Enhancing Cataract Detection Using Machine Learning Algorithms

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Abstract: Cataracts are a common eye ailment that can cause visual impairment if not diagnosed and treated early. Cataract detection using machine learning, specifically decision tree classifiers, offers a promising approach for the early identification of cataracts in human eyes. By analyzing features extracted from eye images, the study achieved high accuracy in predicting cataract presence, providing a reliable method for timely intervention and treatment to preserve vision health. Conventional methods of diagnosing cataracts frequently depend on the subjective assessments of ophthalmologists and tests of visual acuity. These methods, however, can be inconsistent and might miss cataracts that are still in the early stages. By utilizing large databases of ocular images and computer vision techniques, machine learning provides a workable solution for cataract detection.

Keywords: Computer vision, machine learning, decision tree, cataract detection, algorithms

1. Introduction

Cataracts are a common and curable cause of vision impairment that affects millions of people worldwide. It results in hazy and fuzzy vision, which may eventually cause partial or total blindness [1–13]. Recent technological developments in cataract surgery have made it more crucial than ever to anticipate postoperative refractive power [7, 14]. Cataracts, which are defined as the clouding of the natural lens of the eye, are among the most common and curable causes of visual impairment in the world, affecting millions of people of all ages. A cataract may develop in one or both of the eyes [15]. Early cataract detection is essential for timely care and the best possible outcomes for patients. To help doctors diagnose cataracts more quickly and reliably, researchers have created a vast array of cutting-edge conventional machine learning techniques to classify and grade cataract levels in recent years [5]. Conventional methods of diagnosing cataracts, which rely on subjective evaluations by ophthalmologists and common visual acuity tests, are generally not effective in identifying cataracts in their early stages. By 2020, there are expected to be 75 million blind individuals [8, 9].

At the moment, ophthalmologists use a slit-lamp microscope to diagnose cataracts directly. Alternatively, physicians grade cataracts by checking the patient's image to a set of standard reference photos to determine cataract [6]. This shortcoming drives the quest for novel approaches to improve cataract diagnosis. We look into the realm of Machine Learning (ML) and highlight the decision tree method as a workable solution. Healthcare has seen a notable increase in the use of machine learning, a field at the intersection of statistics and computer science that holds great promise for revolutionary advances in diagnosis, prognosis, and treatment planning. With its ability to provide more precise, effective, and objective methods for cataract identification, machine learning has become a powerful ally in the field of ophthalmology. The goal is to create a reliable cataract detection system utilizing decision tree algorithms' capabilities within the larger context of machine learning. This method aims to improve diagnosis accuracy, reduce subjectivity associated with human judgments, and automate the process to overcome the shortcomings of traditional diagnostic procedures. By doing this, we want to improve the effectiveness and accessibility of cataract diagnosis, especially in areas where access to specialized eye care may be limited. Our research is based on the decision tree method, which is renowned for its ease of use, interpretability, and capacity to handle both numerical and category data. Decision trees are an excellent substitute for other methods for identifying the presence and degree of cataracts in ocular images since they provide a methodical framework for classification difficulties.

The main issue is the necessity for fast and effective cataract screening to find early diagnosis that would exclude vision loss possibility in future, while upgrading patient's survival. Conventional way of cataract screening usually involves manual assessment by the clinicians which is time-consuming, subjective and human error prone. By leveraging machine learning techniques, specifically decision tree classifiers, we aim to address this challenge by developing a reliable and automated system that can analyze eye images to predict the chances of cataract presence with high precision and sensitivity. This research seeks to bridge the gap between conventional diagnostic approaches and advanced technology to enhance the efficiency and effectiveness of cataract detection processes, ultimately benefiting individuals at risk of vision loss due to cataracts.

The scope of this study on cataract detection using machine learning with decision tree classifiers encompasses the development of a predictive model to assess the likelihood of cataract presence in human eyes. By leveraging image analysis techniques and machine learning algorithms, we aim to enhance early detection capabilities, potentially leading to improved diagnosis and treatment outcomes for individuals at risk of cataracts.

