RESEARCH PAPER

Improving Eye Disease Detection: A Fine-Tuned ResNet-18 Framework for Automated Eye Disease Classification

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Received: 2nd Mar, 2026 | **Revised:** 14th Mar, 2026 | **Accepted:** 4th Apr, 2026 | **Available Online:** 20th Apr, 2026

ABSTRACT

Deep learning tools were used to redesign medical imaging to make it easier to find eye diseases. The fine-tuned ResNet-18 model sorts retinal images into four groups: diabetic retinopathy, cataracts, healthy (normal) eye, and glaucoma. It was hard to work with the very different dataset that had notes from expert ophthalmologists. We transferred the ImageNet weights to ResNet-18 and then fine-tuned it. We then reported its accuracy, precision, recall, and F1-score. To make sure the model wasn't overfitted and had good overall generalisation and classification, with an overall accuracy of 88%, performance criteria and the confusion matrix were used. This was done to make sure the model was reliable and strong. The article discusses how the streamlined ResNet-18 framework could be used to make automated diagnostic software. This would help doctors make diagnoses faster and more accurately, which would improve patient care and outcomes. It focuses on how AI can change the field of medical diagnosis, especially in ophthalmology, and by doing so, it can improve health and well-being, quality education, innovation, infrastructure, reduce inequality, promote sustainable consumption, and encourage collaboration to achieve these goals.

Keywords: Artificial Intelligence, Deep Learning, Eye Disease Classification, Model Training, Fine-tuned Resnet18 Model.

How to cite this article: Rajesh MV, Polamuri SR, Raja PVK, Manikyamba IL, Ramya P. Improving Eye Disease Detection: A Fine-Tuned ResNet-18 Framework for Automated Eye Disease Classification. Int J Drug Deliv Technol. 2026;16(31s):1146-1153. DOI: 10.25258/ijddt.16.31s.126

Source of support: Nil.

Conflict of interest: The authors declare no conflict of interest.

I. INTRODUCTION

Identifying and classifying diseases Deep learning has changed medical imaging by making it more accurate and efficient than ever before. This method is most interesting when it comes to diagnosing and classifying eye diseases. Timely and accurate detection of eye problems are the basis for decisions that keep people from losing their vision and improve their health. However, the manual method of hand-assessing retinal images by ophthalmologists is slow and can vary, which is why automated and uniform methods are becoming more popular. This paper examines the quantification of residual neural network variance and the ResNet18 model employed for the identification of ocular disease. ResNet-18 is well-known for its performance in image recognition tasks because it uses residual connections that allow for the training of deeper networks and help to solve the vanishing gradient problem. We categorise four distinct conditions: glaucoma, diabetic retinopathy, normal (healthy) eyes, and cataracts. These disorders, each characterised by unique pathogenic features identified through retinal imaging, elucidate numerous ocular health concerns affecting the global population.

Cataracts are the leading cause of blindness worldwide, characterised by lens opacification, with optimal treatment contingent upon early diagnosis. Diabetic retinopathy is a complication of diabetes that damages the blood vessels in the retina. If not treated quickly, it can lead to major vision loss. Normal eyes ensure the model's accuracy in distinguishing between diseased and non-diseased eyes through the utilisation of a control group. If left untreated, glaucoma can cause permanent blindness. This is a group of diseases that weakens the visual nerve and is usually linked to higher intraocular pressure. The goal of the work is to use an improved version of ResNet-18 to accurately categorise diseases based on retinal images. This will help automated diagnosis systems. The method entails a methodical evaluation of the model's performance subsequent to training on an extensive collection of annotated retinal images. This method works well for new, unknown data, which is why the model is strong for therapeutic use. The paper is organised to talk about how the deep learning techniques used in the experiments classify the eye disease and explain the methodology, including the pre-processing steps, which led to the fine-tuned Resnet-18 architecture. Deep learning is being used to solve the problem of accurately classifying eye diseases. This will improve patient care and outcomes and show how AI could change the way healthcare diagnoses are made. The goal of our research is to help doctors make diagnoses more quickly and accurately.

