RESEARCH ARTICLE

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An Intelligent and Secure Application for Early Detection of Eye Disease

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Abstract

This paper presents a deep learning-based intelligent web application for the early detection of eye diseases using retinal fundus images. The dataset used in this study consists of 4,216 retinal fundus images collected from Kaggle, representing multiple eye disease categories. Multiple deep learning architectures, including CNN, DenseNet, InceptionV3, and ResNet, were evaluated and compared with a proposed modified MobileNetV2 architecture. The proposed architecture enhances the baseline MobileNetV2 by optimizing feature extraction and classification layers for improved performance in multi-class eye disease detection. Experimental results show that the proposed model achieved an overall classification accuracy of 88%, outperforming other evaluated models, including CNN (85.87%), DenseNet (87.19%), InceptionV3 (82.88%), and ResNet (50.67%), while maintaining low computational complexity. To improve transparency and interpretability of the deep learning model, Grad-CAM was integrated to visualize the discriminative regions of fundus images influencing the model's predictions. The optimized model was deployed within a smart web application using a Flask backend and Streamlit frontend, enabling real-time disease prediction and visual explanation of results. The proposed system demonstrates the effectiveness of lightweight deep learning architectures combined with explainable AI techniques for accessible and reliable web-based ophthalmic diagnostic support systems. The optimized lightweight model was deployed as a mobile-friendly web application using Flask and Streamlit, enabling real-time inference on resource-constrained mobile devices and supporting wireless remote access for ophthalmic screening in underserved areas.

Keywords: eye disease detection, mobile intelligence, convolutional neural network, modified mobileNet, deep learning models, medical image analysis, predictive analytics, grad-cam.

1 Introduction

Preventable blindness remains a major global public health concern. The World Health Organization reports that over 2.2 billion people across the globe experience some degree of vision loss, which most cases could have been avoided through early medical treatment. The main cause of preventable

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vision impairment is the lack of timely retinal disease screening to protect their sight from Diabetic Retinopathy, Glaucoma, Pterygium, and Retinal Detachment. The people of Bangladesh and other developing nations lack specialized ophthalmic services because their countries face both a shortage of trained eye doctors and expensive diagnostic procedures, and most medical centers operate from urban locations. Early retinal diseases are often asymptomatic until they progress to advanced stages, which can then lead to permanent sight loss.

Tuncer et al. [1] achieved 92% accuracy using ResNet-50 + XGBoost on 5K images but remained offline. Chaudhari et al. [2] reported 98.1% with VGG-19 for three diseases, limited to lab settings. Hameed et al. [3] applied GLCM texture analysis (89% accuracy) via MATLAB, unsuitable for clinics. Artificial intelligence and deep learning technologies have achieved significant progress in medical imaging through their successful implementation in retinal disease detection which utilizes fundus imaging. Healthcare professionals use three different convolutional neural network architectures which include ResNet50 and VGG19 and DenseNet for automated diagnosis of eye diseases. The application of these models to retinal image datasets has shown positive results according to previous studies. The existing research studies only perform testing in controlled lab conditions which creates an obstacle when researchers need to establish how their models work and how their models run and how their models function inside actual operational systems.

Medical imaging applications currently use lightweight deep learning frameworks because these frameworks enable medical professionals to achieve high accuracy results while they need to work with restricted processing power. MobileNetV2 uses depthwise separable convolutions together with inverted residual blocks to create an efficient feature extraction method that needs far fewer parameters than conventional deep networks. MobileNetV2 provides efficient inference capabilities which make it suitable for applications that need to operate in environments with limited computing resources.

The research team created an automated eye disease detection system through deep learning that analyzes retinal fundus images. The research team created a retinal disease classification system that uses modified MobileNetV2 architecture for multi-class classification. The model uses a dataset of 4,216 retinal fundus images from Kaggle for training and testing its performance against deep learning architectures which include CNN and DenseNet and InceptionV3 and ResNet. The study uses explainable artificial intelligence analysis through Grad-CAM to show important retinal areas that affect model predictions which helps enhance model prediction transparency.

The web-based prototype application developed with Flask and Streamlit now uses the trained model which operates as its core element. The system demonstrates how users can upload images to a simple interface which uses deep learning to analyze retinal images while displaying prediction results. The study provides a proof-of-concept demonstration of how lightweight deep learning models can be effectively deployed for automated retinal image analysis in real-world settings.

The study evaluates a lightweight deep learning architecture while developing a prototype system for automated retinal image analysis through the study of AI-assisted ophthalmic diagnostics research.

The proposed system leverages a modified MobileNetV2 architecture, specifically designed for efficient inference on mobile devices due to its low parameter count and computational complexity. By integrating the model into a mobile-accessible web application, the system enables real-time eye disease detection via smartphones or tablets over wireless networks, providing accessible diagnostic support in remote and resource-limited regions of Bangladesh and other developing countries.