The objective of this research is to investigate the effectiveness of decision tree classifiers in predicting the chances of having cataracts based on features extracted from eye images. By training and evaluating these models on a comprehensive dataset, we aim to achieve high accuracy, in cataract detection, ultimately contributing to the advancement of automated screening tools for eye health assessment.

Our effort intends to demonstrate how decision trees, and consequently, machine learning, may significantly improve cataract detection through an extensive analysis of ocular data, feature selection, and model training. This is a detailed explanation of the parts and operations of a decision tree:

The decision tree is formed of nodes, with the initial node dubbed the "root node." Each node represents a feature or property from the dataset and serves as a decision point.

At each node, a decision tree algorithm assesses several splitting criteria to determine how to divide the data into subsets. The purpose is to construct splits that result in subsets that are as homogeneous as feasible regarding the target variable (in classification, this is often the class label).

From each node, branches radiate, reflecting the possible values or ranges of values for the specified characteristic. These branches lead to child nodes.

The child nodes represent the subsets of data based on attribute values. As the splitting process occurs recursively until a halting condition. Stopping criterion are only for, e.g., maximum depth of the tree or minimum #samples required to split (similar fitting parameters).

At the bottom of each tree branch are leaf nodes, which is where no more splitting can be done.

Each leaf node typically guide to a predicted class label in a classification job. In regression tasks, leaf nodes may contain anticipated numerical values.

The decision tree is intrinsically interpretable since it creates explicit decision rules depending on the splits. These rules can be easily comprehended, making decision trees a handy tool for explaining the reasoning behind a prediction.

For classification problems, entropy and information gain are two measures often used by decision trees to evaluate the quality of splits. Entropy measures the impurity or disorder of a collection and information gain computes how much entropy has decreased by choosing that split. Goal is to maximize information gain and minimize entropy at each node.

The Gini impurity: It is another metric that used in classification decision tree, and it considers how likely a randomly chosen data point from the split (subset) you generate by this threshold to be misclassified. It tries to reduce the Gini impurity.

Decision trees may create an overfit on the data, i.e., they record noise in training set. The tree is pruned to cut branches and simplify it without losing its predictive power. Thus, ensuring the model does not learn noise in data helping it to generalize better on unseen data.

ETS is the building blocks for ensemble methods like Random Forest and Gradient Boosting where a few 10's to 1000's of single decision trees band together in order increase predictions accuracy and robustness.

Cataracts are a common eye condition that affects millions of people globally to different extents. This sickness clouds the lens of the eye resulting in visible impairment, and if left untreated may lead to blindness. Cataracts are more common with ageing, and the incidence of cataracts is rising in many parts of the world as populations get older. This is not restricted to old age but can also happen in younger individuals due genetic predisposition, trauma or prolonged exposure to certain environmental factors.

For successful therapy to be implemented and serious vision loss to be avoided, prompt detection and diagnosis are essential. Early intervention frequently results in surgical operations that restore vision, improving the affected person's quality of life. However, the conventional approaches to diagnosing and detecting cataracts mostly depend on the subjective evaluations made by ophthalmologists during standard eye exams. These evaluations frequently involve slit-lamp analyses and visual acuity tests, which are useful but heavily reliant on the competence and expertise of the physician doing them. As a result, it is simple to ignore early-stage cataracts, which might not yet be symptomatic.

