Cortex Vision: Detection of Ophthalmic Disease Using Machine Learning Algorithm

Ibtasam Rehman[1,2] and Hoang-Anh Pham[1,2,*][0000−0002−5806−5910]

[1] Ho Chi Minh City University of Technology (HCMUT), Vietnam
[2] Vietnam National University Ho Chi Minh City (VNU-HCM), Vietnam
{ribtasam.sdh231, anhpham}@hcmut.edu.vn

Abstract. Cataracts are one of the leading causes of vision impairment globally, characterized by lens clouding, which can result in blurred vision, faded colors, and halos around lights. This condition affects over 2.2 billion people worldwide, yet diagnosing cataracts often requires time-consuming and costly consultations with healthcare professionals. To address this issue, we developed a cross-platform mobile application designed to facilitate the detection of cataracts using machine learning techniques. Specifically, we implemented Support Vector Machine (SVM) classifiers with three different kernel functions: Linear, Polynomial, and Radial Basis Function (RBF). Through our experiments, we found that the RBF kernel provided the best performance, achieving an accuracy of approximately 95%. The application leverages image processing and classification algorithms to efficiently assess the presence of cataracts, making it accessible to users without the need for professional intervention. Our results, validated through classification reports and accuracy metrics, demonstrate the potential of this mobile solution to improve early diagnosis and accessibility of cataract detection. This study contributes to ongoing efforts to harness technology for medical image analysis and highlights the importance of selecting appropriate machine learning models for effective healthcare solutions.

Keywords: Machine Learning · Support Vector Machine · Image Processing · Cataract

1 Introduction

Vision, the major human sense, contributes an essential responsibility in every stage of our lives. People sometimes take vision for granted, but without vision, we have difficulty learning, walking, reading, and participating in numerous events of life. Vision impairment occurs when an eye condition affects visual functions; however, if left untreated, it shows serious consequences for the individuals throughout the life span. The number of various consequences can be reduced by timely access to eye care. According to the World Health Organization (WHO) for 2023, 2.2 billion people worldwide suffer from vision impairments. Ophthalmic condition that causes vision impairment and blindness resulting in cataract, refractive error, glaucoma, diabetic retinopathy, age-related macular degeneration. It is assumed that around the world 36% of people with distance vision impairment due to refractive error and 17% of the community with vision impairment resulting from cataracts. The decline in visual perception affects all people of all ages; however, visual impairment and blindness are older than 50 years.

The human eye is one of the most important and sensitive organs in the human body. It helps us to see, visualize different objects. Vision is one of the most used sense and one of the essential sources through which we gather different information. The typical human eye can visualize approximately 10 million different types of color. The size of a human eye is approximately 83.07 cm in diameter which consists of different parts such as the iris, puppy, cornea, lens retina, and optic nerves.

The cataract is a cloudy zone in the lens of the human eye. Cataracts are much more common when an individual reaches the age of 50 or older. At an early stage, someone may feel that they have cataracts because they develop slowly and steadily, but with time, cataracts can develop vision blurry or neutral; however, as time passes, cataracts can lead to permanent vision loss. Initially, powerful lightning and corrective lenses can facilitate the treatment of cataracts. Indications of cataract include blurred vision, cloudy or dim vision, it can be sensitive to light, a problem when viewing at night, sudden changes in glasses or lens prescription, dual vision, faded colors, and halos near lights. The mentioned symptoms can fluctuate in terms of severity and may affect daily activities of existence. The root cause of cataracts includes aging, with certain conditions that are generally related to older individuals. Over time, proteins in the lens of the human eye can accumulate together, resulting in cloudiness and a visual perception problem. The continuous involvement to ultraviolet (UV) radiation from sunlight, specific medical condition for example diabetics, hypertension, trauma injury associated with human eye, smoking, genetics can boost the risk of growing cataracts. Recognizing the symptoms and the reason for developing cataracts is important for the early detection and suitable treatment of the condition. Routine eye examination by healthcare professionals is essential for observing eye health and detecting cataracts in initial stages.

According to the World Health Organization, around 51% of cataract cases have been reported. In underdeveloped countries, the rate of cataracts is higher because they do not have investments in the health sector. Currently, approximately 1 billion people suffer from various ophthalmic diseases such as cataracts, glaucoma, corneal opacities, and diabetic retinopathy. Cataracts are the predominant cause of visual impairment worldwide, which has affected about 65.2 million people compared to the second most34 prevalent disease glaucoma with 6.9 million patients. The current cataract statistics reveal that there are about 52.6 million visually impaired people and 12.6 million blind people. The common cause of cataracts is aging. The normal human eye starts to change after the age of 40. That is, when the regular proteins in the lens begin to break down. The lens becomes clouded as a result of this.The lenses of people over the age of 60 frequently begin to fog. Vision problems, on the other hand, may not appear for years.

