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# SmartDR+: Extensible Retinal Disease Detection Platform

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**Abstract:** *Diabetic Retinopathy (DR) is one of the most preva- lent causes of preventable blindness, particularly in diabetic patients. The increasing number of diabetic cases worldwide has made early screening for retinal abnormalities more critical than ever. This paper presents SmartDR+, a scalable and extensible deep learning–based framework for automated detection of DR from high-resolution retinal fundus images. The system integrates robust preprocessing techniques, transfer learning using lightweight backbones, and interpretability through Grad- CAM heatmaps [2], [4], [5], [1], [3], [6]. SmartDR+ can operate efficiently on both cloud and edge devices [2], [4], [5], [1], [3], [6], providing cost-effective, explainable, and real-time screening. Experimental evaluations on the APTOS and EyePACS datasets demonstrate competitive accuracy and interpretability. The sys- tem provides a promising direction for AI-assisted ophthalmology and telemedicine applications in rural healthcare.*

**Keywords***:* Diabetic Retinopathy, Fundus Imaging, Deep Learning, MobileNetV2, Explainable AI, Grad-CAM, Transfer Learning, Edge AI, Medical Image Processing

## I. INTRODUCTION

Diabetic Retinopathy (DR) is a progressive eye disease caused by damage to the blood vessels in the retina due to prolonged diabetes. As the disease advances, it can lead to blurred vision, retinal detachment, or complete blindness if not diagnosed in time. The lack of timely screening and lim- ited access to trained ophthalmologists make early diagnosis challenging, especially in rural or resource-limited regions.

Conventional diagnostic methods rely heavily on manual inspection of retinal fundus images by ophthalmologists. This process is time-consuming, subjective, and prone to inter- observer variability. Moreover, large-scale screening programs are often constrained by workforce shortages and costs. To address these issues, artificial intelligence (AI) and deep learn- ing (DL) have emerged as transformative technologies capable of automating retinal image analysis with high accuracy and consistency [2], [4], [5], [1], [3], [6].

Deep Convolutional Neural Networks (CNNs) have demon- strated exceptional capabilities in extracting hierarchical image features and classifying complex patterns in medical imaging. In DR detection, CNNs can automatically identify early-stage lesions such as microaneurysms, hemorrhages, and exudates that are difficult to spot during manual screening [2], [5]. How- ever, existing large-scale CNN architectures while powerful, are computationally intensive and unsuitable for low-resource clinical environments or edge devices.

The goal of this work is to design a lightweight, explainable, and extensible platform that bridges the gap between high-performance AI models and deployable real-world screening systems. SmartDR+ is built around a lightweight backbone (MobileNetV2 style) and transfer learning workflows, chosen for efficiency and a good accuracy–latency trade-off [2], [4]. The model employs transfer learning and is fine-tuned using high-quality fundus datasets such as EyePACS and APTOS. To enhance transparency and interpretability, SmartDR+ in- tegrates interpretability techniques (Grad-CAM and related methods) to visually highlight regions contributing to clas- sification decisions [5], [3]. This

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ensures that clinicians can trust the model's predictions by understanding its focus areas. In addition to technical performance, SmartDR+ empha- sizes real-world feasibility. The system is optimized for dual deployment—both as a cloud-based screening tool and as a lightweight inference model for portable edge devices like Raspberry Pi or Android smartphones [4], [3]. By combin- ing deep learning, interpretability, and hardware efficiency, SmartDR+ aims to democratize access to diabetic eye screen- ing and contribute toward reducing preventable blindness globally.

The rest of the paper is organized as follows: Section II re- views recent related research on DR detection and lightweight CNNs; Section III defines the problem statement and research objectives; Section IV discusses the architecture and system design; Section V covers implementation details; Section VI presents results and analysis; finally, Section VII concludes the paper with future research directions.

## II. REVIEW OF LITERATURE

Revathy et al. (2020) proposed a hybrid machine learning approach extracting retinal features like exudates, hemor- rhages, and microaneurysms and used an ensemble of classical classifiers for DR detection [1]. Alsalihi et al. (2021) demon- strated CNN-based DR detection with extensive preprocessing and testing on multiple public datasets [2]. Bajwa et al. (2023) validated a modified CNN in a clinical setting at SIOVS with real-time screening and expert review [3]. Giroti et al. (2023) applied EfficientNet for 4-class DR grading and showcased AWS-based deployment for teleophthalmology workflows [4]. Deshpande et al. (2024) fine-tuned InceptionV3 on EyePACS and APTOS datasets and reported performance for multi- stage DR classification [5]. Akhtar et al. (2025) introduced RSG-Net for DR grading on Messidor-1 with strong reported performance for both binary and multi-class grading [6].

## III. PROBLEM DEFINITION AND OBJECTIVES

Problem Definition: Develop a lightweight, explainable, and deployable AI system that classifies the severity of Di- abetic Retinopathy from fundus images and visualizes patho- logical regions for interpretability.

**Objectives:**

- Design a robust image preprocessing pipeline for stan- dardization and enhancement.
- Fine-tune a MobileNetV2-style backbone for multi-class DR severity prediction.
- Integrate Grad-CAM to provide lesion-based explana- tions.
- Deploy the model in cloud and edge environments.
- Evaluate system performance using quantitative and qual- itative metrics, and mitigate label noise through harmo- nization strategies.