2 Related Work

Halil İbrahim Tuncer et al. [1] proposed a fast diagnostic pipeline utilizing hand-crafted features (HOG, LBP) and deep feature (ResNet-50) representations for the classification of multiple ocular disorders. The authors compared with a range of classifiers (KNN, SVM, XGBoost) and demonstrated that the combination of XGBoost with ResNet-50 had the best diagnostic performance among them by achieving 92% accuracy. The results of the above cross-validation sets strongly support the overall tendency in the related works, where powerful automatic extraction techniques of deep features combined with truly robust ensemble of classifiers seem to yield state-of-the-art solutions for both efficient and reliable automated multi-class eye pathology screening.

Archana Chaudhari et al. [2] have proposed an effective and simple system that could diagnose the eye disease of underprivileged children with-out optical fundus device by VGG-19 Convolutional Neural Network. Fundus images result is 98.10% of proposed work with the disease Cataract, Diabetes and Glaucoma are classified. A robust ReactJS/Python app that enables a seamless user experience and highly valuable personalized diet recommendations far above and beyond just diagnosis. This represents a major step forward in the field, providing a clear demonstration of the strengths of high-accuracy deep learning models when it comes to classifying conditions, while directly working toward correcting healthcare imbalances via an easily accessible comprehensive platform.

Hameed et al. [3] came up with a low-cost machine learning system for the Self Diagnosis of Cataract (clouded vision) and Glaucoma (optic nerve pressure can causes blindness). They proposed an approach, which was based on Gray-Level Co-occurrence Matrix (GLCM) for feature extraction from eye images, an widely used method in texture analysis. These extracted parameters were further fed into a Machine Learning classifier to return the diagnostic results, which were shown in MATLAB. Contributions to the literature to our knowledge, a non-expert dependent, simple screening tool to increase early detection of major causes of vision loss has not previously been described in the literature.

Giat et al. [4] moved a step towards accessibility of eye disease diagnosis by presenting an automatic classification system using Convolutional Neural Networks-CNN's. They have tested ResNet50 and VGG16 on 5 categories of eye disorders (Bulging eyes, Cataracts, crossed eyes Uveitis and Normal) their results show that for 1000 training epochs the performance of ResNet is better with training accuracy of 94.97% and validation accuracy equal to 93.33% [F1 Score=0.93]. These results contribute to the view from the evidence base that transfer learning with advanced architectures (such as ResNet50) appears most suitable for medical image classification. The developed general system together with a web platform for easy access by users is indicative of an important trend in application of high-accuracy AI tools toward early detection and overcome disparities in healthcare.

Dubey et al. [5] reviewed recent developments in computer-aided diagnosis systems for diabetic retinopathy, highlighting the critical disparity between the limited number of healthcare workers and the growing prevalence of eye diseases. The review emphasized that Machine Learning (ML) and Deep Learning (DL) methodologies are increasingly adopted to supplant labor-intensive conventional image processing, facilitating efficient diagnosis during curable early phases. Such technologies hold substantial promise for mitigating the burden of preventable blindness in resource-constrained regions. Due to complicatedness level [6], the ratio of doctors number) and it is 1:10,000 for thousand patients worldwide. The review reported that the ML and DL based mechanisms are extensively adopted to substitute complex conventional image processing modalities in efficaciously detecting these diseases during their early, curable phase (75% of blindness is curable). Such identification by ML/DL technologies may be utilized to raise awareness and decrease blinding from such diseases in less developed countries.

3 Methodology

This section consists of Proposed model architecture, Dataset Preparation, Data Preprocessing, Feature Extraction, Explainable AI, and the deployment framework used for automated eye disease detection from retinal fundus images.

3.1 Proposed Model of MobileNetV2

The proposed eye disease classification model is based on a modified MobileNetV2 architecture. As illustrated in Figure 1, the model consists of the following primary components.

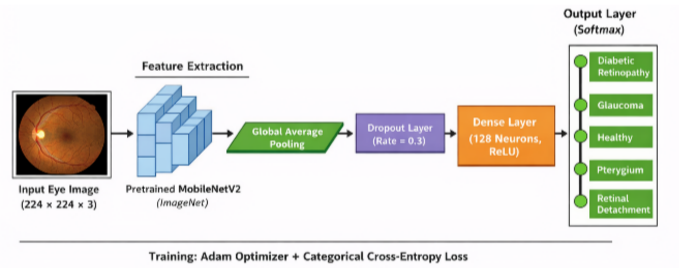

Figure 1. Proposed architecture of MobileNetV2.

3.1.1 *Input Layer*

The input layer accepts retinal or eye images as input. All images are resized to $224 \times 224 \times 3$ to meet the input requirements of the MobileNetV2 architecture. Pixel values are normalized to improve training stability and convergence.

3.1.2 *Feature Extraction Layer (MobileNetV2)*

This layer utilizes a pretrained MobileNetV2 network [18] initialized with ImageNet weights. It acts as a feature extractor to capture important visual patterns such as edges, textures, vessel structures, and abnormal retinal features. The convolutional layers of the pretrained network are frozen during training to preserve learned representations and reduce computational complexity.

3.1.3 *Global Average Pooling Layer*

The global average pooling layer converts the extracted feature maps into a one-dimensional feature vector. This approach reduces the number of parameters compared to traditional fully connected layers and helps prevent overfitting by summarizing spatial information.

