DIABETIC RETINOPATHY DETECTION

A mini project report submitted in partial fulfilment of the requirements for the award of the degree of

MASTER OF SCIENCE

IN

INFORMATION TECHNOLOGY

Submitted by

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Coimbatore – 641008

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This is to certify that the mini project report entitled **"DIABETIC RETINOPATHY DETECTION"** in partial fulfilment of requirements for the award of the degree of Master of Science in Information Technology is a record of bonafied work carried out by **SARAN P (24MIT044)** and that no part of this has been submitted for the awardof any other degree or diploma and the work has not been published in popular journal or magazine.

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I hereby declare that the mini project report entitled **"DIABETIC RETINOPATHY DETECTION**" submitted in partial fulfilment of the requirements for the award of the degree of **Master of Science in Information Technology** is an original work submitted and it has not been previously formed the basis for the award of any other Degree, Diploma, Associate ship, Fellowship or similar titles to any other university or body during the period of my study.

Place: Coimbatore

Date:

Signature of the Candidate

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ABSTRACT

Diabetic Retinopathy (DR) is one of the most common and serious complications of diabetes and has become one of the leading causes of preventable blindness across the globe. According to recent medical reports, millions of people are at risk, particularly in developing countries where regular eye check-ups and specialized diagnostic resources are limited. Early detection and timely treatment of DR can significantly reduce vision impairment, but manual screening through retinal fundus images is both time-consuming and highly dependent on the expertise of ophthalmologists. This creates a pressing need for an automated, reliable, and cost-effective computer-aided diagnosis system.

This project presents a deep learning–driven framework for automated DR detection, classification, and visualization. The system employs a Convolutional Neural Network (CNN) with attention mechanisms, enabling it to focus on key retinal regions while classifying fundus images into five severity stages: No DR, Mild, Moderate, Severe, and Proliferative DR. To enhance interpretability, Gradient-weighted Class Activation Mapping (Grad-CAM) is integrated, generating heatmaps that visually highlight pathological regions influencing predictions. This not only improves trust in model decisions but also provides clinicians with an additional decision-support tool.

A secure and user-friendly web-based interface is implemented, allowing healthcare professionals to upload patient details and retinal images seamlessly. The system instantly generates classification results, confidence scores, and visual explanations. In addition, the platform incorporates robust privacy and security measures: uploaded images are sanitized, restricted to medical file formats, and automatically deleted after prediction, ensuring compliance with healthcare privacy standards.

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CHAPTER 1

INTRODUCTION

1.1 Overview of the Object

Diabetes mellitus is one of the most common chronic diseases worldwide, affecting millions of people across different age groups. Among the several complications associated with long-term diabetes, Diabetic Retinopathy (DR) stands out as a leading cause of preventable blindness. It occurs when prolonged high blood sugar levels damage the tiny blood vessels in the retina, leading to leakage, swelling, or abnormal growth of blood vessels. These changes, if not detected early, can progress silently and result in partial or complete vision loss.

Traditional methods of DR diagnosis rely heavily on manual examination of retinal fundus images by ophthalmologists. However, this process is time-consuming, costly, and prone to human error, especially in regions where there is a shortage of trained specialists. The rapid increase in diabetes cases has made early screening and automated detection of DR an urgent global health priority.

With the rise of machine learning and deep learning techniques, computer-assisted diagnostic systems have gained significant attention. These systems can analyze large volumes of retinal images with high speed and accuracy, providing reliable decision support for medical professionals. By leveraging advanced algorithms such as Convolutional Neural Networks (CNNs), Vision Transformers (ViTs), and hybrid deep learning models, automated systems can classify DR into different severity levels (No DR, Mild, Moderate, Severe, and Proliferative).

This project focuses on developing an automated Diabetic Retinopathy Detection system that integrates state-of-the-art deep learning models with user-friendly web application interfaces. The system accepts retinal images, processes them, and provides predictions regarding the presence and severity of DR along with supportive visualizations such as heatmaps Gradient-Weighted Class Activation Mapping (Grad-CAM) to highlight suspicious regions. This not only aids ophthalmologists but also empowers patients to receive faster and more reliable screenings.

1.2 Problem Statement

Diabetic Retinopathy is often asymptomatic in its early stages, which makes timely detection difficult. Many patients remain unaware of retinal damage until it progresses to advanced stages where vision impairment becomes irreversible. The World Health Organization (WHO) and International Diabetes Federation (IDF) have reported that more than one-third of diabetic patients are at risk of developing DR, and yet, screening programs are insufficient in many parts of the world.

The major challenges in existing diagnostic practices include:

- Limited availability of ophthalmologists: Especially in rural or developing areas where diabetic populations are high.
- Manual diagnosis limitations: Human examination of retinal images is prone to fatigue, subjectivity, and inconsistency.
- Time and cost factors: Regular screenings are expensive and not easily accessible to every patient.
- High patient volume: The exponential rise in diabetes cases has created a burden on healthcare systems.

To address these challenges, there is a clear need for an automated, reliable, and scalable DR detection system. By using deep learning and image processing, the system should be able to quickly classify retinal fundus images, provide severity grading, and assist in early intervention.

This project aims to bridge the gap by developing an intelligent framework that combines image classification, segmentation, disease grading, and localization techniques. Such a solution can significantly reduce the load on ophthalmologists, improve accessibility to screenings, and ultimately help in reducing preventable blindness due to diabetic complications.

1.3 Objective

The key objectives of this project are as follows:

1. Automated Detection of DR: To build a deep learning-based system capable of detecting the presence of Diabetic Retinopathy from retinal fundus images.
2. Severity Grading: To classify the detected cases into different stages such as No DR, Mild, Moderate, Severe, and Proliferative DR.
3. Explainability through Heatmaps: To incorporate visualization techniques like Grad-CAM or saliency maps that highlight affected regions, thereby increasing the interpretability of predictions.
4. Integration into a Web Application: To design a Flask-based user interface where healthcare professionals and patients can upload retinal images and receive diagnostic results in real time.
5. Performance Evaluation: To measure accuracy, sensitivity, specificity, and F1-score using benchmark datasets and compare with existing state-of-the-art models.

CHAPTER 2

2. LITERATURE REVIEW

2.1 INTRODUCTION

Diabetic Retinopathy (DR) detection has become one of the most extensively studied areas in medical imaging and healthcare due to its critical role in preventing vision loss and blindness among diabetic patients. Over the years, researchers have employed a wide range of approaches, beginning with traditional image processing and statistical methods, which offered basic lesion detection but often struggled with scalability and accuracy across diverse datasets.

With the growth of Artificial Intelligence (AI), machine learning algorithms such as Support Vector Machines (SVM), Random Forests, and k-Nearest Neighbors (k-NN) were introduced for automated classification of DR severity. While these models improved detection compared to manual diagnosis, their performance heavily depended on handcrafted features and often failed to capture the complex patterns in retinal fundus images.

In recent years, deep learning methods, particularly Convolutional Neural Networks (CNNs), have shown remarkable success in automatically learning discriminative features from retinal images. Architectures such as ResNet, Inception, EfficientNet, and Vision Transformers (ViTs) have achieved state-of-the-art accuracy in classifying DR severity levels ranging from No DR to Proliferative DR. Furthermore, segmentation-based models like U-Net and its variants have been widely used to localize lesions such as microaneurysms, hemorrhages, and exudates.

Despite these advancements, challenges remain in terms of model interpretability, robustness across diverse populations, and the handling of poor-quality retinal images. To address these issues, researchers are increasingly integrating explainable AI techniques like Grad-CAM and hybrid approaches that combine CNNs with attention mechanisms or ensemble methods. These efforts aim to enhance both diagnostic accuracy and clinical trust, ensuring that DR detection systems can be effectively adopted in real-world healthcare settings.

This review highlights the progression of methods in diabetic retinopathy detection, emphasizing the shift from traditional image analysis to advanced deep learning and hybrid approaches, while also identifying the research gaps that motivate further development of interpretable and reliable DR detection systems.