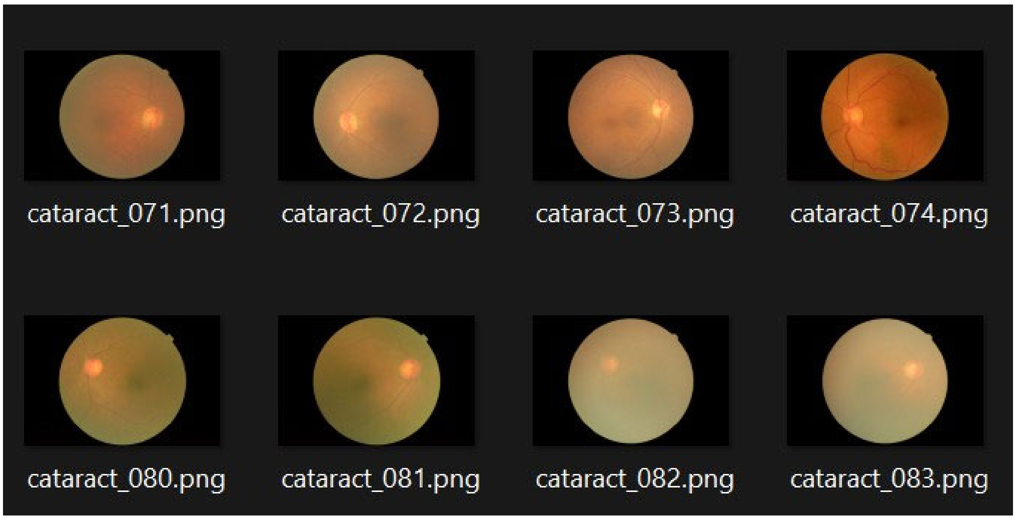

Fig. 1. Labeled cataract eye images.

The issue at hand is the requirement for a cataract detection technique that is more precise, effective, and widely available. The current diagnostic procedures have several serious flaws. First of all, a diagnosis that depends too much on subjective assessments may be erroneous. Second, it can take a while, which could cause delays in the identification and treatment of cataracts. Machine Learning (ML) appears to be very efficient approaches to solving this issue [16, 17]. By automating the procedure, improving diagnostic precision, and guaranteeing prompt action, ML holds the potential to completely transform cataract diagnosis. Large-scale medical imaging data may be used to train machine learning algorithms to identify early signs of cataract development and subtle patterns that may go unnoticed by human observers. By deploying portable and reasonably priced screening technologies, this automation can minimize detection delays, greatly reduce the variability in diagnoses, and expand the accessibility of diagnostic services to disadvantaged locations. Fig. 1 shows the labeled cataract eye images.

2. Literature Review

Cataract is one of the most prevalent ophthalmic disorders worldwide. It creates a partial or complete opacity of the crystalline lens that origins an optical diffraction and, consequently, reduced visibility due to defocusing [10]. Review of the methods for cataract identification In this context here begins an overview of cataract detection using machine learning and computer vision techniques. Certain traditional image processing strategies are then implemented to construct a model which classifies the photos whether it contains cataracts or not using texture, color and shape information in images.

Conversely, machine learning techniques don't require feature extraction; they may be trained to identify cataracts straight from photos. The authors of this research conclude that for the detection of cataracts, machine learning techniques are typically more accurate than conventional image processing techniques. So that nuts and bolts type stuff gets more expensive computationally, for training machine learning techniques they do note sometimes it is cost prohibitive. The parameters treated to calculate the accuracy were True Positive (TP), True Negative (TN) [13, 16]; False Positive (FP); and False Negative (FN) used algorithms. Conventional machine learning methodology consist of the following parts.

- Density histogram method
- Bag-of-Features (BOF) method
- Gabor wavelet transform
- Gray Level Co-Occurrence Matrix (GLCM)
- Haar wavelet transform
- Support Vector Machine (SVM)
- Density-based statistics method

The work of Hasan *et al.* [1] focuses on the use of ensemble machine learning to detect cataracts from retinal fundus images. The paper discusses the urgent need for automated techniques for cataract detection so that early diagnosis and treatment planning can be facilitated. From retinal fundus images, the authors suggest a unique method for accurately identifying cataracts by utilizing ensemble machine learning algorithms. The research assesses the effectiveness of the suggested strategy using empirical analysis and testing, providing insights into its possible uses in medical imaging and healthcare. Fig. 2 shows labeled normal eye images.

