

A Comparative Analysis of Machine Learning Techniques for Cataract Detection and Severity Prediction

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Article History

Received: 10.04.2025

Revised: 14.05.2025

Accepted: 05.06.2025

Published: 08.07.2025

Abstract: Cataracts are a leading cause of vision impairment worldwide, and early detection is crucial for effective treatment. This study explores how machine learning techniques can help predict both the presence and severity of cataracts by analyzing medical images such as fundus photographs, slit-lamp photos, and ultrasound scans. While many AI models have been developed for this purpose, there hasn't been enough direct comparison of their effectiveness across different types of data. To fill this gap, we evaluate several popular machine learning algorithms including deep learning models, support vector machines, and random forests using publicly available datasets. Our analysis also considers important factors like image quality and cataract type to ensure a realistic assessment. By measuring performance through accuracy, sensitivity, specificity, precision, and F1-score, this research aims to identify the most reliable and robust approaches. Ultimately, the findings will contribute to the advancement of AI-driven tools that can assist doctors in diagnosing cataracts more efficiently and accurately, improving patient outcomes.

Keywords: Cataract Detection, Machine Learning, Support Vector Machines (SVM) and Classification techniques.

INTRODUCTION

Cataracts are one of the leading causes of blindness worldwide. They occur when the eye's natural lens becomes cloudy, causing blurred vision that can eventually lead to permanent vision loss if not treated. Currently, the most common way to diagnose cataracts involves a clinical examination by ophthalmologists using a slit-lamp microscope, along with grading systems like the Lens Opacities Classification System III (LOCS III). While this approach is effective, it has some important drawbacks. First, it relies heavily on the expertise of trained specialists, which can be a significant barrier in regions where such professionals are in short supply. Second, because the grading process is subjective, there can be differences in diagnosis between examiners, which may affect patient care. Given the rising number of cataract cases worldwide and these challenges, there is a clear need for new diagnostic methods that are objective, reliable, and more widely accessible (Goh et al., 2020, p. 1,4).

Recent advances in artificial intelligence, especially in machine learning, offer exciting new possibilities to overcome some of the challenges in cataract diagnosis. Machine learning algorithms have the ability to learn and recognize complex patterns from large amounts of data, and they've already shown great promise in analyzing medical images for a variety of eye diseases. Several studies have applied these techniques to cataract detection and grading using different types of images, including slit-lamp photographs, fundus images, and ultrasound scans. While these studies have yielded encouraging results, there's still a lack of thorough comparison between the different machine learning methods and how well they perform across various datasets (Goh et al., 2020, ; Yadav & Yadav, 2023).

This research aims to fill that gap by providing a comprehensive comparison of several machine learning classification techniques for predicting both the presence and severity of cataracts. We will review existing studies on machine learning approaches for cataract detection, focusing on the algorithms used, the datasets involved, and the performance measures reported. Additionally, we will test selected algorithms on a diverse range of publicly available datasets, taking into account important factors such as image quality, cataract type, and severity level. Through this detailed analysis, we hope to identify which machine learning methods work best for accurate and reliable cataract prediction. Ultimately, this work aims to support the creation of AI-powered diagnostic tools that are not only effective but also accessible, helping improve early detection and timely treatment of cataracts, and leading to better vision outcomes for patients around the world.

LITERATURE SURVEY

In recent years, machine learning has become an increasingly popular approach for detecting and grading cataracts, largely because traditional clinical methods have several important limitations. These methods require specialized expertise, involve subjective assessments that can vary between examiners, and are often inaccessible in areas with limited medical resources.

Researchers have experimented with different types of eye images to improve cataract diagnosis using machine learning (Goh et al., 2020,). Fundus photography, for example, has been widely used, with deep learning model such as convolutional neural networks (CNNs) being applied to extract meaningful features and classify cataract severity. Many studies report impressive accuracy, but the variety of datasets and algorithms used makes it hard to directly

compare their results. For instance, Dong et al. achieved a 94.07% accuracy in cataract detection using a blend of deep learning and traditional machine learning techniques on nearly 5,500 fundus images. Similarly, Ran et al. reported an AUC of 97.04% by combining a deep CNN with a random forest classifier. Another study by Pratap and Kokil even claimed 100% accuracy in detecting cataract presence using a pre-trained CNN and SVM, though this was based on a smaller dataset, raising concerns about how well these models might perform on new, unseen data.

