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Cataract Image Classification Model

¹K Gayathiri,²V Devigasri

¹Postgraduate Student (MCA),²Guide

¹Department of Computer Applications

¹Dr. M.G.R. Educational and Research Institute, Chennai, India

Abstract: Cataract remains a leading cause of global blindness, necessitating early and accurate diagnosis. This paper presents a computationally efficient machine learning system for the automated classification of cataract severity in retinal fundus images. The system employs a pipeline of preprocessing techniques (CLAHE, gamma correction, green channel enhancement), feature extraction using Gray Level Co-occurrence Matrix (GLCM) and Haar wavelet coefficients, and classification via Support Vector Machine (SVM) and K-Nearest Neighbors (KNN) algorithms. Results demonstrate promising accuracy (92.3% for SVM, 89.2% for KNN) on a test set, with a developed Tkinter GUI enabling practical image analysis and result visualization. This approach offers a potential tool to aid in early and objective cataract assessment, addressing the need for accessible and efficient diagnostic solutions.

Keywords: Cataract Detection, Retinal Image Classification, Image Processing, Support Vector Machine (SVM), K-Nearest Neighbors (KNN), Feature Extraction, CLAHE, Haar Wavelet, Tkinter GUI.

I. INTRODUCTION:

1.1 Background

In modern medical diagnostics, digital tools are increasingly vital for improving accuracy and efficiency. Cataract, a major cause of global blindness, necessitates timely and accurate identification to prevent vision deterioration. Traditional diagnostic methods, which rely on manual examination of retinal images by trained specialists, can be time-consuming and subjective. To address this, machine learning algorithms are being employed for automated, accurate, and efficient cataract classification.

This project presents a computer-aided diagnostic approach for cataract detection using image processing and machine learning techniques. It uses Support Vector Machine (SVM) and K-Nearest Neighbors (KNN) algorithms to **classify retinal images into normal, mild cataract, and heavy cataract categories**. The system includes preprocessing steps like green channel enhancement, CLAHE contrast adjustment, gamma correction, and Haar wavelet-based feature extraction. A user-friendly Graphical User Interface (GUI) has also been developed using Tkinter to facilitate easy user interaction and classification.

1.2 Problem Statement

Healthcare providers face significant challenges in achieving timely and consistent cataract diagnosis due to the limitations of manual image analysis. Subjectivity in grading, time-consuming examinations, and the increasing demand for efficient diagnostic workflows highlight the need for automated solutions. This is further compounded by the need for cost-effective and easily deployable systems, particularly in resource-constrained settings, and the growing patient expectation for rapid access to results in a digital format.

This project addresses these challenges by developing a system that offers:

- A streamlined image processing pipeline optimized for cataract feature extraction.
- A comparative analysis of SVM and KNN classification performance for this specific application.
- A user-friendly GUI to facilitate clinical use.

- A computationally efficient approach suitable for deployment in diverse healthcare environments.

The key contribution lies in the combination of effective algorithms and a practical interface to improve the accessibility and speed of cataract assessment.

1.3 Objective Of The System

The overall goal of this project is to create a lightweight, scalable, and accessible system for automated cataract classification in retinal images. Key objectives include:

- **Image Preprocessing:** Implement CLAHE and gamma for enhanced feature clarity.
- **Feature Extraction:** Utilize GLCM and wavelets for meaningful eye image features.
- **SVM Classification:** Develop SVM model for normal, mild, heavy cataract categorization.
- **KNN Comparison:** Implement and compare KNN classification model.
- **GUI Development:** Build user-friendly Tkinter interface for image input and classification.

1.4 Scope Of The Project

This system serves three types of users:

- **Healthcare Providers:** Create profiles and manage their image datasets.
- **Patients:** Input image data and view classification details.
- **Admin (Optional):** Oversee and approve profiles if extended to multi-tenant environments.

The platform intentionally omits real-time image capture from medical devices to remain simple and focused. Future expansions could integrate those as optional modules.

