Comparing Binary and Multiclass Classification in a Hybrid ML-DL Approach for Diabetic Retinopathy and Color Blindness Detection.

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I. Abstract

Diabetic Retinopathy (DR) is a progressive eye disease caused by diabetes, which can lead to severe vision impairment, including color blindness. Early and accurate detection of DR is essential to prevent irreversible damage and provide timely treatment. This research presents a hybrid deep learning and machine learning approach for detecting Diabetic Retinopathy and its impact on color vision. The proposed model integrates deep feature extraction using InceptionV3 and MobileNetV2 with MLP-based classification, enabling both binary (DR vs. No DR) and multiclass (different DR stages) classification.

By leveraging a combination of convolutional neural networks (CNNs) and machine learning classifiers, this study compares the effectiveness of different methodologies in identifying DR and its association with color vision deficiency. A Flask-based backend, coupled with a user-friendly frontend, ensures real-time image processing and disease prediction. The experimental results demonstrate that the hybrid approach outperforms traditional ML and DL standalone models in terms of accuracy, sensitivity, and specificity. This research contributes to automated ophthalmic screening by providing an efficient, scalable, and accessible tool for early DR detection and color blindness assessment.

Index Terms: Diabetic Retinopathy, Color Blindness Detection, Machine Learning, Deep Learning, Convolutional Neural Networks, Feature Extraction, Hybrid Classification, InceptionV3, MobileNetV2, MLP Classifier, Medical Image Processing, Automated Screening, Ophthalmic Diagnosis.

II. Introduction

Diabetic Retinopathy (DR) is one of the leading causes of vision impairment and blindness, particularly among individuals with diabetes. A significant yet often overlooked consequence of DR is its impact on color vision, leading to varying degrees of color blindness. As DR progresses, damage to the retina affects the eye's ability to perceive colors correctly, impairing daily activities and overall quality of life. Early detection of DR is crucial for preventing irreversible vision loss and mitigating its impact on color perception. However, traditional diagnostic methods rely on manual assessment by ophthalmologists, which can be time-consuming, subjective, and inaccessible in remote areas.

Advancements in Artificial Intelligence (AI), Deep Learning (DL), and Machine Learning (ML) have significantly improved medical image analysis, enabling automated, accurate, and efficient disease detection. While CNN-based deep learning models such as InceptionV3 and MobileNetV2 excel at extracting features from retinal images, machine learning models like Multi-Layer Perceptron (MLP) are effective for classification tasks. A hybrid ML-DL approach integrates the strengths of both techniques, combining feature extraction from deep learning models with ML-based classification to enhance diagnostic accuracy.

This research focuses on developing a hybrid deep learning and machine learning model for detecting Diabetic Retinopathy and its impact on color vision. The study evaluates and compares binary (DR vs. No DR) and multiclass (different DR stages) classification approaches, highlighting their effectiveness in disease detection. By analyzing retinal images and their correlation with color blindness, this research provides a comprehensive framework for diagnosing DR and associated visual impairments.

A Flask-based backend is integrated with a user-friendly frontend interface, enabling real-time image processing and prediction. The proposed system leverages pretrained deep learning models for feature extraction and MLP classifiers for decision-making, optimizing accuracy and computational efficiency. The findings of this research contribute to automated ophthalmic screening, offering an accessible, scalable, and efficient solution for early DR detection and color blindness assessment. The broader implications of this study extend to clinical decision support, telemedicine, and AI-driven healthcare solutions, enhancing early diagnosis and treatment strategies for vision-related disorders.

III. Literature review

IA literature review of **color blindness detection using AI models** encompasses a broad spectrum of research studies, methodologies, and technological advancements in this domain. Numerous studies have focused on identifying critical features, including **iris image patterns, color perception deficiencies, and spectral sensitivity**, that influence the accurate classification of color blindness. Research emphasizes the increasing need for automated and efficient screening systems, driven by the growing demand for early and precise detection. The integration of **deep learning and machine learning techniques** has been explored to enhance classification accuracy. Various algorithms, such as **Convolutional Neural Networks (CNNs), Support Vector Machines (SVM) and Multi-Layer Perceptron (MLP),**, have been applied for both **binary classification** (detecting the presence of color blindness) and **multiclass classification** (identifying severity levels) to develop robust and scalable diagnostic models.

"Diabetic Retinopathy Detection through Deep Learning Techniques" explores the use of deep learning models for automated detection and classification of diabetic retinopathy (DR). The study evaluates convolutional neural networks (CNNs) trained on large-scale retinal fundus image datasets. By leveraging transfer learning with a pre-trained ResNet-50, the model achieves 92.5% accuracy, outperforming traditional machine learning methods. The findings suggest that deep learning-based DR detection enhances efficiency and reduces reliance on manual clinical screening. [1]

In "Uncertainty-Aware Diabetic Retinopathy Detection Using Deep Learning," the authors propose a Bayesian deep learning approach to assess uncertainty in DR diagnosis. Using DenseNet-121 with Monte Carlo dropout, the study improves model reliability by reducing misclassification rates. Evaluation on the Kaggle EyePACS dataset shows an accuracy of 91.8%, demonstrating enhanced confidence calibration compared to standard CNNs. The research highlights the importance of uncertainty estimation in automated DR detection. [2]

A study titled "Deep Learning for the Detection and Classification of Diabetic Retinopathy" investigates CNN-based techniques for distinguishing different stages of DR. The research introduces a novel activation function to improve classification performance and employs ResNet-152 with data augmentation. Results from the APTOS 2019 dataset indicate 94.6% accuracy, proving the superiority of deep learning models over conventional machine learning classifiers. The study underscores the role of AI in early DR detection and prevention. [3]

A comprehensive review, "Systematic Analysis of Diabetic Retinopathy Detection Using Deep Learning," examines the effectiveness of CNN architectures such as VGG-16, InceptionV3, and EfficientNet in diagnosing DR. The paper discusses dataset challenges, interpretability concerns, and the potential of AI-driven methods. It concludes that while deep learning models achieve high accuracy, further research is required for clinical adoption and real-world deployment. [4]

In "A Deep Learning-Based Model for Diabetic Retinopathy Grading," the authors present an automated DR grading system using CNNs with feature extraction and attention mechanisms. The study achieves 93.2% accuracy on the Messidor dataset, surpassing traditional feature-based classifiers. The findings emphasize the need for high-quality dataset curation and explainability for AI-driven diagnostic tools in ophthalmology. [5]

"Advancements in Deep Learning for Diabetic Retinopathy Detection" explores various AI-driven methodologies, comparing deep learning techniques with conventional diagnostic methods. The study reviews segmentation techniques like U-Net and Mask R-CNN for lesion detection in retinal images. The findings indicate that CNN-based approaches outperform traditional feature-engineering methods, highlighting the potential of AI in improving diagnostic accuracy and efficiency. [6]

The research work "Deep Learning for Diabetic Retinopathy Analysis: A Review" delves into CNNs, recurrent neural networks (RNNs), and hybrid models for DR detection. The authors analyze loss functions like focal loss and cross-entropy loss to optimize performance. They also discuss the importance of synthetic data generation in addressing dataset limitations. The study suggests that while CNNs achieve high accuracy, enhancing model interpretability remains a challenge for clinical applications. [7]

A systematic review, "Diabetic Retinopathy Detection and Classification Using Deep Learning Techniques," investigates the impact of AI-driven feature extraction on DR classification. The authors compare fully connected CNNs with hybrid models incorporating classical feature descriptors. The research emphasizes the integration of explainable AI (XAI) for model transparency. While deep learning models show promising results, challenges related to data privacy and real-world deployment persist. [8]