2.2 LITERATURE REVIEW

A. R. W. Sait et al. (2023) – A Lightweight Diabetic Retinopathy Detection Model Using YOLOv7 Features This paper introduces a YOLOv7-based feature extraction model with a lightweight classifier for DR detection. The study highlights its suitability for real-time systems with low computational costs. Preprocessing methods enhanced contrast and improved model accuracy. Results show that even lightweight models can achieve competitive performance compared to heavy architectures. The solution is designed for portable devices, helping rural healthcare. The authors emphasize that speed and efficiency are key for adoption in screening programs.

Bhulakshmi et al. (2024) – A Systematic Review on Diabetic Retinopathy Detection and AI Methods This review covers a wide range of AI approaches for DR detection. It examines preprocessing, segmentation, feature engineering, and classification strategies. CNN-based methods, ensemble learning, and transfer learning approaches are discussed. The review also notes challenges such as data scarcity, imbalance, and explainability. The authors recommend hybrid approaches for clinical deployment.

Ş. Y. Atcı et al. (2024) – Diabetic Retinopathy Detection in the Human Eye (Explainability Focus) This study emphasizes explainability in DR models. Using Grad-CAM and SHAP, the authors visualized which retinal regions influenced model predictions. Validation with ophthalmologists showed that highlighted areas aligned with clinical lesions. The paper warns against models relying on irrelevant features. It concludes that trust in AI systems can only grow through transparent decision-making. The integration of explainability tools is crucial for medical AI applications.

M. Oulhadj et al. (2024) – Vision Transformer (ViT)-Based Diabetic Retinopathy Prediction The authors apply Vision Transformers to fundus image classification. Unlike CNNs, ViTs use patch embeddings and self-attention to capture global relationships. Results showed that ViTs outperformed CNNs on cross-dataset evaluations. Transfer learning was used to fine-tune the model for DR detection. The paper demonstrates ViTs' strength in identifying subtle retinal changes. The findings suggest transformers could dominate future ophthalmic AI research.

V. Selvakumar et al. (2023) – Effective Diabetic Retinopathy Diagnosis Using U-Net Segmentation This study combines U-Net for retinal lesion segmentation with KNN for

classification. U-Net effectively isolates blood vessels and lesions like hemorrhages and exudates. KNN then classifies DR severity based on segmented features. The method improves interpretability by showing lesion maps. It reduces misclassification caused by noisy fundus images. The approach bridges deep learning with traditional ML for reliable results.

G. J. Panda et al. (2023) – DR Classification Using Hybrid Deep Learning Models This work proposes a hybrid model combining CNN feature extraction with Random Forest classification. CNNs learn hierarchical features from fundus images, while RF improves decision robustness. The approach balances accuracy and interpretability. Results outperform standalone CNN models in cross-validation tests. The paper also discusses computational trade-offs of hybrid systems. The combination is recommended for clinical AI pipelines needing both power and explainability.

K. Zhang et al. (2022) – Screening Diabetic Retinopathy with Deep Residual Networks This study applies ResNet-based architectures for DR classification. Residual connections solve the vanishing gradient problem, enabling deeper models. The system achieved high sensitivity in detecting referable DR. The paper highlights ResNets' ability to handle high-resolution fundus images. Their experiments also included augmentation techniques for improved generalization. The findings confirm that ResNet is well-suited for DR tasks.

A. Das et al. (2022) – Diabetic Retinopathy Detection Using Ensemble Learning This research introduces an ensemble combining CNNs and gradient boosting methods. The ensemble approach leverages diverse learning patterns for improved accuracy. Experiments showed the ensemble outperformed individual classifiers. The system demonstrated strong robustness on imbalanced datasets. The authors argue that ensemble learning reduces overfitting risks. The technique is practical for real-world screening scenarios with diverse patient populations.

R. Pratt et al. (2019) – Convolutional Neural Networks for Automatic DR Detection This early CNN-based work laid the foundation for AI in DR detection. CNNs were trained to detect lesions directly from raw fundus images. The study proved that end-to-end learning could bypass manual feature engineering. Despite limited datasets, the model showed strong diagnostic potential. The research emphasized preprocessing to enhance accuracy. This work inspired later large-scale DR deep learning systems.

P. Gulshan et al. (2016) – Development and Validation of a Deep Learning Algorithm for DR Detection One of the landmark studies applying deep learning to DR screening. A large

dataset of retinal images was used to train CNNs. The model achieved sensitivity comparable to ophthalmologists. The study demonstrated that AI could scale screening programs globally. It also stressed the need for high-quality annotations. The paper is widely cited as a turning point in medical AI research.

Q. Li et al. (2021) – Multi-Scale Attention Networks for DR Severity Classification This paper proposes a multi-scale attention mechanism within CNNs. The attention layers highlight key lesion areas like microaneurysms and exudates. Multi-scale design improves detection of both small and large lesions. The model outperformed standard CNNs in severity grading. The authors note improved explainability due to lesion focus. Their method helps in accurate early-stage detection of DR.

S. Kori et al. (2020) – Diabetic Retinopathy Detection Using Capsule Networks Capsule Networks are explored as an alternative to CNNs. Capsules preserve spatial hierarchies between retinal structures. The model achieved strong accuracy in recognizing lesion patterns. It performed particularly well in distinguishing mild DR stages. The paper argues capsules reduce information loss compared to pooling in CNNs. This innovation opens a new path for DR detection research.

T. Lam et al. (2021) – Explainable AI in Ophthalmology: Case of DR Detection This study reviews explainable AI methods in DR detection. Tools like Grad-CAM, LIME, and attention visualization are discussed. The authors stress the importance of clinical trust in AI outputs. Case studies show how visualization aids ophthalmologists' decision-making. They highlight risks of black-box models in critical healthcare. The paper calls for standardized explainability frameworks in medical AI.

M. Islam et al. (2018) – DR Detection Using Transfer Learning with Pretrained CNNs The authors apply transfer learning from ImageNet CNNs for DR tasks. Models like VGG and Inception were fine-tuned on retinal images. Transfer learning enabled strong results with small datasets. The method saves training time and resources. It also reduces risks of overfitting on medical datasets. This work helped popularize transfer learning in ophthalmology AI.

H. Tang et al. (2020) – DR Grading with Attention-Guided CNNs The authors design CNNs with attention modules to focus on lesions. This guided feature learning improved severity grading accuracy. The method was validated across multiple datasets. It also reduced false positives in normal images. The study shows attention

mechanisms improve both accuracy and explainability. The paper contributes to more reliable DR classification pipelines.

J. Li et al. (2019) – Hybrid U-Net and CNN for Lesion Segmentation and DR Classification This research integrates U-Net segmentation with CNN classification. U-Net isolates lesion regions, feeding features to CNNs for severity grading. The pipeline improves accuracy by reducing irrelevant background noise. Results showed strong interpretability with lesion heatmaps. The method balances pixel-level and image-level learning. It is a practical hybrid for clinical adoption.

A. R. Chowdhury et al. (2021) – Deep Learning for Early DR Detection This work emphasizes early DR detection before major vision loss. CNNs were trained on datasets with mild DR cases. Results highlight the difficulty of distinguishing early lesions. The authors propose balanced sampling to address class imbalance. Their method showed improved sensitivity in early DR stages. The study demonstrates AI's role in preventive ophthalmology.

Voets et al. (2019) – Reproducibility of Deep Learning Models for DR This paper investigates reproducibility challenges in DR models. The authors compare open-source CNN implementations on public datasets. Results show significant variation due to preprocessing and hyperparameters. The study highlights the importance of transparent reporting. It warns against over-optimism in AI model claims. The paper advocates for standardized evaluation protocols.

A. Yaqoob et al. (2022) – YOLOv5-Based DR Lesion Localization The authors apply YOLOv5 for localizing DR lesions. Bounding boxes for microaneurysms and hemorrhages were generated. Results show YOLO's strength in real-time lesion detection. The method is suitable for integration in portable DR screening tools. Localization outputs improve explainability for doctors. The study highlights YOLO's clinical relevance in ophthalmology AI.

