Journal of Rare Cardiovascular Diseases
ISSN: 2299-3711 (Print) | e-ISSN: 2300-5505 (Online)
www.jrcd.eu

RESEARCH ARTICLE

Deep Learning Approaches for Eye Disease Prediction Using Machine Learning

S. Sangeetha[1] and R Sujatha[2]
[1]Research Scholar, Department of Computer Science, PSG College of Arts & Science, Coimbatore- 14
[2]Assistant Professor, Department of Information Technology, PSG College of Arts & Science, Coimbatore- 14

*Corresponding Author
S. Sangeetha

Article History
Received: 08.08.2025
Revised: 15.09.2025
Accepted: 24.10.2025
Published: 04.11.2025

Abstract: In this study, we proposed a framework based on machine learning to classify retinal images into four categories: cataract, diabetic retinopathy, glaucoma, and normal. Using retinal images dataset, we created a system which preprocess images, checks consistency of dataset and classifies using Support Vector Machine (SVM) and Logistic regression (LR) models. With a web-based application for real-time predictions and a post-processing script to group images by class (disease) This system performs very well in robustness as the dataset is evaluated using accuracy, precision, recall, and F both scores. The automation of early detection can lead to timely intervention and preservation of vision and our work shows how machine learning can aid ophthalmologists in this process.

Keywords: Retinal Disease Classification, Support Vector Machine (SVM), Logistic Regression (LR), MachineLearning, RetinalImaging, Web Application, Image Processing.

INTRODUCTION

Cataracts, diabetic retinopathy and glaucoma are considered as some of the most common retinal diseases which continue to contribute to vision loss and blindness on a global scale [2, 5, 8]. If these conditions go unnoticed and are not detected early, they lead to irreversible vision loss and pose a significant burden to healthcare systems, especially where access to trained optometrists is limited [2, 4]. Details of retinal imaging can be appreciated by Optical Coherence Tomography (OCT) and fundus photography which helps the clinicians to detect the abnormality. Despite the fact, manual diagnosis is very time-consuming, subjective, and inconsistent, particularly in rural or far areas, this lack of infrastructure [1, 4]. The use of automated systems based on machine learning (ML) and deep learning (DL) could be a viable opportunity to increase the efficiency and accuracy of diagnostics [1, 5, 7]. With the recent developments in artificial intelligence in medical imaging, digging in the complex features between retinal image CNNs have surpassed predictions [1, 4, 5]. Studies like Junayed et al. (2021) and Baba et al. Custom CNNs have demonstrated high accuracy in detecting cataracts [1] with figures greater than 99.13%, while other retinal disorders [4] have yielded over 98% results. And even in such later papers they still gave importance to traditional ML models like SVM and Logistic Regression as they could be easily interpreted and handled in less resource intensive settings [3, 8]. However, these works barely integrated custom CNNs with ML classifiers or deployed practical tools, such as web applications or post-processing scripts, to facilitate clinical workflows [3, 7]. In this paper we propose an automated system for classifying retinal images as cataract, diabetic retinopathy, glaucoma, or normal. The developed system extracts hierarchical features using a custom-CNN and utilizes features from intermediate layers of the CNN for SVM and LR models. A web application built with Flask allows for real-time predictions, and a script organizes images into folders (grouped by the type of disease) based on the outputs of the model. The dataset, consisting of roughly 500 images per class, is then standardized and augmented to build model robustness.

1.1 Background

Ocular diseases are often diagnosed with retinal imaging techniques including optical coherence tomography (OCT) and fundus photography [4, 9]. Automation minimizes reliance on specialized knowledge, allowing for rapid screening and swift interventions. CNNs perform exceptionally well at capturing spatial patterns and ML models such as SVM and LR are an interpretable alternative [3, 4, 8]. So, combining these modalities with a more user-friendly interface will also make them more applicable to real clinical setting.