Chauhan *et al*. [2] emphasized using a collection of transfer learning models to identify cataracts from eye fundus images. Given that cataracts are a common source of vision impairment, automated detection techniques are critical to prompt diagnosis and treatment. To enhance performance on a particular task, the study suggests a novel strategy utilizing transfer learning, a method that transfers knowledge from pre-trained models. The authors want to improve cataract detection from eye fundus pictures in terms of accuracy and reliability by using an ensemble of transfer learning models. Through the evaluation of the suggested approach, the study advances healthcare technology and medical imaging, perhaps leading to better patient outcomes in ophthalmic illnesses. The paper advances medical diagnosis and healthcare technologies by discussing their findings and providing.

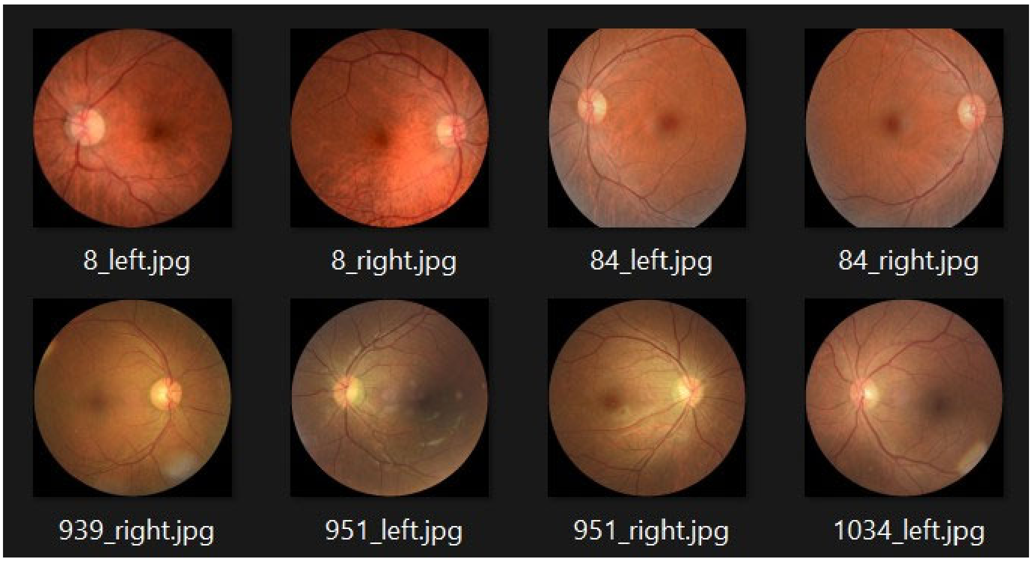

Fig. 2. Labeled normal eye images.

Harshini *et al.* [3] focused on applying a modified vote classifier model to a machine-learning strategy for different types of eye illnesses. Because eye illnesses are major public health concerns, automated diagnostic methods are essential for early identification and treatment. The article presents a novel modified voting classifier model that enhances the resilience and accuracy of diagnosing eye diseases by combining multiple machine learning algorithms. The authors present the effectiveness of their approach in precisely diagnosing and categorizing various forms of eye illnesses through empirical examination and validation. The study offers potential strategies for enhancing patient outcomes in ophthalmology and advances medical diagnosis and healthcare technology by providing their findings.

Shetty *et al.* [4] explored the use of machine learning models in the identification of cataracts in the eye. Given that cataracts are frequently the cause of vision impairment, automated detection techniques are essential for prompt diagnosis and treatment. This chapter explores the application of machine learning methods for the precise detection of cataracts in ocular pictures. The authors' presentation of their research findings advances medical imaging technology and presents viable ways to enhance ophthalmic patient care.

In a study by Zhang *et al.* [5], advancements in machine-learning techniques for cataract grading and classification were comprehensively reviewed. You will find the writers discussing all varieties of ocular imaging modalities that can be used and diverse machine-learning algorithms like SVM, Regression, Backpropagation, Linear Discriminant Analysis LDA with AdaBoost Work outspreading Protocol such as K-Nearest Neighbors (KNN) are applied for the purpose of annotation and grading of cataracts. The authors believe that machine learning could dramatically change the way current approach to cataract diagnosis and management.