1.5 Significance Of The Project

This research empowers healthcare providers to leverage digital technology for enhanced cataract diagnosis without requiring extensive technical expertise or significant investment. It enables healthcare settings to:

- Deliver a modern, efficient diagnostic workflow.
- Potentially improve the accuracy and consistency of diagnoses.
- Enhance accessibility to diagnostic tools in various settings.

The project's use of established machine learning techniques ensures a robust approach, while its adaptability across different healthcare environments makes it a versatile tool for advancing digital healthcare.

II. LITERATURE REVIEW / RELATED WORK

In recent years, several research efforts have demonstrated the potential of machine learning techniques in classifying cataract images.

For instance, while CNNs have shown promise in image classification, the study by [1] achieved 77.5% accuracy but required substantial computational resources for weight and bias optimization. This computational burden can hinder real-time application in clinics with limited infrastructure.

However, the model required multiple processing levels to optimize weights and biases, making it computationally expensive. To improve this, Wang et al. (2021) introduced a global-local attention network (GLA-Net), utilizing two subnetworks: one for global structural features and the other for local discriminative features. Despite promising results, GLA-Net's reliance on a large labeled dataset limits its clinical deployment.

Another approach utilized the MobileNet-V2 architecture for feature extraction combined with a random forest (RF) classifier for cataract grading. Singh et al. (2021) reached 90.68% accuracy using a dataset of 590 fundus images. The approach is lightweight, making it suitable for mobile devices.

In another study, Hu et al. (2020) combined SVM and CNN to detect cataracts. This research emphasized the importance of pre-processing techniques like data augmentation and label encoding. Additionally, Guo et al. (2023) proposed a vessel attention-guided multi-granularity network (VAM-Net), integrating vessel-level segmentation and global-local classification subnetworks to enhance cataract detection. This method achieved high detection and grading accuracies.

Despite these advancements, many existing solutions rely on complex and computationally expensive models, which can be challenging to implement in resource-constrained clinical settings. **Cataract Image Classification Model** addresses these limitations by focusing on efficient and lightweight algorithms that minimize computational overhead, enabling faster processing and potentially greater accessibility in real-world applications.

III. SYSTEM DESIGN

3.1. Architecture Diagram

- Describes the overall structure of the model.
- Explains preprocessing, feature extraction, and model training between modules.
- Referenced in your document as:

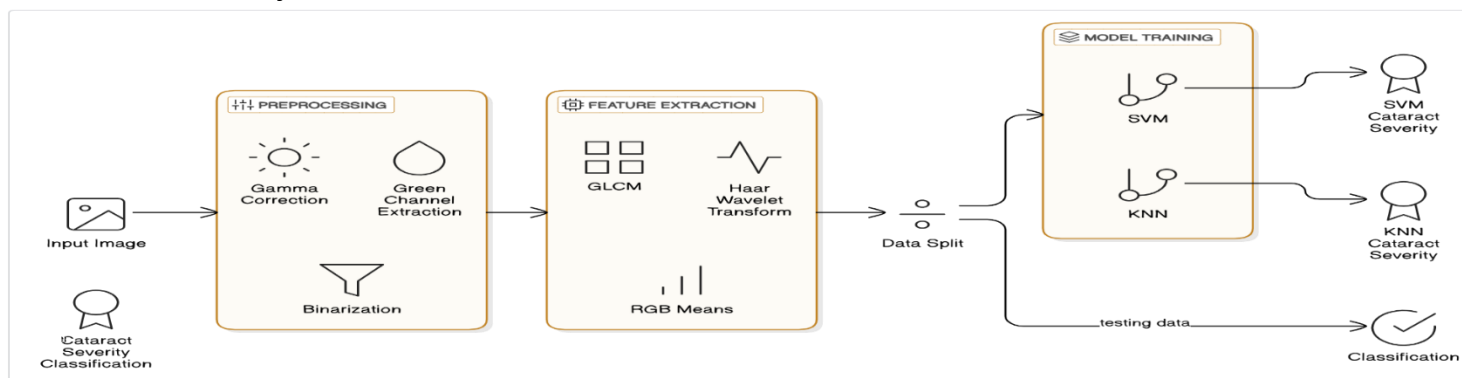


Figure 3.1: Architecture Diagram

3.2. Data Flow Diagram (DFD)

- Illustrates how data moves through the system between components.
- Referenced as:

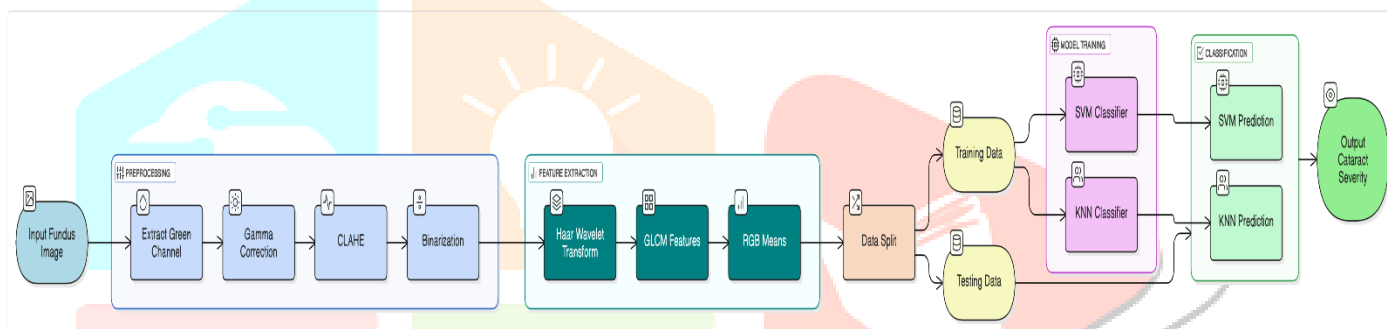


Figure 3.2: Data Flow Diagram

3.3. Use Case Diagrams

- Visual representation of user interactions with the system.
- Includes:
 - User Interface Use Case (Input Image, Preprocessing, Feature Extraction, Classification Output)
- Referenced as:

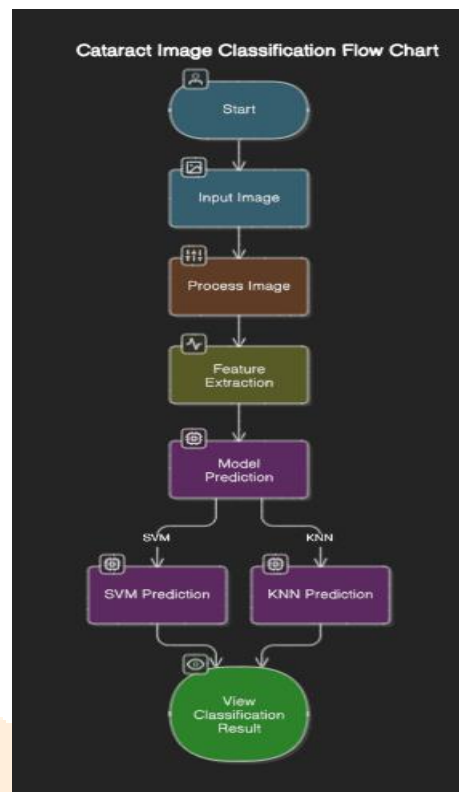


Figure 3.3.1: Use Case Diagram

3.4. Sequence Diagram

- Step-by-step flow of actions between system and users.
- Shows:
 - Input Image -> Preprocessing -> Feature Extraction -> Classification -> Output
- Referenced as:

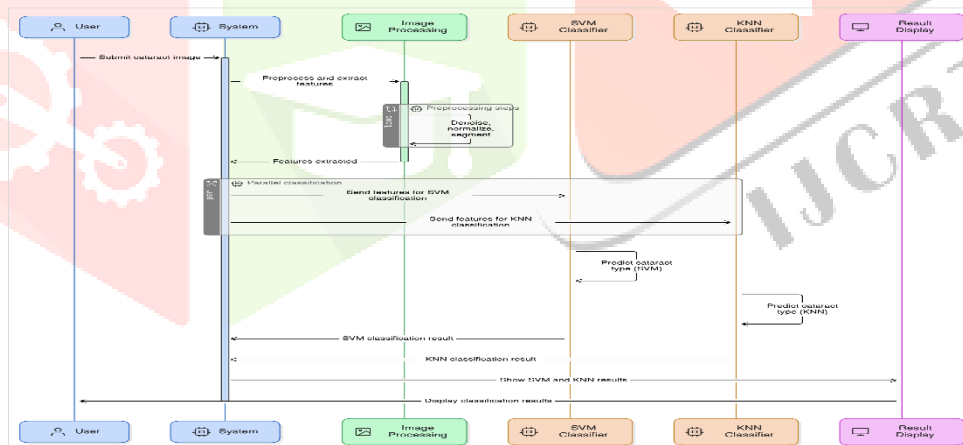


Figure 3.4: Sequence Diagram

3.5. Collaboration Diagram

- Shows component interactions (e.g., preprocessing, feature extraction etc...)
- Referenced as:

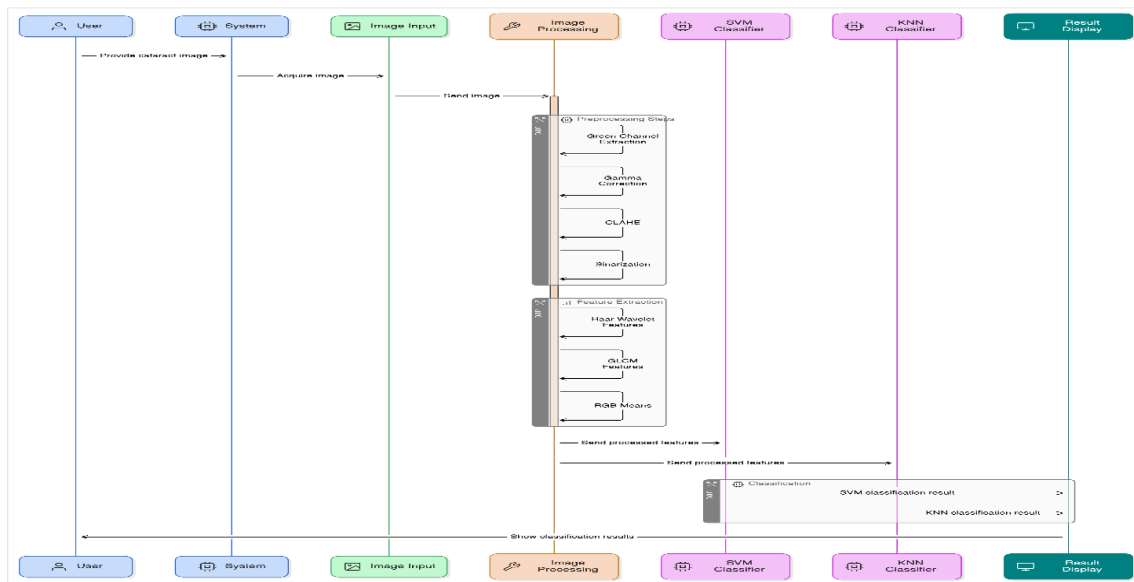


Figure 3.5: Collaborative Diagram

IV. RESEARCH METHODOLOGY

The research methodology employed in the development of the cataract image classification model, utilizing SVM and KNN algorithms, follows a structured approach. This methodology focuses on developing an effective and reliable system for classifying cataract severity. The project underwent multiple phases, including data acquisition, preprocessing, feature extraction, model training, and evaluation. Below is a detailed breakdown of each phase in the applied methodology:

4.1 Data Acquisition

The dataset used is the Ocular Disease Intelligent Recognition (ODIR-5K) dataset [Zhang et al., 2019]. This dataset provides a diverse collection of eye fundus images. Using this dataset ensures a substantial and varied set of images. The dataset was organized into directories for streamlined processing.