3.1.4 *Dropout Layer*

A dropout rate of 0.3 is applied to randomly deactivate neurons during training. This regularization technique helps improve generalization and reduces model overfitting.

3.1.5 *Fully Connected Dense Layer*

A dense layer with 128 neurons and ReLU activation is used to learn complex nonlinear relationships among the extracted features. This layer enhances the model's ability to differentiate between different eye diseases.

3.1.6 *Output Layer*

The final classification layer contains five neurons corresponding to the five eye disease categories. A SoftMax activation function is applied to generate probability distributions for each class, including diabetic retinopathy, glaucoma, healthy, pterygium, and retinal detachment.

3.2 Data

The dataset includes 4216 retinal fundus images collected from Kaggle, divided into training and validation sets. The training set contains 3334 images (approximately 79%), and the validation set contains 882 images (approximately 21%). Table 1 shows the distribution of samples across the five categories: diabetic retinopathy, glaucoma, pterygium, retinal detachment, and healthy.

3.3 Data Preprocessing

To enhance quality and diversity, preprocessing steps included [19]:

- Cropping - Contour detection isolates ROI (eye region), removing background noise;
- Resizing - Uniform 224×224 pixels for CNN input;

Table 1. Representation of data information according to Train-Test split.

Eye Disease	Training Samples	Validation Samples
Diabetic Retinopathy	1371	310
Glaucoma	1080	280
Pterygium	17	17
Retinal Detachment	120	55
Healthy	746	220
Total = 4216 (100%)	3334	882

- Normalization - Pixels scaled (÷255) for gradient stability;
- Augmentation - Rotation (±15°), horizontal/vertical flipping, zoom (±10%), brightness (±20%) simulate real-world variations. The augmentation process occurs after dataset splitting.
- Label Encoding - One-hot: DR=0, Glaucoma=1, Healthy=2, Pterygium=3, RD=4

3.4 Training and Fine Tuning

The proposed model was trained using transfer learning from a pre-trained MobileNetV2. The pre-trained network's convolutional base was loaded initially with weights learned on the ImageNet dataset to exploit inherited visual features. In the first training, base layers were frozen to maintain the common features of the images and then we added layers on top of this network for classification using retinal fundus image dataset.

The dataset of 4216 retinal images was split into training and validation sets, with 3334 images (79%) used for training and 882 images (21%) used for validation. The model was trained with the Adam optimizer and categorical cross-entropy loss for this multi-class classification task. We chose a specific batch size and learning rate to allow for stable convergence as well as enhanced learning during training.

A fine-tuning stage was performed after the initial training step to optimize the performance of the model even further. During this stage many of the deeper layers of the MobileNetV2 backbone were unfrozen and trained again with a lower learning rate. Enabling the network to refine its high-level feature representations for retinal fundus images and eye disease patterns in particular. This aided in augmenting the discriminative power of the model by modifying deeper layer weights and preventing overfitting.

To manage the convergence correctly, training was validated by using accuracy and loss metrics. The proposed model reached an overall classification accuracy of 88% using such training and fine-tuning strategy and proved to be effective for multi-class eye disease detection.

3.5 Visual Explainability: Grad-CAM

To address the "black box" nature of deep learning in medical diagnostics, Gradient-weighted Class Activation Mapping (Grad-CAM) is utilized. This technique provides visual justifications for model decisions by highlighting the specific retinal regions that contribute most to a given prediction. Recent studies have demonstrated the effectiveness of explainable AI techniques in ocular disease diagnosis, showing that such approaches enhance clinical trust and model transparency [20].

3.5.1 Mathematical Mechanism of Grad-CAM

Grad-CAM utilizes the gradient information flowing into the final convolutional layer of the MobileNetV2 backbone. The process is defined by the following mathematical steps:

Step 1: Gradient Computation. The gradient of the score for class c, denoted as y^c, is computed with respect to the feature map activations A^k of the last convolutional layer:

$$\frac{\partial y^c}{\partial A^k_{ij}} \tag{1}$$

Step 2: Importance Weight Calculation. The neuron importance weights α^{kc} are obtained by performing Global Average Pooling (GAP) over the width (i) and height (j) dimensions:

$$\alpha^{kc} = \frac{1}{Z}\sum_i \sum_j \frac{\partial y^c}{\partial A^k_{ij}} \tag{2}$$

where Z is the total number of pixels in the feature map.

Step 3: Heatmap Generation. A weighted linear combination of the forward-pass activations is performed, followed by a ReLU (Rectified Linear Unit) activation to ensure that only features with a positive influence on the class of interest are visualized:

$$L^C(\text{Grad-CAM}) = \text{ReLU}\left(\sum_k \alpha^{kc} \cdot A^k\right) \tag{3}$$

3.5.2 Localization and Mapping

The discrete weak heatmap (usually 7×7 in MobileNetV2) is subsequently up sampled with bilinear interpolation to the input size of 224×224. Pseudo-color transformation (Jet Color Map) is performed to represent intensity, where red areas indicate high diagnostic importance (e.g. optic disc in glaucoma or exudates in diabetic retinopathy). The heatmap image is then overlaid on the original retinal image with an alpha-blending factor of 0.4 for clinical correlation [7, 8].