They make the point that machine learning algorithms are capable of diagnosing and classifying cataracts with an accuracy close to, if not better than, that of human specialists. applied algorithms. When used in conjunction with a low-power microscope, the fundus camera is a special kind of camera that is often controlled by ophthalmologists or other professionals to take fundus images. An extremely specialized type of eye imaging called a fundus picture is capable of capturing both the internal structures of the eye and its outer lining.

Bourne *et al.* [14] conducted a thorough assessment and meta-analysis of the prevalence of blindness and impairments to close and distance vision worldwide, including its magnitude, temporal trends, and projections. The primary cause of blindness globally, according to scientists, is cataracts, which account for 35 of cases. The authors also discovered that aging populations and other variables are contributing to an increase in the prevalence of cataracts. It is projected that by 2020, there will be 588 million cataract sufferers globally. This article emphasizes the need to treat and diagnose cataracts because they are a leading avoidable cause of blindness. Each model which were run with four chains for 1000 iterations independently, with 500 warm-up iterations.

Pavan *et al.* [15] presented a machine-learning technique for automatically detecting cataracts in optical images. The technique is predicated on the Histogram of Oriented Gradients (HOG) feature descriptor, a popular feature descriptor for tasks involving object detection and image classification. Using a collection of optical pictures from individuals with and without cataracts. They discovered that the cataract detection accuracy of their approach was 98.5. The promise of machine learning for automatic cataract identification is demonstrated in this work. The effectiveness and precision of cataract diagnosis could be increased with the use of automated cataract detection technologies. There are two main advantages of SVMs. First, No Complex Parameter Tuning Needed

Yamauchi *et al.* [16], An automatic machine-learning technique was implied in order to predict refraction, a refraction measures the eye's ability to focus light. However, refraction is necessary for the correction of refractive error and, therefore, to achieve an accurate eye prescription in cataract surgery. In their publication, the researchers used a cataract surgery clinic dataset of patient data and established a machine-learning model that could predict refraction after cataract surgery

The model was able to predict refraction very accurately, the average error being only 0.2 diopters Improved refractive predictability may translate in to enhanced outcomes of cataract surgery for patients. Average absolute refractive error (in D) and the percentage of objects with an absolute refraction errors < 0.5 D were evaluated for. The full lens nucleus is analyzed in the clinical diagnosis, while all of these studies only utilized features on the visual axis [11]

Li *et al.* [12] described an automatic nuclear cataract diagnosis system. In our system, more significant features are extracted when compared to previous research. The suggested automated diagnosis system has been verified through the use of over 5,000 clinical photographs and the corresponding clinical grading outcomes.

Ghai *et al.*'s [17] synthesizes machine learning and deep learning techniques with signal and image processing applications, offering a broad view of modern computational techniques in engineering and applied sciences.

Ruzicki *et al.* [18] studied machine learning for assessing the proficiency of cataract surgeons using tool detection. Using sophisticated computer vision, the study aims to enable automated identification and tracking of surgical instruments during operations that can help generate unbiased assessments surgery performance. It represents a new possible way of training and assessment in everyday Ophthalmology practice that could provides objectiveness and reliability. This is a major step towards the incorporation of machine learning into medical training, as shown in this study that may be applied for next generation data driven evaluation systems within surgical education.

Son *et al.* [19] present our process for building and testing a deep learning classifier for cataract detection as well as rating using slit-lamp or retro-illumination photographs. The model is designed to help automate the diagnosis and grading of cataracts, something that could one day decrease dependence on manual human clinician evaluations. In this paper, the researchers trained their model on a large corpus of clinical images and showed that it can be used to accurately predict cataract presence and severity. The policy emphasises artificial intelligence as an approach to augment diagnostic efficiency and consistency in ophthalmology, especially with resource constraints that may limit specialist access.