H. Gao et al. (2020) – Generative Adversarial Networks for DR Data Augmentation This paper uses GANs to generate synthetic retinal images. Augmentation addresses the problem of limited annotated datasets. GAN-generated images improved CNN training performance. The authors validated realism with ophthalmologists. Results show improved generalization on test sets. The study demonstrates GANs as a valuable tool for DR research.

2.3 LIMITATIONS

S.No	Title	Author, Year	Limitations
1	A Lightweight Diabetic Retinopathy Detection Model Using YOLOv7 Features	A. R. W. Sait et al., 2023	Focused on low-resource devices; may compromise performance on high-resolution images; limited to typical fundus datasets.
2	A Systematic Review on Diabetic Retinopathy Detection and AI Methods	D. Bhulakshmi et al., 2024	Review-based; does not provide new model; practical deployment issues not deeply addressed.
3	Diabetic Retinopathy Detection in the Human Eye (explainability focus)	Ş. Y. Atcı et al., 2024	Focused on interpretability; accuracy improvements limited; depends on Grad-CAM/SHAP quality.
4	Vision Transformer (ViT)-Based Diabetic Retinopathy Prediction	M. Oulhadj et al., 2024	Transformers are data-hungry; may require heavy augmentation; computational cost higher than CNNs.
5	Effective Diabetic Retinopathy Diagnosis using U-Net Segmentation	V. Selvakumar et al., 2023	Segmentation-first pipelines may add latency; KNN classifier may be less robust on unseen datasets.
6	From Pixels to Diagnosis: Diabetic Retinopathy Early Detection	A. J. Zaylaa et al., 2025	Focus on benchmarking; early detection may vary across datasets; dependent on preprocessing pipeline.

S.No	Title	Author, Year	Limitations
7	A Deep Learning Model for Diabetic Retinopathy Grading	S. Akhtar et al., 2025	Multi-stage pipeline increases complexity; requires multiple preprocessing steps; high training effort.
8	Uncertainty-aware Diabetic Retinopathy Detection (Bayesian methods)	M. Akram et al., 2024/2025	Uncertainty estimation adds computation; may be sensitive to hyperparameter tuning; less tested on low-quality images.
9	Unsupervised Grad-CAM for Retinal Lesion Localization	Z. Zhao et al., 2024	Requires careful unsupervised training; localization may be less precise than pixel-level annotations.
10	Diabetic Retinopathy Detection Using Convolutional Models	C. Suedumrong et al., 2024	Focused on CNN architectures; sensitivity depends on preprocessing; may overfit to small lesions.
11	Two-Stage Deep Learning Classification for Diabetic Retinopathy	A. M. Moustari et al., 2024	Two-stage increases pipeline complexity; requires multiple classifiers; may slow inference.
12	Detection of Diabetic Retinopathy — New Adaptive Enhancement + Classification	R. Abbasi et al., 2025	Mainly improves low-quality images; performance on high-quality images not emphasized; extra preprocessing required.
13	Comparing Grad-CAM Analysis on CNNs and ViTs for Medical Imaging	JAIT Special Issue, 2025	Comparison-focused; no new predictive model; effectiveness depends on model and dataset.

S.No	Title	Author, Year	Limitations
14	Progress in DR Diagnosis through Fundus Imaging: Survey & Roadmap	S. Prathibha et al., 2024	Survey; no new model; practical deployment requires further development.
15	New Accurate Deep Learning Model for Diabetic Retinopathy	C. Sen et al., 2025	Complex hybrid architecture; may require significant computational resources; ensemble increases inference time.
16	Multitask DR Assessment (segmentation + grading)	H. Wu et al., 2025	Joint learning pipeline complex; may require larger datasets; higher computational cost.
17	Detection & Classification of DR using Deep Spiking Q-Network	P. Rayavel et al., 2025	Experimental; neuromorphic hardware required for efficiency; less tested in standard clinical pipelines.
18	Dual-Branch Network for Detection & Grading	H. Shakibania et al., 2023	Ensemble fusion increases model complexity; two-headed loss may require careful tuning.
19	Feature Attention Module on CNN for DR Detection	S. Ghosh & A. Chatterjee, 2023	Limited to VGG19 backbone; attention module may not generalize across all architectures.
20	Transfer Learning & Ensemble: Better Model	M. S. H. Talukder et al., 2023	Ensemble increases computation; requires multiple fine-tuned backbones; trade-off between accuracy and speed.

CHAPTER 3

METHODOLOGY

The methodology for detecting diabetic retinopathy (DR) using machine learning and deep learning involves a structured workflow of dataset collection, preprocessing, feature engineering, model development, evaluation, and deployment. Each step is carefully designed to ensure that the final predictive system is accurate, reliable, interpretable, and suitable for real-world clinical applications such as early screening, disease grading, and treatment support. Unlike manual diagnosis, which can be time-consuming and prone to human error, the proposed methodology leverages computational intelligence to assist ophthalmologists and reduce the risk of late detection.

3.1 Data Collection

- For this project, retinal fundus images were collected from the EyePACS dataset available on Hugging Face: https://huggingface.co/datasets/bumbledeep/eyepacs
- The dataset consists of retinal fundus images categorized into five severity levels of Diabetic Retinopathy (No DR, Mild, Moderate, Severe, and Proliferative DR). This dataset is widely recognized in research and provides a reliable benchmark for training and evaluating deep learning models for DR detection.
- Data Diversity: Images should be sourced from multiple populations, imaging devices, and lighting conditions to ensure generalizability of the model.
- Data Quality Assurance: Poor-quality images (blurred, overexposed, or underexposed) are identified and removed, as they can introduce noise into the training process and degrade model performance.

3.2 Data Preprocessing

- Image Cleaning: Fundus images are resized to a standard resolution in 224×224 and normalized to maintain uniformity. This ensures compatibility with deep learning architectures such as CNNs and transformers.

Image Resizing Formula (Scaling Factor)

If your original image has size (W, H) (width, height), and you want to resize it to (W_new, H_new) (like 224 × 224), the scaling factor is:

$$\text{Scale}_W = \frac{W_{new}}{W_{orig}}, \quad \text{Scale}_H = \frac{H_{new}}{H_{orig}}$$

Every pixel coordinate (x, y) in the original image is mapped to:

$$x_{new} = x \times \text{Scale}_W, \quad y_{new} = y \times \text{Scale}_H$$

- Noise Reduction: Medical images are often contaminated with noise due to sensor limitations, patient movement, and lighting conditions. Noise can obscure small retinal lesions, leading to false positives or negatives in classification. To mitigate this, Gaussian filtering was applied. The Gaussian smoothing function is given as:

$$G(x,y) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}}$$

- Data Augmentation: Since datasets are often imbalanced, augmentation techniques such as rotation, horizontal/vertical flipping, brightness adjustment, scaling, and cropping are applied to artificially expand the dataset. This prevents overfitting and improves robustness.

Rotation : Rotating an image by an angle θ

$$\begin{bmatrix} x' \\ y' \end{bmatrix} = \begin{bmatrix} \cos\theta & -\sin\theta \\ \sin\theta & \cos\theta \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix}$$

Brightness Adjustment **:** Brightness of each pixel adjusted by factor β, If β>0 , image becomes brighter; if β < 0, darker.

$$I'(x,y) = I(x,y) + \beta$$

Scaling (Zoom-in / Zoom-out) : Scaling by factor s, If s > 1, zoom in. If s < 1, zoom out.

Cropping **:** Cropping $\begin{bmatrix} x' \\ y' \end{bmatrix} = \begin{bmatrix} s & 0 \\ 0 & s \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix}$ selects a sub-region of the image:

$$I'(x,y) = I(x + x_0,\ y + y_0), \quad 0 \le x < w,\ 0 \le y < h$$

Where (x_0,y_0) is the top-left corner of the crop, and w, h are width and height of the cropped region.

