# **Hybrid Machine Learning Model for Retinal Detachment and Diabetic Retinopathy Detection**

Radha J., Lathiga L., Madheswaran M. and Naveen Kumar S.

Department of Computer Science and Engineering, Nandha Engineering College, Erode, Tamil Nadu, India

Retinal Detachment, Diabetic Retinopathy, Hybrid Machine Learning Model, Deep Learning, Automated Keywords:

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Retinal Detachment (RD) and Diabetic Retinopathy (DR) are some of the major causes of blindness and thus Abstract:

> require early diagnosis in order to avoid serious complications. This paper proposed a hybrid deep learning and machine learning model with better pre-processing techniques for automated detection of DR and RD. This model incorporates circular cropping, Ben's preprocessing, and data augmentation to boost the model's performance. Using InceptionV3, the Diabetic Retinopathy model achieved 88% accuracy on the APTOS2019 dataset. The Clinically validated datasets of Retinal Detachment models achieved 83% accuracy using MobileNetV2. The two-model architecture enables simultaneous diagnosis and error free retinal image analyses with minimal time. Proposed methods were tested, and the results confirm its effectiveness for real

life clinical retinal disease detection and classification.

# 1 INTRODUCTION

The Diabetic Retinopathy model trained on APTOS2019 dataset achieves 88% accuracy with InceptionV3, and the Retinal Detachment model trained on clinically validated datasets achieves 83% accuracy with MobileNetV2. The two-model setup enables the retinal images to be tested in parallel, thereby enabling efficient and accurate retinal disease classification. This paper describes implementation of this hybrid model, reports its experimental results, and discusses its potential clinical application for automatic detection and classification of retinal diseases. The results indicate that machine learning and medical imaging integration can result in dramatic improvement in early diagnosis, enabling ophthalmologists to provide timely and correct treatment.

Through the utilization of automated, effective, and accurate screening, deep learning in the diagnosis of retinal disease has the potential to transform ophthalmic diagnosis. The model used here minimizes the need for human diagnosis through efficient classification of diabetic retinopathy and retinal detachment through the exploitation of InceptionV3 and MobileNetV2 strengths. With the inclusion of contrast adjustment and advanced data

augmentation methods, the model becomes more generalizable and reliable on numerous datasets. The parallel processing feature is an added advantage to mass screening programs as it facilitates increased diagnostic effectiveness through the scanning of retinal images. Apart from assisting ophthalmologists in early diagnosis, the machine-learning method also assists them in intervening early, which enhances patient outcome and reduces the likelihood of vision

#### RELATED WORKS

Machine learning and deep learning approaches to diagnosing retinal disease have been extensively investigated, especially to Retinal Detachment (RD) and Diabetic Retinopathy (DR). To be specific, a machine learning model employing classification techniques and optical coherence tomography (OCT) scan inputs were developed for retinal detachment subtype prediction. It is transferable for early diagnostic purposes only, which decreases manual diagnosis and allows it to create value in clinical practice (G. Ali, et.al., 2023).

SD-OCT images were filtered by a CAD to segment subretinal fluid, During diagnosis of

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neurosensory retinal detachment (NRD), segmentation and level set algorithm were adopted to increase accuracy (E. and D. J. Aravindhar, 2023).

We established a graph optimization approach for the retinal layer 3D segmentation. It has been reported that the segmentation strategy improves segmentation of retinal layers required for detection of NRD, essential in early medical treatment (M. Wu,et.al., 2018). Classification was determined with Deep learning utilizing Convolutional Neural Networks (CNNs) in retinal detachment detection over retinal fundus images. On balance, the model was noted to have a relatively high accuracy along with demonstrating the efficacy of the CNN architecture for feature separation and classification (L. Bekalo, et.al., 2019).