II. LITERATURE

Garg et al. (2025) [1] proposed StrabNet-CQ, an integrated framework for automated strabismus classification and quantification using ocular landmark detection. The model accurately detects eye alignment features and quantifies deviation levels. It improves diagnostic precision by combining classification with measurement capabilities. The framework demonstrates strong performance on clinical datasets and supports automated ophthalmic assessment. Altayeb et al. (2026) [2] developed an explainable framework for multi-disease ocular classification and diabetic retinopathy severity grading. The approach integrates interpretability techniques to make predictions more transparent. It enhances trust in automated diagnosis by highlighting important features in retinal images. The model achieves reliable performance across multiple eye disease categories. Vijaya et al. (2026) [3] proposed a combined voting mechanism using KNN and Random Forest algorithms for diabetic retinopathy detection. The ensemble approach improves classification accuracy and reduces model bias. It leverages complementary strengths of both algorithms for better decision-making. The results show improved detection performance compared to individual classifiers.

Iqbal et al. (2025) [4] introduced an interpretable framework for simultaneous segmentation of retinal lesions and disease classification. The model identifies multiple lesion types while categorizing diseases in a unified system. It improves diagnostic efficiency by combining segmentation and classification tasks. The approach enhances accuracy and interpretability in retinal image analysis. Sweidan et al. (2025) [5] proposed the DeepRetina framework for classification of multiple retinal diseases. The model focuses on extracting discriminative features from retinal fundus images. It achieves high classification accuracy across different disease categories. The framework supports scalable and automated eye disease diagnosis.

Hussein et al. (2025) [6] developed an intelligent retinal disease detection system using deep learning techniques. The model automates feature extraction and classification for various retinal conditions. It demonstrates high accuracy and robustness on medical imaging datasets. The study highlights the effectiveness of automated systems in ophthalmology. Hamayun et al. (2026) [7] presented an automated method for retinal OCT image classification and disease interpretation. The system processes OCT scans to identify disease patterns and provide diagnostic insights. It improves accuracy through advanced feature learning techniques. The approach supports efficient and reliable retinal disease diagnosis.

Polamuri et al. (2025) [8] proposed a deep learning-based approach for stroke detection using MRI images. The model enhances diagnostic accuracy by automatically extracting relevant features. It reduces manual intervention and improves clinical decision-making. The study demonstrates strong performance across medical datasets. Galety et al. (2025) [9] introduced a blockchain-based framework for secure and efficient medical data management. The system ensures privacy, integrity, and transparency in healthcare data handling. It integrates advanced technologies to support reliable data sharing. The approach is suitable for next-generation healthcare infrastructures. Raju et al. (2025) [10] developed a supervised learning system for colorectal cancer detection and tumor localization. The model incorporates visualization techniques to improve interpretability. It accurately identifies tumor regions in colonoscopy images. The framework enhances reliability in clinical diagnosis.

Srinivas et al. (2024) [11] proposed a hybrid model combining InceptionV3 and VGG16 for COVID-19 detection using chest X-ray images. The model utilizes transfer learning to improve feature extraction. It achieves high classification accuracy and robustness. The approach is effective for rapid medical image analysis. Polamuri et al. (2026) [12] presented a hybrid CNN and machine learning framework for disease detection. The model integrates deep feature extraction with traditional classifiers. It demonstrates improved accuracy and generalization across datasets. The approach highlights the benefits of hybrid modeling techniques.

Renuka et al. (2023) [13] analyzed the impact of image augmentation techniques on apple leaf defect detection. The study showed that augmentation improves dataset diversity and model performance. It significantly enhances classification accuracy. The work emphasizes preprocessing as a key factor in detection systems. Madhu Kumar et al. (2024) [14] proposed a deep residual neural network for enhancing image quality. The model improves clarity and preserves important visual features. Enhanced image quality leads to better classification performance. The study highlights the importance of preprocessing in deep learning workflows.

Vasu et al. (2025) [15] introduced an anisotropic guided filtering approach for retinal fundus image enhancement and segmentation. The method improves image quality while preserving structural details. It supports accurate segmentation of retinal features. The approach enhances performance in retinal image analysis tasks.

