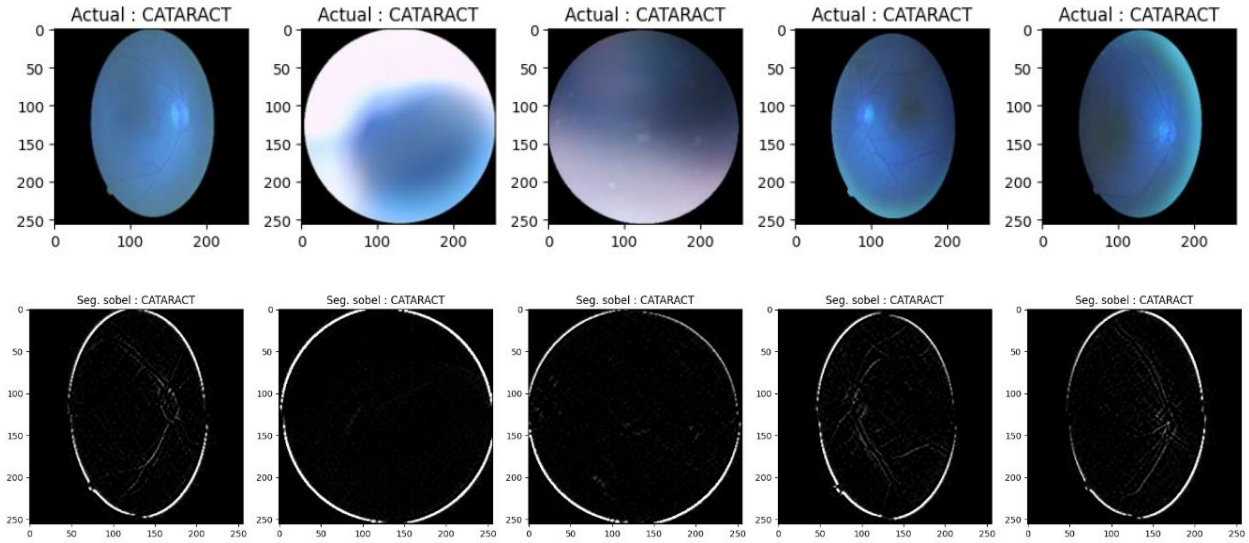

Figure 3: Cataract Class

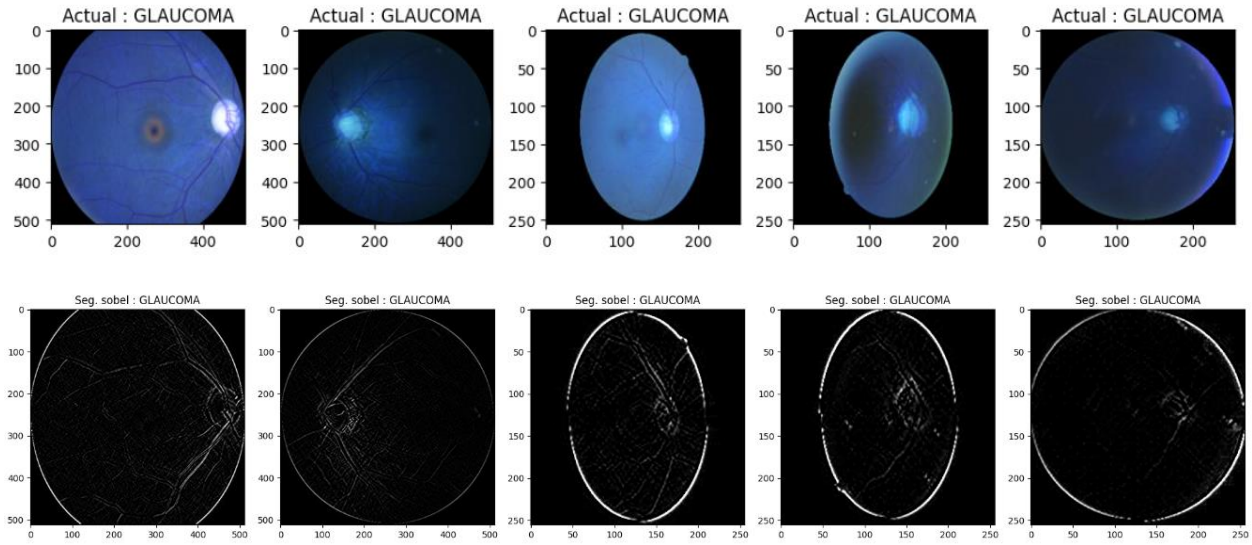

Figure 4: Glaucoma Class

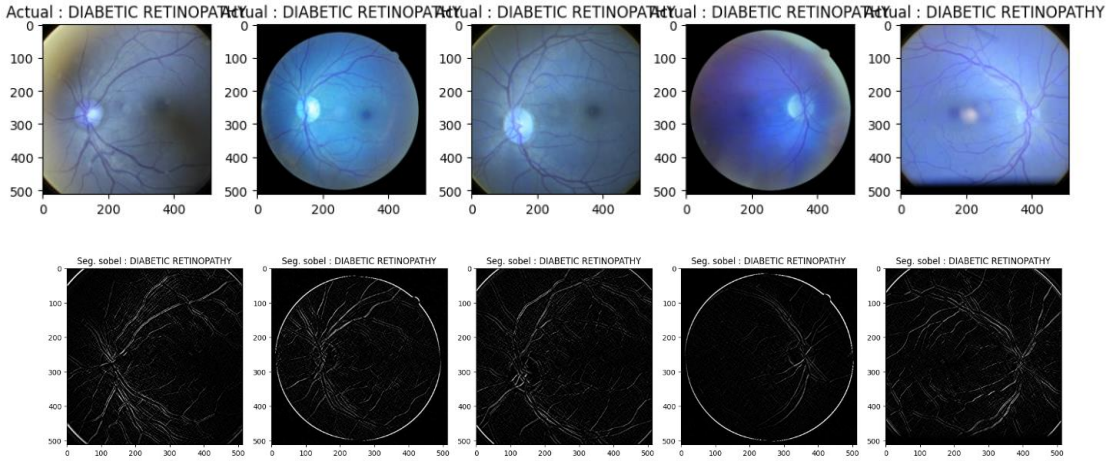

Figure 5: Diabetic Retinopathy Class

Data Analysis Methods

The segmented images are then processed to extract Hu Moments [14], [15], which are invariant to scale, rotation, and translation, making them suitable for distinguishing between different classes of eye diseases. Hu Moments are calculated using the following seven moments:

$$\begin{aligned} H_1 &= \mu_{20} + \mu_{02} \\ H_2 &= (\mu_{20} + \mu_{02})^2 + 4\mu_{11}^2 \\ &\vdots \\ H_7 &= \mu_{30}\mu_{12} - \mu_{21}\mu_{03} - 3\mu_{12}^2\mu_{03} + 3\mu_{21}^2\mu_{12} \end{aligned} \tag{3}$$

These moments are extracted for each image, creating a feature vector used for classification. **Figures 6** and **7** present scatter plots and boxplots of the Hu Moments, showing their distribution and relationships.