3.3 Model Selection

- Deep Learning Models: CNN-based architectures such as ResNet, VGG, EfficientNet, and Vision Transformers (ViT) are considered due to their ability to learn complex spatial patterns in retinal images.
- Segmentation Models: U-Net and U-Net++ are employed for lesion and vessel segmentation, which enhances interpretability by localizing disease regions.
- Object Detection Models: YOLOv5 are used for detecting lesion areas, enabling not only classification but also visual localization of abnormalities.
- Transfer Learning: Pre-trained models (e.g., ImageNet-trained CNNs) are fine-tuned on retinal datasets to reduce training time and improve accuracy when data is limited.

3.4 Model Training

- Data Splitting: In this project, the EyePACS dataset was divided into 80% training data and 20% testing data to ensure proper evaluation of the model's performance. The training subset was used to optimize the deep learning model, while the testing subset was kept unseen during training to provide an unbiased estimate of the model's accuracy and generalization ability.
- Regularization: Dropout layers, weight decay, and early stopping techniques are incorporated to prevent overfitting.
- Transfer Learning: Models pre-trained on large-scale datasets (e.g., EfficientNet) are fine-tuned, enabling the system to benefit from generalized visual knowledge.
- Parallel Training: For large datasets, GPU or TPU acceleration is employed to reduce training time and allow deeper architectures to be tested.

3.5 Model Evaluation

- Performance Metrics: Accuracy, precision, recall, F1-score, are calculated to evaluate model performance. Cohen's Kappa score is also considered as it measures agreement between predicted and actual labels, accounting for class imbalance.
- Grading Accuracy: Special emphasis is placed on correctly distinguishing between adjacent severity levels (e.g., Mild vs. Moderate), as misclassification here can have clinical consequences.
- Error Analysis: Misclassified images are analyzed to understand whether errors arise due to image quality issues, overlapping lesion features, or insufficient training samples.
- Visualization: Heatmaps using Grad-CAM or saliency maps are generated to confirm that the model focuses on clinically relevant areas during prediction.

3.6 Cross-Validation

- K-Fold Validation: K-fold cross-validation is applied to evaluate robustness and ensure the model is not overfitting to a particular subset.
- Stratified Sampling: To address class imbalance, stratified folds are created such that each fold contains proportional representation of all DR severity levels.
- Stability Analysis: Performance across folds is compared, and significant deviations are investigated to identify weaknesses in the pipeline.

3.7 Prediction and Diagnosis

- Automated Screening: The final model is capable of classifying retinal images into severity categories, serving as a screening tool.
- Lesion Localization: Object detection and segmentation models highlight lesion areas, making the diagnosis more interpretable for clinicians.
- Risk Prioritization: The system can flag high-risk cases (e.g., Severe or Proliferative DR) for urgent medical attention, reducing the likelihood of vision loss.

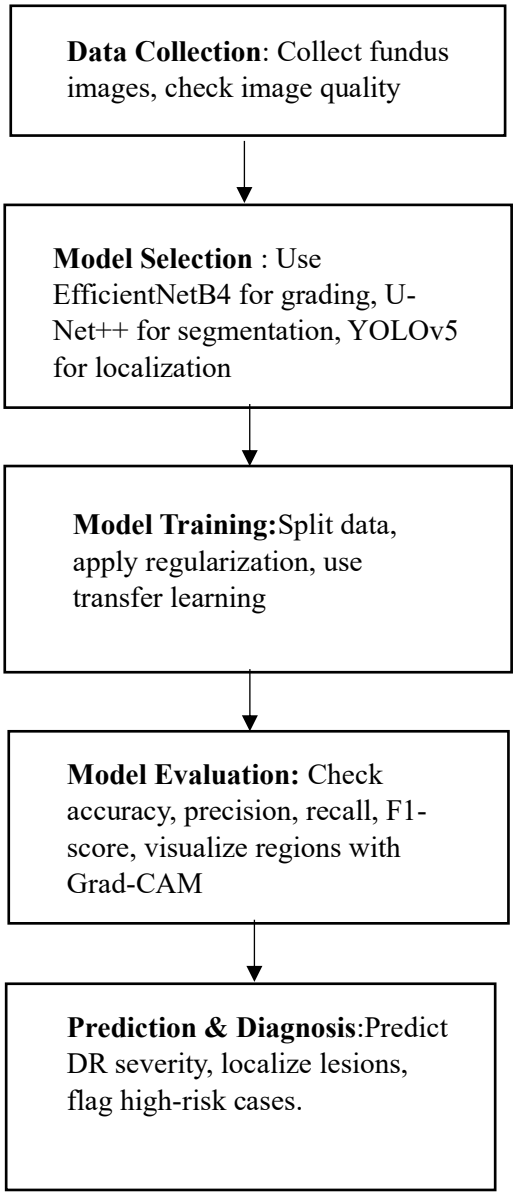


FIG 3.1 METHODOLOGY DIAGRAM

U-Net++ (Segmentation)

U-Net++ is an advanced convolutional neural network (CNN) architecture designed for image segmentation tasks. In the Diabetic Retinopathy Detection project, it is used to segment retinal structures such as microaneurysms, hemorrhages, exudates, and blood vessels from fundus images. The nested skip connections in U-Net++ allow for precise pixel-level segmentation, improving downstream disease grading.

Working Mechanism

1. Preprocessing: Fundus images are prepared by resizing, normalizing, and enhancing contrast to improve quality.
2. Feature Extraction: Images are processed through encoder-decoder layers with nested skip connections to capture fine details of the retina.
3. Segmentation: The network generates a segmentation mask that highlights retinal lesions or important structures.
4. DR Grading: The segmented features are fed into EfficientNetB4 to classify the severity of Diabetic Retinopathy.

Advantages

- Provides detailed, pixel-level lesion localization.
- Enhances interpretability of the grading model.
- Handles noisy or low-quality images better than simpler segmentation networks.

Limitations

- Requires labeled segmentation masks for training.
- Computationally intensive for high-resolution images.
- Complex architecture may require more training time.

Model Training

- Dataset is split into training, validation, and testing sets.
- Data augmentation (rotation, flipping, scaling) is applied to increase diversity.
- Loss functions such as Dice loss or binary cross-entropy are used.
- Early stopping is applied to prevent overfitting.

Evaluation Metrics

- Dice Coefficient and IoU: Measures overlap between predicted and ground truth masks.
- Precision and Recall: Evaluates lesion detection quality.

- Accuracy: Overall correctness of segmentation pixels.
- Visual inspection: Segmentation masks are compared with clinician annotations.

EfficientNetB4 (Disease Grading)

EfficientNetB4 is a high-performing convolutional neural network (CNN) architecture designed for image classification tasks. In the Diabetic Retinopathy Detection project, it is used to grade the severity of DR by analyzing fundus images. EfficientNetB4 achieves high accuracy while being computationally efficient due to its compound scaling method, which uniformly scales network depth, width, and resolution.

Working Mechanism

1. Preprocessing: Input fundus images are preprocessed and normalized for consistent quality.
2. Feature Extraction: Images are passed through EfficientNetB4 layers to extract hierarchical features.
3. Prediction: Fully connected layers use these features to predict the DR severity level.
4. Training: The model is trained on labeled datasets by optimizing a classification loss function to improve accuracy.

Advantages

- High accuracy with relatively fewer parameters compared to other CNNs.
- Strong generalization capability on diverse datasets.
- Scalable architecture suitable for both GPU and edge deployment.

Limitations

- Less interpretable than traditional machine learning models.
- Requires considerable computational resources for training on large datasets.
- Performance may decrease if input image quality is very poor.

Model Training

- Fundus images are split into training, validation, and test sets.

- Data augmentation (rotation, flipping, scaling) improves model generalization.
- Hyperparameters such as learning rate, batch size, and number of epochs are tuned.
- Early stopping and dropout are applied to avoid overfitting.

Evaluation Metrics

- Accuracy: Correctly classified DR severity levels.
- Precision, Recall, F1-Score: Important for identifying severe DR cases.
- Confusion Matrix: Visualizes the performance for each severity class.