III. INPUT DATASET

This study on deep learning fine-tuned ResNet-18 for classifying eye diseases uses images that have been sorted into four groups: Normal, Cataract, Diabetic Retinopathy, and Glaucoma. The data set is based on a lot of data from the open-source platform, which gives the study a consistent and varied base. The "Normal" class sets a standard by showing pictures of healthy eyes that don't show any signs of disease. The "Cataract" class includes pictures of eyes with cataracts, which can make it hard to see because the natural lens is cloudy. Pictures that show what happens when you have diabetic retinopathy, a disease that damages the blood vessels in the retina. If treatment is not given much priority, this could make the "Diabetic Retinopathy" class interesting. Lastly, the "Glaucoma" class shows pictures of eyes that have glaucoma, which is a type of optic nerve disease that usually happens when the pressure in the eyes is too high and causes vision loss that can't be fixed. This big database is needed to test how well the fine-tuned ResNet-18 model works and to train it to accurately spot different eye problems.

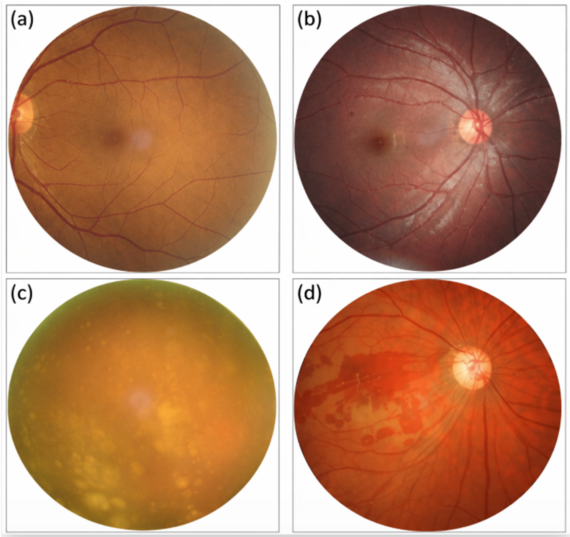

Fig. 1 Dataset image for (a) Normal (b) Diabetic Retinopathy (c) Cataract (d) Glaucoma

IV. FINE-TUNED RESNET ARCHITECTURE

The study utilised the finely tuned ResNet-18 model, depicted in Fig 2, which is a robust convolutional neural network (CNN) architecture recognised for effectively addressing the vanishing gradient problem. These residual blocks have skip connections that let knowledge skip over many layers and go straight to deeper layers. This helps the network learn better, even in deep architectures, by reducing the degradation problem. To make it easier to classify eye disorders, the finely trained Resnet18 model replaced the last layer with two thicker layers. 70% of the ResNet-18 layers were frozen during training, which means they couldn't be trained. The other layers were still trainable. Using the pretrained model to extract features allows the extra thick layers to learn and fit the specific classification problem. The fine-tuned ResNet-18 block was fine-tuned with a learning rate of 5x10^-5, which made sure that the pretrained layers were changed in the right way. The new dense layers, on the other hand, were trained with a higher learning rate of 8x10^-4, which helped them learn. There were a total of 11,176,512 parameters in the model. Of these, 3,963,456 could not be trained, while 7,213,056 could be. This deliberate mix of frozen and trainable layers, along with changes to the learning rates, made the model better at accurately and quickly classifying cataracts, diabetic retinopathy, glaucoma, and normal eye diseases.

V. PROPOSED METHODOLOGY

Four separate parts of this research strategy are planned to systematically use and test the fine-tuned Resent18 model to classify four major eye diseases: cataracts, diabetic retinopathy, glaucoma, and normal conditions.