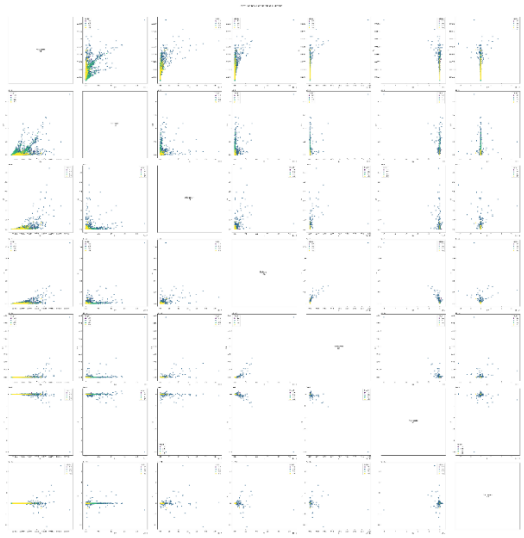

Figure 6: Scatter Plots for All Combinations of Hu Moments

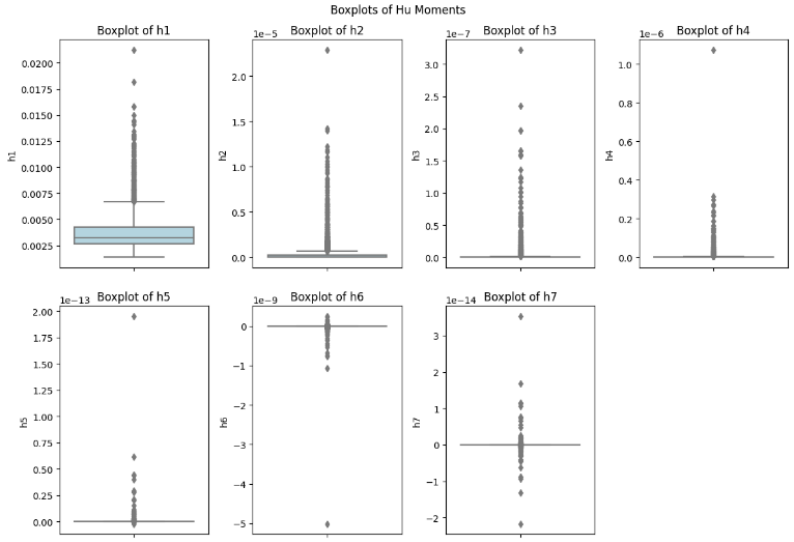

Figure 7: Boxplots of Hu Moments

The dataset is then scaled to have a mean of 0 and variance of 1, ensuring that all features contribute equally to the classification process. The scaled features are used to train the Linear SVC [16]–[18], which aims to find the optimal hyperplane that separates the classes. The SVC is trained using the following optimization objective:

$$min_{w,b}\frac{1}{2}\boldsymbol{w}^T\,\boldsymbol{w} + C\sum_{i=1}^{n}\max(0,1-y_i(\boldsymbol{w^T x_i}+b)) \tag{4}$$

where $\boldsymbol{w}$ is the weight vector, b is the bias term, C is the regularization parameter, y_i is the class label, and x_i is the feature vector.