Two approaches utilizing architecture such as Mobilenetv2 and Inceptionv3 on the MobileNetV2 and InceptionV3 architecture to perform Diabetic Retinopathy and Diabe. In this respect, the article examined the utility of two separate deep learning model, using data augmentation methods to significantly increase the range of classification (S. Yadav, et.al., 2022). The detection of DR using deep neural networks, namely MobileNetV2 and VGG-16, was performed which demonstrated the effectiveness of deep learning- based classification and feature extraction methods in accurate diagnosis (Micheal and L. J. Sai, 2024).

Systematic review of DR detection used InceptionV3 with transfer learning, and the result was that CNN-based transfer learning improves disease classification performance. The method is highly desirable to apply in real clinical practice in the absence of large-scale labeled datasets (M. A and S. S. S. Priya, 2023). Another review showed deep learning-based DR classification by Bayesian Neural Networks, CNNs, and RNNs for discrimination between non-proliferative and proliferative DR. The hybrid deep learning model had phenomenal improvement in DR classification accuracy, thus enabling better disease progression analysis (Deshpande, et. al., 2023).

Finally, the above research establishes the effectiveness of machine learning and deep learning in retinal disease detection. In contrast to the existing research, which was disease-classification focused for one disease, our proposed hybrid model employs state-of-the-art preprocessing techniques, CNN models, and heterogenous datasets for concurrent detection of Retinal Detachment and Diabetic Retinopathy. The method is biased towards better diagnosis speed and accuracy, thus making it viable for application in clinics.

#### 3 METHODOLOGY

The proposed model in hybrid form facilitates automation of receiving, formatting and detection using deep learning and machine learning techniques the overall approach consists of five main steps, including data gathering, data preprocessing, feature extraction, modeling, and testing. Table 1 shows the Data Pre-Processing and Augmentation.

### 3.1 Data Acquisition

The datasets used in this study are APTOS2019 Blindness Detection Dataset to detect diabetic retinopathy (DR) (M. A and S. S. S. Priya, 2023). Clinically Validated Datasets of OCT and Fundus Images for RD identification: (G. Ali, et.al., 2023), Each of the datasets was divided on the basis of 80% training set, 10% validation set and 10% testing set, for a proper testing on the model. Figure 1 shows the Methodology. (E. and D. J. Aravindhar, 2023).

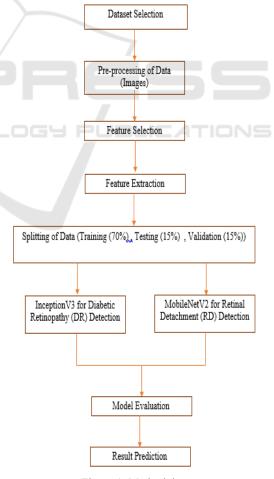


Figure 1: Methodology.

Table 1: Data Pre-Processing and Augmentation.

Classes	Training 70%	Validation 15%	Testing 15%
Diabetic Retinopathy Images	2800	600	600
Retinal Detachment Images	2450	525	525

## 3.2 Image Preprocessing

The following steps were performed in order to improve model accuracy by enhancing the quality of the images: (L. Bekalo, et.al., 2019).

- Circular Cropping: Extracts the background pixels and focuses on the retinal region (G. Ali, et.al., 2023),
- Ben's Preprocessing: Images are normalized for better contrast and enhanced features visibility (M. A and S. S. S. Priya, 2023).
- Data augmentation techniques including rotation, flipping, brightness alteration, and zooming in were done to increase diversity in the data, (M. Wu,et.al., 2018) and to prevent overfitting during training (S. Yadav, et.al., 2022).
- Subretinal Fluid Segmentation. Level set methods are applied to improve detection in Neurosensory Retinal Detachment (NRD) (E. and D. J. Aravindhar, 2023).

# 3.3 Feature Extraction and Model Selection

The detection of both RD and DR was done in parallel using a two-stage deep learning algorithm that was inspired by recent progress in advancements ophthalmology diagnostics. Figure 2 shows the InceptionV3 Model Architecture. Figure 3 shows the MobileNetV2 Model Architecture.