2 Related Works

For the past few years, machine learning models in the healthcare sector have supported professionals in diagnosing different diseases. These machine learning methods have achieved compelling performance with the help of hand-engineered features.

Agarwal et al. [1] presented a smartphone-based Android application for cataract detection, designed to save time and minimize costs compared to traditional clinical methods. The application uses machine learning (KNN, SVM, Nave Bayes) and image processing, with the OpenCV library. Users can upload eye images from their gallery or take new photos, which are processed to detect cataracts by comparing eye features against pre-trained datasets. This approach includes numerous steps: image collection, data preprocessing (using Orange Tool), classification by KNN, and validation under ophthalmologists' supervision. The KNN model outperformed SVM and Naïve Bayes, achieving 83.07% accuracy.

Behera et al. [2] demonstrate a systemized model to identify nuclear cataracts using fundus retinal images. The model processes images to develop binary exhibits that focus on blood vessels, which serve as the feature matrix for a Support Vector Machine (SVM) classifier. Various SVM kernels were tested, with the Radial Basis Function (RBF) gaining the highest precision of 95. 2%. The study concluded that RBF-based SVM is effective for real-time detection and recommends future exploration of Convolutional Neural Networks (CNNs) for enhanced performance.

Setiawan [3] developed a mobile application for cataract detection utilizing statistical texture analysis and K-Nearest-Neighbor (k-NN) classification. It addresses the problem faced in rural areas of Indonesia, where access to ophthalmologists and diagnostic tools is minimal, resulting in cataracts being the leading cause of blindness. The research analyzed 160 eye images: 80 normal and 80 cataract using pre-processing techniques such as cropping and grayscale conversion, along with feature extraction using the gray level cooccurrence matrix (GLCM). The findings demonstrated a precision of 97. 5%, identifying optimal features such as distinction, contrast, and uniformity, with the best k value for k-NN determined to be 1. Ultimately, the study shows that this approach effectively classifies normal and cataract conditions, paving the way for mobile solutions in underserved regions.

Gao et al. [4] intended to enhance the detection of cataract and classification with Artificial Intelligence using Fundus Images. They obtained 1340 fundus images; however, they developed a dual-stream cataract evaluation network (DCEN) to classify and grade cataract. They trained and tested the DCEN model using deep learning algorithms, most significantly ResNet models. The DCEN achieved high accuracy, sensitivity, F1 score, and kappa coefficient for both cataract classification and severity grading tasks. The model performs in general with an accuracy of 97.62%.

Gupta [5] presented two algorithms applied to eye images to assess intensivness. The first algorithm used feature extraction and histogram evaluation to classify eyes as healthy or with various degrees of cataract based on mean intensity. The second method computes the area of the cataract relative to the pupil using contour detection and Hough transforms. The feature extraction method proved to be more versatile, while the area calculation approach required specific conditions for accuracy. The research highlights the need for automation and the development of mobile applications to improve accessibility to cataract detection.

Junayed et al. [6] have come up with the observation of cataract using deep learning with the use of fundus images. They use multiple datasets such as HRF, FIRE, ACHIKO-I , IDRiD for training and testing goals. The algorithm which is used for cataract detection is Convolution Neural Networks (CNN), however, they proposed a name of model is Cataract- Net. The performance of the proposed CataractNet is compared with five pre-trained CNN models across different dataset splitting conditions. CataractNet outperforms the other models in terms of accuracy and other evaluation metrics, while also demonstrating lower time complexity. The study concludes by highlighting the achievements of CataractNet in terms of accuracy, precision, recall, specificity, MCC, and F1-score.

Khalaf et al. [7] studied and performed an experiment to classify ophthalmic diseases using YOLOv8. Besides they used fundus images form various resource for example Robotflow, Kaggle and Medical clinics and they standardized those image to 224*224 pixels. The aggregate of collected image are 5887, and furthermore the dataset was divided into training and testing. YOLOv8n-cls (nano) was selected die because of its efficiency, dense size, speed, and performance. After all, the model was trained on data applying specific parameters, including ADAM optimizer, learning rate, batch size, weight decay, and 30 epochs. To access the model numerous metrics such as accuracy, precision recall and F1 score are used. In addition, the proposed model achieved an accuracy rate 94% in classifying various eye diseases, surpassing traditional CNNs.