"Automated Diagnosis of Diabetic Retinopathy: A Survey on Deep Learning Approaches" provides a structured review of AI-driven DR detection techniques, including CNNs, transformer models, and ensemble learning strategies. The paper categorizes existing approaches based on preprocessing, feature extraction, and classification paradigms. The authors stress the importance of dataset standardization and performance benchmarking. The study concludes that AI-based DR screening has the potential to improve accessibility to eye care, especially in resource-limited regions. [9]

The paper "Transfer Learning-Based Approaches for Diabetic Retinopathy Detection" examines how transfer learning enhances DR classification. It evaluates pre-trained architectures such as InceptionResNetV2, EfficientNet, and MobileNetV3, along with various fine-tuning and data augmentation techniques. Results indicate that transfer learning improves diagnostic accuracy while reducing computational overhead. The study concludes that transfer learning-based solutions offer a scalable and efficient alternative for real-world DR screening. [10]

Our Unique Contribution (Comparing Binary vs. Multiclass Classification for DR & Color Blindness Detection)

Despite extensive research in AI-based retinal disease detection, comparing binary and multiclass classification while simultaneously evaluating DR's impact on color blindness remains an unexplored area. By focusing on this unique aspect, our proposed research fills a critical gap in the literature by:

1. Developing a hybrid ML-DL model combining feature extraction from deep learning models (InceptionV3, MobileNetV2) with ML classifiers (MLP).

2. Comparing the performance of binary vs. multiclass classification models for DR detection. Exploring the correlation between DR and color blindness, enhancing early screening for both conditions.

3. Deploying the model in a real-time Flask-based application, making it accessible for clinical and telemedicine use.By integrating hybrid AI techniques with medical imaging and ophthalmic diagnosis,

4. Our research enhances automated screening tools for DR and color blindness, contributing to improved early detection and disease management.

IV. Types of Diabetic Retinopathy and Their Characteristics

Diabetic Retinopathy (DR) is a progressive eye disease that develops as a complication of diabetes. Over time, high blood sugar levels can damage the small blood vessels in the retina, the light-sensitive tissue at the back of the eye. As the condition advances, these blood vessels may become weak, swell, leak fluid, or even close off completely, leading to inadequate oxygen supply to the retina. In response, the eye may attempt to grow new, fragile blood vessels, which can cause severe complications such as bleeding, scarring, and retinal detachment.

The progression of DR occurs in distinct stages, each characterized by specific retinal abnormalities and varying levels of vision impairment. In the early stages, there may be no noticeable symptoms, making regular eye screenings essential for early detection. As the disease advances, vision problems such as blurriness, dark spots, and even complete blindness can occur if left untreated.

The severity of DR depends on how much damage has occurred in the retinal blood vessels. In the **early stages**, mild changes like small bulges in blood vessels (microaneurysms) appear, often without affecting vision. As the disease **progresses**, more blood vessels become blocked, leading to the accumulation of fluids and proteins in the retina, causing vision impairment. In the **most advanced stage**, the eye attempts to compensate by growing new abnormal blood vessels (neovascularization), which are weak and prone to bleeding, potentially resulting in blindness.Understanding these stages is crucial for early diagnosis and timely intervention. Below is a detailed classification of the five types of Diabetic Retinopathy based on your research, each representing a different level of disease progression.
The following are the detailed information about Diabetic Retinopathy.

1. No DR (Healthy Retina)

  - The retina is completely healthy with no signs of blood vessel damage.
  - There are no visible hemorrhages, microaneurysms, or fluid leakage.
- **Symptoms:**
  - Normal vision, no abnormalities detected.
- **Medical Advice:**
  - Patients with diabetes should still have regular eye checkups to monitor changes.

2. Mild Non-Proliferative Diabetic Retinopathy (Mild NPDR)

  - Small **microaneurysms** (tiny balloon-like swellings in blood vessels) start forming.
  - Minor **leakage of blood and fluid** may be observed.
  - No significant damage to vision yet.
- **Symptoms:**
  - No noticeable vision changes in most cases.
- **Medical Advice:**
  - Regular monitoring is required to check for progression.

3. Moderate Non-Proliferative Diabetic Retinopathy (Moderate NPDR)

  - Increased number of **microaneurysms and hemorrhages** in the retina.
  - Blood vessels become more **blocked**, reducing oxygen supply.
  - Presence of **hard exudates** (yellowish deposits due to fluid leakage).
- **Symptoms:**
  - Blurred vision, especially when fluid accumulates near the macula.

- **Medical Advice:**
  - More frequent eye exams and lifestyle changes to prevent worsening.

4. Severe Non-Proliferative Diabetic Retinopathy (Severe NPDR)

- Large areas of **blood vessel blockage**, causing significant oxygen deprivation.
- Development of **cotton wool spots** (damaged nerve fibers).
- The eye starts signaling for new blood vessel growth (which leads to PDR).

- **Symptoms:**
  - Significant vision loss may occur.
- **Medical Advice:**
  - Close monitoring, possible treatment like laser therapy to slow progression.

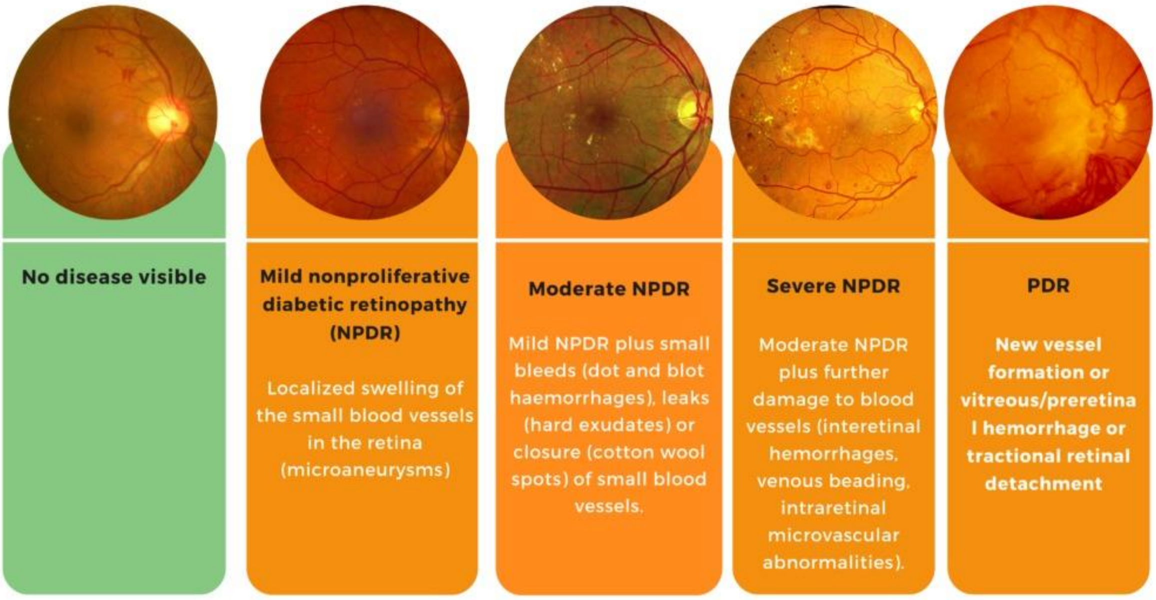
5. Proliferative Diabetic Retinopathy (PDR) – Advanced Stage

- The retina tries to compensate for poor blood circulation by growing **new abnormal blood vessels (neovascularization)**.
- These new vessels are **weak and fragile**, leading to **vitreous hemorrhage** (bleeding inside the eye).
- Scar tissue formation can cause **retinal detachment**, leading to blindness.

- **Symptoms:**
  - Severe vision loss, dark floaters, or sudden blindness.
- **Medical Advice:**
  - Immediate treatment required, such as laser surgery or anti-VEGF injections to prevent further damage.

