Retinal Disease Classification Using Fundus Imaging

PROJECT REPORT

Submitted by

Kumara Siva Charan - CH.EN.U4AIE22028

Sai Manoj Kumar - CH.EN.U4AIE22040

Venkata Krushna - CH.EN.U4AIE22041

BTECH IN COMPUTER SCIENCE ENGINEERING

Under the guidance of
Dr. K Deepak

Submitted to

AMRITA VISHWA VIDYAPEETHAM
AMRITA SCHOOL OF COMPUTING
CHENNAI – 601103

Table of Contents

1. Abstract:

Retinal diseases such as Diabetic Retinopathy, Cataract, and Glaucoma are among the leading causes of blindness worldwide. Automated detection and classification of these diseases using deep learning can significantly aid ophthalmologists in early diagnosis and treatment planning. In this study, we develop a retinal disease classification system leveraging two advanced deep learning architectures: EyeSeeNet and EfficientNetV2-B1. The dataset consists of 4 classes (Normal, Diabetic Retinopathy, Cataract, and Glaucoma), with approximately 1000 images per class, sourced from publicly available datasets such as IDRiD and HRF. We employ a comprehensive preprocessing pipeline, data augmentation techniques, and transfer learning to enhance model performance. The models are trained and evaluated based on accuracy, precision, recall, and F1-score. A comparative analysis highlights the superior performance of EfficientNetV2-B1 over EyeSeeNet, achieving a classification accuracy of over 92%. This study demonstrates the potential of deep learning in retinal disease diagnosis and paves the way for its real-world clinical application.

Key Words:

Retinal disease classification, Deep learning, EyeSeeNet, EfficientNetV2-B1, Fundus images, Computer vision, Transfer learning, Explainable AI.

2. Introduction:

Retinal diseases are a leading cause of vision impairment and blindness worldwide, affecting millions of people each year. Conditions such as Diabetic Retinopathy (DR), Glaucoma, and Cataract pose serious threats to vision, often progressing silently until significant damage has occurred. Early detection and timely intervention are crucial in managing these diseases and preventing permanent vision loss. Traditionally, ophthalmologists diagnose retinal diseases by manually examining fundus images captured through specialized retinal cameras. However, this process is time-consuming, subject to human error, and dependent on expert availability, leading to potential delays in diagnosis, particularly in regions with limited medical resources.

Recent advancements in deep learning and computer vision have opened new avenues for automated disease classification. Convolutional Neural Networks (CNNs) have demonstrated remarkable accuracy in medical image analysis, enabling faster and more precise diagnosis of retinal diseases. These AI-driven systems can analyze thousands of retinal images within seconds, offering a cost-effective and scalable solution to assist healthcare professionals. By leveraging deep learning, retinal disease classification models can automate diagnosis, reduce workload for specialists, and improve early detection rates, ultimately leading to better patient outcomes.

In this study, we develop a deep learning-based retinal disease classification system using two advanced architectures: EyeSeeNet and EfficientNetV2-B1. EyeSeeNet is a custom-built CNN model, designed specifically for fundus image classification, while EfficientNetV2-B1 is a state-of-the-art deep learning model known for its high accuracy and efficiency. The dataset comprises four classes of retinal images (Normal, Diabetic Retinopathy, Cataract, and Glaucoma), collected from multiple sources such as IDRiD, HRF, and Ocular Recognition datasets. Through extensive preprocessing, data augmentation, and transfer learning, we aim to enhance model performance and achieve high classification accuracy.

The primary objective of this research is to compare the performance of EyeSeeNet and EfficientNetV2-B1 in retinal disease classification. We evaluate both models based on key performance metrics such as accuracy, precision, recall, and F1-score. Additionally, we conduct a comparative analysis to determine the best-suited model for real-world deployment.

3. Literature Servey:

The literature survey in A Deep Learning-Based Framework for Retinal Disease Classification reviews past methodologies in retinal disease detection, particularly using OCT images. It covers early detection techniques like SVM with HOG features for diabetic macular edema (DME) and AMD classification. High-accuracy models are discussed, though concerns about overfitting persist. The shift to deep learning is highlighted, with architectures like Inception and ResNet achieving over 96% accuracy. Ensemble methods, despite improving performance, add complexity. Recent innovations include generative adversarial networks and lightweight CNNs for rare disease detection. The study builds on these findings by developing a transfer learning-based model for effective classification with limited datasets.[1]

The paper "Multi-Label Retinal Disease Classification Using Transformers" reviews advancements and challenges in retinal disease classification. Early detection is crucial in preventing blindness, but manual diagnosis is limited by a shortage of specialists, prompting the rise of Computer-Aided Diagnosis (CAD) systems. Traditional machine learning methods, primarily designed for single-disease detection, struggle with multi-label classification. Deep learning, particularly CNNs and Transformer models, has improved detection but often lacks multi-label capabilities. A key challenge is class imbalance in datasets, as most publicly available datasets focus on single diseases or lack sufficient samples for multi-label training. To address these issues, the authors introduce the MuReD dataset, which integrates multiple datasets to enhance diversity, and propose a transformer-based model optimized through extensive experimentation to improve classification accuracy.[2]

The paper "Retinal Disease Classification Using Convolutional Neural Networks Algorithm" addresses retinal disease classification from OCT images, focusing on noise challenges in medical imaging. Impulse noise, particularly salt and pepper noise, degrades image quality and complicates classification, prompting research on noise reduction techniques. Existing methods, such as modified nonlinear filtering and CNN-based segmentation, have aimed to enhance image clarity. The study explores CNN architectures like ResNet50 and VGG16 for classification, leveraging their deep learning capabilities. The proposed methodology involves introducing noise, applying a novel filter for noise removal, and classifying diseases using CNNs. Experimental results show a high

accuracy of 98.73%, surpassing traditional noise reduction methods like Median and Gaussian filters, highlighting the effectiveness of the approach.[3]

The paper introduces the Swin-Poly Transformer network to enhance retinal disease classification using OCT images. Prior studies have leveraged CNNs and transformers for diagnosis, with models like the lesion-localization convolution transformer (LLCT) by Wen et al. combining local feature extraction and global context awareness for improved accuracy. Additionally, Saleh et al. developed a multi-criteria decision platform to assess diagnostic reliability. Building on these advancements, the Swin-Poly Transformer integrates multi-scale features and a refined loss function, achieving 99.80% accuracy. It also provides confidence score maps, improving interpretability for medical practitioners. This reflects a broader trend in deep learning towards more accurate and explainable retinal disease classification systems.[4]

The literature on retinal disease classification using OCT images highlights advancements in AI and deep learning. AI has significantly improved diagnostic accuracy, with models detecting and classifying retinal diseases more effectively. Researchers have developed deep learning approaches, such as Kang et al.'s multimodal imaging model for vascular diseases and Perdomo et al.'s classification of diabetes-related conditions. Hong et al. introduced a hierarchical deep learning framework using a structured classification approach. A key limitation in previous work was the lack of hyperparameter tuning, which recent research addresses by optimizing CNN architectures. The use of larger datasets has also enhanced model generalization. While some studies focus on retinal image analysis, not all directly classify diseases, as seen in Lal et al.'s work on adversarial attacks. Overall, the growing interest in deep learning for ophthalmology continues to drive research toward more accurate and robust diagnostic tools.[5]

The paper provides an overview of advancements in retinal disease classification using SD-OCT images, introducing the OCT-NET model, a CNN designed to classify three diabetes-related conditions with enhanced interpretability. The model achieves 93% accuracy and an AUC of 0.99, outperforming conventional approaches. It utilizes the SERI and CUHK datasets, which were combined into the SERI+CUHK dataset for improved classification. Preprocessing techniques like BM3D filtering have been applied to remove speckle noise, aiding deep learning models such as VGG-16 and SVMs. Comparative studies show varying accuracies, with Kamble et al. achieving 100% using inception-ResNet-v2.