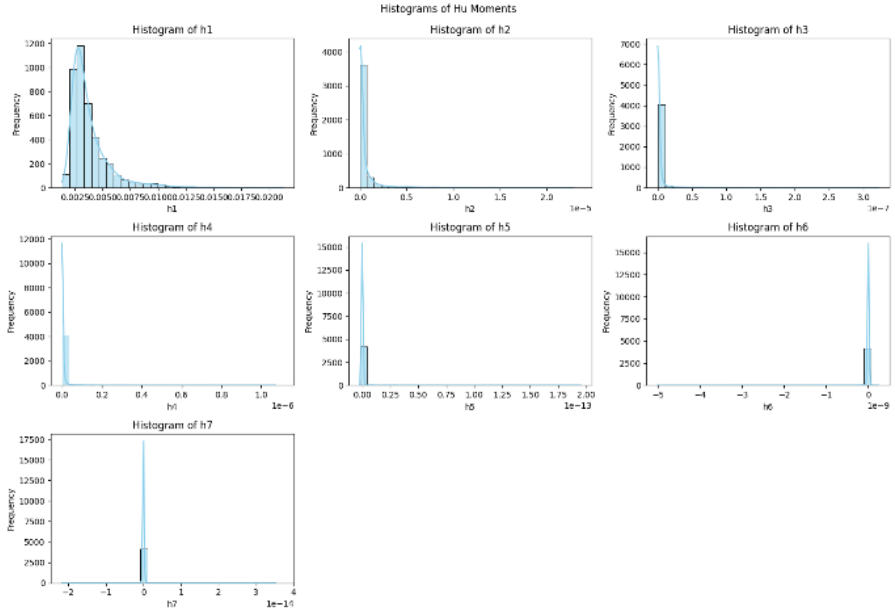

Figure 8: Histogram of Hu Moments

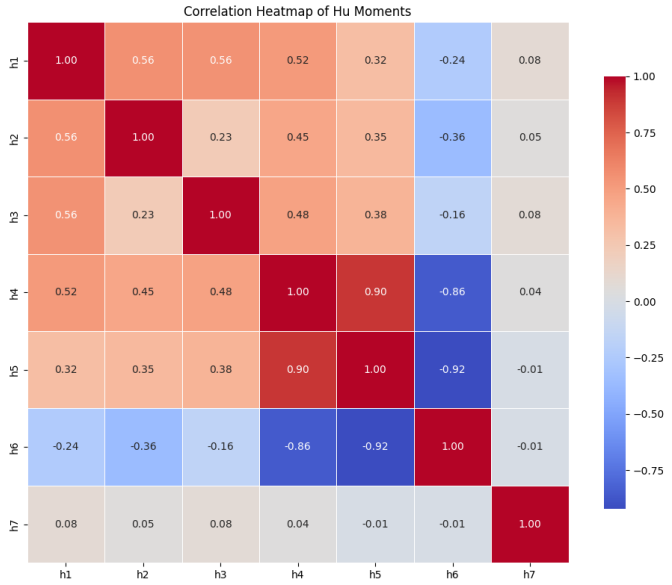

Figure 9: Correlation Heatmap of Hu Moments

Several visualizations are used to illustrate the data and model performance. **Figure 8** presents histograms of the Hu Moments class distribution, while Figure 9 shows a correlation heatmap of the Hu Moments.

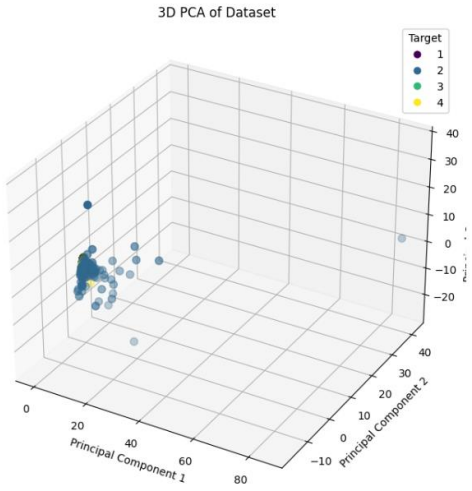

Figure 10: 3D PCA of dataset

Figure 10 provides a 3D PCA of the dataset, highlighting the separation between classes. Parallel coordinates plots (**Figure 11**) visualize the feature distributions by target class. Advanced visualizations, such as 3D UMAP (Figure 12), provide deeper insights into the dataset structure and classification results.