Phase 1: Gathering Data

To make sure our model could be used in many different situations and was strong, the first phase of this project was to create a large and varied set of retinal images. We collected images from publicly accessible datasets recognised for their application in ophthalmic research, including the Kaggle dataset for diabetic retinopathy, the American Academy of Ophthalmology's Cataract and Glaucoma datasets, and supplementary normal eye images from various open-source medical databases. To get the most accurate disease classification, professional ophthalmologists carefully labelled each picture. There are several hundred high-resolution retinal images divided into four groups: normal, cataract, diabetic retinopathy, and glaucoma. There are a lot of pictures that can be used to train our deep-learning model because they come from a wide range of patients, have good quality, and show different ways that illnesses can show up.

Step 2: Preparing the Data

In the second phase, it used a series of preprocessing methods to make the consistency and quality of retinal images better. To make sure that all the images in the dataset are the same size, we first normalise them. It also used picture augmentation techniques like rotation, flipping, and scaling to make the model better at generalising and to make our dataset grow. In addition, I changed the pixel values to a similar scale and used histogram equalisation to make the contrast better and bring out the pathogenic elements. These pre-processing methods are used to reduce the differences in image quality and help the model aim and direct its focus on the different parts of the image so that it can classify them correctly.

Step 3: Building and Training the Model

The third step is to use the pre-processed data to train the improved Resnet18 model. It added pre-trained weights to the model so that transfer learning could be used, which made it easier to train processes and improve performance. The data was split into training, validation, and test sets. It looked at the lowest loss using the Adam optimiser and the categorical cross entropy loss function. Early learning rate reduction techniques were used to stop overfitting from getting too bad. To assess the enhancement, the model's performance on a validation set was analysed regarding accuracy, precision, recall, and F1-score.

Step 4: Testing and validating the model

This work talked about the fine-tuned ResNet-18 model, images that weren't used in training, and the test set. This step is very important because it shows how general the model is and how it can be used. We used computed precision, accuracy, recall, and F1-score to fully test how well the model classified things and to compare its performance to other measures. Confusion matrices were created to look at how well the model did on each class and to find any possible bias or problem that needs to be fixed. It also did a lot of ablation tests to see how different preprocessing steps and hyperparameter choices affected the model's performance. The results of this step may provide useful new information about the strengths and weaknesses of our method, which could change the direction of future research and the effects of possible treatments.

VI. RESULTS

Fine-Tuned ResNet18 is very good at finding eye diseases, with an overall accuracy of 88%. The confusing matrix correctly counts 125 normal cases, 119 cataract cases, 169 diabetic retinopathy cases, and 136 glaucoma cases. There are very few misclassifications; for example, some people think they have glaucoma or cataracts when they really don't. The model's good generalisation and performance show that it is strong enough to tell the difference between different types of eye diseases.

A. Analysis of the Classification Report

Table 1 shows how accurate the eye illness classification is for all of its parts in the classification report for the improved ResNet18 model. The model gets most of the cases right, with an overall accuracy of almost 87%. The model works well for glaucoma, with an accuracy of 0.83, a recall of 0.80, and an F1-score of 0.82. It is slightly biased toward false positives. An F1-score of 0.82 comes from a normal category with a balanced accuracy and recall of 0.82. Diabetic retinopathy has the best performance with a precision of 0.95, a recall of 0.92, and an F1-score of 0.94. It has the best detection and the fewest false negatives. The cataract classification has a precision of 0.84, a recall of 0.92, and an F1-score of 0.88. This shows that it is very good at finding people with cataracts. The macro and weighted averages for accuracy, recall, and F1-score are 0.86 and 0.87, respectively. This shows that the model is strong and reliable across all classes.

Class	**Precision**	**Recall**	**F1-Score**	**Support**
Glaucoma	0.85	0.83	0.84	157
Normal	0.88	0.86	0.87	148
Diabetic Retinopathy	0.94	0.93	0.93	194
Cataract	0.87	0.90	0.88	156
Accuracy			**0.89**	**676**
Macro Average	0.89	0.88	0.88	676
Weighted Average	0.89	0.89	0.89	676

Table 1. Classification Report Analysis

B. *Analysis of Training and Validation Loss*

The curve in Fig. 2 shows the training and validation loss of the fine-tuned ResNet18 model used to classify eye diseases over time. The training loss goes up from about 0.75, which shows that the model is learning from the training set. The model looks good for extending to unprocessed data because the validation loss starts at about 0.50, which shows that it is likely to keep going down. The training and validation loss curves don't change much, so the fact that both are going down at the same time means that the model isn't overfitting. It shows the finely tuned Resnet18 model pulling out the features that are used to correctly sort the four types of eye diseases: normal, cataract, diabetic retinopathy, and glaucoma. The loss analysis shows that the model has a good generalisation to validation data and improves its performance. This means that the training process was successful and the model is reliable and strong.