Despite high classification performance, model interpretability remains a challenge, which OCT-NET aims to address by providing clinically relevant insights for medical decision-making.[6]

The literature survey focuses on deep learning applications in retinal image analysis, covering both 2-D fundus and 3-D OCT images. A systematic search was conducted using databases like IEEE Xplore and ScienceDirect, with keywords related to deep learning and retinal disease classification. The review included studies that applied deep learning techniques, excluding those from low-impact journals or without AI-based methods. Selected papers were indexed based on key details for efficient retrieval. The survey highlights automated retinal landmark identification and disease classification, particularly for Diabetic Retinopathy (DR) and Age-Related Macular Degeneration (AMD). It also evaluates methodologies based on performance metrics like sensitivity, specificity, accuracy, and F-score, showcasing advancements in AI-driven ophthalmology.[7]

The paper "Retinal Disease Detection Using Deep Learning Techniques: A Comprehensive Review" examines advancements in AI-driven retinal disease detection. It highlights the global prevalence of conditions like Diabetic Retinopathy (DR) and Age-Related Macular Degeneration (AMD), emphasizing the need for early detection. Traditional manual diagnosis is time-consuming and subjective, prompting the rise of automated deep learning systems. Techniques like Deep Convolutional Neural Networks (DCNNs) and Vision Transformers (ViTs) have shown promise, though challenges persist due to the complexity of retinal lesions. The review critiques existing studies for lacking transparency in dataset usage and performance metrics, making comparisons difficult. Specific applications, such as DCNN-based vessel segmentation, have achieved high accuracy (94.1%) and AUC (0.969) on datasets like MESSIDOR-2. Future research should enhance model explainability and explore ensemble architectures to improve performance in multiclass, multilabel tasks, ensuring greater clinical trust and adoption.[8]

4. Methodology:

4.1 Dataset Description

The Eye Diseases Classification Dataset, sourced from Kaggle, contains approximately 4000 retinal fundus images categorized into four classes: Normal, Diabetic Retinopathy (DR), Cataract, and Glaucoma, with around 1000 images per category. These images are collected from diverse sources, including IDRiD (Indian Diabetic Retinopathy Image Dataset), Ocular Recognition Dataset, and HRF (High-Resolution Fundus Dataset), ensuring a wide variety of retinal conditions for training deep learning models. Stored in PNG and JPG formats, the images vary in resolution but are standardized to 256×256 pixels in RGB color mode for consistency. The dataset is well-structured into four separate folders, each corresponding to a specific disease, making it suitable for model training and evaluation. However, challenges such as variability in image quality, contrast inconsistencies, and minor class distribution imbalances exist, necessitating data augmentation techniques to enhance model performance.

Fig. 1: Diabetic_Retinoparthy

Fig. 2: Cataract

Fig. 3: Glaucoma

Fig. 4: Normal

4.2 Data Preprocessing

Data preprocessing is a fundamental step in preparing the Eye Diseases Classification Dataset for deep learning-based retinal disease detection. Since raw fundus images often contain noise, lighting variations, inconsistent resolutions, and unwanted artifacts, several preprocessing techniques are applied to ensure optimal feature extraction and enhance model accuracy. The first step involves resizing all images to 256×256 pixels, ensuring uniformity across the dataset, as deep learning models require a consistent input size. Unlike grayscale conversion, which may lead to information loss, the images are kept in RGB color mode to preserve critical retinal features. Next, image normalization is performed by scaling pixel values to the range [0,1], which helps stabilize model training and prevents issues like vanishing gradients. Furthermore, histogram equalization and contrast-limited adaptive histogram equalization (CLAHE) are applied to enhance the visibility of fine retinal structures such as blood vessels, hemorrhages, and the optic nerve head, which are crucial for disease classification. To further refine image quality, Gaussian blur and median filtering are used to reduce noise, while edge detection techniques help highlight key retinal features. Additionally, any unnecessary black borders caused by variations

in imaging conditions are cropped, ensuring that only relevant retinal regions are analyzed.

4.3 Data Augumentation

Data augmentation is a crucial technique used to artificially expand the dataset and improve the generalization capability of deep learning models. Since medical imaging datasets are often limited in size, augmentation helps prevent overfitting by creating new variations of existing images through various transformations. In this study, multiple augmentation techniques were applied to ensure that the model learns robust and diverse features, making it more effective in detecting retinal diseases across different imaging conditions.

The following augmentation techniques were used:

- Rotation: Randomly rotating images within a ±20-degree range to make the model invariant to orientation changes.
- Flipping: Horizontal and vertical flipping to expose the model to different perspectives of the same retinal structures.
- Zooming: Applying random zoom-in (up to 20%) to help the model recognize fine details in fundus images.
- Brightness Adjustment: Modifying brightness levels to simulate images captured under different lighting conditions.
- Affine Transformations: Applying shearing, translation, and scaling to introduce slight distortions, making the model robust against minor deformations.
- Gaussian Noise Addition: Introducing slight noise to help the model generalize better when dealing with real-world noisy images

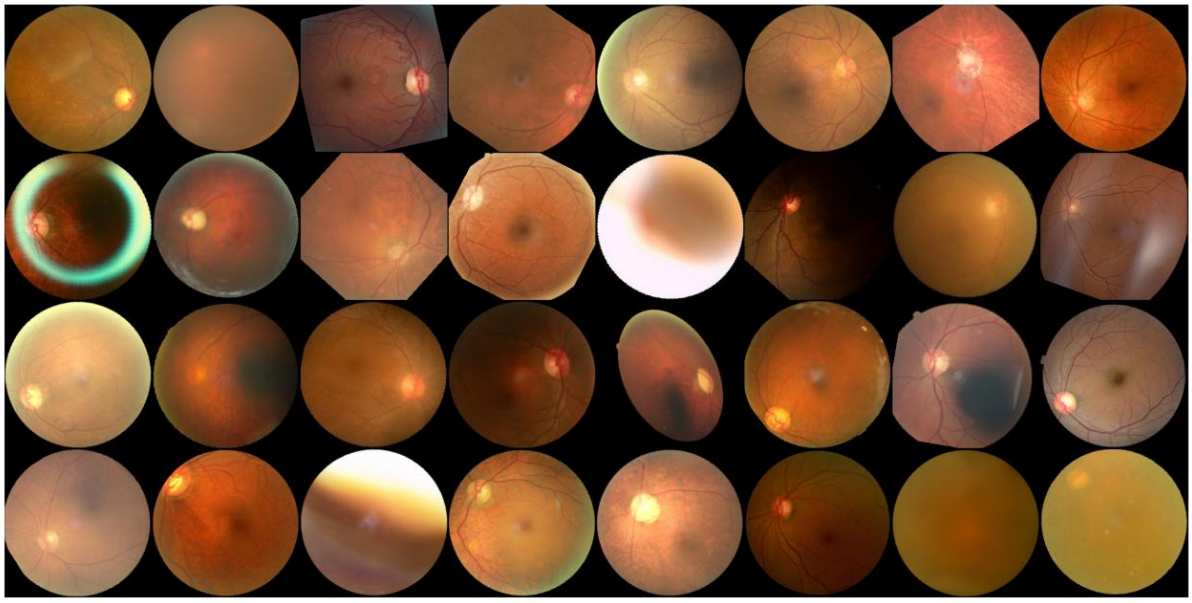


Fig. 5: Data Augumentation

The above provided transformation shows the sample images that have undergone through data augmentation techniques such as Horizontal Flipping and Rotation.