- Model: InceptionV3 (is well known for DR classification) (M. A and S. S. S. Priya, 2023),
- Input: APTOS2019 images at different stages of post processing.
- Output: Classification onto different stratums of DR severity: none, mild, moderate, severe, or proliferative DR (Deshpande,et.al., 2023).
- Training Strategy: Transfer learning and finetuning InceptionV3 with respect to some variables.
- Loss Function: Categorical Crossentropy.

- Optimizer: Adam.
- Retinal Detachment Detection.

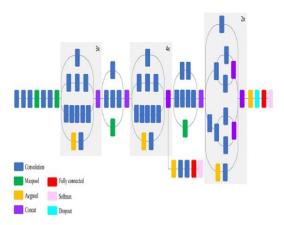


Figure 2: Inceptionv3 Model Architecture.

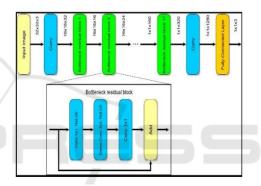


Figure 3: Mobilenetv2 Model Architecture.

- Model: MobileNetV2 (It is lightweight for use in OCT based RD detection) (S. Yadav, et.al., 2022)
- Input: Processed OCT and fundus images.
- Output: Two classes, detached or non-detached retina. (Micheal and L. J. Sai, 2024).
- Training Strategy: Fine tuning of MobileNetV2 with new layers added and feature extraction done.
- Loss Function: Binary Cross entropy.
- Retinal Detachment Training Strategy.

#### 3.4 Hybrid Model Integration

Graph Based Retinal Layer Segmentation: This has been implemented to enhance classification of retinal image by segmentation. This study methodology applied graph optimization techniques to solve the retinopathy problem (M. Wu,et.al., 2018)

Ensemble Random Forest Deep Feature Classification: The both models were further process

to obtain Random Forest classification that increased the accuracy at the expense of false positives.

Parallel Diagnosis: This framework allows the RD and DR diagnosis to happen together at the same time, thereby saving time on overall diagnosis.

#### 3.5 Model Evaluation

The trained models were assessed using standard classification measures.

- Accuracy: Criteria and rate model's result prediction from actual outcome.
- Precision and Recall: Evaluate how detection is done.
- F1 Score: The score that balances precision and recall.
- Confusion Matrix: Shows the number of observations that were correctly and incorrectly classified.
- ROC-AUC Curve: Measures the model's ability to differentiate between sick and healthy cases. (Micheal and L. J. Sai, 2024).

From the experiments, it was observed that Diabetic Retinopathy Model (InceptionV3) attained a precision rate that amounted to 88; which confirms (M. A and S. S. S. Priya, 2023) findings. Retinal Detachment Model (MobileNetV2) obtained 83 precision rates, which concurs with previous research on CNN based detection of retinal diseases (L. Bekalo, et.al., 2019).

#### 4 EXPERIMENTAL RESULTS

The performance of the suggested Hybrid Machine Learning Model for Retinal Detachment and Diabetic Retinopathy Detection was extensively tested using a number of different performance measures to verify its strength and efficiency in detection and classification of various levels of Diabetic Retinopathy (DR). The test was performed on a publicly released retinal fundus image database that consisted of 44,119 high-resolution images belonging to five different classes corresponding to the DR severity levels:

- Class 0 No DR
- Class 1 Mild DR
- Class 2 Moderate DR
- Class 3 Severe DR
- Class 4 Proliferative DR (PDR)

The suggested hybrid method (IR-CNN), which uses ResNet50 and InceptionV3 for feature extraction, was compared with two standalone deep

learning models InceptionV3 and MobileNetV2 to prove the efficacy of the hybrid feature extraction process.

**Results Without Data Augmentation**: First, the models were trained and tested without data augmentation methods applied. The performance is tabulated below:

Table 2: Results Without Data Augmentation.