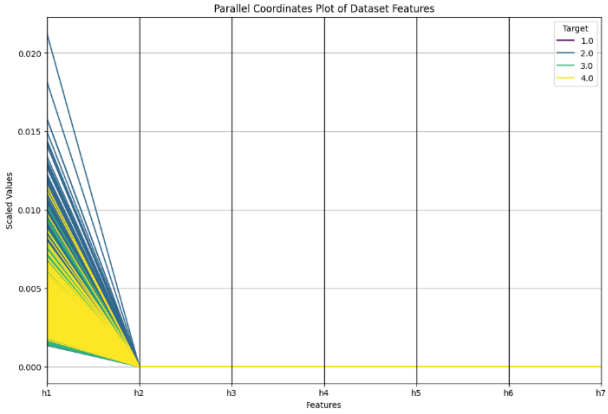

Figure 11: Parallel Coordinates Plot of Dataset Features

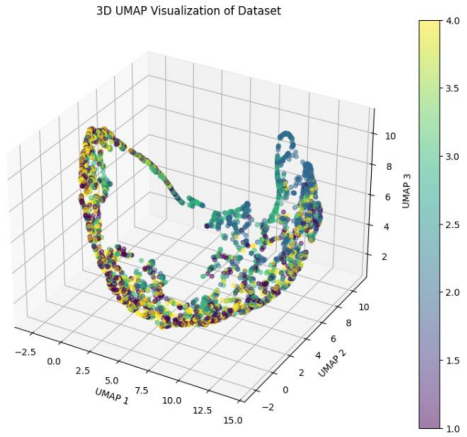

Figure 12: 3D UMAP Visualization of Dataset

The model's performance is evaluated using the following metrics [19]–[21]:

a. **Accuracy:** Accuracy is the proportion of true results (both true positives and true negatives) among the total number of cases examined. It is calculated as:

$$\text{Accuracy} = \frac{\text{Number of Correct Predictions}}{\text{Total Number of Predictions}} \tag{5}$$

b. **Precision:** Precision is the ratio of correctly predicted positive observations to the total predicted positives. It is calculated as:

$$\text{Precision} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Positives}} \tag{6}$$

c. **Recall:** Recall is the ratio of correctly predicted positive observations to all observations in the actual class. It is calculated as:

$$\text{Recall} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Negatives}} \tag{7}$$

d. **F1-Score:** The F1-Score is the weighted average of Precision and Recall. It is calculated as:

$$F1 = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \quad (8)$$

This comprehensive methodology ensures a detailed analysis of the dataset and a robust evaluation of the classification model, contributing valuable insights to the field of automated eye disease diagnosis.

3. Result and Discussion

The results of the study were obtained by performing 5-fold cross-validation using the Linear SVC classifier. The performance metrics including accuracy, precision, recall, and F1-score were calculated for each fold. The following **Table 1** summarizes the average performance metrics in percentages.

Table 2: Performance Metrics Across 5-Fold Cross-Validation for the Linear SVC

K-n	Metrics			
	Accuracy	***Precision***	***Recall***	***F-Measure***
K-1	42.89%	47.94%	42.89%	41.31%
K-2	41.82%	45.59%	41.82%	38.54%
K-3	46.62%	49.56%	46.62%	44.11%
K-4	45.67%	51.90%	45.67%	42.67%
K-5	44.72%	46.33%	44.72%	42.17%
$\sum$ ***Avg***	44.34%	48.26%	44.34%	41.76%

To provide a clear visualization of the results, we have included graphs showing the performance metrics across the folds and a confusion matrix that summarizes the model's classification performance. Figure 13 presents the bar graphs for each performance metric, illustrating the variability and overall trend across the folds. Figure 14 displays the confusion matrix, highlighting the true positives, false positives, true negatives, and false negatives for each class.