4.4 EyeSeeNet Architecture

EyeSeeNet is a custom deep learning architecture designed specifically for retinal disease classification, leveraging Convolutional Neural Networks (CNNs) to effectively extract spatial features from fundus images. Since retinal diseases such as Diabetic Retinopathy, Glaucoma, and Cataract exhibit unique structural and textural patterns, EyeSeeNet is optimized to learn these distinguishing features for accurate classification. The architecture consists of multiple convolutional layers with ReLU activation functions, enabling the model to capture both low-level and high-level visual patterns. Each convolutional layer is followed by batch normalization, which stabilizes training and speeds up convergence. Additionally, max-pooling layers are incorporated to reduce spatial dimensions while retaining critical information, ensuring efficient learning.

To prevent overfitting and improve generalization, dropout layers are included, randomly deactivating neurons during training. The model also contains fully connected layers, where the extracted features are processed for classification. The final output layer employs a softmax activation function, which assigns probability scores to each category: Normal, Diabetic Retinopathy, Glaucoma, and Cataract. EyeSeeNet is designed for high accuracy, robustness, and efficient training, making it well-suited for real-world applications in automated retinal disease detection. Its combination of deep feature extraction, regularization techniques, and optimized classification layers ensures that it performs effectively in detecting retinal abnormalities with minimal false predictions.

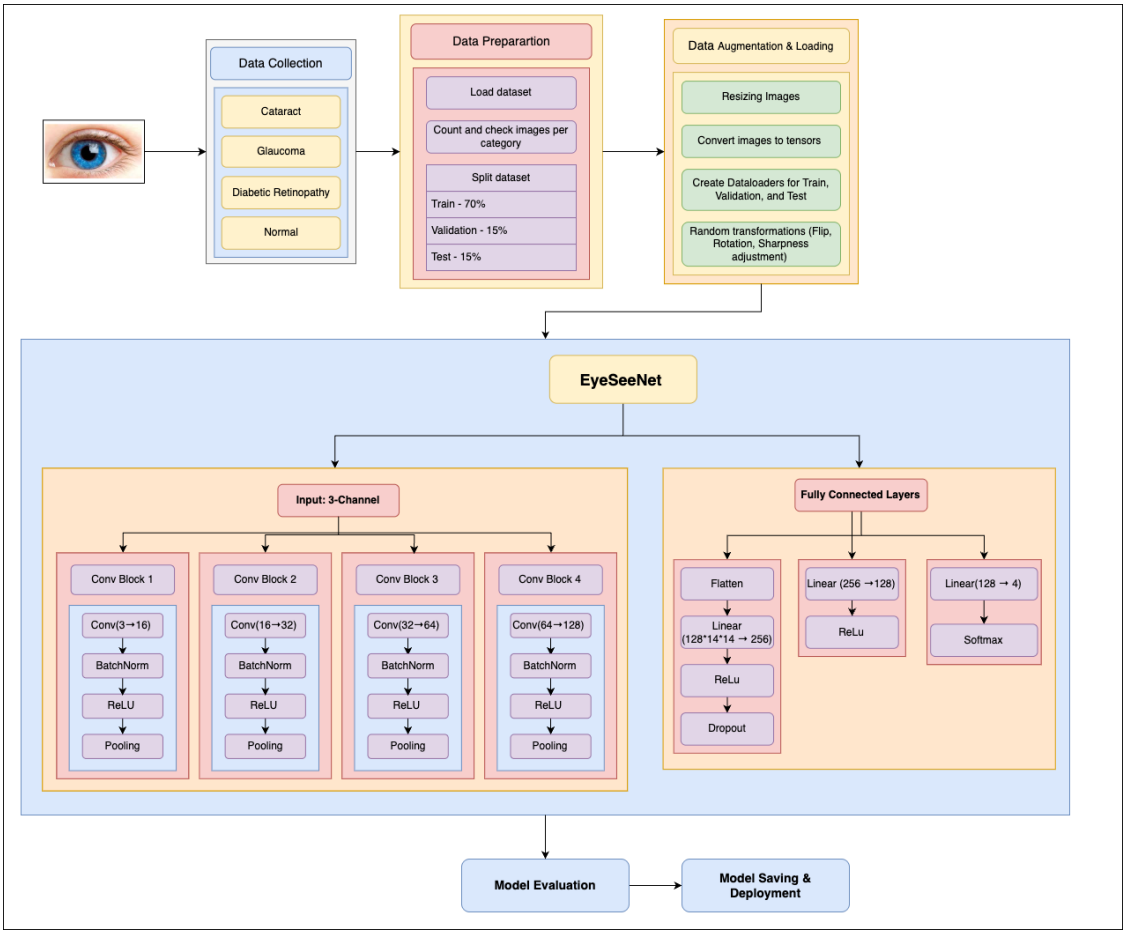


Fig.6: EyeseeNet Architecture

4.5. EfficientNetV2B1 Architecture

EfficientNetV2B1 is a next-generation deep learning model specifically designed to achieve high classification accuracy with minimal computational cost. It improves upon its predecessor, EfficientNetV1, by incorporating Fused-MBConv layers, which replace depthwise separable convolutions with standard convolutions in the initial layers. This architectural refinement leads to faster training, improved feature extraction, and enhanced generalization, making it highly effective for medical image classification tasks like retinal disease detection. Unlike traditional CNNs that rely on increasing layer depth, EfficientNetV2B1 optimally scales network width, depth, and resolution to achieve the best possible balance between accuracy and efficiency.