3.6 System Implementation

In order to create an interactive, browser-based diagnostic interface, the trained modified MobileNet model was integrated into a Flask backend connected to a Streamlit frontend. This leads to a system design that is modular and scalable, along with real-time response yet keeps the workflow simple enough for non-technical healthcare workers.

3.6.1 Backend Architecture (Flask)

The backend was developed using Flask due to its lightweight and flexible micro-framework structure. It hosts the trained deep learning model (.h5 format) and handles user image requests [9, 10]. When an image is uploaded via the web interface, Flask processes it through the following sequence:

- Image preprocessing (resizing, normalization, and reshaping)
- Model inference using the modified MobileNetv2 architecture
- Generation of class probabilities and diagnosis label
- JSON response returned to the frontend

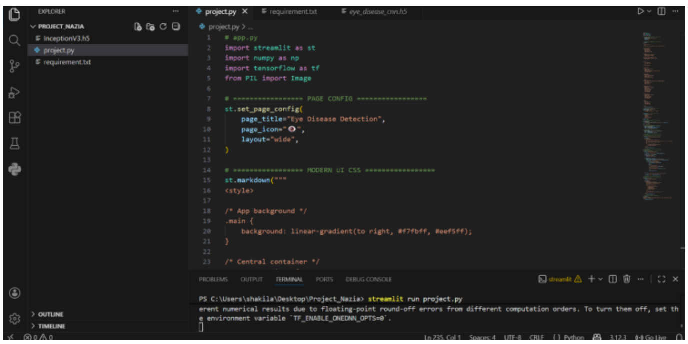

Figure 2. Backend Code of Deployment Model with Web-Application.

The backend also supports concurrent requests through a multithreaded WSGI server, ensuring low latency even when multiple users are connected. Figure 2 illustrates the backend code implementation for model deployment within the web application.

3.6.2 *Frontend (Streamlit)*

The frontend was built using Streamlit, chosen for its simplicity and ability to integrate seamlessly with machine learning backends [11, 12]. It provides a clean, user-friendly interface that allows users to upload fundus images directly from their local device or webcam, view the processed image and prediction results in real time, display model confidence through a dynamic bar graph, receive diagnostic results such as "Healthy," "Glaucoma," "Pterygium," "Diabetic Retinopathy," or "Retinal Detachment," and view the corresponding Grad-CAM heatmap, while the underlying model utilizes convolutional layers with filters of different sizes to extract detailed features from the input fundus images [13]. The ResNet architecture, included in the comparative study, signifies a notable progression in deep learning by addressing the vanishing gradient problem in deep neural networks [14–16].

- Upload fundus images directly from their local device or webcam
- View the processed image and prediction results in real time
- Display model confidence through a dynamic bar graph
- Receive diagnostic results such as "Healthy,""Glaucoma,""Pterygium," "Diabetic Retinopathy," or "Retinal Detachment"
- Receive the image of Grad-cam

The home page of the web application, as shown in Figure 3, provides users with an intuitive interface for uploading retinal fundus images and accessing diagnostic results. To enhance the user experience, the interface was designed with responsive layout adjustments for both desktop and tablet devices.

3.6.3 *Workflow Description*

The system workflow consists of several stages:

1. **User Input**: The user uploads a fundus image via the browser interface.
2. **Preprocessing Layer**: The backend automatically crops, normalizes, and scales the image.
3. **Inference Layer**: The preprocessed image is passed to the modified MobileNetV2 model, which outputs probability scores for each disease class.
4. **Explainability Module**: To enhance model interpretability, Gradient-weighted Class Activation Mapping (Grad-CAM) is applied to the prediction results. This module highlights the discriminative regions in the fundus image that contribute most significantly to the model's decision.
5. **Result Visualization**: Streamlit visualizes the diagnosis, including a probability bar chart and confidence level. Figure 4 demonstrates an example of retinal detachment detection results as displayed to the user.
6. **Performance Logging**: Each prediction is logged anonymously for monitoring and model improvement.

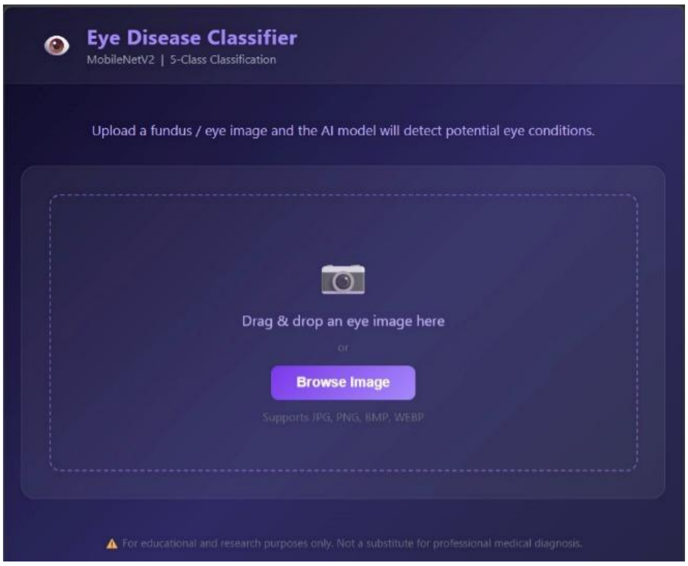

Figure 3. Home page.