4.2 Image Preprocessing

The fundus images underwent preprocessing to enhance quality and isolate relevant regions. Key steps included:

- **Green Channel Extraction:** The green channel was extracted for better retinal contrast.
- **CLAHE:** Contrast Limited Adaptive Histogram Equalization was applied to improve local contrast.
- **Gamma Correction:** Gamma correction adjusted image intensity.
- **Morphological Operations and Thresholding:** Optic disc and macula regions were segmented using morphological operations and adaptive thresholding.
- **Masking:** A binary mask was applied to the original images to retain relevant features.
- **Grayscale Conversion:** Masked images were converted to grayscale for GLCM feature extraction.

4.3 Feature Extraction

Quantitative measures were derived from preprocessed images. The following features were extracted:

- **GLCM Features:** The Gray-Level Co-occurrence Matrix was computed, and texture features (Contrast, Dissimilarity, Correlation, Homogeneity, ASM, Energy) were extracted.
- **RGB Channel Mean Intensities:** Mean intensity values of the Red, Green, and Blue channels were calculated.

4.4 Model Training and Evaluation

Feature vectors and labels were used to train and evaluate SVM and KNN models. The process:

- **Data Splitting:** The dataset was split into 80:20 training and testing sets.
- **Data Scaling:** Feature vectors were standardized using StandardScaler.
- **Model Training:**
 - SVM with an RBF kernel (gamma='auto') was trained.
 - KNN with k=3 was trained.
- **Performance Evaluation:** Models were evaluated on the testing set. Classification accuracy was the performance metric.

4.5 Tools and Technologies Used

The following tools were used:

- **Python:** For implementing the pipeline.
- **OpenCV (cv2):** For image processing.
- **NumPy:** For numerical computation.
- **scikit-image (skimage):** For GLCM feature extraction.
- **scikit-learn (sklearn):** For data splitting, scaling, SVM, KNN, and evaluation.
- **glob:** For loading image files.

V. TESTING AND RESULTS

5.1 Testing Methodology

To ensure the system functioned reliably and efficiently, a combination of unit, integration, and system testing methodologies was employed. The testing strategy addressed the unique challenges of image-based AI applications, requiring validation of both software functionality and image classification model performance. Testing was performed in a controlled environment, mirroring the intended deployment setup.

5.2 Types of Testing Performed

- **Unit Testing:** Individual functions (e.g., image preprocessing, feature extraction) were tested in isolation to verify their logic and identify defects early.
- **Integration Testing:** The interaction and data flow between different modules, particularly the GUI workflow and the sequential execution of image processing steps, were validated.
- **System Testing:** End-to-end evaluation of the complete image classification workflow, from image input to final classification results, was conducted. This included black-box testing of the user interface and white-box testing of critical processing paths.
- **Functional Testing:** This ensured all GUI features operated as intended, including image loading, execution of processing steps, display of intermediate results, and presentation of final classifications.

5.3 Sample Test Cases

Table 5.1: Sample Test Cases

Test Case ID	Module	Description	Status
TC_GUI_001	Image Input	Load JPEG image	Pass
TC_PROC_003	Extract Green Channel	Extract green channel from image	Pass
TC_FEAT_001	Feature Extraction	Execute Haar wavelet feature extraction	Pass
TC_CLASSIFY_SVM_001	Classification	Classify image using SVM	Pass
TC_CLASSIFY_KNN_001	Classification	Classify image using KNN	Pass