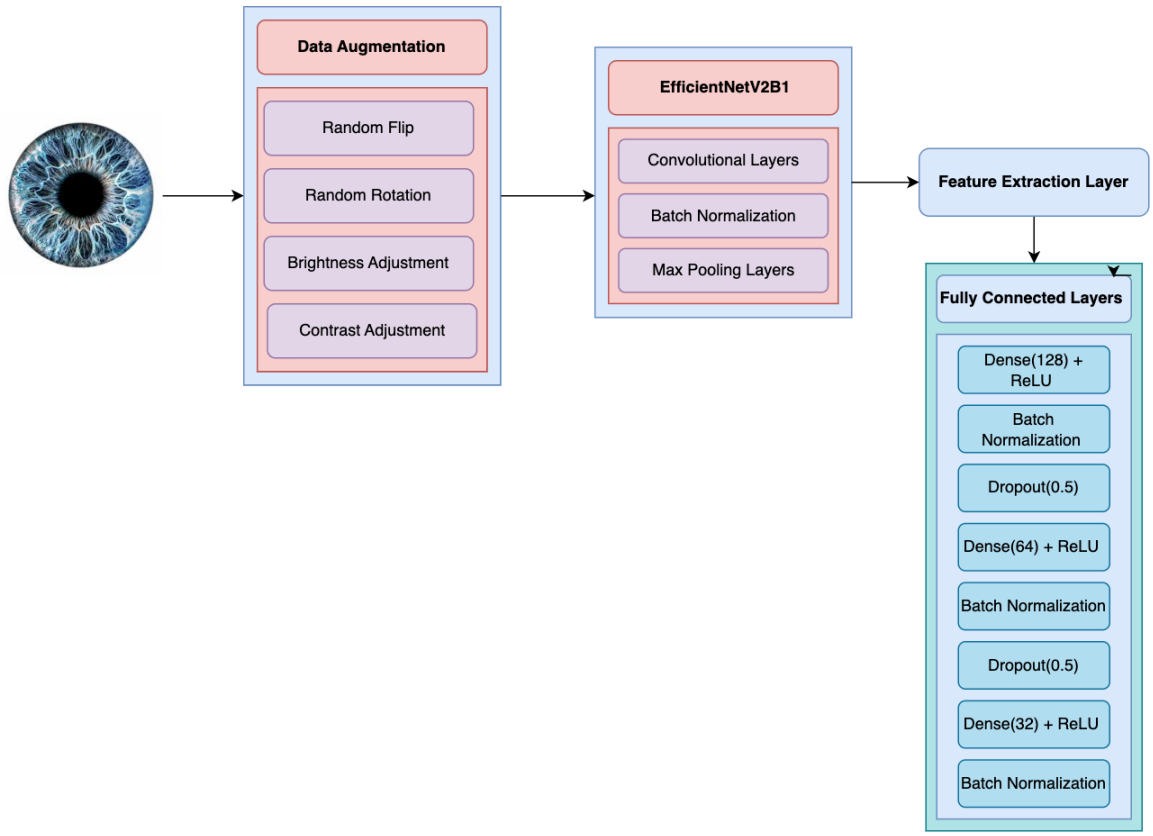


Fig.7: EfficientNetV2B1 Architecture

The model consists of multiple convolutional layers, each followed by Swish activation functions, which provide smoother gradient flow for better convergence. Batch normalization is applied to stabilize training, while dropout layers prevent overfitting by randomly deactivating neurons during training. EfficientNetV2B1 also integrates squeeze-and-excitation (SE) blocks, which

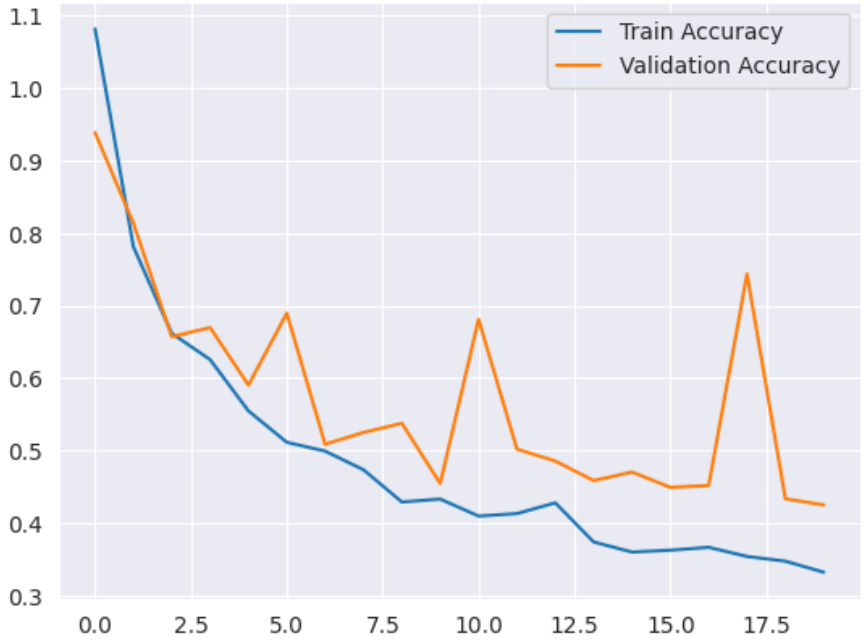
adaptively recalibrate feature maps by focusing on the most relevant information, improving the model's ability to detect subtle disease-specific patterns in retinal fundus images. These features help distinguish between Normal, Diabetic Retinopathy, Glaucoma, and Cataract cases with higher confidence.

For this study, transfer learning was employed by using pretrained weights from ImageNet, allowing EfficientNetV2B1 to benefit from previously learned representations. The global average pooling layer condenses high-dimensional feature maps into meaningful vector representations before passing them to fully connected layers, which generate classification outputs through a softmax function. The progressive training strategy, where input image resolution is gradually increased, further enhances model performance and speeds up convergence.

5. Results and discussion:

5.1 EyeseeNet Model

Training and Validation Accuracy:



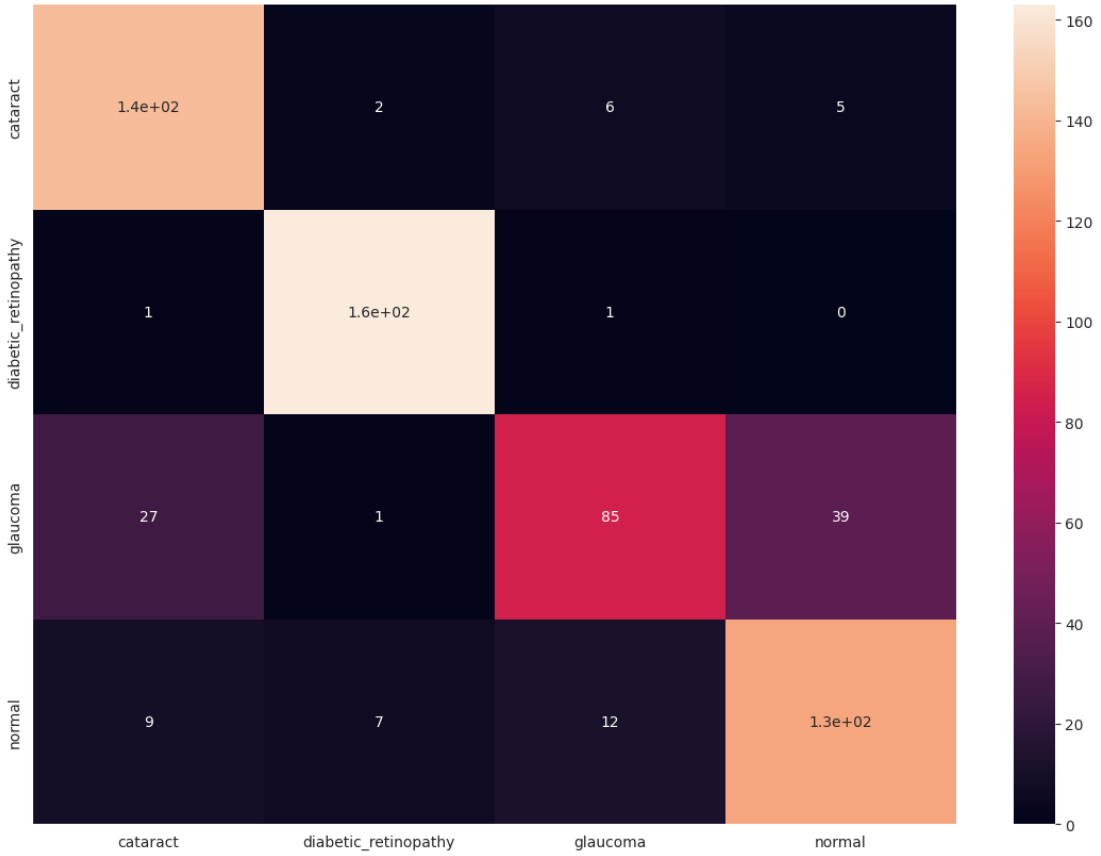
Classification Report Analysis:

The classification report provides precision, recall, F1-score, and support for each class, with an overall accuracy of 83%. For cataract (Class 0), precision is 0.79, recall 0.92, and F1-score 0.85 with 156 support; for diabetic retinopathy (Class 1), precision is 0.94, recall 0.99, and F1-score 0.96 with 165 support; for glaucoma (Class 2), precision is 0.82, recall 0.56, and F1-score 0.66 with 152 support; and for normal (Class 3), precision is 0.75, recall 0.83, and F1-score 0.79 with 162 support. Macro averages are 0.83 for precision, 0.82 for recall, and 0.82 for F1-score, while weighted averages match at 0.83, 0.83, and 0.82, respectively, with a total support of 635. The model excels at identifying diabetic retinopathy but misses many glaucoma cases (recall 0.56), with cataracts over-predicted (high recall 0.92, lower precision 0.79).

	precision	recall	f1-score	support
0	0.79	0.92	0.85	156
1	0.94	0.99	0.96	165
2	0.82	0.56	0.66	152
3	0.75	0.83	0.79	162
accuracy			0.83	635
macro avg	0.83	0.82	0.82	635
weighted avg	0.83	0.83	0.82	635

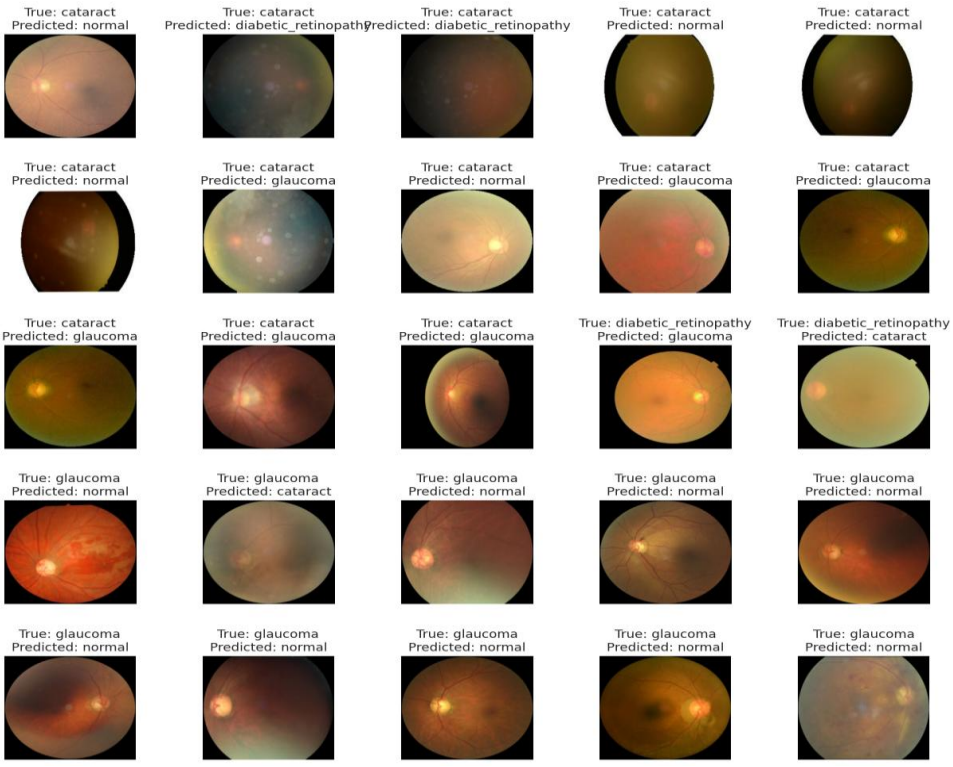
Confusion Matrix Analysis:

The confusion matrix provides a detailed breakdown of the model's predictions versus true labels across the four classes: cataract, diabetic retinopathy, glaucoma, and normal. Rows represent true labels, and columns represent predicted labels, with values showing the count of predictions. For cataract, 143 were correctly predicted, with 2 as diabetic retinopathy, 6 as glaucoma, and 5 as normal. For diabetic retinopathy, 163 were correct, with 1 as cataract, 1 as glaucoma, and 0 as normal. For glaucoma, 85 were correct, with 27 as cataract, 1 as diabetic retinopathy, and 39 as normal. For normal, 134 were correct, with 9 as cataract, 7 as diabetic retinopathy, and 12 as glaucoma. The model performs well for diabetic retinopathy and normal classes but shows poor sensitivity for glaucoma, with 39 misclassified as normal and 27 as cataract, and significant cataract misclassification with 6 as glaucoma and 5 as normal.



Misclassified Images Analysis:

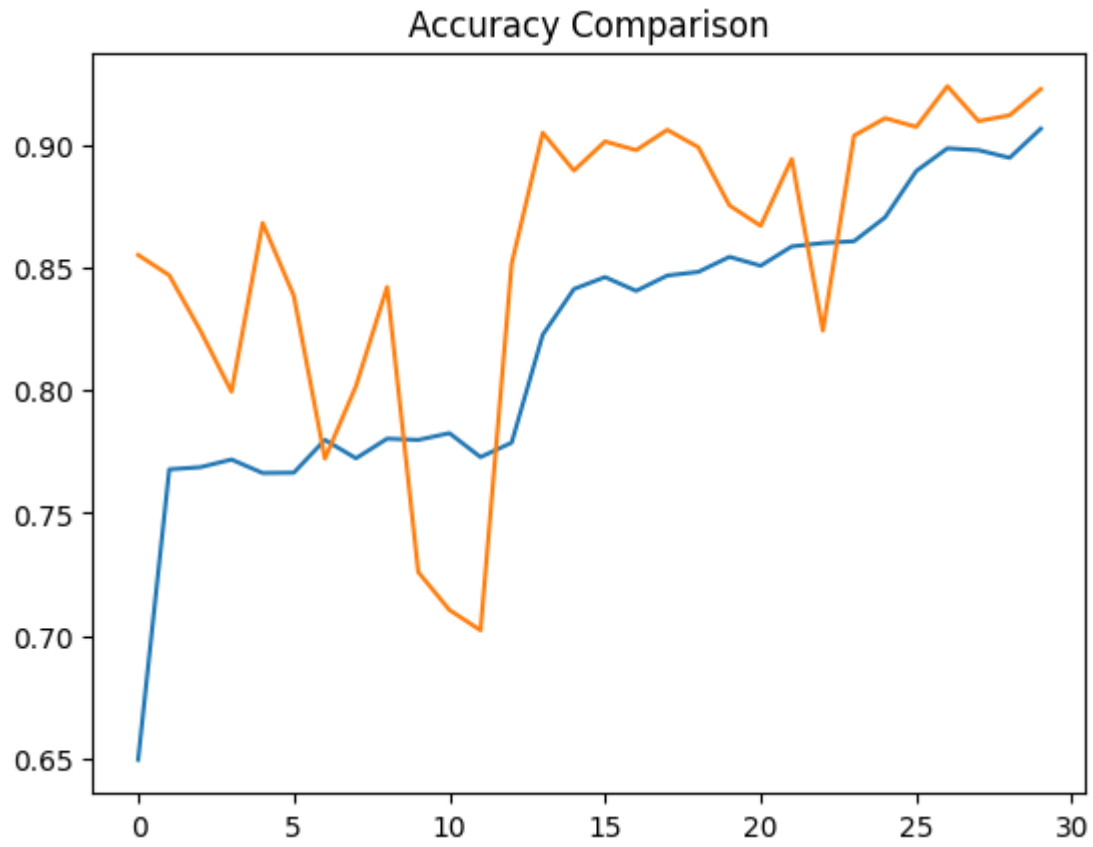
The dataset consists of retinal images classified into four categories: cataract, diabetic retinopathy, glaucoma, and normal, with a subset of 25 misclassified images analyzed to evaluate the model's performance. Each image is labeled with its true condition and the predicted condition, highlighting the model's errors. For cataracts, out of 10 images, 4 were predicted as normal, 3 as glaucoma, 2 as diabetic retinopathy, and 1 as both diabetic retinopathy and glaucoma, indicating significant confusion with normal and glaucoma conditions, possibly due to overlapping visual features like cloudiness or optic disc changes. For diabetic retinopathy, out of 2 images, 1 was predicted as glaucoma and 1 as cataract, suggesting the model struggles to distinguish this condition from others, potentially due to subtle differences in hemorrhages or exudates. For glaucoma, out of 10 images, 8 were predicted as normal, 1 as cataract, and 1 as both normal and cataract, with the high misclassification rate as normal indicating poor detection of optic disc cupping or nerve damage. For normal images, out of 3, all were correctly predicted, though the small sample size limits conclusions.