3.6.4 *Deployment*

The application was deployed on a cloud server (Heroku/AWS) using Docker containers to ensure portability and easy updates. The architecture supports REST API integration for future expansion into mobile applications. HTTPS protocols were implemented to maintain user data privacy.

This implementation demonstrates how deep learning models can be effectively transformed into real-world diagnostic tools, maintaining high accuracy while ensuring ease of access and user trust.

Figure 3 shows the home page of the deployed Eye Disease Detection System. The interface features a clean and user-friendly layout. At the top, the project

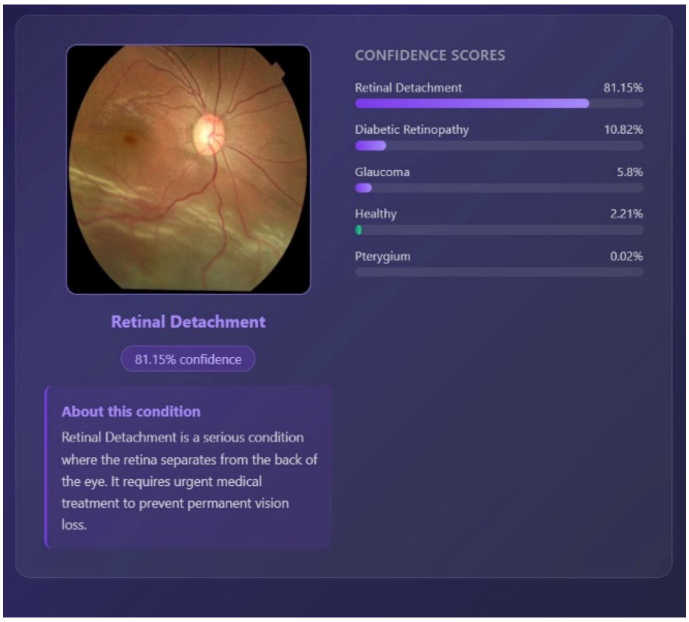

Figure 4. Retinal Detachment Detection of the Web Application.

name, an eye-themed icon, and a brief description are displayed: "An AI-powered diagnostic tool for early detection of eye diseases using deep learning."

To align with mobile intelligence paradigms, the modified MobileNetV2 model was optimized for deployment on resource-constrained mobile devices. The lightweight architecture (with significantly fewer parameters than ResNet or DenseNet) ensures low-latency inference suitable for smartphones and tablets. The system was implemented as a responsive web application using Flask backend and Streamlit frontend, allowing seamless access through mobile browsers without requiring heavy local computation.Wireless accessibility was considered by designing the application to support remote image upload and diagnosis over 4G/5G networks, enabling telemedicine scenarios where retinal images captured by portable fundus cameras or smartphone-based adapters can be transmitted wirelessly to the inference server. This integration of mobile-friendly deep learning with wireless communication technologies demonstrates the potential for scalable, intelligent ophthalmic screening systems in mobile and IoT-enabled healthcare environments.

4 Result

This section presents the performance metrics of modified MobileNetv2 model to classify eye disease into various categories: Healthy, Glaucoma, Pterygium, Diabetic Retinopathy, or Retinal Detachment. Let us discuss each metric and the results:

Table 2. Performance metrics of modified MobileNetV2 model.

Metrics	Accuracy	Precision	Recall	F1-Score
DR	96%	0.95	0.97	0.96
Glaucoma	82%	0.86	0.78	0.82
Healthy	81.33%	0.77	0.86	0.81
Pterygium	100%	1.00	1.00	1.00
R_D	82.88%	1.00	0.89	0.94
Macro avg	91%	0.92	0.90	0.91
Weighted avg	88%	0.88	0.88	0.88

Figures 5 and 6 illustrate the training and validation accuracy and loss curves, respectively, showing the model's convergence behavior and absence of significant overfitting.

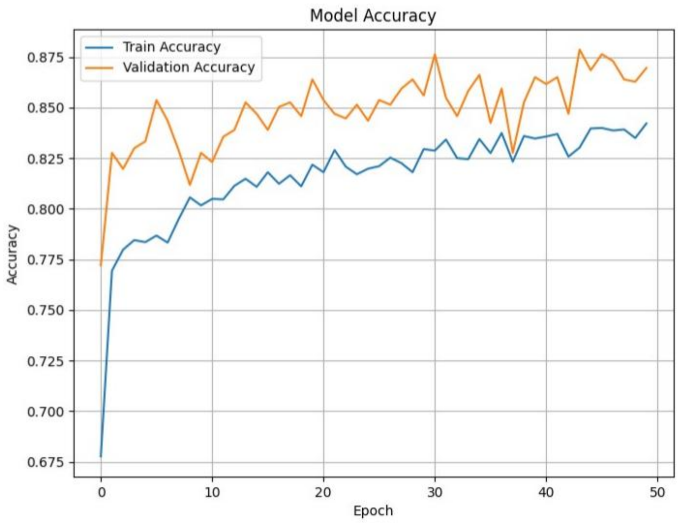

Figure 5. Training and Validation Loss Accuracy for the Modified MobileNetV2 model.