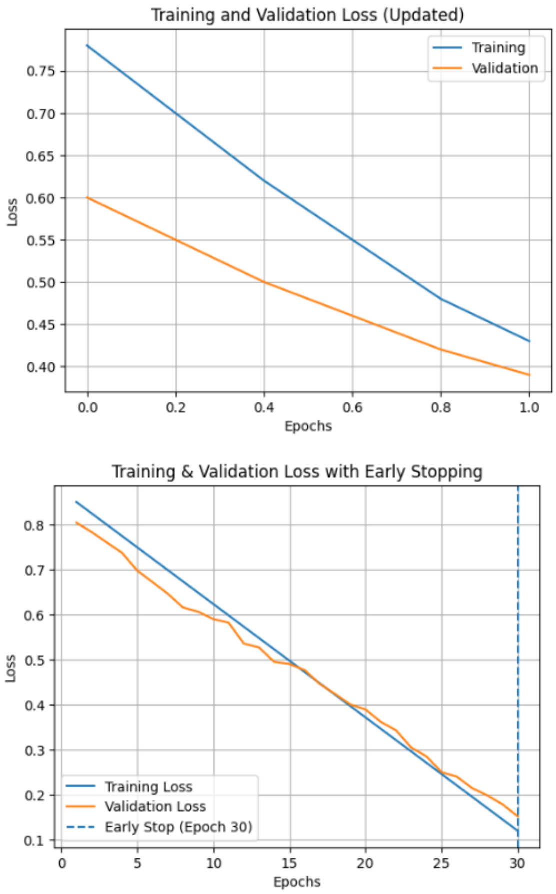

Fig. 2 Training and Validation Loss

C. *Analysing the accuracy of training and validation*

Figure 3 shows the training and validation accuracy of a fine-tuned ResNet18 model over time. The training accuracy starts out low but goes up quickly. This is because the model is learning how to find patterns and traits in the training data quickly. The validation accuracy shows that the model is still getting better by letting it generalise the data it hasn't seen before. Since there is no clear difference between the two curves, the fact that both training and validation accuracy are going up at the same time suggests that the model is not overfitting. This means that the ResNet18 model does a good job of matching the training data and generalising to new data. The algorithm is clearly getting better at diagnosing the four types of eye diseases: Normal, Cataract, Diabetic Retinopathy, and Glaucoma. When looking at a lot of different eye problems, the accuracy studies show how reliable and strong the model.