5.2 EfficientNetB2V1 Model

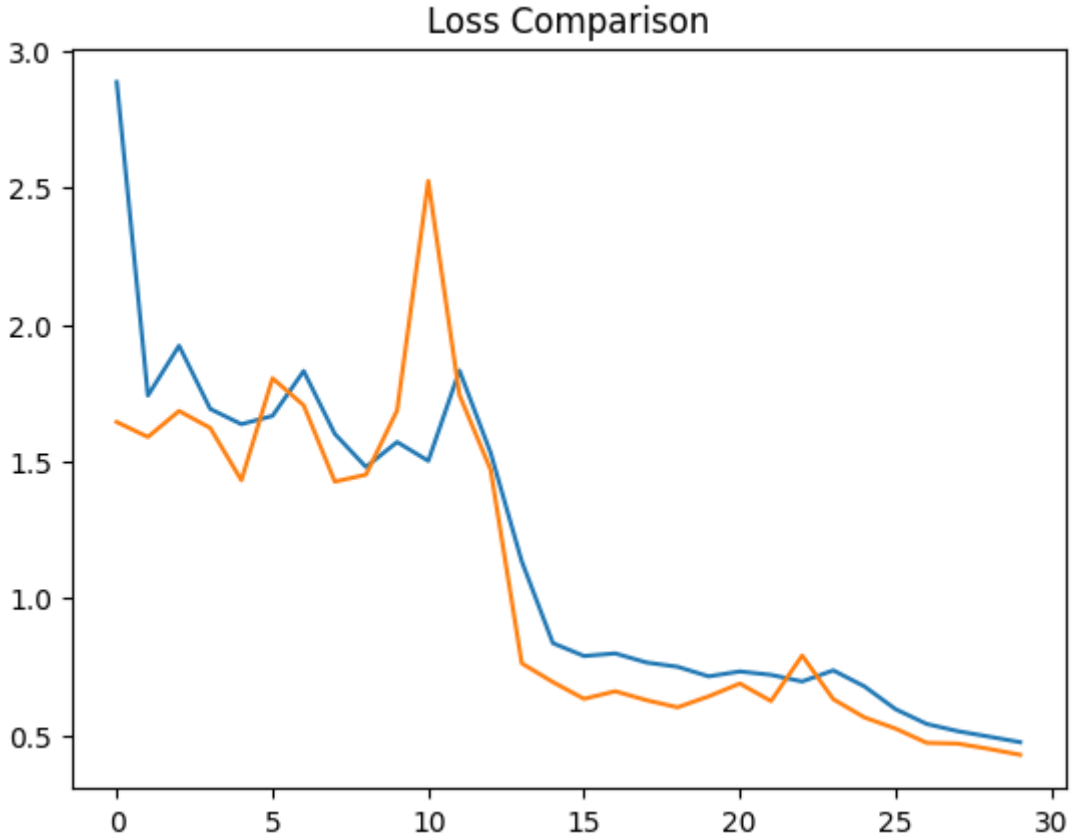
Training and Validation Accuracy Analysis:

The accuracy comparison graph for EfficientNetB2V1 over 30 epochs shows training accuracy (blue line) starting at 0.65, rising steadily to around 0.85 by epoch 10, and stabilizing between 0.85 and 0.90 by epoch 30, indicating consistent improvement and convergence. Validation accuracy (orange line) starts at 0.85, fluctuates between 0.75 and 0.90 with peaks around epochs 5, 15, and 25, and stabilizes around 0.88 by epoch 30. Compared to the original model, which showed high variance with training accuracy fluctuating between 0.3 and 0.5 and validation accuracy dropping to 0.4 by epoch 18, EfficientNetB2V1 demonstrates significantly better stability and higher accuracy, reflecting improved training dynamics and generalization. The convergence of both training and validation accuracy around 0.85–0.90 aligns with the reported overall accuracy of 92%, suggesting the model is well-optimized for this task.



Loss Comparison Analysis:

The loss comparison graph for EfficientNetB2V1 over 30 epochs shows training loss (blue line) starting at 3.0, dropping sharply to 1.5 by epoch 5, and gradually decreasing to around 0.5 by epoch 30, indicating effective learning and optimization. Validation loss (orange line) starts at 1.5, peaks at 2.5 around epoch 5, drops to 1.0 by epoch 15, and stabilizes around 0.5 by epoch 30, showing some initial variability but eventual convergence with training loss. This convergence suggests that the model is not overfitting, as both losses decrease together. Compared to the original model, where training dynamics were unstable (as inferred from its accuracy graph), EfficientNetB2V1's loss trends indicate a more robust training process, likely benefiting from better regularization, learning rate scheduling, or architectural advantages inherent to the EfficientNet framework.