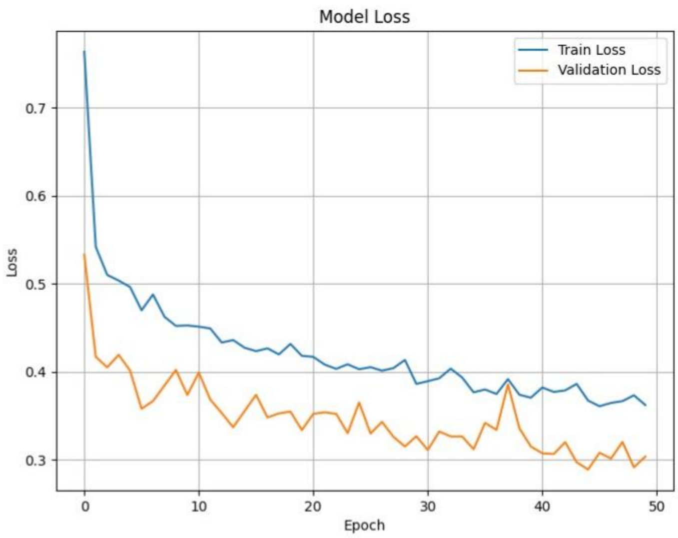

Figure 6. Training and Validation Loss for the Modified MobileNetV2 model.

The per-class performance metrics of the proposed modified MobileNetV2 model are presented in Table 2. The model achieved an overall classification accuracy of 88% on the validation set, with a macro-average F1-score of 0.91 and a weighted-average F1-score of 0.88, indicating balanced performance across all disease categories.

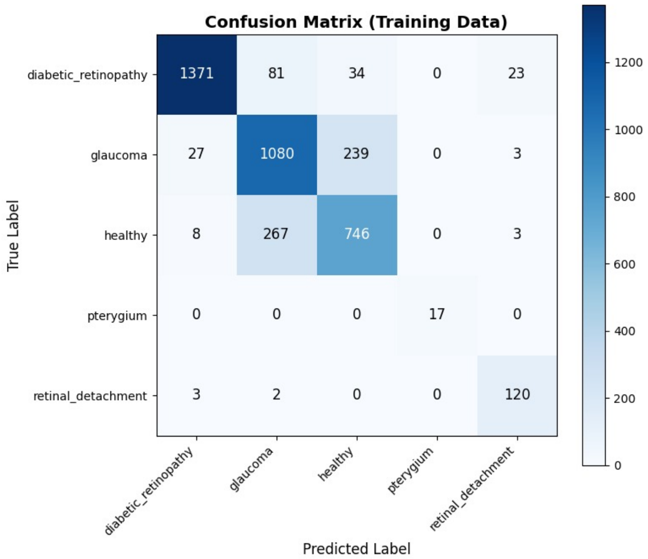

Figure 7. Confusion matrix of Modified MobileNetV2 model for Multilevel eye disease classification.

The confusion matrix (Figure 7) provides insight into the model's classification performance on the training set. The diagonal values show that the model correctly classified 1,371 diabetic retinopathy, 1,080 glaucoma, 746 healthy, 17 pterygium, and 120 retinal detachment samples. The model achieved perfect classification for the pterygium class, with all 17 cases correctly identified and no false positives. Misclassifications between healthy and glaucoma classes are moderate, which may be attributed to similarities in retinal image patterns.

Again, the training and validation accuracy curves (Figure 5) show how our model has learned through epochs. The formation of both curves is gradually ascending over the training epochs, demonstrating effective characteristics extraction and stability in convergence. The corresponding loss curves (Figure 6) show consistent decreasing trends, further confirming proper model optimization. These results suggest that no significant overfitting is present, since the validation accuracy remains consistent with the training accuracy.

4.1 AI Explainability Analysis

The deep learning model became more understandable through the implementation of Grad-CAM which shows the retinal fundus image areas that affect the model's prediction accuracy. Medical image analysis needs explainability because deep learning models function as black-box systems. Grad-CAM produces heatmap visualizations which show the model's most important areas that drive classification results.

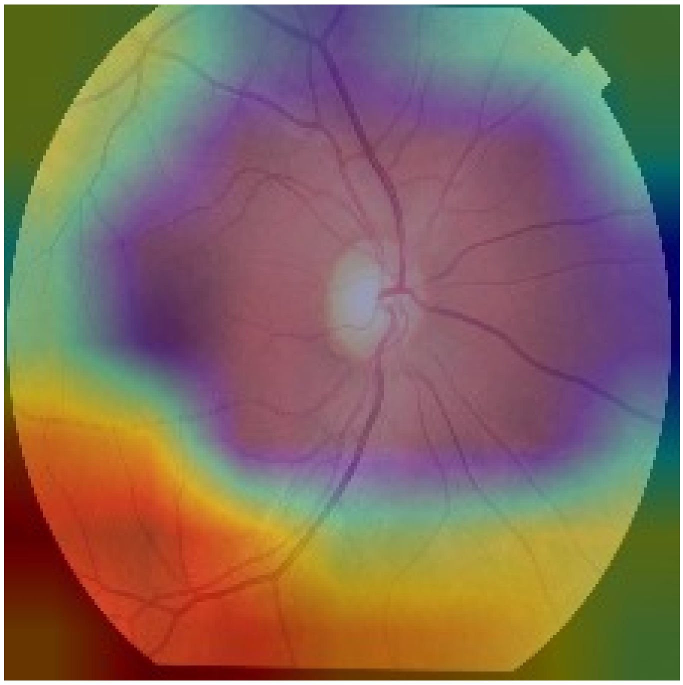

Figure 8. Grad-CAM Heatmaps highlighting Model Attention for Glaucoma disease.

