Diabetic Retinopathy Classification Using Deep Learning Techniques

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1. Introduction:

The human eye is an amazing sensory organ that is the gateway to visual perception. It detects light and sends signals to the brain through the optic nerve to form images, colors and depth perception [paper 7]. This complex process allows us to recognize face's help detect objects and do many activities that require visual input. But many medical conditions can impair the eye and cause significant visual loss, Diabetic Retinopathy (DR)is one of them.

Diabetic retinopathy is a complication of diabetes that leads to vision loss. It happens due to prolonged diabetes that damage blood vessels in the retina and is the prominent reason for blindness worldwide. It affects the thin blood vessels in the retina that are responsible for capturing light and can cause blockage and bleeding in the retina, and ultimately leads to permanent vision loss if not detected early. Roughly, one-third of the 463 million people worldwide who have diabetes are affected by it [paper 2]. The International Diabetes Federation (IDF) projects that there will be a significant increase in the global diabetes population from roughly 552 million in 2035 to 642 million in 2040 [from paper 2].

DR can be classified into five distinct stages including No DR(DR0), Mild (DR1), Moderate (DR2), Severe Non-proliferative (DR3), Proliferative (DR4) [paper 4]. Non-proliferative diabetic retinopathy (NPDR) causes retinal swelling and leakage of tiny blood vessels while Proliferative diabetic retinopathy (PDR) is the most severe stage of the disease, in which new blood vessels start developing in the retina.

Deep learning (DL) methods have shown great promise in automatically detecting the accurate stages of DR. These models showed great accuracy in detecting DR but still many ophthalmologists heavily relay on manual detection. Manual detection of DR is time-consuming and requires trained clinical experts to analyze digital color fundus images. However, the delayed outcomes can result in a lack of follow-up and severe outcomes for patients [paper 5].

Convolutional Neural Networks (CNNs) have showed great performance in recognizing DR-related features, such as microaneurysms, hemorrhages, and exudates, directly from images without the need for handcrafted features [paper mid analysis] Despite the progress in Machine learning based Diabetic Retinopathy (DR) detection, we need to address the current limitations. Existing models although work well in many controlled settings, fail to generalize across different datasets and real-world clinical environments. This is mainly due to issues like: Data Imbalance, Limited diversity in training datasets, Subtle Visual differences and inability to capture Regions of Interest (ROI) which are important for detection and classification of DR. Moreover, existing models have high computational cost that makes them unable to operate in resource limited areas.

Many DL techniques showed great accuracy in detecting and classifying DR but now the focus is towards using Hybrid techniques which combines different CNN models to make the output more clinically explainable because they don’t only classify DR but also provide ophthalmologists enough information to use them in real time diagnosis. Moreover, hybrid models also help’s in detecting progression of disease.

This research proposes advanced computational techniques, state of the art learning frameworks and robust validation processes, we hope to set a new benchmark in DR detection. Our model integrates CNNs for local feature extraction with attention mechanisms for highlighting critical regions, and employs feature fusion and contrastive learning to enhance the separation between classes.

The main goal of this research is to develop a light-weight and scalable AI-based screening tool that can be deployed in both urban hospitals and rural healthcare centers. Such a system would not only reduce the workload on specialists but also make early detection more accessible to at-risk populations. By enabling timely intervention, this technology could play a vital role in preventing vision loss and improving the quality of life for millions of diabetic patients worldwide.

1.1. Background:

Diabetic retinopathy is a severe eye condition caused by diabetes where the retinal blood vessels get damaged and can lead to vision loss and blindness if not treated. Early and accurate detection is key to intervention and stopping the disease progressing. Though the traditional and DL techniques provide numerous advantages in detecting DR but there exist several limitations like class imbalance and poor-quality images that causes several limitations in detecting DR.

1.2. Research Challenges

There are several challenges that arise during the classification process and model training. Some of them are as follows:

- **Limited Generalization:** Many models perform well on specific datasets but fail to adapt to real-world clinical data due to limited training on big datasets.
- **Lack of Interpretability:** DL models often lack transparency, reducing

their acceptance in clinical practice. They are treated as “Black boxes”.

- **Insufficient Dataset Diversity:** Variations in imaging conditions like color, contrast and device type affect model performance and accuracy.
- **Subtle Lesion Differences:** Small visual variations between DR stages make precise classification difficult.
- **High Computational Cost:** Many deep models require high processing power, making deployment difficult in low-resource areas.

1.3. Research Questions

- Can a hybrid deep learning model improve the classification of diabetic retinopathy stages compared to standard CNN models?
- Does adding attention and feature fusion help the model handle image quality issues and class imbalance in DR datasets?

1.4. Research Objectives:

The main goal of this research is to improve diabetic retinopathy classification using a hybrid deep learning approach. Specific objectives include:

- To develop a lightweight and efficient CNN model enhanced with dual attention mechanisms (Global and Category Attention Blocks).
- To handle class imbalance in DR datasets through architecture-level improvements rather than oversampling techniques.
- To provide interpretable visual explanations using Grad-CAM for increased clinical trust.
- To validate the model on benchmark datasets like APTOS and Eye PACS.