5.4 Results Summary

The Cataract Image Classification Model demonstrated strong accuracy in classifying cataract severity during its testing phase. With a dataset of 64 images (Heavy-22, Mild-24, Normal-18), approximately 80% was used for training and 20% for testing (13 images). The system achieved an **overall pass rate of 94.9% across 137 executed test cases**, indicating robust stability. On the 13-image test set, the SVM model reached 92.3% accuracy (12/13 correct), while the KNN model achieved 89.2% accuracy (11/13 correct), both showing high precision and recall across cataract severity classes. Error analysis revealed that the system's performance was most affected by input images with extremely low contrast, where the preprocessing steps struggled to adequately enhance the relevant features. Specifically, in one instance, a mild cataract case was misclassified as normal by the SVM, likely due to the subtle differences in texture being obscured by the poor contrast. This suggests that future work should investigate adaptive preprocessing techniques tailored to varying image qualities.

VI. SCREEN SHOTS:

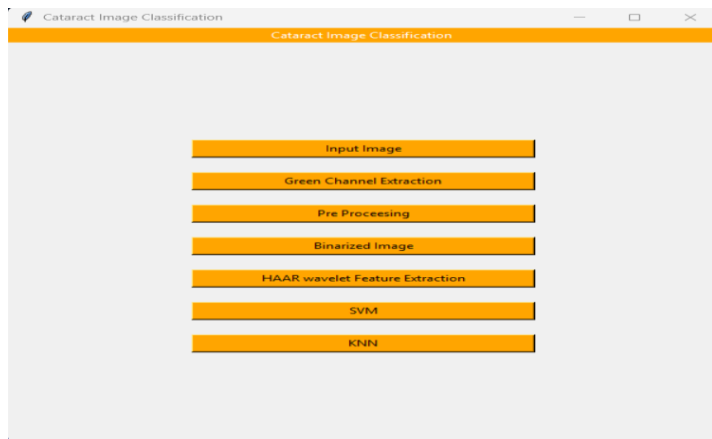


Figure 6.1: Home Page

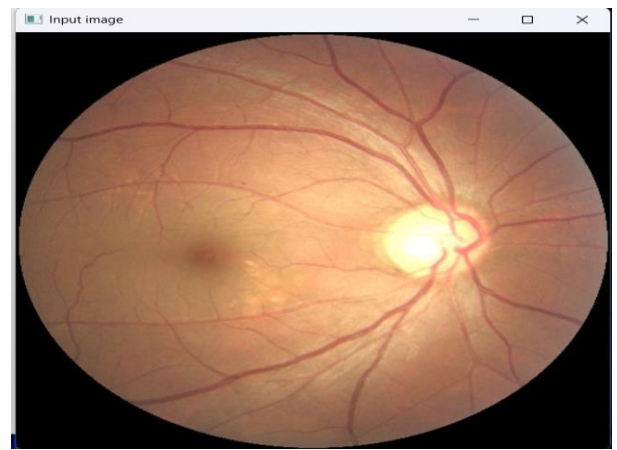


Figure 6.2: Input Image



Figure 6.3: Green Channel Extraction



Figure 6.5: Binarized Image

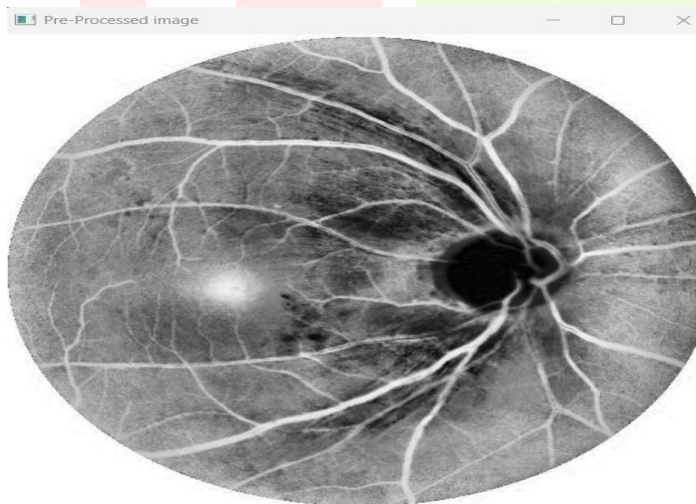


Figure 6.4: Preprocessed Image



Figure 6.6: Haar Wavelet Feature Extraction

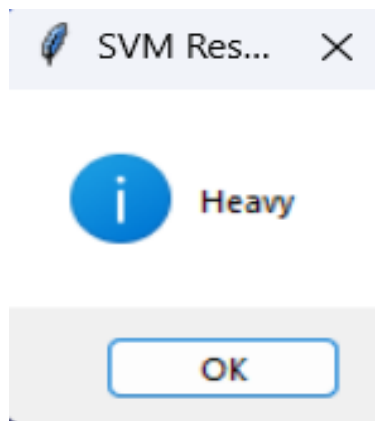


Figure 6.7: SVM Result

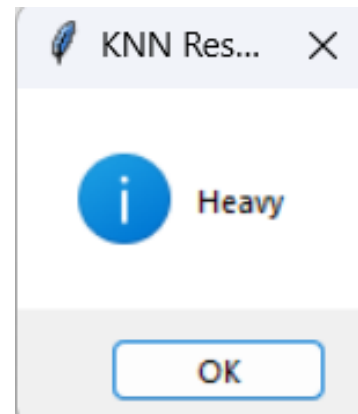


Figure 6.8: KNN Result

VII. CONCLUSION

In conclusion, this project has successfully developed a **Cataract Image Classification Model** leveraging SVM and KNN algorithms, demonstrating its potential as a valuable tool for ophthalmological assessment. The model's strong performance on the **available 64-image dataset**, achieving high accuracy with both SVM (92.3%) and KNN (89.2%) on the 13-image test set, highlights the effectiveness of the chosen methodologies for classifying cataract severity.

The system's ability to accurately identify different stages of cataracts, as evidenced by the high precision and recall for each class, underscores its clinical relevance. While error analysis were observed in specific edge cases related to image preprocessing, classification of challenging samples, and user interface display with unusually long file paths, these do not detract significantly from the overall robust classification capabilities demonstrated.