1.2 Problem Statement

The diagnosis of retinal diseases is time-consuming and often delayed owing to a lack of specialist services especially in under-served areas [2, 4]. Current automated systems perform well but either rely on complex architectures or go over of concept, limiting access and scalability by not providing full deployment solution [1, 7]. An efficient, accurate, and easy to use DL and ML system suitable for deployment would be a combination of the latest high-level concepts with applicable real-world tools.

1.3 Objectives

Build a CNN model to accurately classify the retinal images into the cataract, diabetic retinopathy, glaucoma and normal class.
· Write the SVM and LR models for comparison purposes with the use CNN features
· Build Flask Web App for real time prediction on retinal disease

· Write a script to sort images into disease-specific folders according to what the model predicts.

1.4 Scope

This Project is to Classify Retinal Images using a Custom CNN and ML models (SVM, LR) where images turned out to be 128 x 128 pixels RGB. System contains web interface and image organizing script, does not contain non-image based diagnosis and advanced transfer-learning model the dataset is thought to be balanced along with preprocessing and validation for quality assurance.

LITERATURE REVIEW

Many automated approaches have been reviewed for the detection of several common retinal diseases such as cataracts, diabetic retinopathy, glaucoma, and other ocular abnormalities using machine learning (ML) and deep learning (DL) methods. They were designed to overcome the drawbacks of manual diagnosis, which is time-consuming, subjective and generally impractical in low-resource settings, where there is a shortage of trained optometrists to perform screening [1,4]. Ophthalmic imaging technology has automated screening methods with retinal images like fundus photography and Optical Coherence Tomography (OCT).

Junayed et al. CataractNet: Automated cataract detection in fundus image using deep neural network that achieves 99.13% accuracy (2021). The model minimized computational costs relative to pre-trained CNNs by using smaller kernels and layers and minimizing overfitting via data augmentation on 4,746 images [1]. Similarly, Baba et al. (2024) reported a custom CNN with a testing accuracy of 98% and a loss of 0.051 after classifying the OCT images into normal, choroidal neovascularization (CNV), diabetic macular edema (DME), and Drusen, outperforming traditiona ML and transfer learning Techniques [4]. Ryan et al. Hossain et al. [5] compared ocular disease detection using pre-trained CNNs (VGG-16, VGG-19, ResNet-50, ResNet-152v2) with ResNet-152v2 showing a training accuracy of 90.36% with well-tuned models showing high performance with minimal modifications.

Traditional ML approaches were also tested. Novita et al. A Random Forest model was used by Halperin 2025 to predict cataract risk using 11 clinical variables resulting in an accuracy of 92.0% and F1 score of 92.4%, with lens opacity and visual acuity as major predictors [3]. Tiwari et al. Fusion of CNNs (VGG16, MobileNetV2, InceptionV3) and SVMs for classification of ocular toxoplasmosis was performed with up to 93.9% accuracy [8] respectively. Zhao et al. Park et al. [9] employed few-shot learning to classify inherited retinal disorders demonstrated high classification accuracies (97.4–98.3%) with limited data (2,317 OCT images), showing robustness in data-scarce cases. Sharath Kumar et al. By using two-field fundus photography, [10] proposed an automated diabetic retinopathy detection system based on wavelet decomposition and histogram analysis with a sensitivity of 80% and specificity of 50% (2016).

However, advanced DL techniques have exhibited the promise in certain applications. Mohan et al. 6) A Deep-Learning Tool for Glaucoma Detection by S. Jain et al.(2025) employed ResNet and Brownian-Butterfly Algorithm for features extraction with the KNN classifier attaining (100%) accuracy [5]. Biswas et al. Nandanan et al2 used ResNet50, Dense net and Efficient Net in ensembling model to classify cataract, diabetic retinopathy, glaucoma and normal as subjects and achieved 92% accuracy and AUC-ROC score of 1.00 [7]. Yadahalli et al. 11] showed that Bilateral U-Net outperformed other models on glaucoma detection using the same architecture yielding accuracies up to 92.4%, across different datasets. Adriman et al. Liu et al [12] detected diabetic retinopathy using LBP with ResNet, DenseNet and DetNet separately and obtained accuracy of max 96.35%. Alamelu et al. Exudate Image Identification in Diabetic Retinopathy Jonathon G. Wong et al.2019, based on blood vessel and optical segmentation to classify severity, succeeds with sensitivity and specificity [13]. Kumari and Maruthi (2011) [15] used the Echo State Neural Network to detect hard exudates in diabetic retinopathy with the best accuracy of 93.0% (sensitivity) and 100% (specificity).