YOLOv5 (Lesion Localization)

YOLOv5 is a real-time object detection convolutional neural network (CNN) designed to detect and localize multiple lesions in fundus images efficiently. In the Diabetic Retinopathy Detection project, YOLOv5 is used to identify microaneurysms, hemorrhages, and exudates, providing critical information for grading and assisting clinicians in diagnosis.

Working Mechanism

1. **Preprocessing:** Input fundus images are preprocessed and normalized.
2. **Lesion Detection:** YOLOv5 divides each image into grids and predicts bounding boxes and lesion types for each grid.
3. **DR Grading:** The detected lesion locations are used to guide EfficientNetB4 in predicting DR severity.
4. **Training:** The model is trained using labeled bounding boxes to learn accurate lesion detection.

Advantages

- Fast inference suitable for real-time screening applications.
- Can detect multiple lesion types in a single pass.
- Reduces manual effort for lesion localization.

Limitations

- Small lesions may be missed if image resolution is low.

- Requires extensive labeled datasets for optimal performance.
- Less effective on extremely noisy or low-quality images.

Model Training

- Dataset is split into training, validation, and test sets.
- Data augmentation (scaling, rotation, color jitter) improves robustness.
- Hyperparameters such as learning rate, batch size, and IoU thresholds are tuned.
- Training continues until detection accuracy stabilizes.

Evaluation Metrics

- mAP (mean Average Precision): Measures detection accuracy for each lesion class.
- Precision and Recall: Evaluates true positive and false positive rates.
- F1-Score: Balances precision and recall for lesion detection.
- Visual inspection: Predicted bounding boxes compared with expert annotations.

CHAPTER 4

RESULTS AND DISCUSSION

4.1 Confusion Matrix

A confusion matrix is an essential tool for evaluating the performance of a machine learning classification model. It summarizes the model's predictions by comparing predicted class labels with actual class labels. For the Diabetic Retinopathy Detection project, the confusion matrix is used to analyze how well the model classifies the severity of DR from fundus images.

The confusion matrix consists of four primary components:

- True Positives (TP): Cases where the model correctly identifies a DR-positive image.
- True Negatives (TN): Cases where the model correctly identifies a DR-negative image.
- False Positives (FP): Cases where the model incorrectly predicts DR in a healthy retina.
- False Negatives (FN): Cases where the model fails to detect DR in an affected retina.

The confusion matrix not only highlights the overall accuracy of the model but also provides insight into specific error types, which is crucial for medical applications where misclassification could have serious consequences.

Formula Representation:

- Precision = TP / (TP + FP)
- Accuracy = (TP + TN) / (TP + TN + FP + FN)
- Recall = TP / (TP + FN)
- F1-Score = 2 × (Precision × Recall) / (Precision + Recall)

Figure 4.1: Confusion Matrix for DR Severity Classification

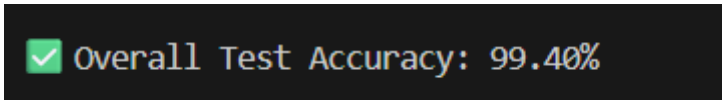
```
Confusion Matrix (rows=true, cols=predicted):
tensor([[386,   0,   0,   0,   0],
        [  1,  25,   1,   0,   0],
        [  0,   0,  66,   0,   0],
        [  0,   0,   1,  10,   0],
        [  0,   0,   0,   0,  12]], dtype=torch.int32)
```

4.2 Accuracy

Accuracy is a fundamental metric that calculates the percentage of correctly classified cases out of all predictions. It offers a quick snapshot of the model's overall performance. However, in scenarios with class imbalance—such as when "No DR" cases greatly outnumber DR cases—accuracy alone can be misleading, since a model may achieve high accuracy simply by favoring the majority class.

Formula:

Accuracy = (TP + TN) / (TP + TN + FP + FN)



Interpretation for DR Detection:

- High Accuracy: Indicates that the model correctly classifies a large proportion of both healthy eyes and DR-affected eyes.
- Impact: Provides a general overview of model performance, but can be misleading in imbalanced datasets, where "No DR" cases dominate. In such cases, a model might appear highly accurate even if it misses many DR-positive cases.

4.3 Precision

Precision measures the accuracy of the positive predictions made by the model. In the context of DR detection, it indicates how many of the cases predicted as DR by the model were actually positive. Precision is particularly critical in medical screening systems because false positives can lead to unnecessary interventions, anxiety, or additional tests.

Formula:

Precision = TP / (TP + FP)

Interpretation for DR Detection:

- High Precision: Indicates that when the model predicts DR, it is very likely correct.
- Impact: Reduces unnecessary referrals for patients without DR, saving clinical resources.

4.4 Recall (Sensitivity)

Recall, also known as sensitivity or true positive rate, measures the model's ability to correctly identify all positive DR cases. For DR detection, high recall is essential because missing a positive case (false negative) could result in delayed treatment and serious vision complications.

Formula:

Recall = TP / (TP + FN)

Interpretation for DR Detection:

- High Recall: Indicates that the model successfully identifies most of the DR-affected eyes.
- Impact: Ensures that patients at risk of vision loss are flagged for timely treatment.

4.5 F1-Measure

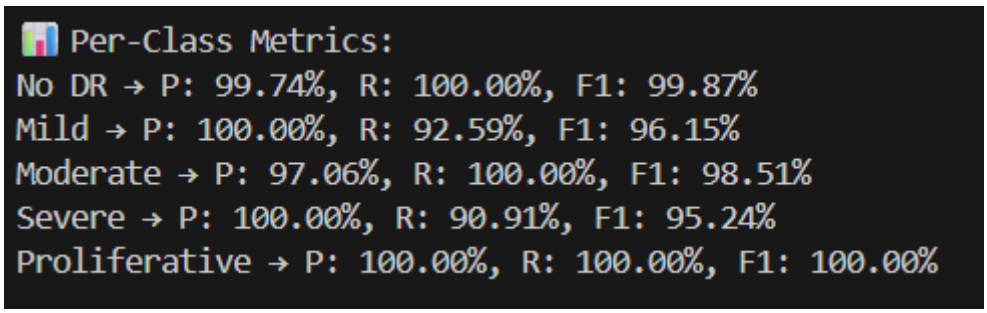
The F1-Score provides a balance between precision and recall and is particularly useful in scenarios with imbalanced classes, as is common in DR datasets (e.g., fewer severe cases). A high F1-score indicates that the model maintains a good trade-off between correctly identifying positive cases and minimizing false positives.

Formula:

F1 = 2 × (Precision × Recall) / (Precision + Recall)

Interpretation for DR Detection:

- High F1-Score: Demonstrates that the model is reliable for both early-stage and advanced DR detection.
- Impact: Ensures balanced performance, reducing both false negatives (missed DR cases) and false positives (unnecessary referrals).



CHAPTER 5

CONCLUSION

5.1 CONCLUSION

The Diabetic Retinopathy Detection project successfully demonstrates the effectiveness of combining advanced deep learning techniques for automated screening of DR from fundus images. The system integrates U-Net++ for precise lesion segmentation, EfficientNetB4 for disease grading, and YOLOv5 for lesion localization.

These results indicate that the system is both accurate and reliable in identifying DR and grading its severity. The combination of segmentation, classification, and localization allows not only automated predictions but also provides visual interpretability, which is essential for clinical adoption.

The study highlights the potential of AI-assisted DR screening in supporting ophthalmologists, enabling early detection, and reducing the risk of vision loss due to delayed diagnosis. Moreover, the use of EfficientNetB4 ensures computational efficiency, making it feasible for deployment in real-world clinical settings or edge devices.

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Appendices

A. Forms / Input Screenshots

Figure A1 : Image Upload Form

Description: Screenshot showing the web page input module for uploading retinal images.