Lahari *et al.* [20] discover CSDNediscoveredp learning framework intended to improve the identification of cataract stages. In this image-based cataract study, the use of a powerful neural network structure is proposed that targets to successfully process clinical photo images and carry out precise classification of how serious or not an eye has cataracts. This should be validated against existing diagnostic methods in order to demonstrate the model has signficatly improved precision and reliability. Our study also emphasizes the potential capacity of deep learning technologies to facilitate clinical diagnostics and deliver affordable, high evidentiary quality solutions for providing scalable eye care especially in detecting cataract progression and assisting with timely medical intervention.

A study on cataract detection with the utilization of deep learning has been presented by Panda and Panjwani [21]. The study investigates the construction of an automatic system to detect cataracts in eye images. The deep learning model, designed to present a possible reliable and practical methodology versus traditional diagnostic approaches for faster diagnosis with accuracy. A burgeoning body of literature is using artificial intelligence to advance diagnostic ophthalmology and these technologies are increasingly showing promise in enhancing clinical practice and improving patient outcomes.

The article by Patil *et al.* [22] situates itself within a growing body of research that applies deep learning and convolutional neural networks to the early detection of melanoma skin cancer—a type of cancer responsible for a high proportion of skin-cancer-related deaths due to late diagnosis. Traditional diagnosis methods, such as manual visual inspection and biopsy, are often subjective and time-consuming, leading researchers to explore automated image-based systems that can improve efficiency and accuracy.

Patil *et el.* [23] presents a deep-learning-based object detection method designed to work reliably in challenging environmental conditions such as fog, rain, and low visibility. The authors build on the popular YOLOv4 object detection framework by incorporating hybrid feature enhancement techniques that improve the network's ability to extract and fuse meaningful features from degraded inputs.

3. Proposed Work

The proposed work involves implementing a cataract detection system using decision tree classifiers and machine learning techniques.

The project will begin with the collection of a diverse dataset of eye images, including both cataract and non-cataract cases, to train and test the decision tree classifiers. Preprocessing steps will be applied to extract relevant features such as opacity levels, texture patterns, and structural irregularities from the images. The decision tree classifiers will then be trained on this feature-rich dataset to learn patterns indicative of cataract presence. Evaluation metrics such as accuracy, specificity and sensitivity will be used to get the performance of the models in predicting cataract presence in human eyes.

The steps involved in Cataract Detection are listed as follows:

a) Data Collection: Gather a dataset of eye images with labels indicating cataracts presence.

b) Preprocessing: Extract features like opacity levels, texture patterns, and structural irregularities from the images.

c) Training: Train decision tree classifiers on the feature-rich dataset to learn patterns indicative of cataract presence.

d) Testing: Evaluate the performance of the models using metrics like accuracy, sensitivity, specificity and sensitivity,.

e) Labeling and Balance: We double-checked that every image was correctly labeled (e.g., cataract or normal). If some eye conditions had more images than others, we tried to balance things out so the model could learn from all classes.

f) Data Exploration: We took a good look at our dataset to understand it better. We used graphs and charts to see things like how big the images were, their colors, and other details. We made sure we had a good mix of all eye conditions in our dataset.

3.1. Implementation

The simulation environment for the cataract detection project is centered around the utilization of a machine learning framework implemented in Python, with a primary focus on the scikit-learn library for Decision Tree algorithm implementation. The project maintains transparency and interpretability as core objectives. The dataset, sourced from Kaggle, undergoes preprocessing steps such as image resizing and format conversion. The training process involves optimizing hyperparameters, ensuring diverse data, and striving for a well-generalized model. Jupyter Notebooks or a similar environment facilitates code development and experimentation. The flowchart for the cataract detection system is shown in Fig. 3.

a) Data Collection and Preprocessing: Read and preprocess images from cataract and normal folders. For each image in the cataract folder, preprocess the image and append features and labels to lists. Repeat the process for images in the normal folder. Convert features and labels to NumPy arrays for further processing.

b) Model Training: Split the dataset into training and testing sets. Standardize the data by scaling it. Create and train a Decision Tree classifier on the scaled data. Save the trained classifier to a model file for future use. Evaluate the classifier on the test set to assess its performance. Display accuracy, confusion matrix, and classification report for evaluation.

c) Model Evaluation: Evaluate the classifier on the test set to assess its performance. Calculate accuracy, and confusion matrix, and generate a classification report for evaluation metrics.

d) Prediction and Deployment: Load the trained classifier from the saved model file. Predict cataract likelihood for new eye images using the loaded classifier. Display the predicted probability of cataract presence in the new image.