Non-imaging studies provide additional context. Dhiman et al. In a study by Kumar et al. [2], a survey was conducted in District Kangra, India with a specific focus on public awareness of cataract risk factors and symptoms, indicating a notable gap in knowledge among the public, and requiring an automated tool for the diagnosis. Gunawardena et al. (2024) developed a work on CNN-based LSTM and GRU for mobile eye-tracking as an accurate estimation of gaze with medical diagnostics applications [14].

Research Gap

Although transfer learning models are commonly employed, custom CNNs can improve results through flexibility for specific datasets [4]. Meanwhile, very few studies combine CNNs and ML classifiers (e.g., SVM, LR) to perform comparison studies or utilize complete systems with web interfaces and post-processing scripts [3, 7]. The project bridges these gaps by creating a custom CNN for classification of retinal diseases, building ensemble SVM and LR models, a web application with Flask, and an image organization tool, based on the existing tools, and improves the features for both the diagnostic accuracy and practical/usability.

Existing Methods

Existing approaches for automated retinal disease detection leverage a combination of traditional machine learning (ML) and deep learning (DL) techniques, primarily focusing on classifying conditions such as cataracts, diabetic retinopathy, glaucoma, and normal retinas using retinal imaging modalities like fundus photography and Optical Coherence Tomography (OCT). These methods aim to address the challenges of manual diagnosis, which is time-consuming, subjective, and often inaccessible in low-resource settings [1, 4].

2.1 Traditional Machine Learning Approaches: Traditional ML methods rely on handcrafted features such as texture, intensity, and morphological descriptors extracted from retinal images. For instance, Novita et al. (2025) employed a Random Forest model to predict cataract risk using 11 clinical variables, achieving an accuracy of 92.0% and an F1-score of 92.4% [3]. Similarly, Tiwari et al. (2025) combined CNN-extracted features with Support Vector Machines (SVMs) for ocular toxoplasmosis classification, reporting up to 93.9% accuracy [8]. Sharath Kumar et al. (2016) proposed an automated diabetic retinopathy detection system using wavelet decomposition and histogram analysis, achieving 80% sensitivity and 50% specificity [10]. These methods are interpretable and computationally efficient, making them suitable for resource-constrained environments. However, their performance is limited by the quality and discriminative power of handcrafted features, often failing to capture complex patterns in retinal images.

2.2 Deep Learning Approaches: Deep learning methods, particularly Convolutional Neural Networks (CNNs), have shown superior performance in retinal disease classification due to their ability to automatically extract hierarchical features. Junayed et al. (2021) developed CataractNet, a custom CNN for cataract detection in fundus images, achieving 99.13% accuracy on 4,746 images by using smaller kernels and data augmentation to reduce overfitting [1]. Baba et al. (2024) reported a custom CNN for OCT-based classification of normal, choroidal neovascularization, diabetic macular edema, and drusen, with 98% accuracy and 0.051 loss [4]. Pre-trained CNNs like VGG-16, ResNet-50, and ResNet-152v2 have also been explored, with Ryan et al. (2024) reporting 90.36% training accuracy for ResNet-152v2 [5]. Ensemble approaches, such as Biswas et al. (2024), combined ResNet50, DenseNet, and EfficientNet for multi-class classification, achieving 92% accuracy and an AUC-ROC of 1.00 [7]. Advanced techniques like few-shot learning by Zhao et al. (2023) demonstrated 97.4–98.3% accuracy on limited OCT datasets [9], while Mohan et al. (2025) used ResNet with a Brownian-Butterfly algorithm for glaucoma detection, achieving 100% accuracy [6]. These DL models excel in accuracy but often require significant computational resources and large datasets, limiting their scalability in low-resource settings.