2. Literature Review

2.1. Deep Learning approaches

Deep learning especially Convolutional Neural Networks (CNNs) has transformed automated DR detection by eliminating the limits of manual, handcrafted features. CNNs learn layered features directly from retinal images, allowing them to detect both fine lesions (microaneurysms, hemorrhages, exudates) and overall retinal patterns. Popular models like VGG, ResNet, DenseNet, and Inception consistently outperform traditional methods in multi-class DR grading.

These models work especially well on large datasets such as EyePACS and APTOS, where thousands of images help them learn strong, generalizable features. Approaches like transfer learning, fine-tuning, and data augmentation further boost accuracy when data is limited.

CNN-based systems are often paired with preprocessing steps normalization, resizing, and lesion enhancement to reduce noise and highlight important structures. However, they still struggle with issues like class imbalance, reliance on annotated labels, and high training costs.

Even with these challenges, CNNs remain the core of DR detection research because of their high accuracy, flexibility, and suitability for real-world clinical use.

Ref	Title	Method/Approaches	Dataset	Acc (%)
7	DR Classification Using Hybrid Color-Based CLAHE and Blood Vessel in Deep CNN	BV segmentation + CLAHE-TH enhancement, fused features into VGG19 / InceptionV3 classifier.	Kaggle DR detection dataset	96%
8	A DL based model for diabetic retinopathy grading	Retinopathy Severity Grading Network (RSG-NET) CNN with preprocessing and augmentation.	Messidor-1	99%

9	A Lightweight Robust Deep Learning Model for DR classification	Improved base CNN through hyperparameter tuning to create RetNet-10.	APTOS, Messidor2, and IDRiD (combined)	98.65%
6	DR classification through dual attention mechanism	CNN with spatial and channel dual attention modules combined with trans former encoder layers for enhanced feature extraction	APTOS /EyePACS	95.7%

Table 2.2 Deep Learning Approaches for Diabetic Retinopathy (2023-2025)

2.2. Hybrid Approaches

Hybrid models have gained attention as a strong alternative to using a single CNN because they merge different deep learning models. These approaches are designed to overcome issues like limited generalization, Lack of Interpretability and class imbalance. Typical hybrid models include combining networks such as Inception V3 with ResNet50, Dense-Net with Inception blocks, VGG19 with ResNet50 or running parallel architectures that capture both low-level texture patterns and high-level semantic details.

By combining complementary components, hybrid pipelines improve the depth and richness of features, increase model efficiency, and boost diagnostic performance across all DR grades. These systems handle varied image quality and subtle lesion differences more effectively.

However, these benefits come with drawbacks hybrid methods usually require more computation, longer training, and can be harder to interpret. Even so, they provide a solid base for building scalable, multi-stage DR classification systems that often surpass single-model setups.

Ref	Title	Method/Approaches	Dataset	Acc (%)
1	Hybrid CNN Model for Automatic DR Classification	combines ResNet50 and InceptionV3 features, fuses them, and classifies DR	Kaggle DR dataset	96.85%
2	Fusion of heterogeneous	VGG19 + ResNet50V2 / Hybrid Deep Learning	Aptos/Messidor-2/DDR/IDRID	91.82%

	fundus data			
3	A Comprehensive Survey and Comparison of Methods	ResNet-50 + SVM	APTOS/EyePACS	Up-to 99%
4	Lesion based DR detection using hybrid deep learning model	Hybrid CNN (ResNet-16 + Google-Net) with APSO + ML Classifiers	EyePACS	94%
5	Hybrid deep learning framework for early detection	CNN+RNN(LSTM)/ Feature fusion	DRIVE/EyePACS	N/R
6	DR classification through dual attention mechanism	CNN with spatial and channel dual attention modules combined with trans former encoder layers for enhanced feature extraction	APTOS /EyePACS	95.7%

Table 2.2 Hybrid Approaches for Diabetic Retinopathy (2023-2025)

3. Research Tentative Methodology

3.1. Proposed Methodology

The proposed methodology for multi-stage Diabetic Retinopathy (DR) classification consists of three main phases:

3.1.1. Dataset Preparation

- **Datasets:** APTOS (3,669 images) + EyePACS (35,000 images).
- **Class balance:** Oversample classes or use class-weighted loss to address dataset imbalance.
- **Augmentation:** Flips, rotations for class balancing and dataset diversity.

- **Super-Resolution Enhancement:** Apply SRGAN (Super-Resolution Generative Adversarial Network) to enhance low resolution fundus images, improving visibility.

3.1.2. Model Design

- **Feature Extraction:** Use VGG54 as the backbone CNN to extract features from fundus images.
- **Attention Modules:** Channel and Spatial attention modules will be used to extract more important features.
- **Fusion:** Combination of outputs from multiple layers of CNN.
- **Lightweight Optimization:** Model efficiency will be improved using knowledge transfer and compression, creating smaller, faster versions for deployment.