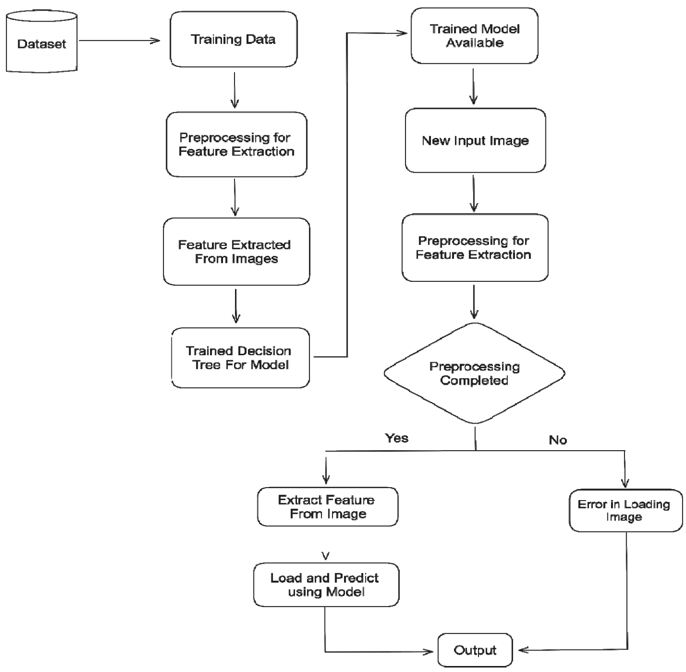

Fig. 3. Flowchart for cataract detection system.

The pseudocode for the cataract detection system (Fig. 4) is explained as follows:

Pseudocode:
Convert features and labels to NumPy arrays
X-train, X-test, y-train, y-test = split-dataset(features, labels) Standardize the data
X-train-scaled, X-test-scaled = scale-data(X-train, X-test)
Create and train a Decision Tree classifier classifier = create-decision-tree-classifier()
train-classifier(classifier, X-train-scaled, y-train)
Save the trained classifier to a model file
save-model(classifier, 'decision-tree-model.pkl')
Evaluate the classifier on the test set
y-pred = predict-labels(classifier, X-test-scaled)
Display accuracy, confusion matrix, and classification report display-evaluation-results(y-test, y-pred)
Load the trained classifier from the model file loaded-classifier = load-model('decision- tree-model.pkl')

```
# Split the dataset into training and test sets
X_train, X_test, y_train, y_test = train_test_split(features, labels, test_size=0.2, random_state=42)

# Flatten the image data (convert to 1D arrays)
X_train = np.array(X_train).reshape(len(X_train), -1)
X_test = np.array(X_test).reshape(len(X_test), -1)

# Create a decision tree classifier
clf = DecisionTreeClassifier()

# Train the classifier on the training set
clf.fit(X_train, y_train)

# Predict the labels for the test set
y_pred = clf.predict(X_test)

# Calculate the accuracy of the classifier
accuracy = accuracy_score(y_test, y_pred)
print('Accuracy:', accuracy)

# Print the confusion matrix
confusion_matrix_result = confusion_matrix(y_test, y_pred)
print('Confusion matrix:')
print(confusion_matrix_result)

# Print the classification report
classification_report_result = classification_report(y_test, y_pred)
print('Classification report:')
print(classification_report_result)
```

Fig. 4. Pseudo code for cataract detection system.