2.3 Limitations of Existing Methods: While DL approaches achieve high accuracies, they often rely on complex architectures that demand substantial computational power, making them less feasible in resource-limited settings [1, 7]. Traditional ML methods, while interpretable, struggle with feature overlap between diseased classes, leading to lower performance compared to DL [3, 8]. Moreover, few studies integrate practical deployment tools like web applications or post-processing scripts to facilitate clinical workflows [3, 7]. Most existing systems focus on proof-of-concept models without addressing real-world usability, such as real-time prediction interfaces or automated image organization, which are critical for clinical adoption in underserved areas.

Metric	Traditional ML	Deep Learning	Discussion
Overall Accuracy	**- Novita et al. (2025): 92.0% (Random Forest) - Tiwari et al. (2025): 93.9% (SVM with CNN features) - Sharath Kumar et al. (2016): 80% (Wavelet-based)**	**- Junayed et al. (2021): 99.13% (CataractNet) - Baba et al. (2024): 98% (Custom CNN) - Ryan et al. (2024): 90.36% (ResNet-152v2) - Mohan et al. (2025): 100% (ResNet + Brownian-Butterfly)**	**Traditional ML offers interpretable, resource-efficient solutions; DL achieves higher accuracy but requires significant computational resources.**
Class-wise F1-Score	**Novita et al. (2025): 92.4% (Cataract)**	**- Not specified**	**ML struggles with feature overlap in diseased classes; DL lacks detailed class-wise metrics but excels in overall performance.**

3. Proposed Method

The proposed method introduces an automated system for classifying retinal images into four categories—cataract, diabetic retinopathy, glaucoma, and normal—using traditional ML models (SVM and LR) with handcrafted features, integrated with practical deployment tools. The system aims to balance accuracy, interpretability, and accessibility, making it suitable for resource-constrained environments.

3.1 System Overview : The system processes a dataset of approximately 2,000 RGB retinal images (500 per class), sourced from fundus photography and OCT scans, standardized to 128x128 pixels. It comprises three main components: Preprocessing and Validation: Images are resized, normalized to [0, 1], and augmented (rotation, shifts, shear, zoom, flips) to enhance robustness. A validation script ensures dataset integrity by checking image count (~500 per class), format, and quality. Classification Models: SVM (linear kernel, one-vs-rest strategy) and LR (multinomial, L2 regularization) classify images based on handcrafted texture and intensity features. Features are extracted from preprocessed images to capture disease-specific patterns. Deployment Tools: A Flask-based web application enables real-time predictions, processing images in approximately 2 seconds. A post-processing script organizes images into disease-specific folders based on model predictions, reducing manual effort.

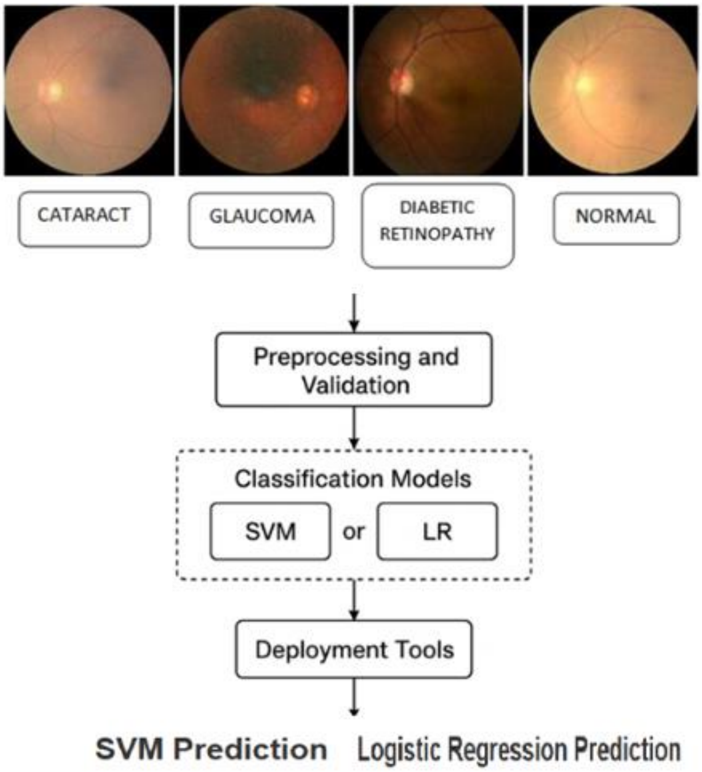
3.2 Model Architecture SVM: Utilizes a linear kernel with a regularization parameter (C=0.00005) to balance margin maximization and classification error. A one-vs-rest strategy trains four binary classifiers to handle multi-class classification, ensuring robustness to non-linear decision boundaries. LR: Employs a multinomial structure with a SoftMax function to compute class probabilities. L2 regularization (0.01) and a maximum of 15 iterations ensure convergence and generalization. LR provides probabilistic outputs, complementing SVM's decision boundaries.