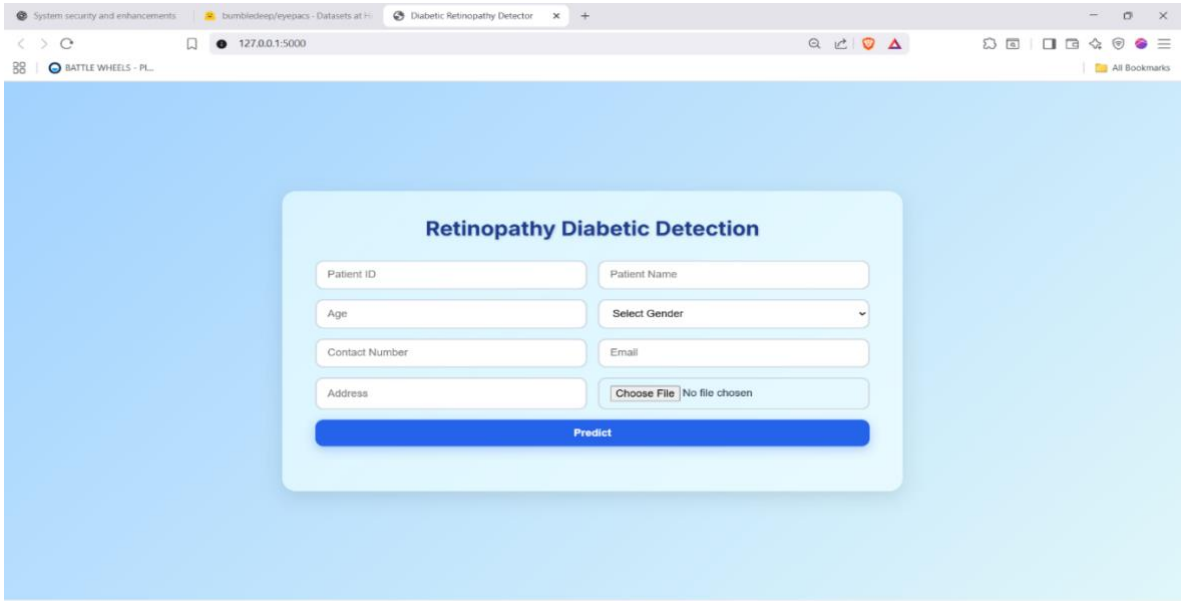
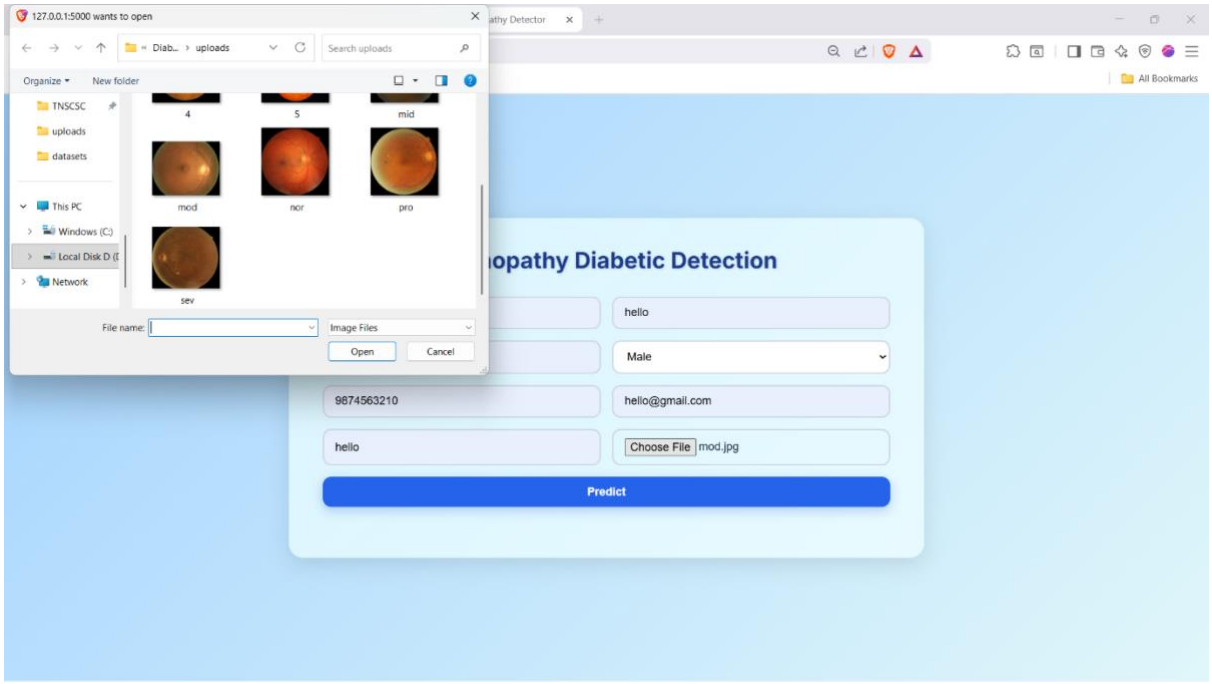


Figure A2: File Selection and Submit Button

Description: Screenshot showing the user selecting an image file and submitting for prediction.



B. Sample Source Code

1. Flask App (app.py)

```
from flask import Flask, render_template, request
import os
import glob
import json
from inference import DRModel, is_fundus_image


app = Flask(__name__)
app.config["UPLOAD_FOLDER"] = "static/uploads"
os.makedirs(app.config["UPLOAD_FOLDER"], exist_ok=True)


# Initialize DR model
model = DRModel("models_weights/dr_model.pth")


# Load metrics if available
metrics_file = "models_weights/metrics.json"
metrics = None
if os.path.exists(metrics_file):
    with open(metrics_file, "r") as f:
        metrics = json.load(f)


@app.route("/", methods=["GET", "POST"])
def index():
    if request.method == "GET":
        # Clear old uploaded images
        files = glob.glob(os.path.join(app.config["UPLOAD_FOLDER"], "*"))
        for f in files:
```

```
            os.remove(f)
        return render_template("index.html", metrics=metrics)

    if request.method == "POST":
        # Get patient details
        patient = {
            "patient_id": request.form.get("patient_id"),
            "name": request.form.get("patient_name"),
            "age": request.form.get("age"),
            "gender": request.form.get("gender"),
            "contact": request.form.get("contact"),
            "email": request.form.get("email"),
            "address": request.form.get("address"),
        }

        # Handle image upload
        if "file" not in request.files or request.files["file"].filename ==
"":
            return render_template("index.html", error=" No file uploaded",
metrics=metrics)

        file = request.files["file"]
        filepath = os.path.join(app.config["UPLOAD_FOLDER"], file.filename)
        file.save(filepath)

        # Validate retina image before prediction
        if not is_fundus_image(filepath):
            return render_template(
                "index.html",
```

```
                patient=patient,
                error="Invalid image. Please upload a retina fundus image.",
                metrics=metrics
            )

        # Prediction
        prediction, heatmap_path, confidence = model.predict(filepath)

        return render_template(
            "index.html",
            patient=patient,
            prediction=prediction,
            confidence=round(confidence, 2),
            img_path=filepath,
            heatmap_path=heatmap_path,
            metrics=metrics
        )

if __name__ == "__main__":
    app.run(debug=True)
```