3.1.3. Training & Evaluation

- **Datasets:** Training and testing on public fundus datasets such as EyePACS and APTOS.
- **Optimizer:** Adam (Adaptive Moment Estimation), learning rate schedule.
- **Metrics:** Accuracy, Sensitivity, Specificity
- **Explainability:** Grad-CAM and lesion-specific saliency maps are used to highlight critical retinal regions influencing predictions.

3.1.4. Validation

- Cross-dataset evaluation (train on APTOS, test on EyePACS, and vice versa).
- Comparison with existing methods (baseline CNNs, single-attention, and hybrid models for improvements).

4. Results and Discussions

4.1. Datasets

Datasets	No of images	Challenges
APTOS	3,662 images	Small dataset size, uneven classes
EyePACS	88,702 images	Class imbalance, low resolution

4.2. Evaluation Metrices

- Accuracy
- Sensitivity
- Specificity

High Level Project Plan

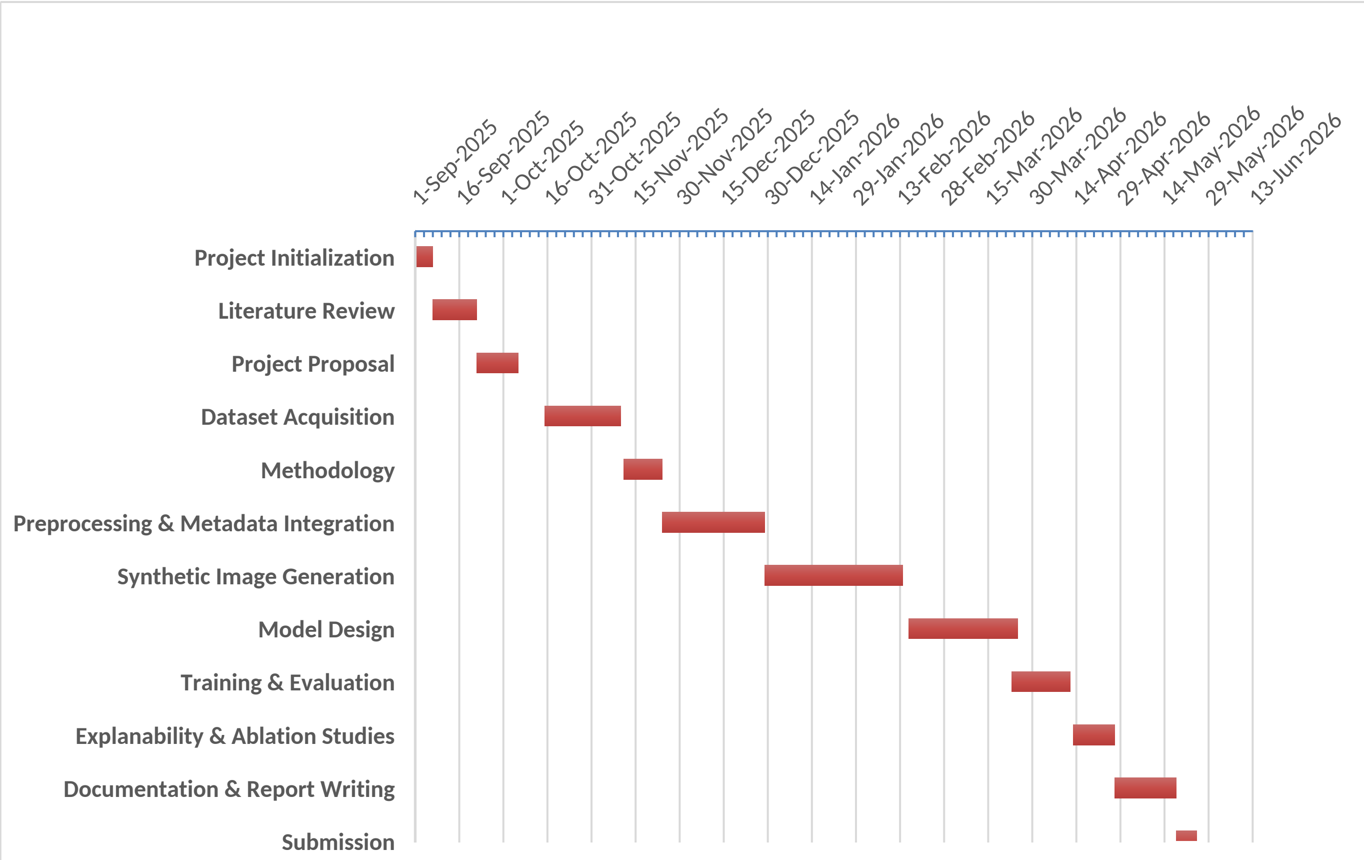

Fig: Gantt Chart

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