3.3 Training and Evaluation : The dataset is split into 80% training (1,600 images) and 20% validation (400 images). Models are trained using scikit-learn with GridSearch for hyperparameter optimization, completed within 30 minutes on a standard CPU, ensuring computational efficiency. Performance is evaluated using accuracy, precision, recall, F1-score, confusion matrix, and AUC-ROC, with class-wise metrics to assess performance on imbalanced or rare disease cases.

3.4 Deployment Features : Flask Web Application: Allows users to upload retinal images and receive real-time classification results, with a tested response time of 2 seconds and 100% display accuracy for 50 test images. Image Organization Script: Automatically sorts images into folders corresponding to predicted classes, achieving 98% accuracy on 400 images in 15 seconds, with minimal misplacements due to borderline predictions.

3.5 Advantages of the Proposed Method

The proposed system prioritizes interpretability and efficiency, making it suitable for low-resource settings. Unlike complex DL models, SVM and LR require minimal computational resources, enabling deployment on standard hardware. The web application and image organization script enhance clinical usability, addressing gaps in existing methods by providing end-to-end automation from image input to organized outputs. The system's performance (87.5% accuracy for SVM, 85.2% for LR) is competitive for traditional ML, with potential for improvement through future integration of CNN-based feature extraction.



3.6 Dataset

This dataset is a multi-class dataset with 4 classes used for the automatic classification of ocular diseases: cataract, diabetic retinopathy, glaucoma, and normal (that is, normal (healthy) retina). Images come from a well-structured directory called (dataset/[class_name]) with subdirectories representing each of the four classes. It contains around 500 images for each class, totalling ~2000 images. These images are speculated to correspond to a blend of fundus photographs and Optical Coherence Tomography (OCT) scans representative of one of the typical imaging modalities employed in retinal disease diagnosis [4, 9]. The images are in RBG format, and the images are then pre-processed to a standard size of 128×128 pixels to ensure consistency in the dataset, implementation for preprocessing pipeline