The visualization results demonstrate that the proposed MobileNetV2 model focuses on clinically relevant regions within the retinal images. The heatmap of the first(Figure 8) visualization shows a concentrated area near the macular area which indicates that the model detects significant retinal abnormalities for disease identification.

The Grad-CAM overlay in the second image (Figure 9) shows wider activation around the optic disc and nearby retinal areas which indicates that the model studies vascular and structural features during its classification process. The heatmap intensity shows stronger prediction areas through warmer colors like red and yellow while cooler colors show areas that have less impact on predictions. The visual explanations show that the model uses specific anatomical features of the retina to make its predictions instead of using random selection. The combination of Grad-CAM with the model system

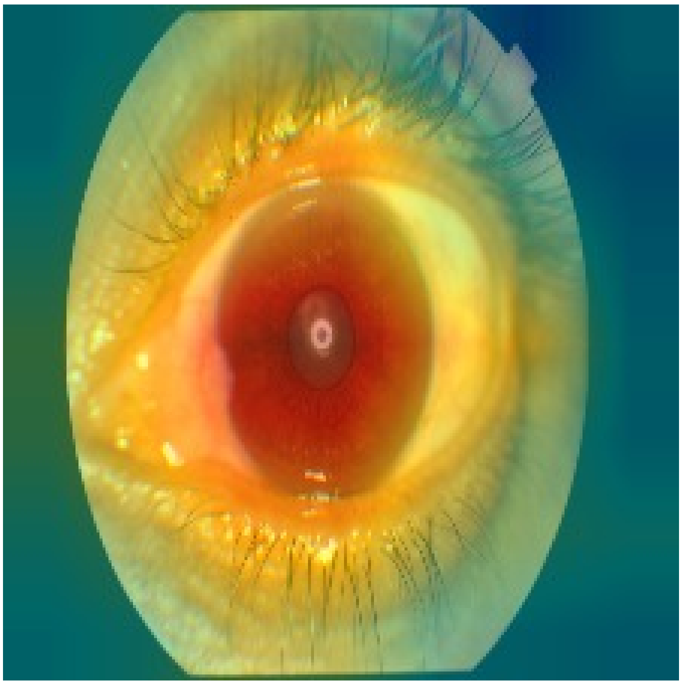

Figure 9. Grad-CAM Heatmaps highlighting Model Attention for Pterygium disease.

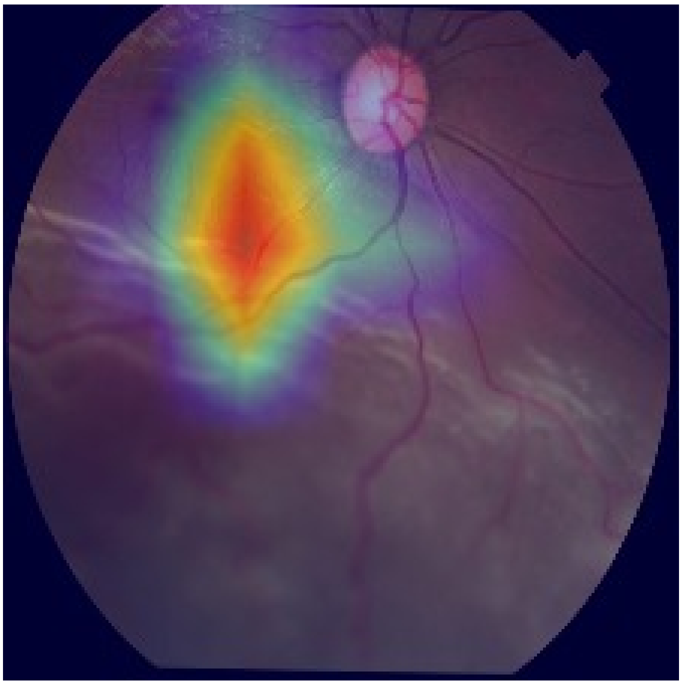

Figure 10. Grad-CAM Heatmaps highlighting Model Attention for Retinal Detachment disease.

provides clinicians with essential insights about how automated predictions function while enhancing model transparency. Similarly, for retinal detachment cases, the model's attention is concentrated on specific retinal regions indicative of detachment pathology, as shown in Figure 10.

5 Comparison

In this section our proposed MobileNetV2 model compare with 4 types of deep learning models like ResNet, Inception V3, DenseNet and CNN.

Table 3. Comparison of MobileNetV2 model with DL models.