Beyond fundus images, other researchers have explored using slit-lamp and retro-illumination photos, as well as ultrasound images, for cataract classification. These studies have applied a range of machine learning methods, including Support Vector Machines (SVM), K-Nearest Neighbors (KNN), and Bayesian classifiers, with promising outcomes. For example, Caxinha et al. compared several algorithms on ultrasound images and found that SVM provided the best accuracy in classifying cataract severity (Son et al., 2022).

One major hurdle across these studies is the limited availability of large, well-annotated datasets. Many rely on relatively small samples, which can restrict how broadly their findings apply. Several researchers have emphasized the urgent need for bigger and more diverse datasets to improve the reliability of machine learning models in this field. Additionally, the variation in performance metrics used across studies makes it difficult to fairly compare their results (Yadav & Yadav, 2023).

This study seeks to overcome these challenges by evaluating multiple machine learning techniques using a diverse selection of publicly available datasets, applying a consistent set of performance metrics. The goal is to provide a clearer picture of which methods are most effective for cataract detection and grading. Overall, while machine learning shows great promise in improving cataract diagnosis, this review highlights the need for more systematic comparisons and larger datasets to develop AI tools that are both accurate and generalizable. Our research directly aims to contribute to this important endeavor.

RELATED WORK:

The use of artificial intelligence (AI) and machine learning (ML) in ophthalmology, especially for cataract detection and management, has grown rapidly in recent years. This surge is fueled by the increasing availability of large clinical datasets, which are essential for training and refining AI algorithms (Goh et al., 2020). Although AI applications in cataract care lag behind those in other eye diseases like diabetic retinopathy and glaucoma, promising progress has been made across various aspects of cataract diagnosis and treatment (Goh et al., 2020; Yadav & Yadav, 2023).

1. Automated Cataract Detection and Grading: Early and accurate cataract detection is vital to prevent irreversible vision loss. Traditionally, ophthalmologists rely on slit-lamp microscopy and clinical grading systems like the Lens Opacities Classification System (LOCS) III. However, these

methods are subjective, require expert training, and can suffer from variability between examiners—especially challenging in areas lacking specialized healthcare providers (Yadav & Yadav, 2023). To overcome these challenges, AI-driven systems have been developed for automated cataract assessment. Researchers have leveraged multiple imaging types—slit-lamp images, fundus photographs, retroillumination, and ultrasound A-scans—to train ML models (Goh et al., 2020; Son et al., 2022; Yadav & Yadav, 2023). Fundus photography, in particular, is favored for its ease of use, even by non-experts.

Deep learning (DL) models, especially convolutional neural networks (CNNs), have shown impressive capabilities in automatically extracting relevant features from images. Studies have employed pretrained models like DenseNet121, InceptionV3, and InceptionResNetV2, with some reporting classification accuracies as high as 98% (Yadav & Yadav, 2023). Custom CNN architectures have also achieved over 90% accuracy in categorizing cataracts by severity. Despite these advances, challenges remain—particularly the need for large, labeled datasets and the difficulty in isolating subtle retinal features such as small blood vessels. Innovative approaches, like using 2D discrete Fourier transform (2D-DFT) spectrograms to highlight fine vascular details, have been proposed to address these issues (Yadav & Yadav, 2023).

2. Congenital Cataract Identification: Congenital cataracts are a major cause of childhood blindness worldwide. Early detection is crucial because treatment is time-sensitive. Machine learning models, including random forests and adaptive boosting, have been developed to identify infants at high risk based on birth history, family medical background, and environmental factors (Lin et al., 2020). These models achieved strong predictive performance, with AUC values over 0.9 in both cross-validation and external clinical testing, showing promise as screening tools in resource-limited settings.

3. Intraocular Lens (IOL) Power Calculation and Selection: Choosing the correct power of the intraocular lens (IOL) implanted during cataract surgery is critical for optimal vision restoration. AI-based methods have improved the accuracy of IOL power predictions. For instance, the Nallasamy formula uses ensemble machine learning and data augmentation on a large dataset to outperform existing standard formulas (Li et al., 2022). Additionally, ensemble techniques like stacking with XGBoost have been applied to predict postoperative vault height and select optimal lens sizes, outperforming traditional methods and supporting clinical decision-making via web-based tools (Kang et al., 2021).