Meegada et al. [8] recommended efficient cataract detection using deep learning and machine learning modals. For the purpose of extracting the feature, they use Convolution Neural Network (CNN), however, for classification apply diverse ML and DL modals as an example support vector machine (SVM), random forest (RF) along with deep neural network (DNN). The experiment may involve multiple steps for example, data preparation, augmentation, model selection training and optimization. The end result of the proposed experiment to detect cataracts gives an accuracy of 98. 4%.

Rana and Galib [9] proposed a mobile-based cataract detection solution using a phone camera. The application identify cataracts by examine pupil images through color detection and classification. The system addresses challenges in rural areas where access to medical professionals and specialized equipment such as slit-lamp cameras is minimal. The method utilizes OpenCV, SDK, and NDK for image processing and offers a cost-effective solution for early cataract detection. Primary experiments illustrate the accuracy of 90% in detecting cataracts in different stages.

Rajhan et al. [10] developed a mobile app to detect cataracts using deep learning algorithms. The proposed system came up with an accuracy of 98. 79%, however, the procedure also has high sensitivity and specificity. CNN is used to detect cataracts because it has three layers consisting of a convolution layer, a pooling layer, and a fully connected layer that support pattern recognition. The user uses the mobile camera to get a picture of the eye to check the presence of a cataract. If the algorithm discovers the cataract, the user will be notified by the alert dialog box with the severity level of the cataract.

Vasan et al. [11] given a study on cataract detection using an artificially based mobile application. They used a convolutional neural network (CNN) as a foundation for deep learning. Both the convolution and pooling layer fulfilll the feature extraction from images, This app works on 16 layers of convolutions, 2 sampling layers, 4 concatenation layers and a soft-max classification layer. The model approach is to obtain the lens concerning the shadow of the nontransparent part of the lens to forecast if the eye has a cataract or not.

Yang et al. [12] proposed a study in which they performed an experiment using 504 sets of images labeled by the experienced ophthalmologist for cataract detection and classification. The use back-propagation neural network and the classification of cataract however they extracted various number of features e.g. Luminance feature that catch the clarity of retinal images, Gray Co-Occurrence Matrix Feature is used which provides the information regarding the image, the matrix include entropy, contrast, inverse and Gray-Gradient Co-occurrence Matrix Features it have the ability to get the gray level and grey gradient information of the image. Performance is measured using Receiver 18 Operating Characteristic (ROC) and confusion matrix because by using the ROC it depicts the information between the true positive rate and false positive rate.

3 Methodology

This section outlines the proposed approach to develop and implement a machine learning-based system for cataract detection using Support Vector Machine (SVM) classifiers. The methodology is segmented into three key steps: data set loading, data pre-processing, and image classification using SVM. Each step is critical to ensure that the application performs well and meets its intended purpose.

As depicted in Fig. 1, the methodology for cataract detection using Support Vector Machine (SVM) classifiers begins by loading a data set sourced from Kaggle repositories. The data set is structured into separate folders for training and testing, with images classified into 'cataract' and 'normal' classes. Each image is labeled according to its folder name, where images from the 'cataract' folder are assigned a label of 1, and images from the 'normal' folder are labeled

0. This labeling ensures that each image has a corresponding label, making it ready for preprocessing.

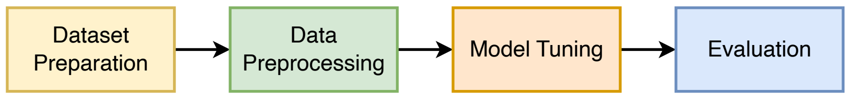

Fig. 1. Work flow of the proposed method

Each image undergoes a series of pre-processing steps to prepare it for analysis. Initially, the images are converted to grayscale to reduce complexity, resized to a uniform dimension of 100x100 pixels, and normalized to scale pixel values between 0 and 1. An unsharp masking technique is applied to enhance image clarity, defined by (1).

$$\text{Sharpened\_Image} = I \times (1 + s) - G \times s \tag{1}$$

where I is the original image, G is the blurred image obtained through Gaussian filtering, and s is a scaling factor. Following this, features such as edges and textures are extracted, which are essential for effective classification.