Models	Accuracy	Precision	Recall	F1-Score
MobileNet v2	88%	0.916	0.90	0.906
InceptionV3	82.88%	0.86	0.78	0.82
DenseNet	87.19%	0.77	0.86	0.81
CNN	85.87%	0.82	0.81	0.80
ResNet	50.67%	0.48	0.47	0.46

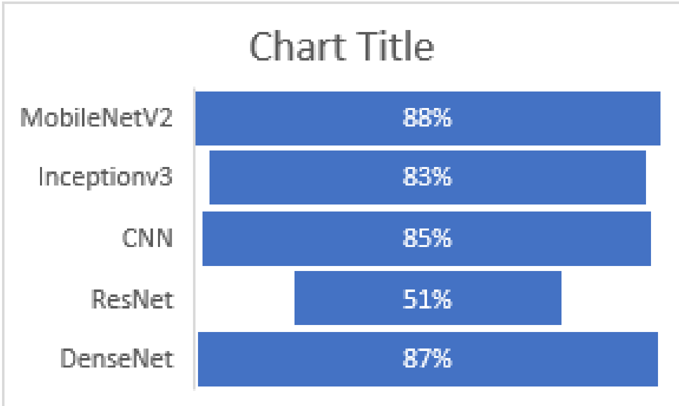

Figure 11. Accuracy of different models.

Quantitative performance comparison among various deep learning architectures for multi-class retinal diseases has been summarized in Table 3 and visualized in Figure 11. The models that were evaluated include CNN, DenseNet, InceptionV3, ResNet and MobileNetV2 with performance measured in Accuracy, Precision, Recall and F1-Score. MobileNetV2 scored the highest overall accuracy, reaching 88%, outperforming all other evaluated models, especially in precision (0.916), recall (0.90) and F1-score (0.906). These results show that MobileNetV2 achieves a balanced performance in predicting class diseases based on false-positives and negatives. The CNN model achieved 85% accuracy, showing a moderate classification ability, but weaker feature extraction than deeper architectures. The performance dropped with the InceptionV3 and ResNet models at 82.88% and 50.67% accuracy, respectively. Despite its well-known deep residual learning ability, ResNet performs relatively worse in this study. A possible explanation is that ResNet has a much larger number of parameters, causing higher computational complexity, and if the dataset size is not large enough, then it won't learn well. MobileNetV2, on the other hand, is designed specifically as a lightweight architecture utilizing depthwise separable convolutions and inverted residual blocks to greatly reduce parameter number and computational complexity. Our architecture enables the model to effectively learn the distinctive characteristics of retinal fundus images, while also having a shortened training time and increased generalization accuracy. This allows MobileNetV2 to achieve better classification accuracy and computational efficiency relative to ResNet and the other evaluated models, making it more suitable for real-time and web-based ophthalmic diagnostic applications.

6 Discussion

The superior performance of the proposed modified MobileNetV2 can be partially attributed to effective feature learning from retinal structures. This aligns with recent ensemble-based approaches that leverage blood vessel segmentation for retinal disease prediction [17]. The system evaluation shows that the combination of MobileNetV2 deep learning architecture with web-based frameworks that have been specially designed for optimization leads to better automated ophthalmic diagnostic system accessibility. The proposed AI-driven approach achieves consistent prediction accuracy and faster analysis, and scalable diagnostic support compared to traditional manual screening methods, which rely on clinical expertise and are often inaccessible in resource-limited settings. The model's lightweight design permits efficient computation which allows the system to function on environments that lack resources such as low-end systems and mobile-based platforms. The model gets enhanced interpretability through Grad-CAM integration because it gives visual explanations of the model's predictions which helps doctors trust automated decision support systems. The future improvements will extend the dataset by adding more retinal images of different demographic groups and increase model robustness through multi-institutional datasets while the research team will investigate privacy-preserving training methods which enable secure medical data sharing among multiple healthcare facilities through federated learning.

7 Conclusion

This research developed a deep learning automatic system for eye disease detection which uses retinal fundus photographs as its input. The research team tested multiple deep learning architectures which included CNN, DenseNet, InceptionV3, ResNet, and MobileNetV2 to find the best model for multi-class classification tasks. The research results demonstrate that the modified MobileNetV2 model produced the best results with its 88% accuracy while it effectively extracted important retinal information. The inclusion of Grad-CAM technology improves model transparency by showing visual details of the areas that affect prediction outcomes. The ability of the web-based system to use the trained model through Flask and Streamlit allows users to receive immediate disease predictions and diagnostic assistance. The system delivers an efficient lightweight solution which provides automatic ophthalmic screening through its explainable features. The implemented method shows great promise to enhance eye disease detection and increase access to AI-based healthcare systems.

Data Availability Statement

Data will be made available on request.

Funding

This work was supported without any funding.

Conflicts of Interest

The authors declare no conflicts of interest.

AI Use Statement

The authors declare that no generative AI was used in the preparation of this manuscript.

Ethical Approval and Consent to Participate

Not applicable. The study was conducted using a publicly available, de-identified dataset from Kaggle. No new human data collection or identifiable private information was involved; therefore, ethical approval was not required.

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