4. Results and Discussion

To assess the effectiveness of our cataract detection system, we performed rigorous testing using three different approaches:

Based on the characteristics we retrieved during the data preparation stage, the model was trained to differentiate between normal and cataract-affected eyes to predict the chance of the disease.

4.1. Decision Tree Model Accuracy

In our first accuracy test, we measured the performance of the Decision Tree model on a separate dataset as shown in Table 1 This dataset contained images of eyes, and we compared the model's predictions against ground truth labels and features of the eyes.

The accuracy of the Decision Tree model on this test data provided us with a baseline for evaluating its performance.

Here the accuracy we achieved was 82.29%.

Table 1. Decision Tree Model Accuracy

Class	Precision	Recall	F1-Score	Support
0	0.84	0.81	0.83	210
1	0.82	0.85	0.83	213
Average/Total	0.83		0.83	423
Macro avg	0.83	0.83	0.83	423
Weighted avg	0.83	0.83	0.83	423

Note: (0-Non-Cataract , 1-Cataract)

4.2. Decision Tree with Bagging

To enhance the robustness and accuracy of our model, we implemented a Decision Tree with bagging, a technique that combines multiple Decision Trees to reduce overfitting.

We evaluated its performance using the same test dataset to measure any improvements in the accuracy of the system after bagging.

Using bagging, we get a jump in accuracy to 89.62% of our model.

As a result, we get an increase of 7.33% rather than simply using a decision tree in the system which is very efficient for a Machine Learning model, thus bagging an increase in accuracy as shown in Table 2.

Table 2. Decision Tree Model Accuracy Using Bagging

Class	Precision	Recall	F1-Score	Support
0	0.84	0.97	0.9	103
1	0.91	0.83	0.89	109
Average/Total			0.9	212
Macro avg	0.9	0.9	0.9	212
Weighted avg	0.91	0.9	0.9	212

Note: (0-Non-Cataract , 1-Cataract)

4.3. Decision Tree with Scaling

Additionally, we incorporated feature scaling into the Decision Tree model to ensure that different features contributed equally to the decision-making process as shown in Table 3.

We assessed the accuracy of this scaled Decision Tree model on the test data.

Table 3. Decision Tree Model Accuracy Using Scaler

Class	Precision	Recall	F1-Score	Support
0	0.84	0.98	0.91	103
1	0.98	0.83	0.9	109
Average/Total			0.9	212
Macro avg	0.91	0.9	0.9	212
Weighted avg	0.91	0.9	0.9	212

Note: (0-Non-Cataract , 1-Cataract)

The accuracy comparison between decision tree, decision tree with bagging, and decision tree with scaling is shown in Table 4.

Table 4. Accuracy Comparison

Method	Accuracy (%)
Decision Tree	82.97
Decision Tree with Bagging	89.62
Decision tree with Scaler	90.09

5. Conclusion

This study presents an interpretable machine learning–based framework for automated cataract detection using Decision Tree classifiers and ensemble learning techniques. The proposed system effectively reduces diagnostic subjectivity while maintaining low computational complexity and high transparency. Experimental results demonstrate that bagging and feature scaling significantly enhance classification performance. The findings suggest that the proposed approach can serve as a practical screening tool in tele-ophthalmology and resource-limited healthcare environments, supporting early cataract detection and improved patient outcomes.

6. Future Work

Future research work will focus on integrating deep learning techniques such as Convolutional Neural Networks for automated feature learning. Hybrid models combining CNN-based feature extraction with interpretable classifiers will be explored. Additionally, clinical validation using real patient data and deployment on edge or mobile platforms for real-time cataract screening will be considered.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

Shankar M. Patil conceived the study, supervised the research, and finalized the manuscript. Soheb Dalvi and Satyaprakash Tiwari performed data collection, preprocessing, designed the methodology, and model implementation, assisted in manuscript writing, formatting, and reference management. Anish Rane and Avadhut Mulaye conducted experiments, analyzed results, and contributed to the results section, supported literature review, system implementation, and figure preparation. All authors had approved the final version.

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