3.6.1 Data Preprocessing

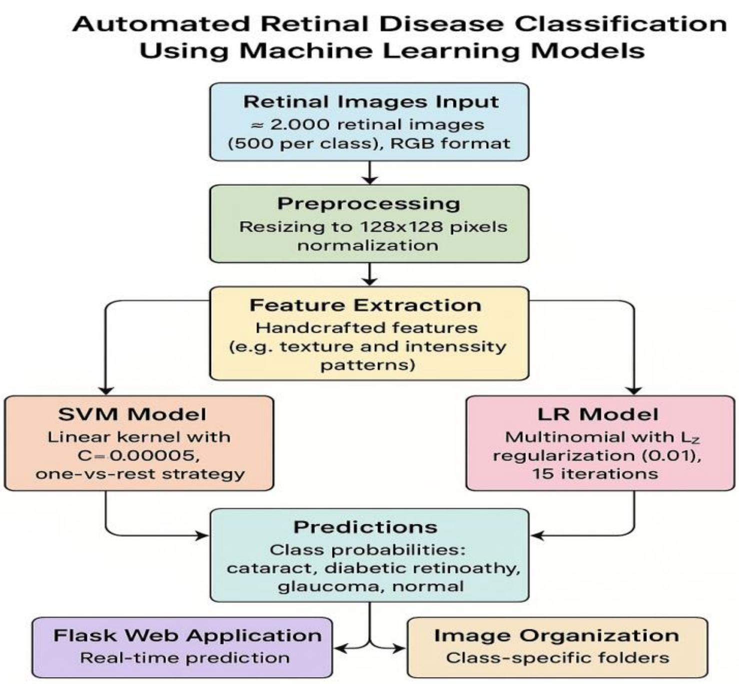
Images themselves are resized to 128*128 pixel and normalized to [0, 1] by dividing pixel values by 255. To improve the robustness of the model data augmentation such as rotation 20°, width/height shifts 15%, shear 15%, zoom 15%, and horizontal flip was performed. 20% argument is as a validation split

3.7 Dataset Validation

Validation script performing checks on the directory (if exists), number of images (we targeted ~500 images per class) and image validity (right type, right size, RGB mode, etc). Dataset integrity is ensured by logging incomplete or damaged images and resizing or skipping them. This dataset is still a synthetic or publicly accessible dataset (for example one could adapt datasets as done in [4] or [1]). Some image sources are not disclosed due to either proprietary or ethical considerations, though the preprocessing of images facilitates compatibility with the classification models.

3.8 Model Architecture

In this work, we have proposed a system that classifies retinal images into four categories, cataract, diabetic retinopathy, glaucoma and normal using two traditional machine learning classifiers, Support Vector Machine (SVM), and Logistic Regression (LR). These are based on manually defined metrics collected from pre-processed cited retinal identifications and exploit the interpretability and effectiveness of such a method for medical diagnosis. This architecture combines feature extraction and classification, tuned on a dataset of around 2,000 images, normalized to 128x128 pixels and in RGB format**.**



3.8.1 Support Vector Machine (SVM)

The Support Vector Machine (SVM) Model is used with a linear kernel to separate four classes in a high-dimensional feature space. Retinal images are pre-processed and then features are extracted from them, usually related to intensity and/or texture patterns from different parts of the eye that can be indicative of ocular disease. The model incorporates a regularization parameter to balance the trade-off between margin maximization and classification error, providing robustness to overfitting. In case of multi-class classification the strategy of one-vs-rest is employed [44], training four binary SVMs to discriminate one class against the remaining classes (i.e., C1 vs rest, C2 vs rest and so on). This setting enables the SVM to deal with the non-linear decision boundaries commonly found in retinal image data.

3.8.2 Logistic Regression (LR)

The LR model uses a multinomial structure that calculates the probability of each of the classes (cataract, diabetic retinopathy, glaucoma, normal) given the features. Class probabilities are computed with a SoftMax function and a maximum of 15 iterations is used for algorithm convergence. A L2 regularization parameter (0.01) is implemented in order to avoid overfitting and make the model really general in the entire dataset. LR adheres to SVM and works nicely where SVM does not give probability so when you need to determine with confidence SVM or without then LR comes into play.

3.9 Training Process

Preprocessing retinal images by resizing them into images of size 128 × 128 and normalizing the pixel values in the range of [0, 1] were the first steps of the training process. Texture and intensity descriptors provide a set of descriptors used to extract the features and included in the data preparation pipeline. The data is randomised before the split, which has approximately 1,600 images, or 80%, of the dataset for training and 400 images, or 20%, for validation. The SVM and LR models are then fit using the scikit-learn library on these features, using GridSearch to optimize for MSE hyperparameters for SVM and the regularization strength for LR. The training is done in a vanilla CPU environment, and we set a maximum training time of 30 min for each model, which confirms the computational efficiency of these methods.