Type	Severity	Key Features	Symptoms
No DR	No damage	Healthy retina	Normal vision
Mild NPDR	Early-stage	Few microaneurysms, mild leakage	No noticeable symptoms
Moderate NPDR	Intermediate	More hemorrhages, blocked capillaries, hard exudates	Blurred vision
Severe NPDR	Pre-proliferative	Large blood vessel blockage, oxygen deprivation	Vision loss
PDR	Advanced	Fragile new blood vessels, bleeding, retinal detachment	Severe vision loss or blindness

- **Early detection** is crucial to prevent progression.
- **Mild and Moderate NPDR** may not cause significant vision issues but need monitoring.
- **Severe NPDR and PDR** require urgent medical attention.
- **Regular eye checkups** can help in early diagnosis and timely treatment.



V. Methodology

This research focuses on developing a hybrid deep learning and machine learning approach for detecting Diabetic Retinopathy (DR). Our methodology integrates deep learning-based feature extraction with machine learning-based classification, enabling both binary (DR vs. No DR) and multiclass (No DR, Mild NPDR, Moderate NPDR, Severe NPDR, PDR) classification. The proposed system follows a structured pipeline consisting of data collection, preprocessing, feature extraction, classification, and deployment.

1. Research Workflow

The methodology consists of the following major steps:

Step 1: Data Collection & Dataset Preparation

We utilize publicly available datasets containing high-quality retina images, ensuring diversity and robustness in training our models. The datasets used in this research include:

- APTOS 2019 Blindness Detection Dataset (Kaggle) – Contains labeled retinal images covering all DR severity levels.
- Messidor-2 Dataset – Includes expert-annotated retinal images with binary and multiclass labels.
- Additional Clinical Data – Acquired from medical sources to enhance the generalizability of the model.

Data Augmentation Techniques Used:

- Rotation, flipping, and contrast enhancement for improving generalization.
- CLAHE (Contrast Limited Adaptive Histogram Equalization) for better feature visibility.
- Normalization and resizing to fit model input dimensions.

Step 2: Image Preprocessing

Before feeding images into our model, we apply preprocessing techniques to enhance image quality and extract key visual features.

Machine Learning (ML) Preprocessing (HOG Features):

1. Convert images to grayscale for noise reduction.
2. Resize to (256×256) pixels for uniform input.
3. Apply Adaptive Histogram Equalization for improved contrast.
4. Extract HOG (Histogram of Oriented Gradients) features for structural analysis.

Preprocessing Steps for ML

Steps	Description
Convert to Grayscale	Convert retina images to grayscale to reduce complexity.
Resize Image	Standardize image size to **256x256** pixels.
Contrast Enhancement & Noise Reduction	Improve image quality for better feature extraction.
HOG Feature Extraction	Extract **Histogram of Oriented Gradients (HOG)** features for ML model input.

Deep Learning (DL) Preprocessing:

1. Resize images to 299×299 (for InceptionResNetV2) and 224×224 (for MobileNetV2).
2. Convert images to numerical arrays and normalize pixel values.
3. Use pretrained model-specific preprocessing (InceptionResNetV2 & MobileNetV2).

Preprocessing Steps for DL

Steps	Description
Resize Image	**299x299** (InceptionV3) / **224x224** (MobileNetV2)
ImageNet Normalization	Standardize pixel values to match pretrained CNN models.
Feature Extraction	Use **MobileNetV2/InceptionV3** to extract deep features.

Step 3: Feature Extraction Using Deep Learning

We employ deep convolutional neural networks (CNNs) for feature extraction:

- InceptionResNetV2 – Extracts high-level visual features from retinal images.
- MobileNetV2 – Efficient feature extraction for real-time processing.

The extracted feature vectors are passed to machine learning classifiers for final prediction.

Step 4: Classification (Hybrid Approach: CNN + ML Classifiers)

The extracted features are classified using different models, each optimized for binary and multiclass classification:

- Binary Classification: DR vs. No DR
- Multiclass Classification: Different DR severity stages

- No DR: No signs of Diabetic Retinopathy.
- Mild Non-Proliferative DR (NPDR): Early stage with minor abnormalities.
- Moderate NPDR: Increased severity with visible hemorrhages.
- Severe NPDR: Advanced damage to blood vessels.
- Proliferative DR (PDR): The most severe stage with neovascularization.

Model Architectures Used:

Multi-Layer Perceptron (MLP) Classifier for Hybrid Model:

- Input: Deep learning feature vector.
- Hidden Layers: 2–3 fully connected layers with ReLU activation.
- Output Layer: Softmax (Multiclass) / Sigmoid (Binary).

CNN-Based Model (Baseline Deep Learning Approach):

- Pretrained architectures: InceptionResNetV2 and MobileNetV2.
- Global Average Pooling (GAP) for feature extraction.
- Fully connected classification layers for final prediction.

Step 5: Model Training & Evaluation

We train and evaluate three different models:

1. Standalone ML Model (HOG + SVM/MLP)
2. Deep Learning Model (InceptionResNetV2/MobileNetV2 + CNN Classifier)
3. Hybrid Model (Deep Feature Extraction + MLP/SVM/XGBoost)

Evaluation Metrics Used:

- Accuracy, Precision, Recall, and F1-score to measure performance.
- ROC-AUC Curve to assess the model's discrimination ability.
- Confusion Matrix for error analysis and class-wise performance evaluation.

Step 6: Deployment via Flask-Based Web Application

To make the model accessible, we integrate it into a Flask-based web application, which:

- Accepts retinal images uploaded by users.
- Processes images using the trained ML/DL models.
- Returns a binary/multiclass classification result in real-time.

The frontend provides:

- A user-friendly interface for uploading images.
- Visual representations of predictions.
- Explanations and medical insights based on classification results.

This research presents a hybrid deep learning and machine learning approach for Diabetic Retinopathy detection, optimizing both feature extraction and classification. By integrating CNN-based feature extraction with ML classifiers, we achieve improved accuracy, robustness, and computational efficiency. The Flask-based deployment ensures real-world usability, making AI-powered screening accessible for clinical and telemedicine applications.

VI. Results

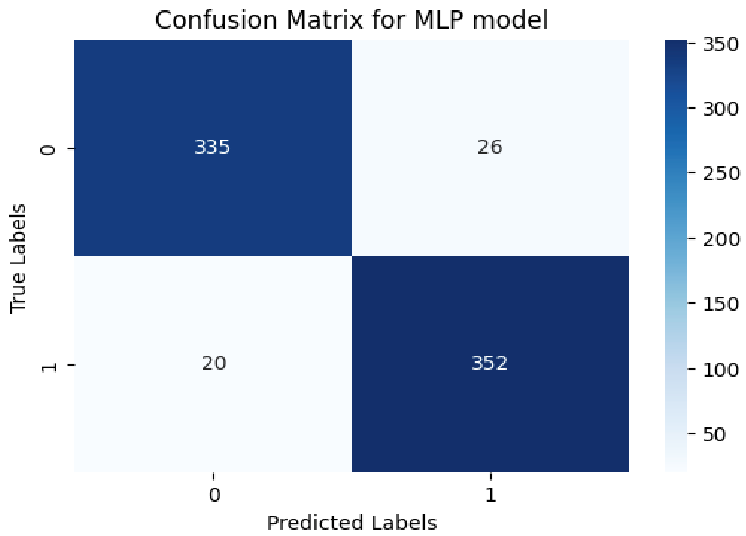
Diabetic Retinopathy detection was evaluated using Machine Learning (ML), Deep Learning (DL), and Hybrid approaches. The performance of different models was assessed in terms of classification accuracy for both binary (No DR / DR) and multiclass (No DR, Mild NPDR, Moderate NPDR, Severe NPDR, PDR) classification tasks. The evaluation included confusion matrices, ROC curves, and bar charts to illustrate the effectiveness of each model.