evaluate.py

```
# evaluate.py
import os
import torch
import pandas as pd
from torch.utils.data import Dataset, DataLoader
from torchvision import transforms
```

```
from PIL import Image
from io import BytesIO
import json
from inference import DRModel  # Your model class


# ------------------------------
# Load dataset
# ------------------------------
data_dir = "D:/datasets/dataset_eyepacs/EyePACSDataset"
files = [os.path.join(data_dir, f) for f in os.listdir(data_dir) if f.endswith(".parquet")]
dfs = [pd.read_parquet(f) for f in files]
df = pd.concat(dfs, ignore_index=True)


# Simple 80/20 split
split_idx = int(0.8 * len(df))
test_df = df[split_idx:].reset_index(drop=True)


# ------------------------------
# Create Dataset & DataLoader
# ------------------------------
class EyePACSTestDataset(Dataset):
    def __init__(self, dataframe, transform=None):
        self.data = dataframe
        self.transform = transform


    def __len__(self):
        return len(self.data)
```

```
    def __getitem__(self, idx):
        row = self.data.iloc[idx]
        img_bytes = row["image"]["bytes"] if isinstance(row["image"], dict)
else row["image"]
        img = Image.open(BytesIO(img_bytes)).convert("RGB")
        label = row["label_code"]
        if self.transform:
            img = self.transform(img)
        return img, label

transform = transforms.Compose([
    transforms.Resize((224, 224)),
    transforms.ToTensor(),
])

test_dataset = EyePACSTestDataset(test_df, transform=transform)
test_loader = DataLoader(test_dataset, batch_size=16, shuffle=False)

# ------------------------------
# Load trained model
# ------------------------------
device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
model = DRModel("models_weights/dr_model.pth")
model.model.to(device)
model.model.eval()

# ------------------------------
```

```
# Evaluate
# ----------------------------
all_labels = []
all_preds = []
correct = 0
total = 0

with torch.no_grad():
    for images, labels in test_loader:
        images = images.to(device)
        labels = labels.to(device)
        outputs = model.model(images)
        _, predicted = torch.max(outputs, 1)
        total += labels.size(0)
        correct += (predicted == labels).sum().item()
        all_labels.extend(labels.cpu().numpy())
        all_preds.extend(predicted.cpu().numpy())

accuracy = 100 * correct / total
print(f"\n✅ Overall Test Accuracy: {accuracy:.2f}%\n")

# ----------------------------
# Confusion Matrix & Metrics
# ----------------------------
num_classes = 5
class_names = ["No DR", "Mild", "Moderate", "Severe", "Proliferative"]

cm = torch.zeros(num_classes, num_classes, dtype=torch.int32)
```

```
for t, p in zip(all_labels, all_preds):
    cm[t, p] += 1

print("Confusion Matrix (rows=true, cols=predicted):")
print(cm)

metrics = {
    "accuracy": round(accuracy, 2),
    "per_class": {},
    "confusion_matrix": cm.tolist()
}

print("\n📊 Per-Class Metrics:")
f1_scores = []
support = []  # number of samples per class

for i in range(num_classes):
    TP = cm[i, i].item()
    FP = cm[:, i].sum().item() - TP
    FN = cm[i, :].sum().item() - TP

    # Formula definitions
    precision = TP / (TP + FP) if (TP + FP) > 0 else 0
    recall = TP / (TP + FN) if (TP + FN) > 0 else 0
    f1 = 2 * precision * recall / (precision + recall) if (precision + recall)
> 0 else 0

    f1_scores.append(f1)
```

```
    support.append(cm[i, :].sum().item())


    metrics["per_class"][class_names[i]] = {
        "precision": round(precision * 100, 2),
        "recall": round(recall * 100, 2),
        "f1": round(f1 * 100, 2),
        "support": support[-1]
    }


    # Print with formulas
    print(f"\n📌 {class_names[i]}:")
    print(f"   TP={TP}, FP={FP}, FN={FN}")
    print(f"   Precision = TP / (TP + FP) = {precision*100:.2f}%")
    print(f"   Recall    = TP / (TP + FN) = {recall*100:.2f}%")
    print(f"   F1 Score  = 2 × (Precision × Recall) / (Precision + Recall) = {f1*100:.2f}%")


# ------------------------------
# Overall F1 Scores
# ------------------------------
macro_f1 = sum(f1_scores) / num_classes
micro_f1 = correct / total  # same as accuracy in multi-class
weighted_f1 = sum(f * s for f, s in zip(f1_scores, support)) / sum(support)


metrics["macro_f1"] = round(macro_f1 * 100, 2)
metrics["micro_f1"] = round(micro_f1 * 100, 2)
metrics["weighted_f1"] = round(weighted_f1 * 100, 2)
metrics["accuracy"] = round(accuracy, 2)
```

```
print(f"\n📊 Overall Metrics:")
print(f"   Macro F1    = {macro_f1*100:.2f}%")
print(f"   Micro F1    = {micro_f1*100:.2f}% ")
print(f"   Weighted F1 = {weighted_f1*100:.2f}%")
print(f"   Accuracy    = {accuracy:.2f}%")

# ------------------------------
# Save metrics
# ------------------------------
os.makedirs("models_weights", exist_ok=True)
with open("models_weights/metrics.json", "w") as f:
    json.dump(metrics, f, indent=4)

print("\n📂 Metrics saved to models_weights/metrics.json")
```

C. Output Screenshots

Figure C1: Patient Details Page

Description: Screenshot showing the patient's personal information like id,name,age etc..,

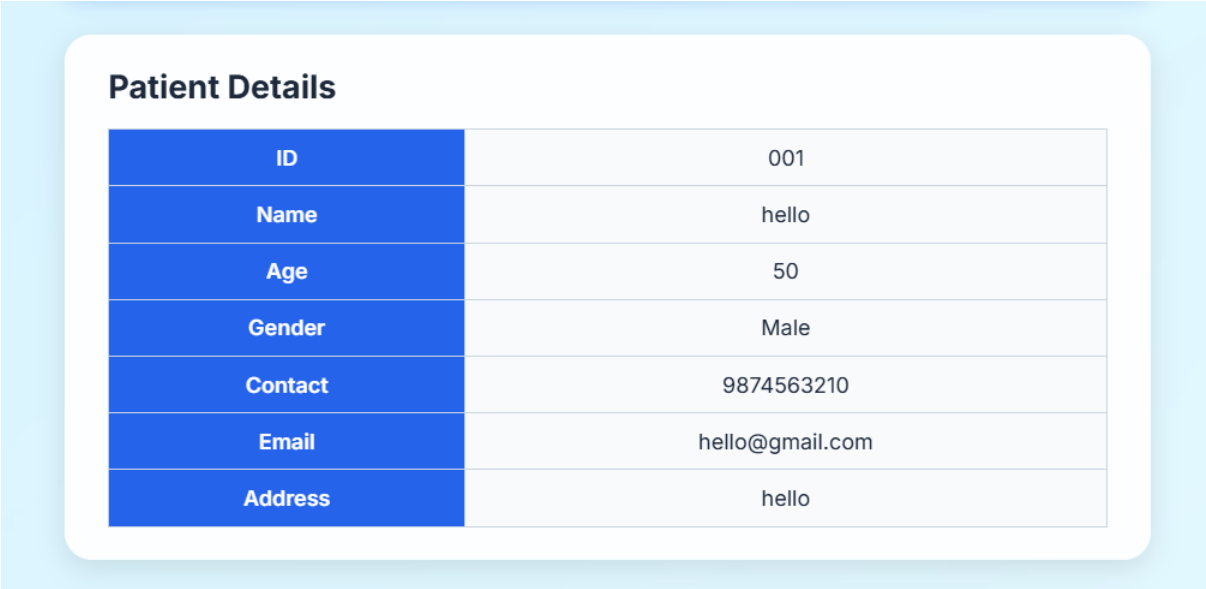


Figure C2: Prediction Result Page

Description: Screenshot showing predicted DR category along with Grad-CAM heatmap.