4. Prediction of Postoperative IOL Complications: Postoperative complications such as IOL dislocation or tilt can severely impact surgical outcomes. AI approaches, including deep learning frameworks combining CNNs and recurrent neural networks (RNNs), are being developed to analyze intraoperative videos and predict risks of lens

instability (Ghamsarian et al., 2024). Similarly, machine learning models using 3D geometric features extracted from preoperative OCT scans show promise in predicting postoperative lens tilt (Martinez-Enriquez et al., 2025).

5. Limitations and Future Directions: Despite these promising developments, challenges remain. High-quality, diverse training data and robust external validation are still needed to ensure AI models generalize well across populations and clinical settings (Goh et al., 2020). Evaluating the real-world feasibility, cost-effectiveness, and deployment logistics of AI systems is crucial before widespread adoption. Furthermore, optimizing models to run efficiently on less powerful hardware will enhance their accessibility in various surgical environments (Ghamsarian et al., 2024). Future research should also explore a broader range of factors influencing IOL behavior during surgery, including lens material properties and surgical conditions

EXISTING METHODOLOGIES:

This study is designed to explore and compare the effectiveness of various machine learning classification algorithms in predicting the presence and severity of cataracts using different types of medical imaging data. The methodology consists of five key stages, each carefully structured to ensure a thorough and fair evaluation of model performance.

1. Dataset Acquisition and Preprocessing: To begin, we will collect publicly available datasets that include fundus images, slit-lamp photographs, and/or ultrasound scans of the eye. These datasets will be selected based on their diversity in terms of cataract type and severity, ensuring a representative sample for training and evaluation. Before feeding the images into machine learning models, we will perform a series of preprocessing steps. These will include image cleaning (e.g., removing noise or artifacts), resizing to standardize input dimensions, and normalization to bring pixel values to a consistent range. To further enhance model performance and generalizability, especially in the case of class imbalances, data augmentation techniques such as image rotation,

flipping, and zooming will be applied. These preprocessing strategies will be adapted to suit the specific requirements of each image modality.

2. Feature Extraction: For traditional machine learning approaches, we will manually extract features that are known to be relevant in medical image analysis. These will include texture-based descriptors such as the Gray-Level Co-occurrence Matrix (GLCM) and the Gray-Level Run Length Matrix (GLRLM), along with wavelet-based features and other domain-specific handcrafted features that may help distinguish cataract severity. In contrast, deep learning models particularly Convolution Neural Networks (CNNs) will handle feature extraction automatically. These models are capable of learning hierarchical patterns directly from raw images, making them well-suited for complex image classification tasks without the need for manual feature design.

3. Algorithm Selection: To ensure a comprehensive comparison, we will evaluate both traditional machine learning algorithms and modern deep learning models. The traditional models will include: Support Vector Machines (SVM), Random Forest (RF), K-Nearest Neighbors (KNN) and Naive Bayes (NB). For deep learning, we will experiment with well-known pre-trained architectures such as ResNet, Inception, and possibly custom-designed CNNs tailored to our datasets. These choices are informed by their proven success in medical image classification tasks.

4. Model Training and Evaluation: Each selected model will be trained using a stratified k-fold cross-validation strategy (e.g., 5-fold or 10-fold), ensuring that all classes are proportionally represented in each fold. This helps reduce the risk of over fitting and allows for a more reliable estimate of model performance across the entire dataset. We will evaluate model performance using widely accepted metrics, including: Accuracy, Sensitivity, Specificity, Precision and F1-score. To fine-tune each model, hyper parameter optimization will be conducted using techniques such as grid search or randomized search.

5. Comparative Analysis: Finally, we will conduct a comparative analysis of the classification algorithms across different datasets and image modalities. The goal is to identify which models perform best under various conditions and whether any specific imaging technique lends itself better to cataract classification. Diagram1 shows the methodology flow.