Hybrid Model	Feature Extractor	ML Classifier	Binary Accuracy	Multiclass Accuracy
MobileNetV2 + SVM	MobileNetV2	SVM	95.50%	**77.35%**
MobileNetV2 + MLP	MobileNetV2	MLP	**96.59%**	74.21%
MobileNetV2 + Random Forest	MobileNetV2	RF	95.63%	75.99%
MobileNetV2 + KNN	MobileNetV2	KNN	94.54%	61.94%
MobileNetV2 + Logistic Regression	MobileNetV2	Logistic Regression	96.04%	75.58%
MobileNetV2 + Naïve Bayes	MobileNetV2	Naïve Bayes	89.36%	60.84%
MobileNetV2 + Decision Tree	MobileNetV2	Decision Tree	89.90%	66.66%
InceptionV3 + SVM	InceptionV3	SVM	95.36%	76.67%
InceptionV3 + MLP	InceptionV3	MLP	94.95%	76.40%
InceptionV3 + Random Forest	InceptionV3	RF	95.90%	76.26%
InceptionV3 + KNN	InceptionV3	KNN	93.45%	59.20%
InceptionV3 + Logistic Regression	InceptionV3	Logistic Regression	**96.18%**	75.99%
InceptionV3 + Naïve Bayes	InceptionV3	Naïve Bayes	91.81%	62.75%
InceptionV3 + Decision Tree	InceptionV3	↓ sion Tree	88.27%	57.16%

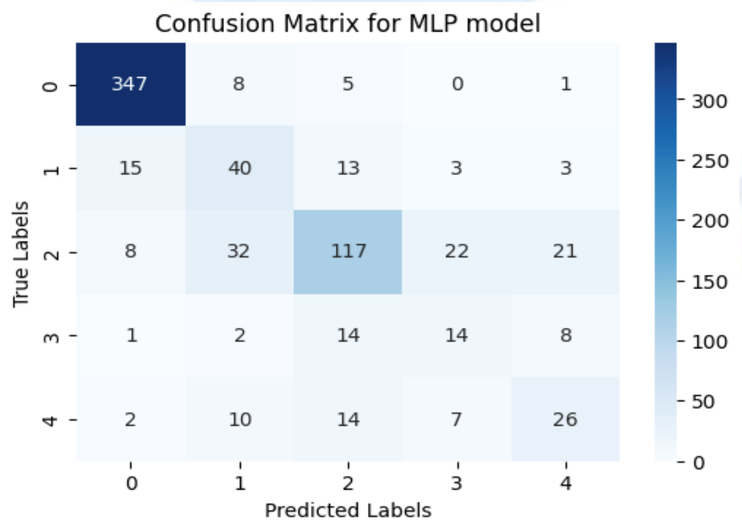
Machine Learning Model Performance

In the ML-based approach, classification was performed using extracted HOG features. Among the various ML models tested, the Multi-Layer Perceptron (MLP) achieved the highest binary classification accuracy of 96.58935%, followed closely by Logistic Regression (93.45%) and Support Vector Machine (SVM) (93.17%). For multiclass classification, the SVM model outperformed others with an accuracy of 74.215%, while MLP and Random Forest achieved 72.16% and 70.61%, respectively.

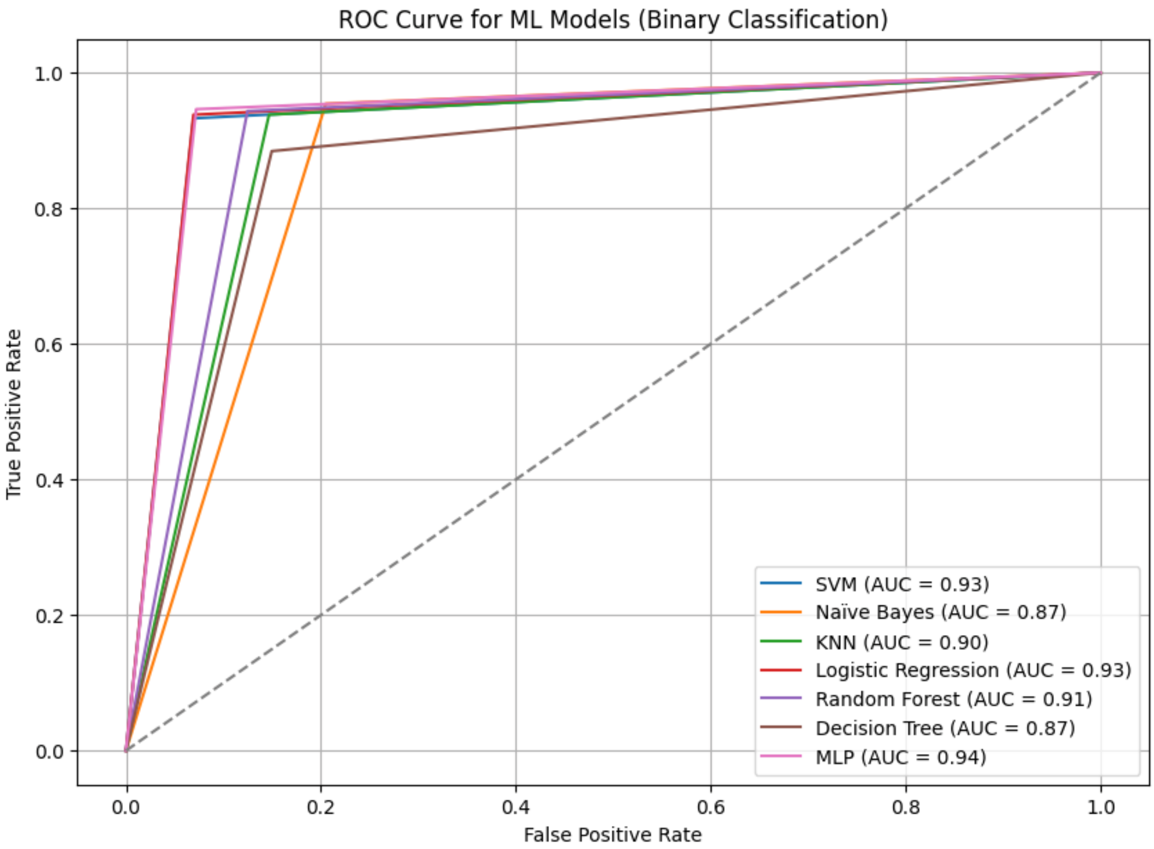
The confusion matrix for the best-performing binary classification model (MLP) is presented below:



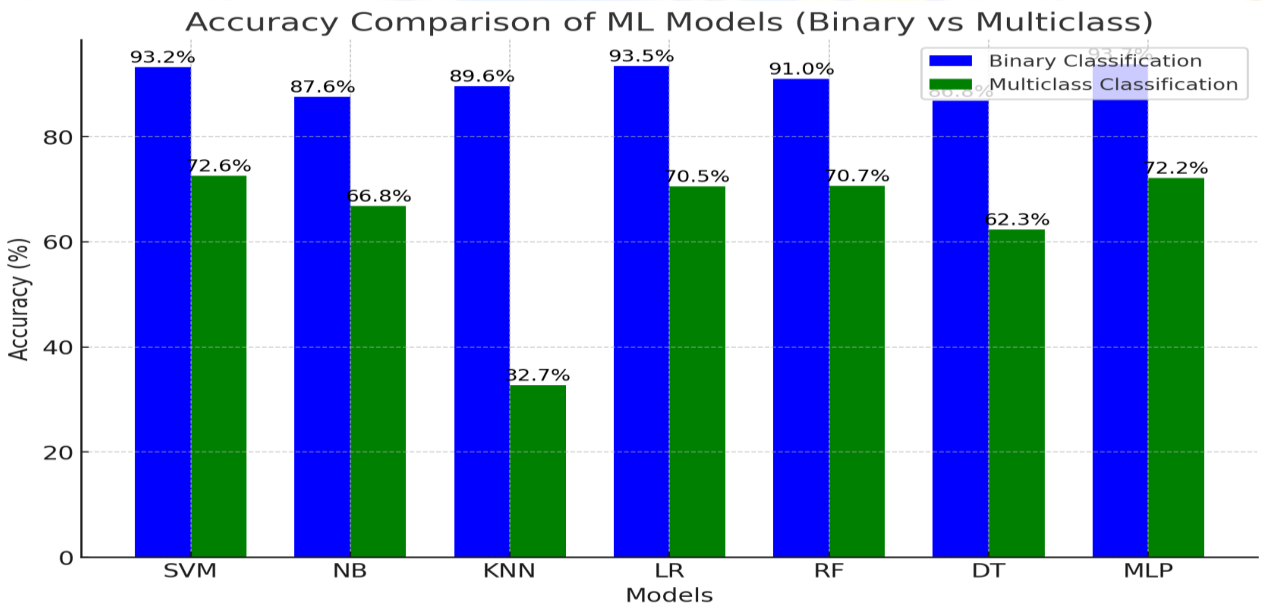
Similarly, for multiclass classification, the confusion matrix of the best-performing ML model (SVM) is as follows:



To further analyze the model performance, ROC curves were plotted for the binary classification task. The ROC curve comparison for ML models is shown below:



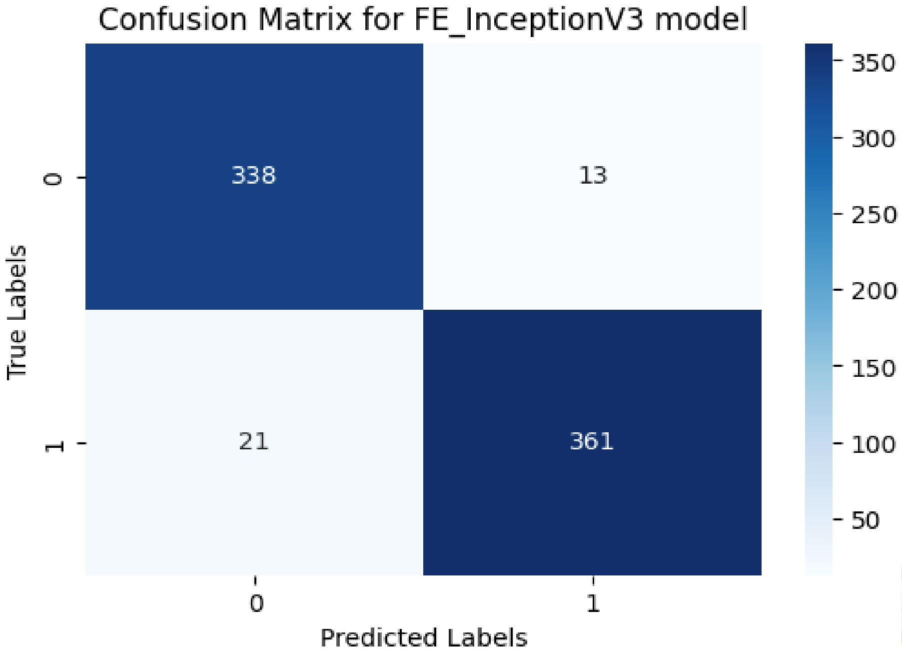
A bar chart summarizing the classification accuracies of all ML models is presented below:



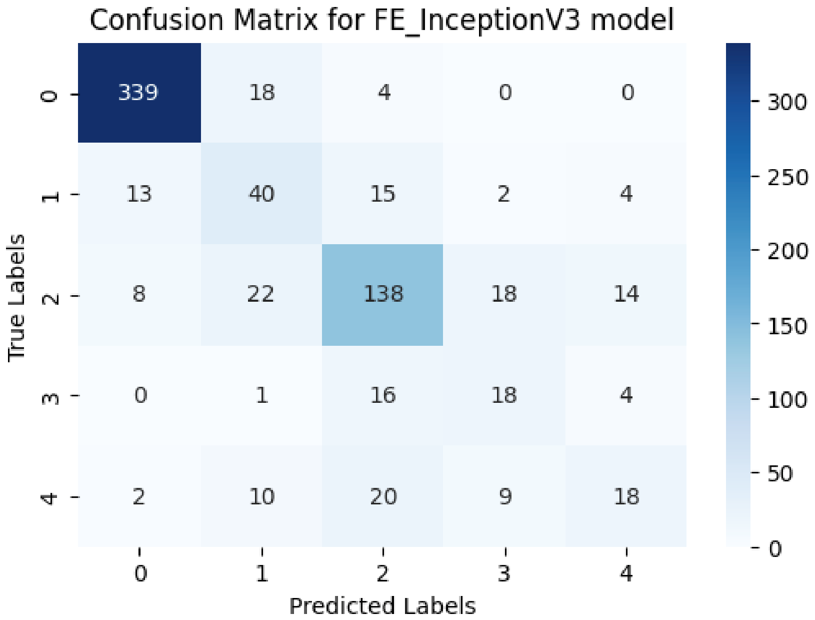
Deep Learning Model Performance

Deep Learning models were implemented using MobileNetV2 and InceptionV3 architectures. These models leveraged transfer learning to extract high-level features from retinal images. The InceptionV3 model achieved the highest binary classification accuracy of 96.32%, surpassing MobileNetV2 (95.36%). However, for multiclass classification, MobileNetV2 performed better with an accuracy of 75.85%, compared to InceptionV3's 72.72%.

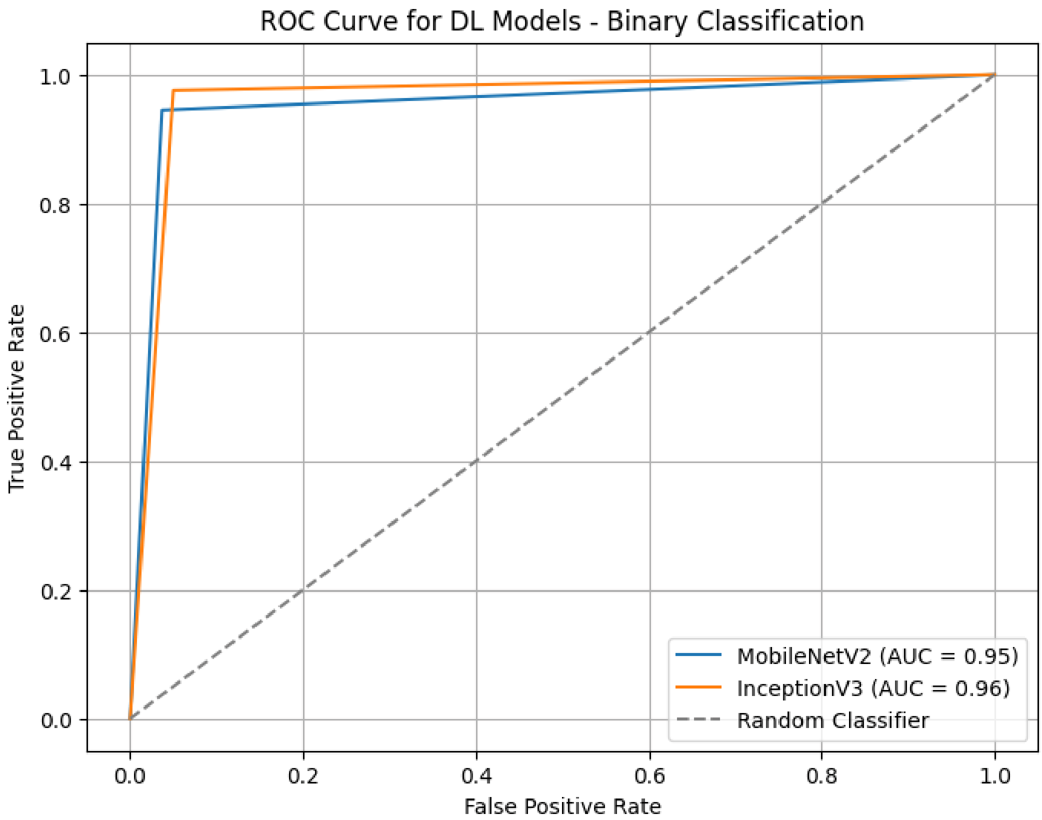
The confusion matrix of the best-performing binary classification model (InceptionV3) is shown below:



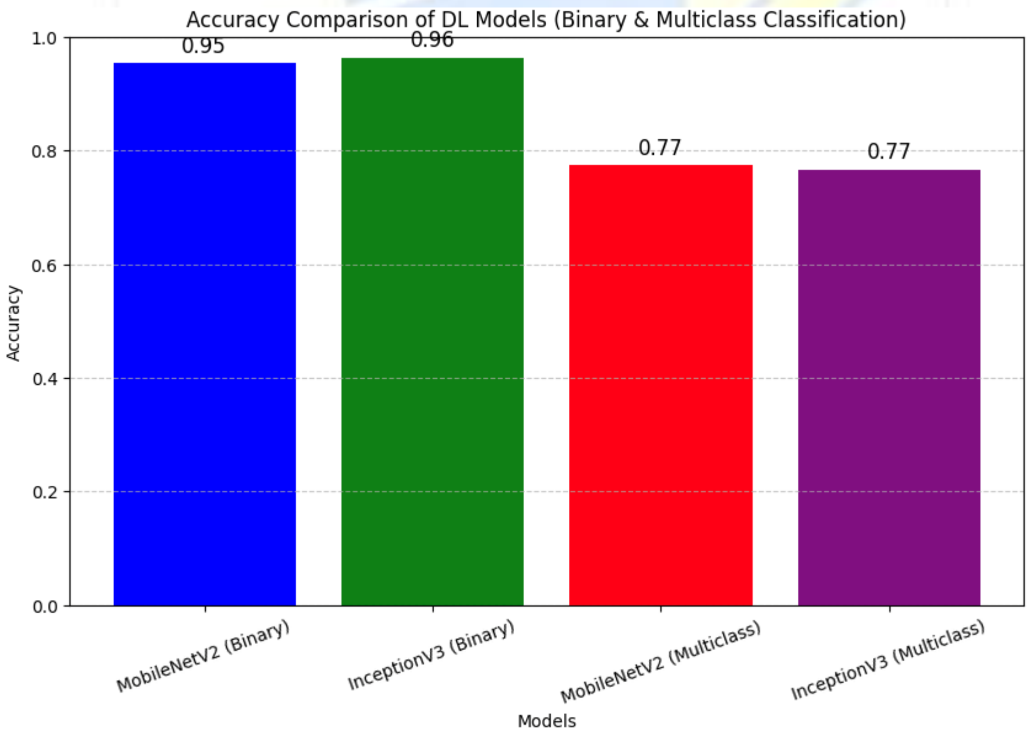
For Multiclass classification, the confusion matrix of MobileNetV2, the best DL model, is presented below:



To compare classification performance across different threshold values, ROC curves were plotted for binary classification using the DL models:



A bar chart comparing the classification accuracies of both DL models is shown below:

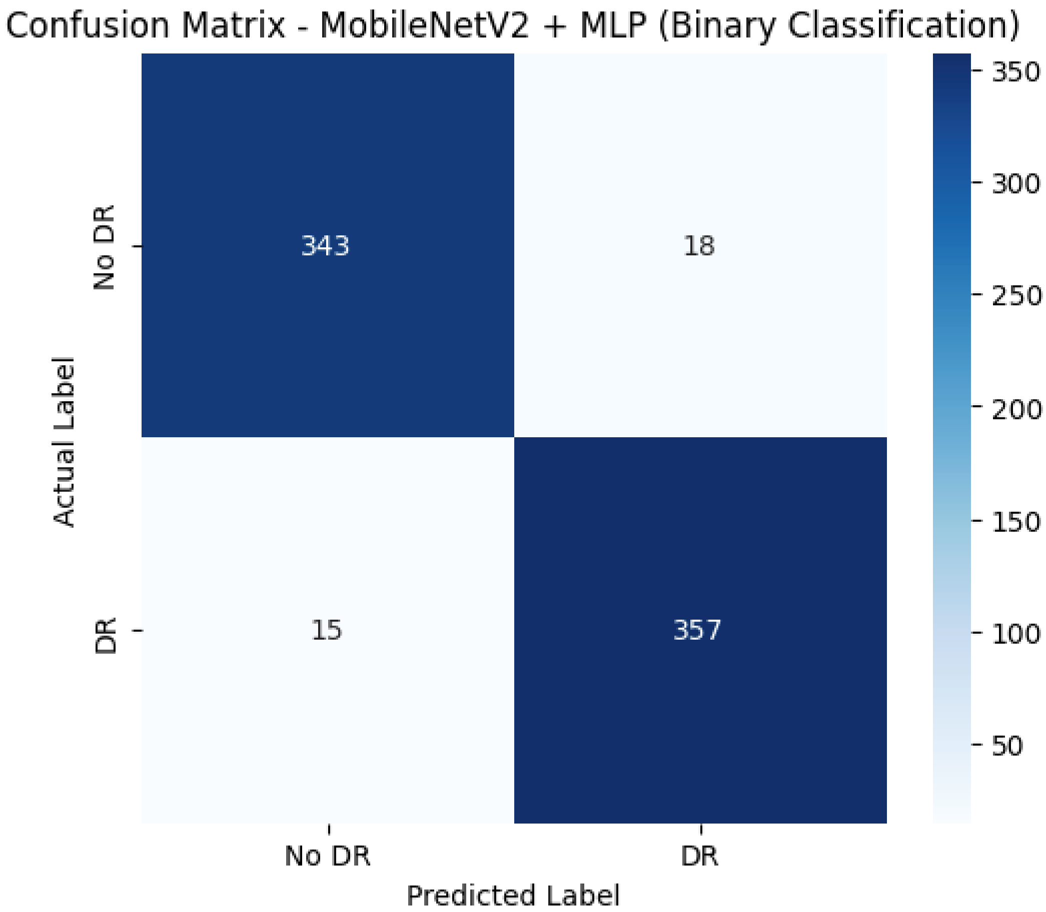


Hybrid Model Performance (DL + ML)