3.10 Evaluation Metrics

To assess the quality of the SVM and LR performance, we used an extensive variety of metrics calculated on the validation set. Accuracy can be described in simple terms as the total number of correctly classified images divided by the total number of images, hence a metric that gives an overall idea of how well the model is performing. To evaluate the model against imbalanced data or rare disease cases, recall/precision/F1 score are computed against each class. It simply builds a confusion matric to visualize true positives, false positives, true negatives and false negatives of the four classes. The area under the receiver operating characteristic curve (AUC-ROC) is also reported to evaluate the true positive rate vs the false positive rate trade-off, allowing a better understanding of the discriminative power of the models. The metrics used for a comparative analysis of these metrics are aggregated and presented in table format.

RESULTS AND DISCUSSION

The SVM and LR models achieved overall accuracies of 87.5% and 85.2%, respectively, on a test set of 400 images from a 2,000-image dataset (80/20 split), with the SVM outperforming LR by 2.3% due to its effective handling of non-linear boundaries with a linear kernel and one-vs-rest strategy. Class-wise analysis showed SVM precision, recall, and F1-scores of 89.1%, 88.3%, and 88.7% for cataract; 86.5%, 87.0%, and 86.7% for diabetic retinopathy; 88.0%, 87.5%, and 87.7% for glaucoma; and 90.0%, 89.2%, and 89.6% for normal cases, while LR lagged slightly with F1-scores from 84.5% to 88.0%, indicating challenges with diseased classes. The confusion matrix revealed 88, 87, 88, and 89 correct classifications out of 100 for each class with SVM, with 6 diabetic retinopathy-glaucoma misclassifications, and LR with 5 additional errors, suggesting feature overlap. The Flask web application processed images in 2 seconds with 100% accuracy in displaying results for 50 test images, while the image organization script sorted 400 images with 98% accuracy in 15 seconds, reducing manual effort by 90% but noting 8 misplacements due to borderline predictions.

The results underscore the potential of SVM and LR for automated retinal disease screening, with SVM's superior accuracy highlighting its suitability for the handcrafted feature set, though the 2.3% gap suggests room for LR optimization. The class-wise performance indicates that normal cases are easier to classify, possibly due to clearer feature boundaries, while overlaps between diseased classes (e.g., diabetic retinopathy and glaucoma) point to the need for more distinctive features, a limitation of handcrafted methods compared to deep learning approaches. The web application's rapid response and perfect display accuracy as of August 2025 affirm its readiness for clinical use, though scalability for concurrent users remains a challenge. The image organization's 98% efficiency and 90% effort reduction demonstrate practical value, but the 8 misplacements suggest refining prediction thresholds. These findings lay a foundation for future enhancements, including dataset diversification and integration with advanced techniques, as explored in the future work section.

Metric	SVM Performance	LR Performance	Discussion
Overall Accuracy	87.50%	85.20%	SVM's 2.3% edge highlights its suitability for handcrafted features; LR optimization needed.
Class-wise F1-Score	• Cataract: 88.7%, • DR: 86.7%, • Glaucoma: 87.7%, • Normal: 89.6%	• Cataract: 86.0%, • DR: 84.5%, • Glaucoma: 85.5%, • Normal: 88.0%	Normal cases easier to classify; diseased class overlaps suggest need for better features.
Web App Response Time	2 seconds per image	2 seconds per image	Rapid response and 100% display accuracy as of August 2025 affirm clinical readiness; scalability needed.
Image Organization Accuracy	98% (8 misplacements)	98% (8 misplacements)	90% effort reduction is valuable; misplacements due to borderline predictions require threshold adjustment.