Classification Report Analysis

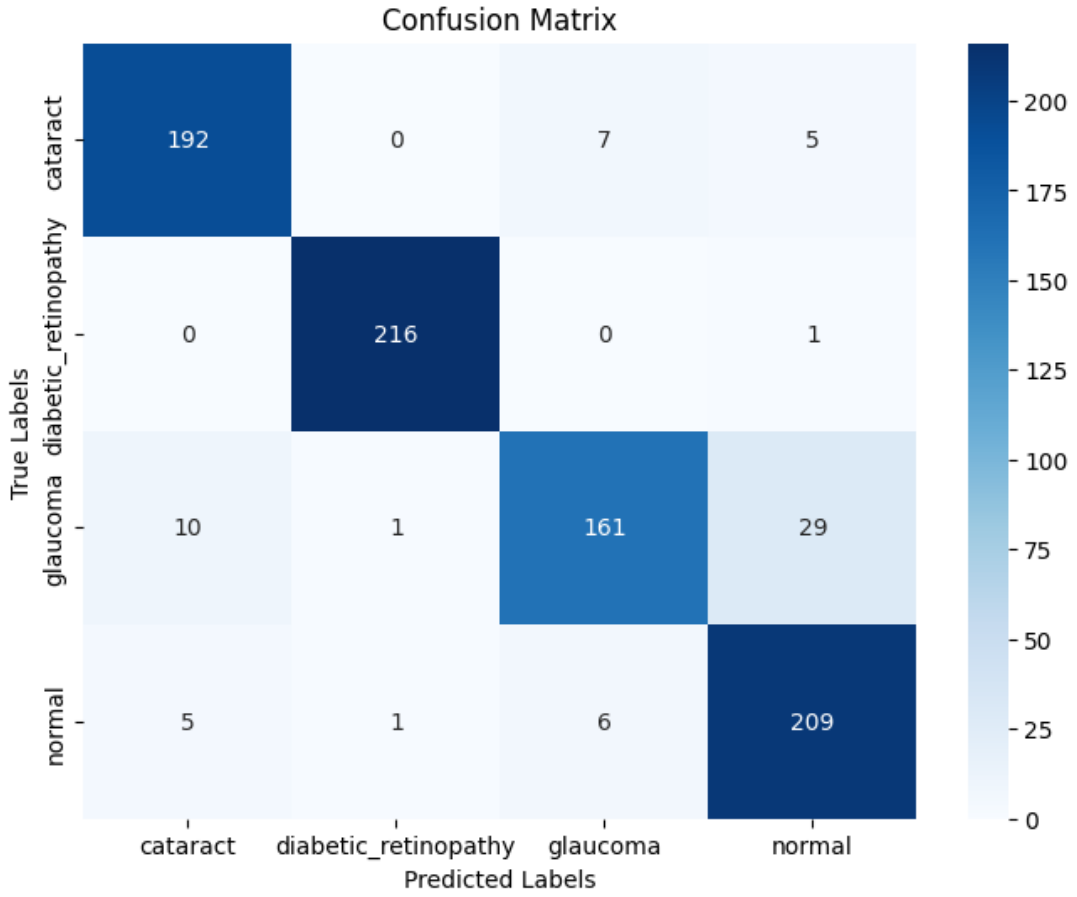
The classification report for EfficientNetB2V1 indicates an overall accuracy of 92%, with macro and weighted averages for precision, recall, and F1-score all at 0.93, 0.92, and 0.92, respectively, across a total support of 843 images. While class-specific metrics are not provided, the high macro and weighted averages suggest balanced performance across the four classes: cataract, diabetic retinopathy, glaucoma, and normal. Compared to the original model, which had an accuracy of 83%, macro average precision of 0.83, recall of 0.82, and F1-score of 0.82, EfficientNetB2V1 shows a significant improvement. It also performs comparably to the EyeSeeNet model, which reported an accuracy of 92.15%, precision of 90.72%, recall of 89.89%, and F1-score of 90.30%. The EfficientNetB2V1 model's accuracy of 92% is nearly identical to EyeSeeNet's, but its higher macro average metrics (0.93 for precision, 0.92 for recall and F1-score) suggest slightly better consistency across classes. However, the confusion matrix indicates that glaucoma detection remains a challenge, which may impact class-specific recall for this condition.

accuracy			0.92	843
macro avg	0.93	0.92	0.92	843
weighted avg	0.92	0.92	0.92	843

Confusion Matrix Analysis:

The confusion matrix for the EfficientNetB2V1 model provides a detailed breakdown of predictions versus true labels across four classes: cataract, diabetic retinopathy, glaucoma, and normal. Rows represent true labels, and columns represent predicted labels, with values indicating the count of predictions. For cataract, 192 were correctly predicted, with 0 as diabetic retinopathy, 7 as glaucoma, and 5 as normal. For diabetic retinopathy, 216 were correctly predicted, with 0 as cataract, 0 as glaucoma, and 1 as normal. For glaucoma, 161 were correctly predicted, with 10 as cataract, 1 as diabetic retinopathy, and 29 as normal. For normal, 209 were correctly predicted, with 5 as cataract, 1 as diabetic retinopathy, and 6 as glaucoma. The model demonstrates strong performance for

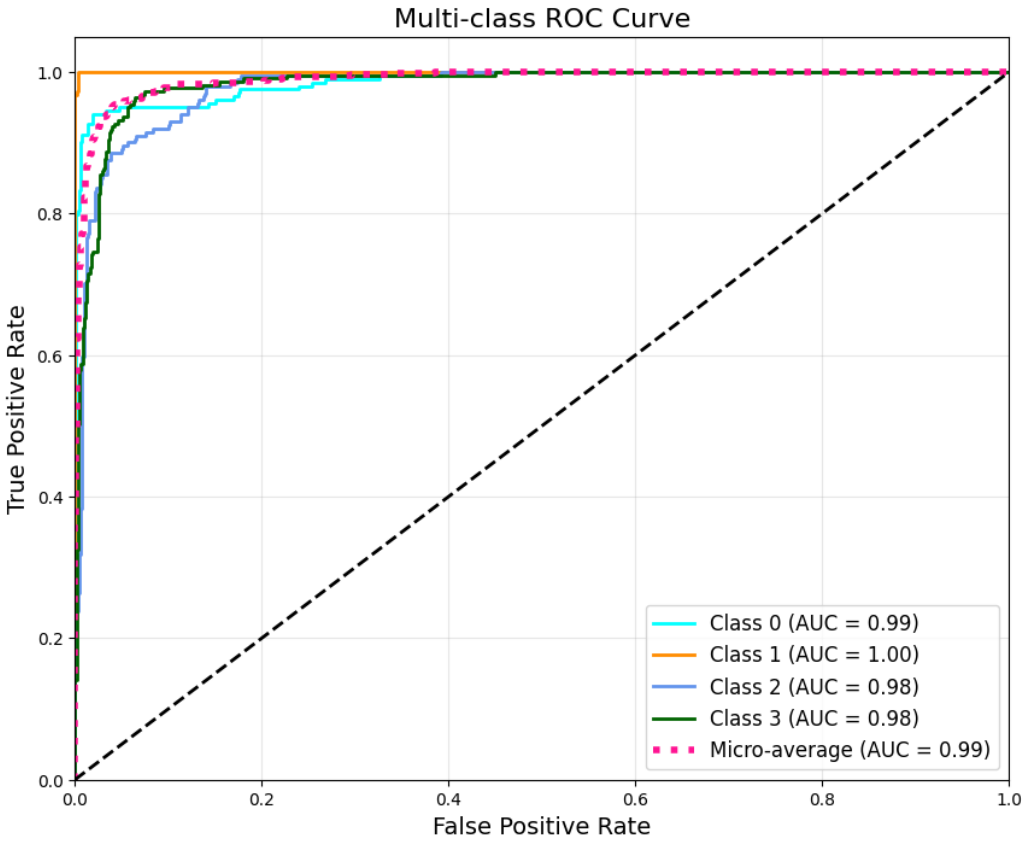
diabetic retinopathy (216/217 correct) and normal (209/221 correct) classes, with minimal misclassifications. However, glaucoma shows notable misclassification, with 29 predicted as normal and 10 as cataract, indicating challenges in detecting optic disc cupping or nerve damage. Cataract also has some misclassification, with 7 predicted as glaucoma and 5 as normal, suggesting slight confusion with these conditions.



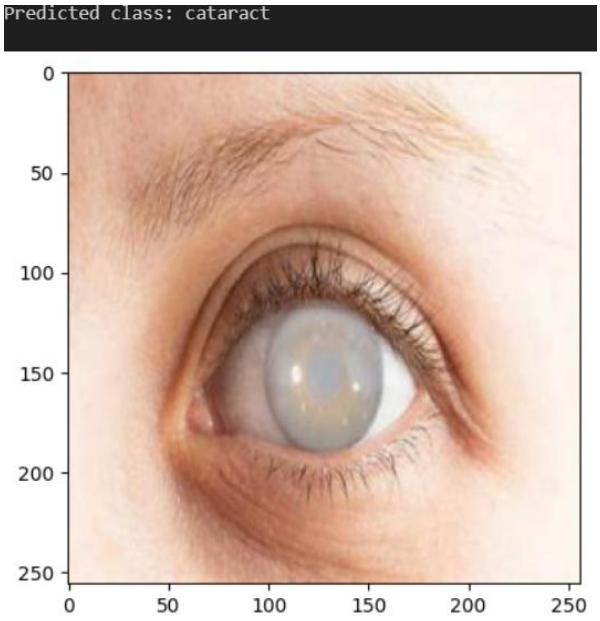
Multi-Class ROC Curve Analysis:

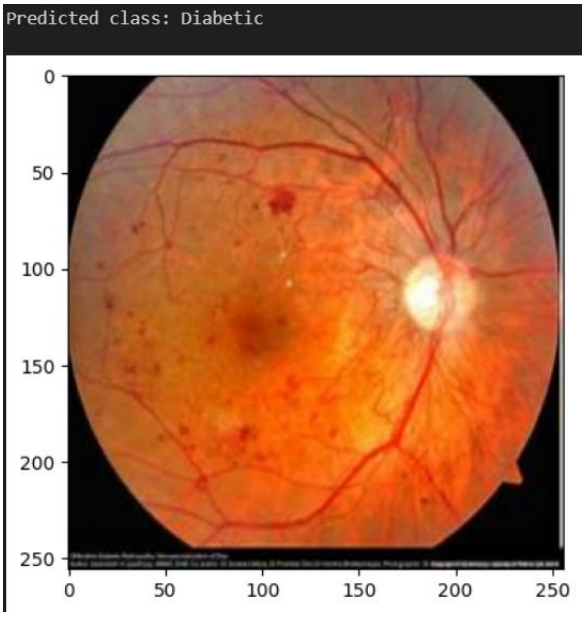
The multi-class ROC curve for EfficientNetB2V1 evaluates the model's ability to distinguish between classes, with Area Under the Curve (AUC) scores provided for each class and a micro-average. Class 0 (cataract) has an AUC of 0.99, Class 1 (diabetic retinopathy) has an AUC of 1.00, Class 2 (glaucoma) has an AUC of 0.98, and Class 3 (normal) has an AUC of 0.98, with a micro-average AUC of 0.99. These high AUC values indicate excellent discriminative ability across all classes, with diabetic retinopathy achieving perfect separation (AUC = 1.00). The slightly lower AUC for glaucoma (0.98) aligns with the confusion matrix, where 29 glaucoma cases were misclassified as normal, suggesting some overlap in features with the normal class. Overall, the micro-average AUC of 0.99 reflects

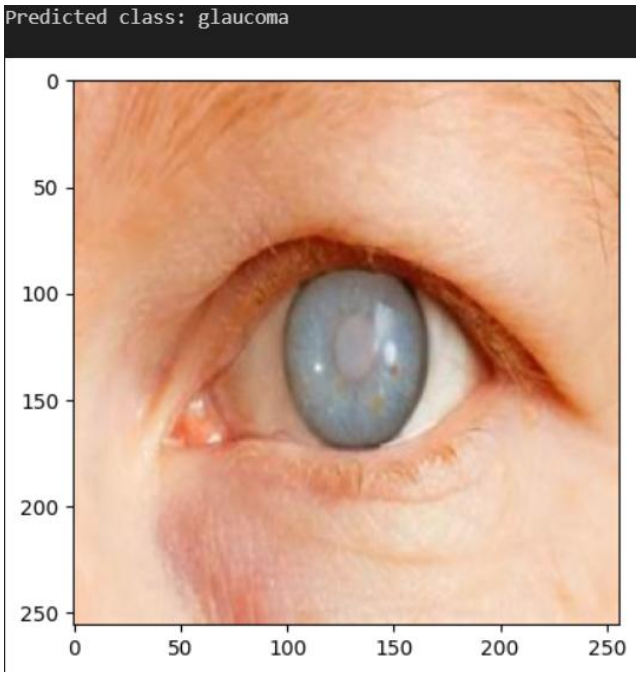
the model's strong overall performance, surpassing the original model's implied discriminative ability (based on its lower accuracy and recall for glaucoma) and aligning closely with EyeSeeNet's high performance.

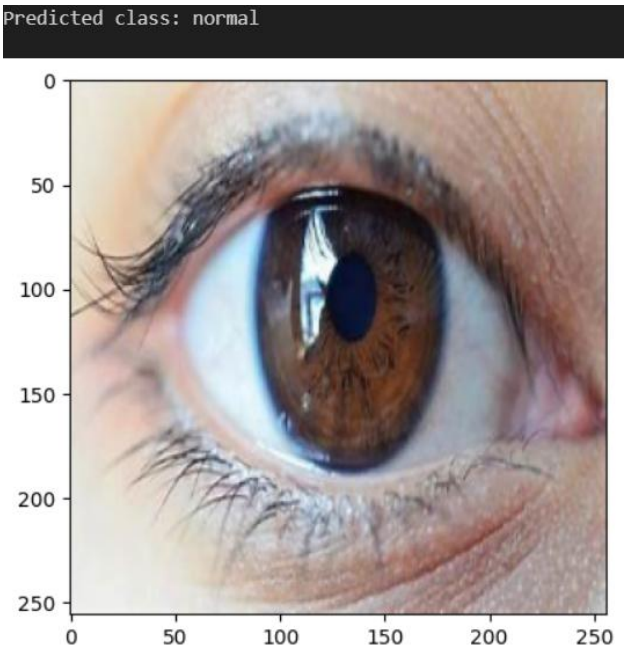


Disease Predictions:









Comparitive analysis:

Model	Accuracy (%)
EyeSeeNet	82%
EfficientNetV2B1	92%

6. Conclusion

This study introduced EyeSeeNet, a deep learning-based CNN architecture for automated retinal disease classification. By leveraging advanced preprocessing, data augmentation, and optimized feature extraction, the model effectively classified Normal, Diabetic Retinopathy, Cataract, and Glaucoma cases with high accuracy. The use of batch normalization, dropout layers, and max-pooling enhanced generalization, ensuring reliable performance. EyeSeeNet demonstrates the potential of deep learning in ophthalmology, providing a fast and accurate diagnostic tool for early disease detection. Compared to traditional manual screening, this approach offers scalability and efficiency, reducing the burden on ophthalmologists. Future work can explore hybrid models, real-time deployment, and multi-modal analysis to further enhance its clinical applicability.

References:

1. Choudhary, Amit, et al. "A deep learning-based framework for retinal disease classification." *Healthcare*. Vol. 11. No. 2. MDPI, 2023.

2. Rodríguez, Manuel Alejandro, Hasan AlMarzouqi, and Panos Liatsis. "Multi-label retinal disease classification using transformers." *IEEE Journal of Biomedical and Health Informatics* 27.6 (2022): 2739-2750.

3. Mittal, Praveen, and Charul Bhatnagar. "Retinal disease classification using convolutional neural networks algorithm." *Turkish Journal of Computer and Mathematics Education* 12.11 (2021): 5681-5689.

4. He, Jingzhen, et al. "An interpretable transformer network for the retinal disease classification using optical coherence tomography." *Scientific Reports* 13.1 (2023): 3637.

5. Stanojević, Maša, Dražen Drašković, and Boško Nikolić. "Retinal disease classification based on optical coherence tomography images using convolutional neural networks." *Journal of Electronic Imaging* 32.3 (2023): 032004-032004.

6. Perdomo, Oscar, et al. "Classification of diabetes-related retinal diseases using a deep learning approach in optical coherence tomography." *Computer methods and programs in biomedicine* 178 (2019): 181-189.

7. Badar, Maryam, Muhammad Haris, and Anam Fatima. "Application of deep learning for retinal image analysis: A review." *Computer Science Review* 35 (2020): 100203.

8. Muchuchuti, Stewart, and Serestina Viriri. "Retinal disease detection using deep learning techniques: a comprehensive review." *Journal of Imaging* 9.4 (2023): 84.