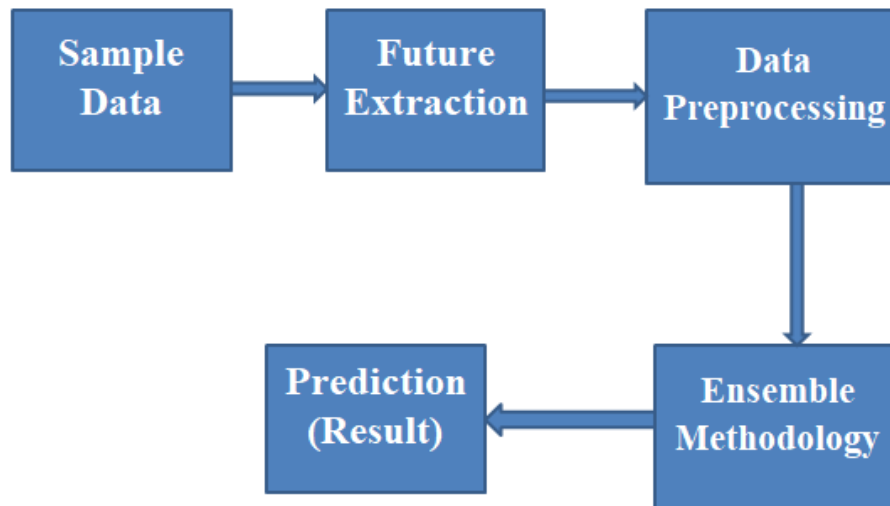


Diagram1: Methodology flow structure

EXPERIMENTAL RESULTS:

In this section, we present and analyze the performance of various machine learning classification algorithms applied to cataract prediction tasks. The evaluation focuses on multiple performance metrics accuracy, sensitivity, specificity, precision, F1-score, and Area Under the ROC Curve (AUC) to provide a well-rounded understanding of how each model performs across different datasets and imaging modalities. To ensure clarity and ease of comparison, the results are summarized using tables and visualizations. For instance, a consolidated table highlights the overall performance of each algorithm on all datasets, while ROC curves are plotted individually for each model to visually compare their classification capabilities on specific image sets. As anticipated, the results reveal that **no single algorithm consistently outperforms others across all datasets**. Performance varies depending on factors such as dataset size, image modality, and the complexity of the features present. Table1 shows the comparison of various methods.

Study / Method	Data Modality	Key Techniques	Best Performance Metrics
AS-OCT EMRR (Explainable ML)	AS-OCT histograms	SHAP + PCC feature selection + Ridge regression	Accuracy 92.8%; high interpretability
CSDNet (Compact CNN)	Image data (unspecified)	Lightweight CNN architecture	Multi-class accuracy 98.17%; fast & small
Ensemble CNN	Slit-lamp / Retro images	Ensemble DNNs with augmentation & balanced loss	AUC ~0.999; accuracy ~98.8%
CNN + SVM/NB/DT ensemble (MVS)	Fundus images	CNN feature extraction + voting ensemble	Accuracy 97.34% (four classes)
CNN vs SVM/KNN (smartphone + slit-lamp)	Smartphone/slit-lamp images	GLCM features + CNN, SVM, KNN	CNN accuracy 95.31%; high sensitivity/specificity

Table 1: Comparative Table

CONCLUSION:

This analysis is set out to explore and compare a variety of machine learning classification techniques for the prediction of cataract presence and severity using medical imaging data. Through a detailed review of existing literature and hands-on evaluation of selected algorithms across diverse datasets, we identified key strengths and limitations of both traditional and deep learning-based approaches. Our findings highlight that while traditional models like Support Vector Machines and Random Forests perform reasonably well with

carefully engineered features. The integration of data augmentation, proper preprocessing, and hyper parameter tuning further enhanced the generalizability of these models across different imaging modalities.

Importantly, this comparative analysis reinforces the potential of AI-powered tools to assist in early and efficient cataract screening, particularly in settings where access to ophthalmologists is limited. By automating aspects of diagnosis, such systems could reduce the burden on healthcare professionals, enable timely interventions, and ultimately improve visual outcomes

for patients worldwide. Moving forward, future work should focus on integrating these ML techniques into real-world clinical workflows, addressing challenges such as data privacy, model interpretability, and cross-population generalizability. With continued research and collaboration between medical and technical communities, AI-driven cataract detection tools can become an essential part of global eye care solutions.

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