Support Vector Machines are characterized by several hyperparameters that dictate their performance. The most crucial hyperparameters for SVMs include:

1. **Regularization parameter** C controls the trade-off between maximizing the margin and minimizing the classification error. The objective function for SVM can be formulated as (2).

$$\min_{\mathbf{w},b} \quad \frac{1}{2}\|\mathbf{w}\|^2 + C\sum_{i=1}^{n} \max(0, 1 - y_i(\mathbf{w}^T\mathbf{x}_i + b)) \tag{2}$$

Here, $\mathbf{w}$ represents the weight vector, b is the bias, y_i are the target labels, and $\mathbf{x}_i$ are the feature vectors. A lower value of C results in a wider margin at the cost of misclassifications, while a higher value C aims to minimize misclassifications by potentially reducing the margin.

2. **Kernel Coefficient** γ determines the influence of a single training example. The decision boundary becomes more complex with larger values of γ. The RBF kernel is given by (3).

$$K(\mathbf{x}, \mathbf{x}') = e^{-\gamma\|\mathbf{x}-\mathbf{x}'\|^2} \tag{3}$$

A low value of γ results in a smooth decision boundary, while a high value allows for more complex decision boundaries.

3. **Degree parameter** is relevant for the Polynomial kernel, determining the degree of the polynomial used in the kernel function as (4).

$$K(\mathbf{x}, \mathbf{x}') = (\mathbf{x}^T\mathbf{x}' + c)^{\text{degree}} \tag{4}$$

Here, c is a constant that trades off the influence of higher-order terms.

4. **coef0** parameter influences the trade-off between the linear and polynomial terms in the kernel. This is particularly relevant in the polynomial kernel, affecting the flexibility of the model.

To systematically evaluate the combinations of hyperparameters for each SVM variant, we utilized the `GridSearchCV` function from the `scikit-learn` library. The process includes three steps as follows:

1. Define the parameter grids for each SVM type
   - **Linear SVM**:

```
param_grid_linear = {'C': [0.01, 0.1, 1, 10, 100]}
```

   - **Polynomial SVM**:

```
param_grid_poly = {'C': [0.01, 0.1, 1, 10, 100],
    'degree': [2, 3, 4],
    'gamma': ['scale', 'auto']
}
```

   - **RBF SVM**:

```
param_grid_rbf = {'C': [0.01, 0.1, 1, 10, 100],
    'gamma': ['scale', 'auto']
}
```

2. Perform 5-fold cross-validation for each model to ensure robust evaluation

$$\text{CV Score} = \frac{1}{K}\sum_{k=1}^{K}\text{Score}_k \tag{5}$$

where K is the number of folds, and Score_k is the score obtained from the k-th fold.

3. Select the best hyperparameters based on accuracy, computed as (6)

$$\text{Accuracy} = \frac{\text{Number of Correct Predictions}}{\text{Total Predictions}} \tag{6}$$

The results of our tuning are summarized in Table 1. Hyperparameter tuning is crucial in maximizing the performance of SVM classifiers. By employing grid search, we effectively optimized the parameters, ensuring that our models are well suited to classify cataract and normal images effectively. Performance metrics observed during the evaluation reflect the improvements achieved through this optimization process. Future work could explore automated techniques such as Bayesian optimization to further enhance performance.

Table 1. Best parameters for each SVM type

SVM Type	Best Parameters
Linear SVM	$C = 0.01$
Polynomial SVM	$C = 1$, $degree = 3$, $\gamma =$ 'scale'
RBF SVM	$C = 10$, $\gamma =$ 'scale'

4 Implementation and Evaluation

After hyperparameter tuning, we implemented a mobile application to evaluate the performance of the proposed models on the test dataset. The evaluation was based on various metrics, including accuracy, precision, recall, F1-score, and the confusion matrix.

4.1 Implementation

A mobile application for cataract detection is developed to make the model accessible to users, as shown in Fig. 2. The application is developed in Flutter and the model is deployed via Flask to create an API for communication.