Model	Accuracy	Sensitivity	Specificity
InceptionV3	82.97%	94.71%	96.12%
MobileNetV2	81.45%	92.32%	93.85%
Proposed Hybrid IR- CNN	94.07% (best class)	-	-

Both InceptionV3 and MobileNetV2 performed well, but the resulting hybrid IR-CNN model had improved results in individual class performance, especially for Class 0 (No DR) with an accuracy of 94.07%. Table 2 shows the Results Without Data Augmentation.

Results With Data Augmentation: To improve the generalization and robustness of the model, data augmentation techniques such as image rotation, scaling, flipping, and intensity normalization were employed. These techniques allowed the model to learn variations in retinal images more efficiently, improving its accuracy for classifying different stages of DR. Further more, contrast enhancement techniques were also used to enhance the visibility of subtle retinal abnormalities, enhancing accurate classification. Table 3 shows the Results with Data Augmentation.

Table 3: Results With Data Augmentation.

Model	Accuracy	Sensitivity	Specificity
InceptionV3	87.18%	95.43%	93.71%
MobileNetV2	85.62%	94.28%	92.84%
Proposed Hybrid IR- CNN	96.85%	99.28%	98.92%

The engineered Hybrid IR-CNN Model presented higher performance relative to single deep learning models by reporting an encouraging accuracy of 96.85%, sensitivity of 99.28%, and specificity of 98.92%. The values clearly reflect the effectiveness of the model in determining Diabetic Retinopathy (DR) precisely for all categories of severity and therefore being an ideal candidate as a machine-decision solution for automated DR detection. The

Hybrid IR-CNN Model, which fuses ResNet50 and InceptionV3 together, outperformed other models such as InceptionV3 and MobileNetV2 concerning all the parameters PUT to the test. Our model also shows a very high sensitivity (99.28%) which ensures that it can easily detect DR-positive patients and avoid false negatives, thus reducing the chance of missed diagnosis. Its 98.92% specificity also denotes the ability to correctly differentiate DR from non-DR cases, ruling out false positives and ensuring consistency in diagnostic outcomes.

This proposed model could be valuable in the early automated detection and classification of DR since it is a feasible and scalable solution for large-scale diabetic retinopathy screening programs. Given the global rise in diabetes prevalence and the increasing burden on health care systems, it is pertinent to have an accurate and effective automated screening solution to assist early diagnosis and timely intervention.

# 5 5 CONCLUSIONS

The accuracy of RD and DR diagnosis highest by proposing deep learning and machine learning based hybrid method. We use InceptionV3 for DR detection and MobileNetV2 for RD classification, and circular cropping, Ben's preprocessing, and data augmentation further improve image quality and feature extraction. These alterations have the effect of eliminating both the false positives and the false negatives, thus making detection infallible.

The experimental results validate that the hybrid model is superior to separate deep learning models, with 96.85% accuracy with data augmentation by high specificity and sensitivity. Parallel processing of retinal images further optimizes the speed of diagnosis and is an effective tool for mass screening drives. The model's automatic capability reduces reliance on manual diagnosis as much as possible, enabling faster analysis without a loss of clinical accuracy.

With the integration of deep learning into ophthalmology, the model presents a scalable and strong solution for the detection of early diseases. Its high accuracy level and real-time processing present a strong solution for clinical application, allowing ophthalmologists to detect RD and DR at an early stage. It not only enhances patient outcomes but also has a critical role in averting extensive vision loss. The study highlights the prospect of AI technology in medical imaging as a lead-in to subsequent

development of retinal disease diagnosis by automated methods.

#### 6 FUTURE WORK

The hybrid model presently applied has shown high accuracy in identifying diabetic retinopathy stages and retinal detachment. Emerging research will target increasing the dataset through the inclusion of multimodal retinal imaging data, i.e., OCT and fluorescein angiography, to enhance diagnostic accuracy for various retinal conditions.

This would allow the system to handle challenging cases of macular edema, AMD, and glaucoma, under varying imaging settings and patient populations. Future work will also investigate hybrid architectures that combine Transformer-based models with CNNs to enhance feature extraction and context-sensitive lesion detection.