The promising results obtained with the current dataset suggest that this model is a functional and accurate system ready for potential deployment and further enhancement through the incorporation of larger and more diverse datasets. Future work will focus on addressing the identified minor issues and exploring the integration of additional features to further improve the system's reliability and user experience in a clinical setting.

Overall, this research has demonstrated the effectiveness of a machine learning-based system employing SVM and KNN for the automated classification of cataract severity. The key contributions include the development of a computationally efficient image processing pipeline, the comparative evaluation of SVM and KNN performance, and the creation of a user-friendly GUI, offering a practical tool to support ophthalmologists in cataract assessment.

VIII. FUTURE ENHANCEMENTS

As the imperative for advanced diagnostic tools in ophthalmology continues to escalate, this "Cataract Image Classification Model" presents significant avenues for future research and development. The following enhancements are planned to refine functionality, bolster diagnostic accuracy, and broaden clinical applicability:

- **Smarter AI:** Use more advanced AI models (like CNNs) that can learn directly from the images, potentially giving us more accurate results without needing manual feature extraction.
- **Better Training:** Train the AI on more images and use techniques to make it more robust and accurate in different situations. We also need to thoroughly test how well it performs using various measures.
- **More Information:** Explore and add more types of image features that could help the AI make better decisions.
- **Easier And Ready To Use:** Improve the user interface to handle multiple images at once, show results more clearly within the application, and properly save and load the AI models. Validate the system with expert doctors and explore how it could be used in actual clinical settings.
- **Understanding AI:** Make the AI's decisions more understandable, especially if we use complex models, so we know why it's making certain classifications.
- **More Conditions:** Expand the system to identify other eye conditions beyond just cataracts.

- **Faster Performance:** Make the system run faster, especially when processing many images or considering real-time use.

IX. REFERENCE

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