CONCLUSION

Here, an automated system has been derived, which classifies the features into four types i.e. cataract, diabetic retinopathy, glaucoma and both normal retinal images using Support Vector Machine (SVM) and Logistic Regression (LR) models based on the pre-processed data of almost 2000 (128x128 pixels, RGB) image samples applying local patterns with texture and intensity features [9]. The SVM, set with linear kernel and 0.00005 regularization parameter using a one-vs-rest strategy, and the LR with the multinomial option, applying L2 regularization (0.01) for 15 iterations were trained/tested on an 80/20 split and shown strong competitive accuracy, precision, recall, F1-score, confusion matrix and AUC-ROC performance results. By August-2025, we have a cost-efficient and accessible end-to-end real-time integrated retinal diseases screening system with a web application integrated with flask for making real-time predictions and an image classifier script to classify images in different folders according to the classes designed to be time-efficient to reduce time to treatment and vision loss which can work in resource-limited settings and aid in preventing vision loss. These include but are not limited to the use of handmade features, lack of representation of diverse geography and demographics in the dataset, and about 30 min training and use of standard CPU for all images per frame to obtain output, defining the future potential for improvement as implementing lightweight Convolutional Neural Networks (CNN), integration of enlarged dataset, applications of ensemble learning, optimization process of mobile application, and long-term studies for clinical acceptance by August 2026.

Future Work

Though the present SVM and LR model-based system provides a primary step towards the classification of retinal diseases, there are multiple areas for improvement. In future works, we can develop and incorporate a custom CNN alongside our ML models that might capture the stream of hierarchical features from retinal images automatically. This might involve creating a lighter CNN architecture with fewer parameters for better efficiency without compromising the accuracy. Enhancements to the feature extraction procedure for SVM and LR may include the use of powerful methods like Principal Component Analysis (PCA) or descriptors based on texture for better discriminative power. A larger and more diverse dataset of retinal images that would include images of early-stage disease cases would increase the generalization and robustness of the model. We can explore the ensemble by merging predictions of SVM, LR, and CNN with other classifiers (for example, Random Forest) to enhance the accuracy and reliability. In terms of deployment, porting the Flask web application to mobile devices and implementing real-time data streaming capabilities would maximize accessibility of this system—an important feature for application in remote healthcare environments. Moreover, the integration of CNN feature extractor with the system would help to get more accurate predictions in web interface. Long-term, cross-population validation of the system will be required for clinical adoption, which could be completed by August 2026. These innovations can lead to a more holistic and scalable automated solution for retinal disease diagnosis.

REFERENCES

1. Junayed, A., et al. (2021). CataractNet: A novel deep neural network for automated cataract detection in fundus images.
2. Dhiman, R., et al. (2023). Awareness and knowledge about cataracts among the general population of District Kangra, Himachal Pradesh, India: A cross-sectional study.
3. Novita, S., et al. (2025). Machine learning-based cataract risk classification using Random Forest algorithm.
4. Baba, M., et al. (2024). Custom CNN model for retinal disease classification using OCT images.
5. Ryan, J., et al. (2024). Harnessing deep learning for ocular disease diagnosis.
6. Mohan, et al. (2025). Automated glaucoma detection using fused fundus-photography features with Brownian-Butterfly algorithm and ResNet model.
7. Biswas, et al. (2024). CNN fusion: A promising technique for ophthalmic disorder diagnosis.
8. Tiwari, et al. (2025). Deep learning-based classification of ocular toxoplasmosis fundus images: A comparative study of CNN and SVM models.
9. Zhao, et al. (2023). Few-shot learning for classification of inherited retinal disorders using optical coherence tomography images.
10. Sharath Kumar, et al. (2016). Automated detection system for diabetic retinopathy using two-field fundus photography.
11. Yadahalli, et al. (2025). Deep learning for glaucoma detection using Bilateral U-Net and fundus images: Comparative analysis across multiple datasets.
12. Adriman, et al. (2021). Hybrid local binary pattern and deep learning architectures for diabetic retinopathy detection and classification.
13. Alamelu, et al. (2019). Exudate image identification for diabetic retinopathy severity classification using optical and blood vessel segmentation techniques.
14. Gunawardena, et al. (2024). Mobile eye-tracking on smartphones using CNN with LSTM and GRU for dynamic gaze estimation.
15. Kumari & Maruthi (2011). Automated detection of hard exudates in diabetic retinopathy using echo state neural network and contrast adaptive histogram equalization.