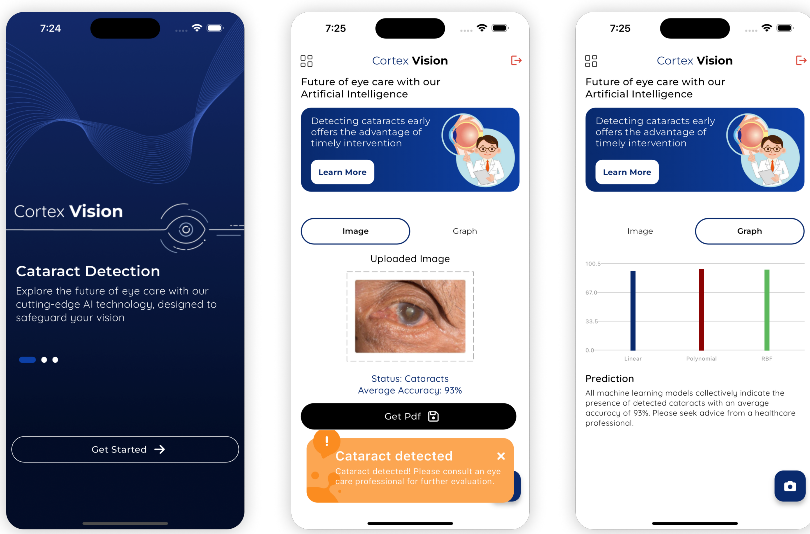

Fig. 2. Example images of the cataract detection process in the mobile application.

The application allows users to input images from two sources. The user can take a photo directly using the mobile camera or select an image from their mobile photo gallery.

Once the image is collected, it is sent to the Flask API, where the image undergoes preprocessing (grayscale conversion, resizing, normalization, and sharpening) before being fed into the trained machine learning model. The model processes the image and returns the result, which includes:

- **Detection Status**: Whether the image shows `cataract` or `normal`.
- **Accuracy**: The confidence of the model in its classification.

The result is displayed in the application interface, providing the user with the status and average accuracy of the prediction.

4.2 Performance Metrics

The key performance metrics used to evaluate the classifiers are defined below.

- **Accuracy**: The proportion of true results among the total number of cases examined.
$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \tag{7}$$
- **Precision**: The ratio of true positives to the sum of true positives and false positives.
$$\text{Precision} = \frac{TP}{TP + FP} \tag{8}$$
- **Recall (Sensitivity)**: The ratio of true positives to the sum of true positives and false negatives.
$$\text{Recall} = \frac{TP}{TP + FN} \tag{9}$$
- **F1 Score**: The harmonic mean of precision and recall.
$$\text{F1 Score} = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}} \tag{10}$$
- **Confusion Matrix**: A table used to describe the performance of a classification model, summarizing the counts of true positive (TP), true negative (TN), false positive (FP), and false negative (FN) predictions.

4.3 Results

The experimental results in terms of various performance metrics of three SVM models are summarized in Table 2. We also provide a detailed classification report for the best performing SVM model with the RBF kernel. The results indicate that the model achieved an overall accuracy of 95% for the SVM RBF kernel. Precision and recall are closely balanced, indicating the model's ability to correctly identify both cataract and normal classes.

Table 2. Comparison of classification performance across different models

SVM Model	Accuracy	Precision	Recall	F1 Score
Linear	0.90	0.86	0.93	0.90
Polynomial	0.93	0.89	0.97	0.93
RBF	0.95	0.95	0.95	0.95

	precision	recall	f1-score	support
0 (Normal)	0.95	0.95	0.95	60
1 (Cataract)	0.96	0.96	0.96	72
accuracy			0.95	132
macro avg	0.95	0.95	0.95	132
weighted avg	0.95	0.95	0.95	132

Table 3 displays the confusion matrix for the best-performing SVM model. The top-left cell (57) represents true positives for class 0 (normal). The bottom-right cell (69) represents true positives for class 1 (cataract). The off-diagonal cells represent misclassifications, with 3 false negatives and 3 false positives.

Table 3. Confusion matrix visualization

	0 (Normal)	**1 (Cataract)**
0 (Normal)	57	3
1 (Cataract)	3	69

5 Conclusion

In this study, three SVM models (Linear, Polynomial, and RBF) were evaluated for cataract detection, achieving accuracies of 90%, 93%, and 95%, respectively. The RBF SVM model demonstrated the best performance, with high precision (95%), recall (96%), and F1 score (95%), indicating its effectiveness in accurately identifying cataract cases. The polynomial SVM followed closely, excelling in sensitivity but with slightly lower precision. Linear SVM, while effective, showed the lowest accuracy and precision. Overall, the RBF SVM model is the most suitable for clinical applications in cataract detection, providing a balance between minimizing false positives and negatives. These findings support the potential of machine learning models in improving diagnostic accuracy in ophthalmology, paving the way for timely interventions and improved patient outcomes. Future work may explore further optimization of these models and the inclusion of additional features or datasets to improve performance.

Acknowledgment

The authors acknowledge Ho Chi Minh City University of Technology (HCMUT), VNU-HCM for supporting this study.

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