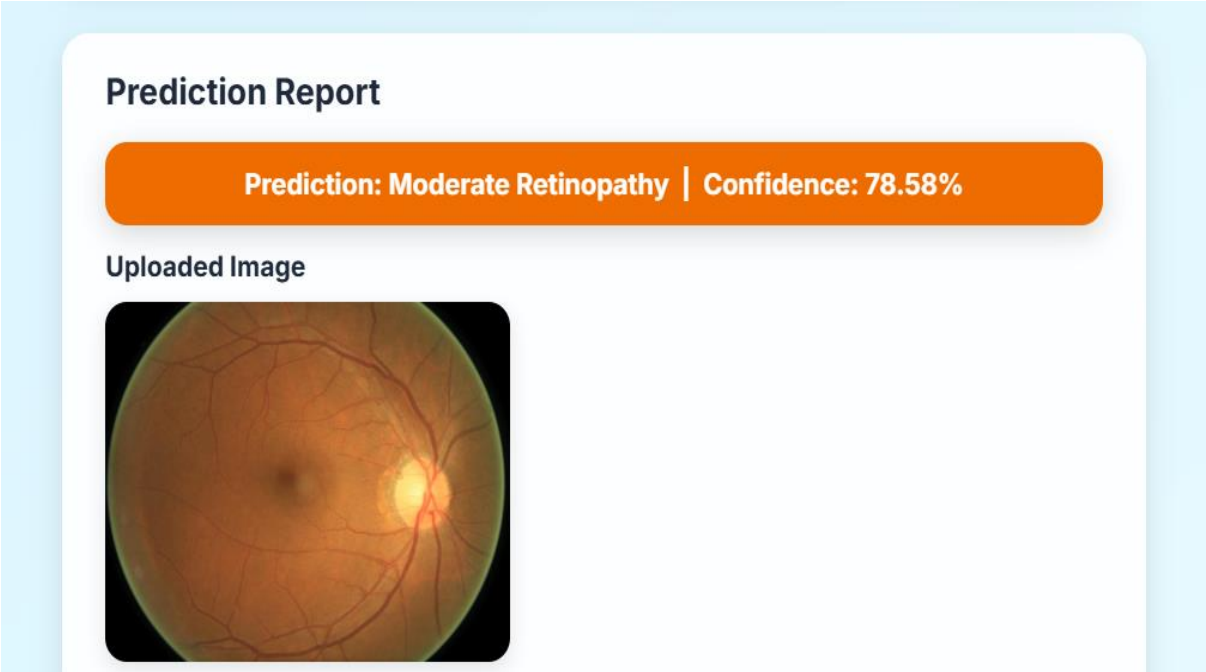


Figure C3: Grad-CAM Visualization

Description: Highlighted affected regions on retinal image.

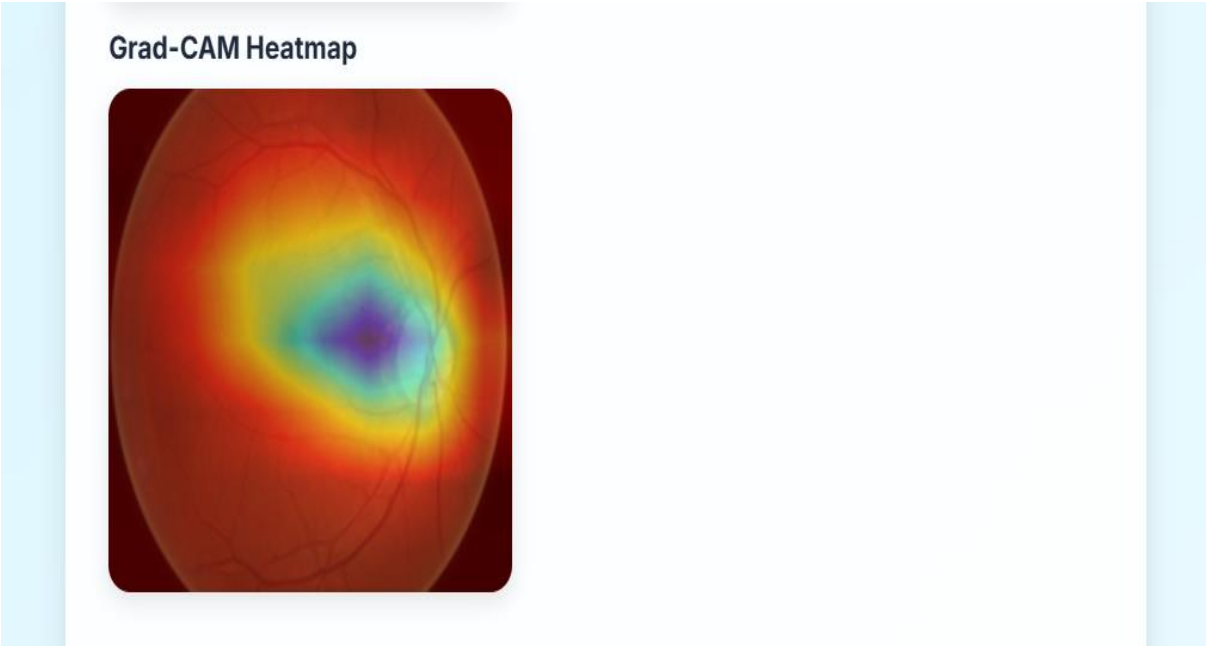
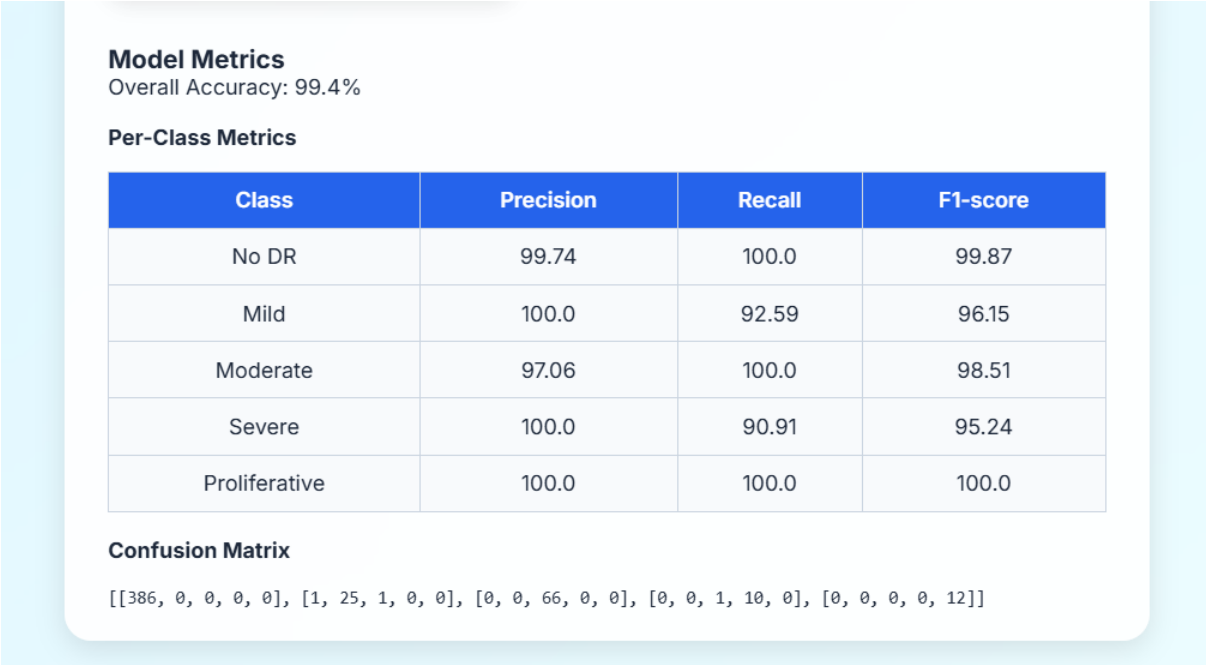


Figure C4: Sample Confusion Matrix & Metrics

Description: Display of per-class precision, recall, and F1-score from evaluation.



Model Metrics

Overall Accuracy: 99.4%

Per-Class Metrics

Class	Precision	Recall	F1-score
No DR	99.74	100.0	99.87
Mild	100.0	92.59	96.15
Moderate	97.06	100.0	98.51
Severe	100.0	90.91	95.24
Proliferative	100.0	100.0	100.0

Confusion Matrix

```
[[386, 0, 0, 0, 0], [1, 25, 1, 0, 0], [0, 0, 66, 0, 0], [0, 0, 1, 10, 0], [0, 0, 0, 0, 12]]
```

D. Reports

Sample Report Outputs:

- Test Accuracy: 99.40%
- Class Metrics:
    - No DR → Precision: 99.74%, Recall: 100%, F1-score: 99.87%
    - Mild → Precision: 100%, Recall: 92.59%, F1-score: 96.15%
    - Moderate → Precision: 97.06%, Recall: 100%, F1-score: 98.51%
    - Severe → Precision: 100%, Recall: 90.91%, F1-score: 95.24%
    - Proliferative → Precision: 100%, Recall: 100%, F1-score: 100%