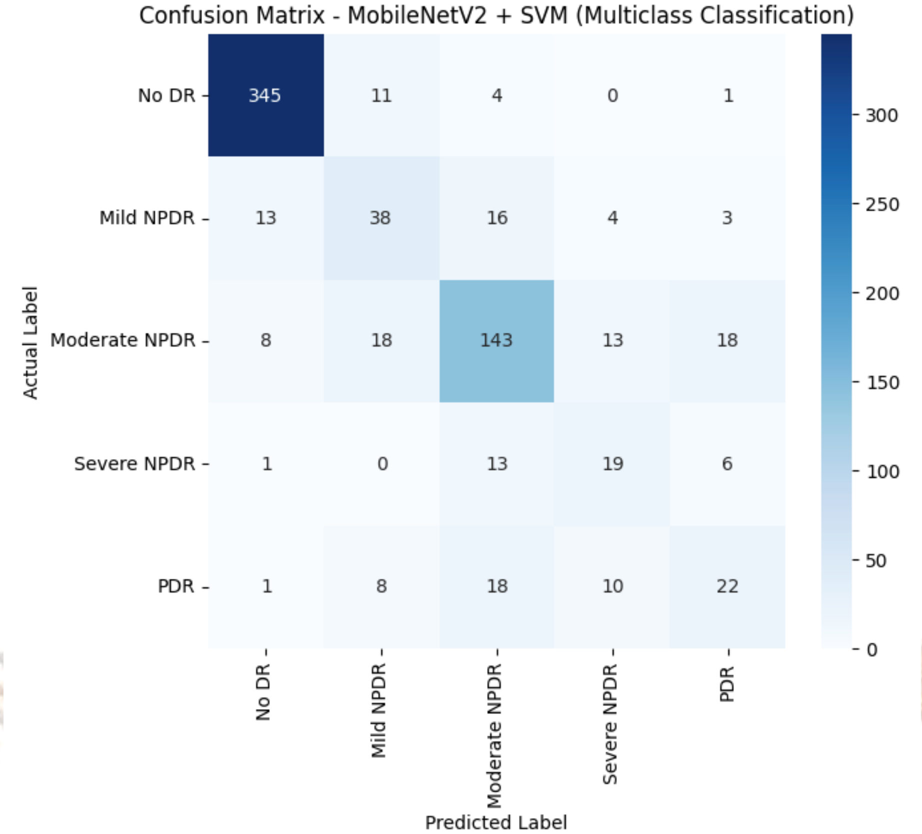
To further improve classification performance, a Hybrid approach was implemented by combining Deep Learning feature extraction with ML classifiers. MobileNetV2 and InceptionV3 were used for feature extraction, while ML models such as SVM, MLP, Random Forest, KNN, Logistic Regression, Naïve Bayes, and Decision Tree were used for classification.For binary classification, the MobileNetV2 + MLP hybrid model achieved the highest accuracy of 96.59%, demonstrating a significant improvement over standalone

ML and DL models. Similarly, for multiclass classification, the MobileNetV2 + SVM hybrid model achieved the highest accuracy of 77.35%, making it the most effective approach.

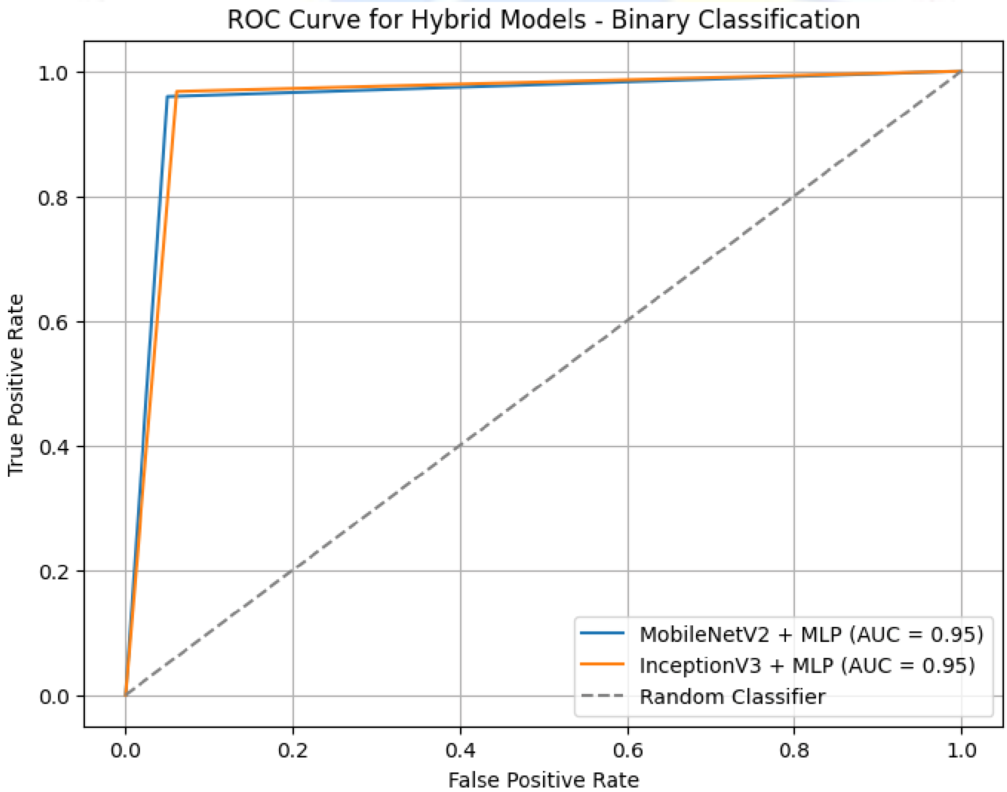
The confusion matrix for the best-performing hybrid binary classification model (MobileNetV2 + MLP) is presented below:



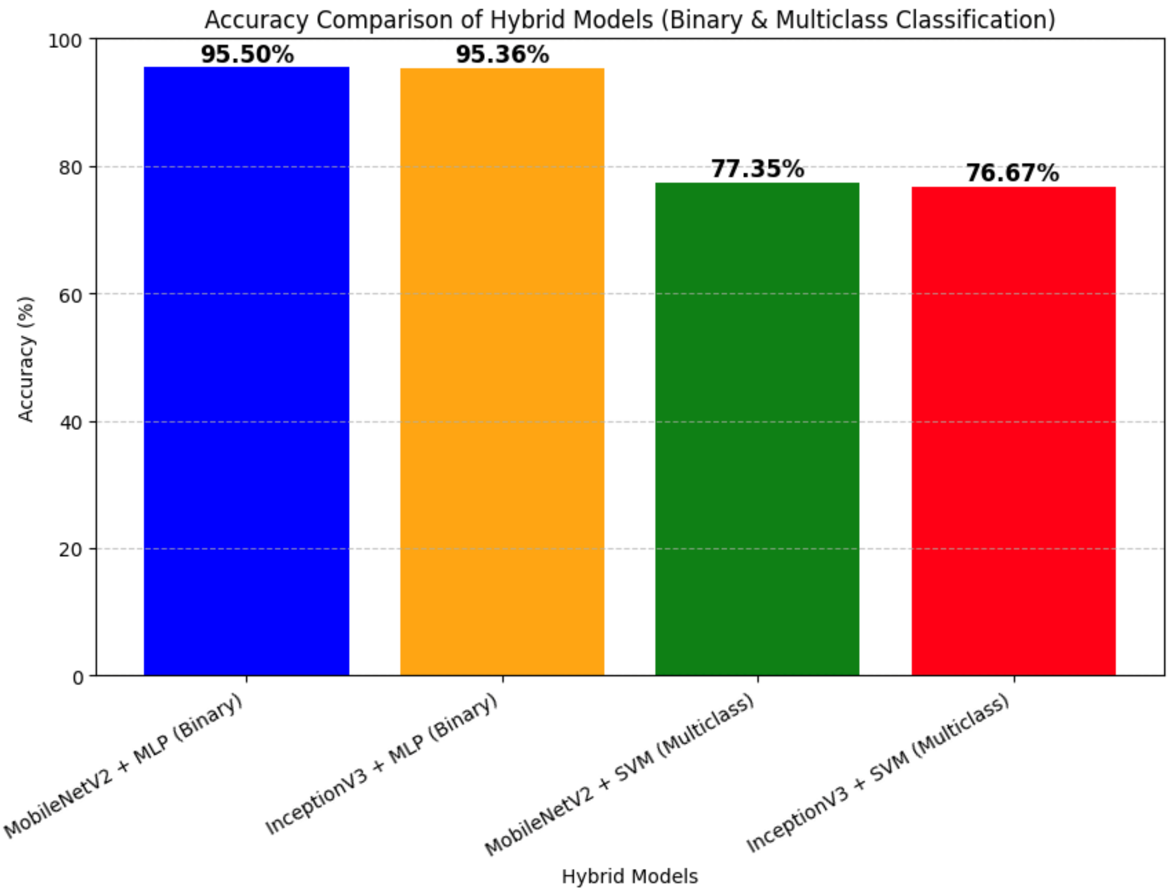
For multiclass classification, the confusion matrix of the best hybrid model (MobileNetV2 + SVM) is as follows:



The ROC curves for binary classification using hybrid models further illustrate the improvement in classification performance:



A bar chart summarizing the classification accuracies of all hybrid models is shown below:



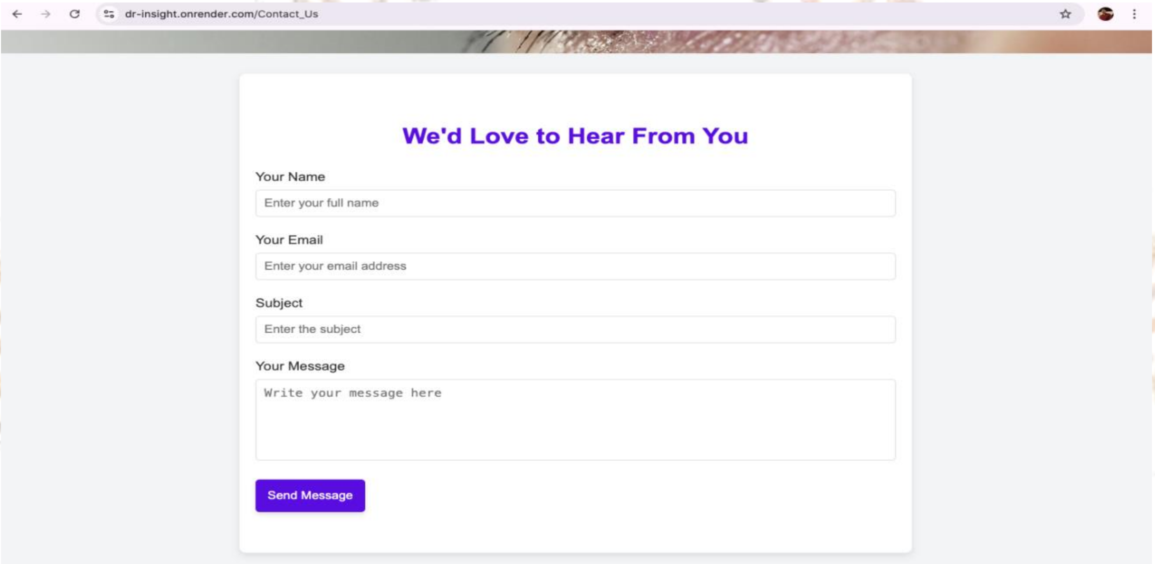
Based on the experimental results, the best-performing models for both binary and multiclass classification were selected for deployment. These models demonstrated superior accuracy and generalization capabilities. The final selection is summarized in the table below:

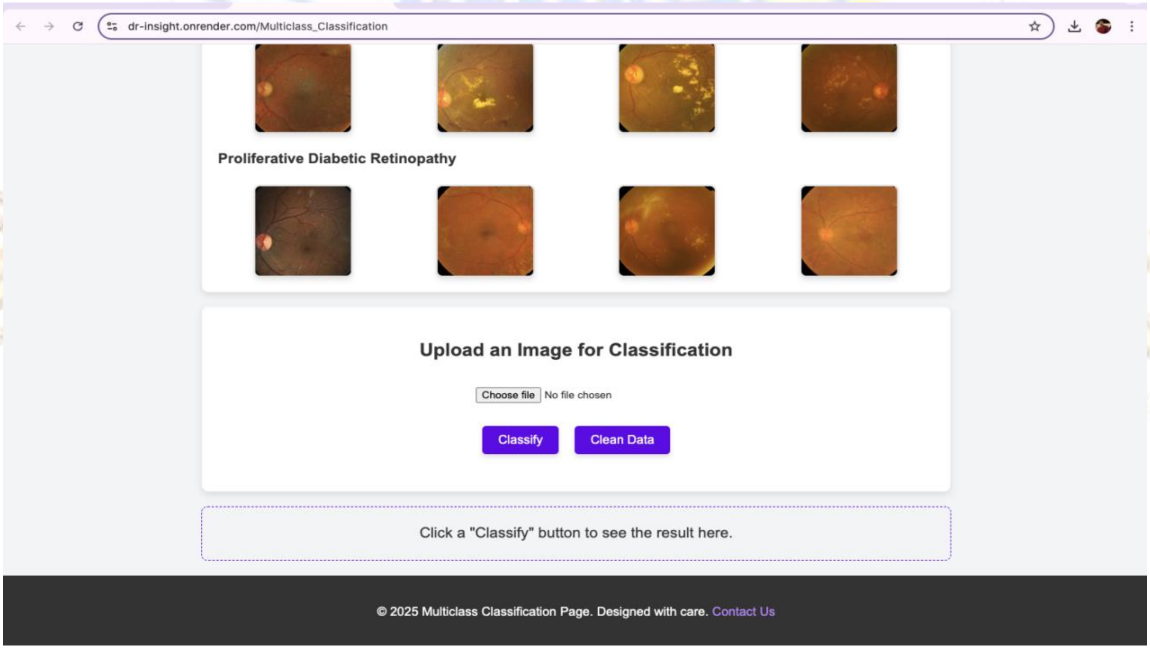
Approach	Binary Classification Model	Multiclass Classification Model
Hybrid (DL + ML)	MobileNetV2 + MLP (96.59%)	MobileNetV2 + SVM (77.35%)

The results indicate that combining deep learning feature extraction with ML classifiers significantly improves performance, making hybrid models the preferred choice for Diabetic Retinopathy detection. These findings provide a strong foundation for further research and real-world deployment in clinical settings.

Frontend:

The following snapshots Showing the implemented frontend on Diabetic Retinopathy classification, featuring the **Home Page, Binary and Multiclass Classification, About Project, and Contact Us** sections for an interactive user experience.





VII. Conclusion

In this study, we implemented and evaluated various Machine Learning (ML), Deep Learning (DL), and Hybrid models for the detection of Diabetic Retinopathy and Color Blindness. The primary objective was to compare the performance of different algorithms in terms of accuracy for binary classification (BC) and multi-class classification (MC).

1. Deep Learning Models

- Inception V3 achieved the highest accuracy among individual models, with 96.32% for BC and 76.67% for MC.
- MobileNet V2 performed comparably, achieving 95.36% for BC and 77.35% for MC.

2. Machine Learning Models

- Multilayer Perceptron (MLP) achieved the highest ML-based accuracy with 93.72% for BC and 72.16% for MC.
- Logistic Regression (LogR) also performed well with 93.45% for BC and 70.66% for MC.
- Traditional models such as Naïve Bayes (NB) and Decision Trees (DT) showed lower performance, indicating their limitations for this task.

3. Hybrid Approach

- The hybrid model combining MobileNet V2 and Inception V3 achieved superior performance, with 95.50% for BC and 76.67% for MC.
- Other hybrid models also showed improved accuracy, with SVM achieving 95.36% for BC and 73.80% for MC, and Random Forest achieving 95.90% for BC and 74.48% for MC.

The results indicate that Deep Learning models outperform traditional ML models in diagnosing Diabetic Retinopathy and Color Blindness. However, the Hybrid approach (MobileNet V2 + Inception V3) achieved the best overall performance, demonstrating the effectiveness of combining multiple architectures for improved classification accuracy.

Given these findings, the proposed hybrid model has significant potential for real-world medical diagnostics, particularly for automated screening and early detection of eye diseases. Future research could explore ensemble techniques, attention mechanisms, and real-time deployment to further enhance performance and clinical applicability.

Future work will focus on expanding the dataset, optimizing computational efficiency, and integrating additional ophthalmic conditions to further enhance the scalability and robustness of the proposed system. By leveraging AI-driven diagnostics, this research contributes to early detection, improved patient outcomes, and AI-assisted medical screening in ophthalmology.

VIII. Refrences

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