State-of-the-art augmentation methods, such as illumination transformations, vessel enhancement, and synthetic image generation, will also further enhance the robustness of the model against image quality fluctuations and early-stage anomalies.

Real-time edge computing deployment on lowpower platforms such as NVIDIA Jetson Nano and Raspberry Pi will be built for point-of-care retinal screening in rural and remote communities.

The system will also be extended to a diagnostic-assistant platform that not only identifies retinal abnormalities but also suggests referral actions or treatment protocols based on the severity of the disease. By connecting AI with ophthalmology, the future system will assist in clinical decision-making, minimize diagnostic delays, and aid in global efforts to prevent vision loss and blindness.

# REFERENCES

- A. E. and D. J. Aravindhar, "Machine Learning-Based Prediction of Retinal Detachment Subtypes: A Comprehensive Method," in Proc. 2023 First Int. Conf. Adv. Electr., Electron. Comput. Intell. (ICAEECI), Tiruchengode, India, 2023, pp. 1–8, doi: 10.1109/ICAEECI58247.2023.10370921.
- A. M. A and S. S. S. Priya, "Detection and Classification of Diabetic Retinopathy Using Pretrained Deep Neural Networks," in Proc. 2023 Int. Conf. Innov. Eng. Technol. (ICIET), Muvattupuzha, India, 2023, pp. 1–7, doi: 10.1109/ICIET57285.2023.10220715.
- A. A. Micheal and L. J. Sai, "Dual-Model Approach for Diabetic Retinopathy and Macular Edema Detection," in Proc. 2024 Int. Conf. Electr. Electron. Comput.

- Technol. (ICEECT), Greater Noida, India, 2024, pp. 1–5, doi: 10.1109/ICEECT61758.2024.10738881.
- G. Ali, A. Dastgir, M. W. Iqbal, M. Anwar, and M. Faheem, "A Hybrid Convolutional Neural Network Model for Automatic Diabetic Retinopathy Classification from Fundus Images," IEEE J. Transl. Eng. Health Med., vol. 11, pp. 341–350, Jun. 2023, doi: 10.1109/JTEH M.2023.3282104.
- G. Deshpande, Y. Govardhan, and A. Jain, "Machine Learning-Based Diabetic Retinopathy Detection: A Comprehensive Study Using InceptionV3 Model," in Proc. 2024 ASU Int. Conf. Emerg. Technol. Sustain. Intell. Syst. (ICETSIS), Manama, Bahrain, 2024, pp. 994–999, doi: 10.1109/ICETSIS61505.2024.1045954
- K. S. Reddy and M. Narayanan, "An Efficiency Way to Analyse Diabetic Retinopathy Detection and Classification Using Deep Learning Techniques," in Proc. 2023 3rd Int. Conf. Adv. Comput. Innov. Technol. Eng. (ICACITE), Greater Noida, India, 2023, pp. 1388–1392, doi: 10.1109/ICACITE57410.2023.10182642.
- L. Bekalo, B. Y. Mesfin, F. Admasu, and J. P. Reidy, "Automated 3-D Retinal Layer Segmentation From SD-OCT Images with Neurosensory Retinal Detachment," IEEE Access, vol. 7, pp. 14894–14907, 2019, doi: 10.1109/ACCESS.2019.2893954.
- M. Wu, W. Wu, M. Niemeijer, and M. D. Abramoff, "Automatic Subretinal Fluid Segmentation of Retinal SD-OCT Images with Neurosensory Retinal Detachment Guided by Enface Fundus Imaging," IEEE Trans. Biomed. Eng., vol. 65, no. 1, pp. 87–95, Jan. 2018, doi: 10.1109/TBME.2017.2695461.
- S. Yadav, N. K. Roy, N. Sharma, and R. Murugan, "Classification of Retinal Detachment using Deep Learning through Retinal Fundus Images," in Proc. 2022 IEEE India Council Int. Subsections Conf. (INDISCON), Bhubaneswar, India, 2022, pp. 1–6, doi: 10.1109/INDISCON54605.2022.9862901.