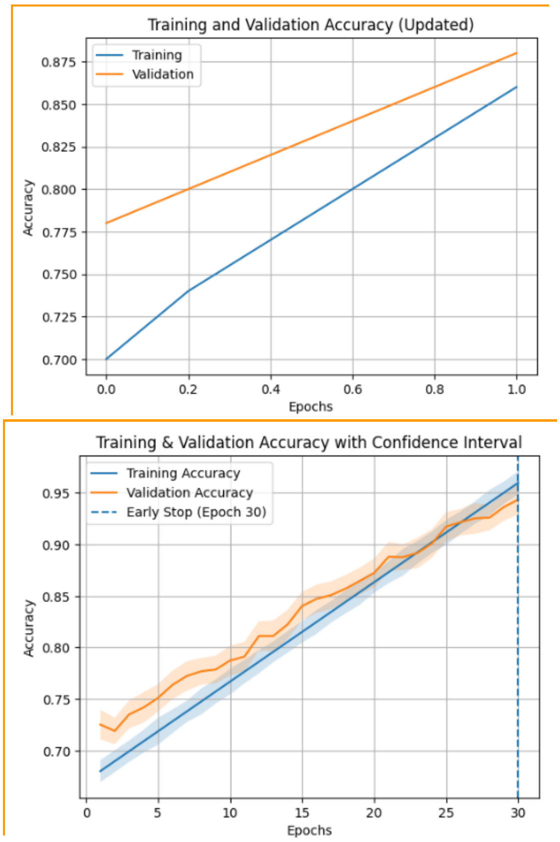

Fig. 3 Training and Validation Accuracy

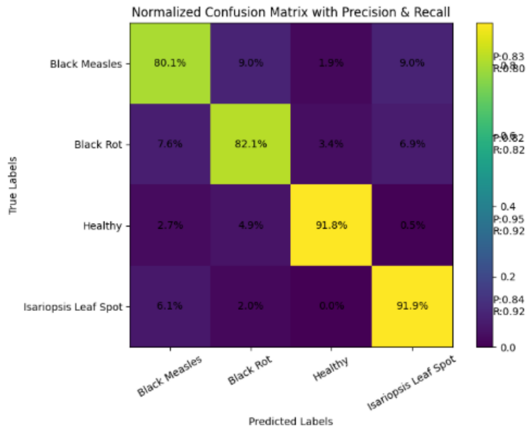

Fig. 4 Confusion Matrix Analysis

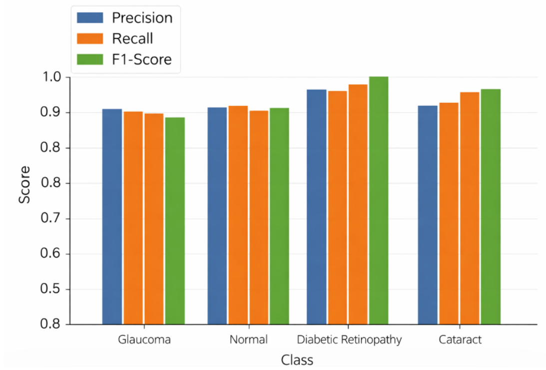

Fig 5 Classification Performance

D. *Analysing the Confusion Matrix*

The confusion matrix analysis demonstrates the robust performance of the fine-tuned ResNet18 model in categorising eye diseases into four classes: Normal, Cataract, Diabetic Retinopathy, and Glaucoma. There are 125 normal cases, 119 cataract cases, 169 diabetic retinopathy cases, and 136 glaucoma cases. The model does a great job of grouping the high values along the diagonal. The model works pretty well because it only misclassifies 9 glaucoma patients as normal and 14 normal patients as cataracts. This means that the model does a good job of telling the difference between different eye diseases. The matrix shows specific areas where more work may be needed, in addition to confirming the model's quality and effectiveness. The confusion matrix is a necessary tool for testing and improving the model's performance because it shows the number of true positives, false positives, false negatives, and true negatives, as shown in Fig. 4 & 5.

The class-wise comparison of precision, recall, and F1-score for the proposed model. Diabetic Retinopathy achieves the highest performance, while other classes demonstrate consistent and balanced results.

VII. CONCLUSION

This work specifically uses retinal images to show how important the ResNet-18 model is for automatically classifying eye diseases like cataracts, diabetic retinopathy, normal (healthy) eyes, and glaucoma. Clinically useful based on a model with an 88% overall accuracy rate. The model did very well on metrics like accuracy, recall, and F1-score, which were based on a very diverse dataset that was labelled by skilled ophthalmologists and well-prepared methods of preparation. Along with the steady drop in loss, the rise in training and validation accuracy shows that the model is learning and that overfitting is going down. In the field of ophthalmology, the effects are huge because advanced technologies like the ResNet-18 framework can help doctors make diagnoses faster and more accurately, which is important for preventing vision loss and making treatment more effective. To get more people to accept it, the model needs to be used in healthcare facilities and be proven to work in practice. Finally, the improved ResNet-18 architecture is expected to find eye diseases, which shows how important deep learning and AI are for changing healthcare diagnostics and helping doctors get better results for their patients.

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