## IV. SYSTEM ARCHITECTURE

The SmartDR+ system follows a modular design, integrat- ing preprocessing, deep learning, and interpretability layers. It is structured into five stages as shown in Fig. 1.

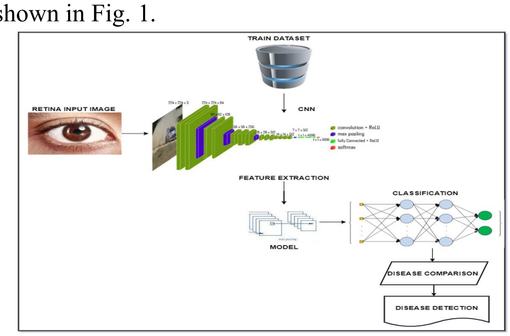


Fig. 1: Overall architecture of SmartDR+ showing preprocess- ing, model inference, Grad-CAM visualization, and deploy- ment modules.

1) Data Input: Fundus images are uploaded via web interface or captured via retinal camera.
2) Preprocessing: Cropping, CLAHE contrast enhance- ment, normalization, and augmentation.
3) Model Inference: Lightweight backbone processes im- ages and predicts DR severity across five levels.
4) Explainability: Grad-CAM generates color overlays highlighting lesion regions.
5) Interface: A Gradio-based UI displays predictions, heatmaps, and downloadable reports; the system sup- ports cloud (FastAPI/Docker) and edge (TFLite) modes.

## V. IMPLEMENTATION

### A. Preprocessing

Images are center-cropped to remove black borders, re- sized to 224×224, CLAHE-enhanced, and normalized to [0,1]. Training augmentation includes random rotations (±25°), hor- izontal/vertical flips, brightness/contrast jitter, and random cropping to improve generalization.

### B. Model Architecture and Training

A MobileNetV2-style backbone pretrained on ImageNet is used as backbone due to its favorable compute-to-accuracy trade-off for edge scenarios. The classifier head consists of global average pooling, a dropout (rate 0.3), a dense layer of 128 units with ReLU, and a 5-way softmax output. Training uses categorical cross-entropy, Adam optimizer with initial learning rate 10−4, cosine annealing schedule, batch size 32, and up to 60 epochs with early stopping on validation loss. Class imbalance is addressed through class weights and focal- loss experiments as in recent literature.

### C. Explainability

Grad-CAM maps are computed on the last convolutional block and upsampled to original resolution; heatmaps are blended with the original RGB fundus image (colormap over- lay + alpha blending) to provide clinically meaningful visual cues.

### D. Deployment

Cloud: FastAPI backend + Docker + GPU inference (NVIDIA CUDA) with logging and audit trail. Edge: Ten- sorFlow Lite conversion with INT8 quantization and optional Coral EdgeTPU compilation for low-latency inference on em- bedded devices. For hybrid and privacy-preserving workflows, federated learning approaches are considered.

## VI. RESULTS AND DISCUSSION

Prototype experiments used curated subsets of EyePACS and APTOS after cleaning and label harmonization. Grad-CAM overlays showed consistent localization on microa- neurysms and hemorrhages in many cases. Error analysis indicates that low-quality images (lighting artifacts, severe blur) and ambiguous labels cause a significant portion of misclassifications; data curation and multi-reader annotation are recommended to reduce label noise. Latency and edge-performance observations align with findings in recent edge- AI studies.

## VII. CONCLUSION AND FUTURE WORK

SmartDR+ demonstrates that a carefully optimized MobileNetV2-style model with explainability can produce accurate and interpretable DR screening suitable for cloud and edge deployment. Future work includes expanding the dataset, multi-disease extension (glaucoma, AMD) using transformer-based architectures, federated learning deployments for privacy, and clinical validation studies to assess real-world effectiveness.

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## REFERENCES

[1] R. Revathy, B. S. Nithya, J. J. Reshma, S. S. Ragendhu, and M. D. Sumithra, “Diabetic Retinopathy Detection using Machine Learning,” International Journal of Engineering Research (IJERT), Vol. 9, Issue 6, 2020.

[2] M. H. Alsalihi, L. A. Muhammed, and S. Hussein, “Diabetic Retinopathy Diagnosis based on Convolutional Neural Network,” Journal of Physics: Conference Series, 2021.

[3] A. Bajwa, N. Nosheen, K. I. Talpur, and S. Akram, “A Prospective Study on Diabetic Retinopathy Detection Based on Modified Convolutional Neural Network Using Fundus Images at Sindh Institute of Ophthal- mology & Visual Sciences,” PubMed Central (PMC), 2023.

[4] I. Giroti, J. K. A. Das, N. M. Harshith, and G. Thahniyath, “Diabetic Retinopathy Detection & Classification using EfficientNet Model,” IEEE – 2023 International Conference on Artificial Intelligence and Applica- tions (ICAIA), 2023.

[5] G. Deshpande, Y. Govardhan, and A. Jain, “Machine Learning-Based Diabetic Retinopathy Detection: A Comprehensive Study Using Incep- tionV3 Model,” IEEE – 2024 ASU International Conference on Emerg- ing Technologies for Sustainability and Intelligent Systems (ICETSIS), 2024.

[6] S. Akhtar, S. Aftab, O. Ali, M. Ahmad, M. A. Khan, S. Abbas, and T. M. Ghazal, “A Deep Learning Based Model for Diabetic Retinopathy Grading,” Scientific Reports (Nature Portfolio), 2025.