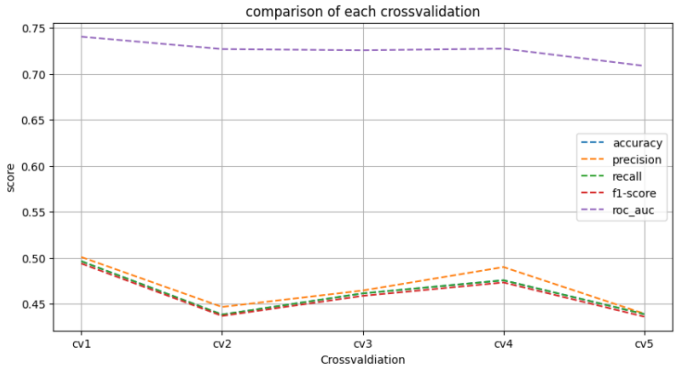

Figure 13: Performance Comparison of Each Cross-validation Fold

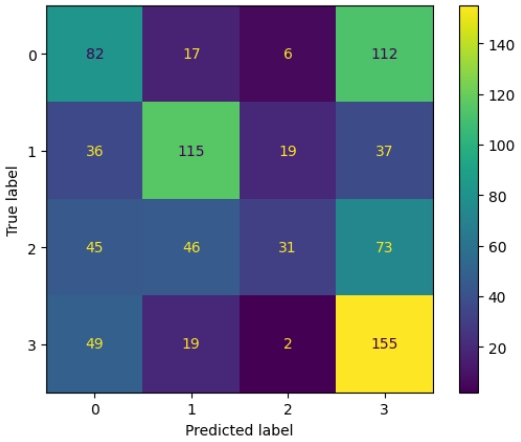

Figure 14: Confusion Matrix of the Linear SVC

The data processing results showed that the use of Sobel segmentation and Hu Moments feature extraction provided a robust set of features for classifying the retinal images. The segmentation effectively highlighted the edges and structures within the retinal images, while the Hu Moments captured the shape characteristics necessary for distinguishing between different eye diseases. The scaling of the dataset ensured that all features contributed equally to the classification process.

Discussion

The results indicate that the Linear SVC classifier, when applied to the pre-processed and feature-extracted retinal images, achieved moderate performance across the metrics. The average accuracy of 44.34% suggests that there is significant room for improvement in the model's ability to correctly classify the retinal images. The precision and recall values, averaging 48.26% and 44.34% respectively, also reflect the need for enhancements in the model's predictive power. The F1-score, averaging 41.76%, further emphasizes the balance between precision and recall, indicating that the model struggles to achieve high performance consistently. The relationship between the research results and previous studies suggests that while Sobel segmentation and Hu Moments are effective in capturing essential features of retinal images, the Linear SVC may not be the optimal classifier for this task. Previous research has explored the use of more complex models, such as convolutional neural networks (CNNs), which have shown superior performance in image classification tasks. The findings from this study support the notion that more advanced models might be necessary to achieve higher accuracy and reliability in classifying eye diseases from retinal images.

Practical implications of the research results highlight the potential for developing automated diagnostic tools that can assist ophthalmologists in early detection and treatment planning. However, the current performance levels suggest that further optimization and exploration of different models and feature extraction techniques are necessary before such tools can be deployed in clinical settings. The limitations of this research include the imbalanced dataset and the choice of classifier, which may have contributed to the moderate performance metrics. Recommendations for further research include exploring more advanced classifiers, such as CNNs or ensemble methods, which might better capture the complex features of retinal images. Additionally, augmenting the dataset to address the class imbalance

and incorporating other feature extraction techniques could improve the model's performance. Future studies should also consider the impact of different pre-processing methods on the classification results.

4. Conclusion

This study investigated the use of Sobel segmentation and Hu Moments feature extraction combined with a Linear SVC classifier for the classification of retinal images into Normal, Diabetic Retinopathy, Cataract, and Glaucoma categories. The results demonstrated that while the proposed method is capable of capturing essential features from retinal images, the classification performance was moderate, with average accuracy, precision, recall, and F1-score values of 44.34%, 48.26%, 44.34%, and 41.76%, respectively. These findings suggest that while Sobel segmentation and Hu Moments provide a robust feature set, the Linear SVC classifier may not be optimal for this task, as evidenced by the modest performance metrics observed across the 5-fold cross-validation. In answering the research questions, it was found that Sobel segmentation and Hu Moments can preprocess retinal images effectively, but the Linear SVC's performance indicates that more advanced classifiers might be necessary for higher accuracy. The research contributes to the field by highlighting the potential and limitations of using classical image processing techniques and simple classifiers for medical image classification. For further research, it is recommended to explore more sophisticated models, such as convolutional neural networks (CNNs), and to address dataset imbalances through augmentation techniques. Additionally, investigating other feature extraction methods and optimizing the pre-processing pipeline could lead to improved classification performance, making automated diagnostic tools more viable for clinical applications.

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