Transparent Diagnosis for Diabetic Retinopathy

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***Abstract*— Diabetic Retinopathy (DR) is a sight-threatening complication of diabetes that demands early and accurate diagnosis. Manual screening methods are often time-consuming, expertise-dependent, and subject to inter-observer variability. To address this, we propose a transparent, explainable deep learning-based system for automated DR diagnosis using retinal fundus images. The system combines EfficientNet and MobileNet feature extractors with an ensemble Random Forest classifier. Enhanced preprocessing, including Gaussian filtering and HSV transformations, is employed alongside robust data augmentation to overcome dataset imbalance. Explainable AI techniques like Grad-CAM are integrated to visualize and justify predictions. The model is deployed through a Flask-powered web application, enabling real-time, interpretable DR diagnosis. This solution aims to bridge the gap between AI efficacy and clinical trust.**

***Keywords—Diabetic Retinopathy, Deep Learning, Explainable AI, EfficientNet, MobileNet, Grad-CAM, Fundus Images, Ensemble Learning, Computer Vision, Medical Imaging*.**

I. INTRODUCTION

Diabetic Retinopathy (DR) is one of the most serious and prevalent complications associated with diabetes mellitus, characterized by progressive damage to the retina's blood vessels. If left undetected or untreated, it can lead to irreversible vision loss and blindness. As the global diabetic population continues to rise, early detection of DR becomes not only a medical priority but also a public health necessity. However, traditional diagnostic methods—primarily manual examination of retinal fundus images—are time-consuming, reliant on specialist availability, and susceptible to subjective variability.

To address these challenges, recent advancements in deep learning have paved the way for automated and scalable solutions in medical imaging. Convolutional Neural

Networks (CNNs), in particular, have demonstrated promising results in classifying retinal images for DR detection. However, a major limitation of many existing models lies in their "black-box" nature. They offer little to no interpretability, leaving healthcare professionals uncertain about the rationale behind their predictions. In high-stakes clinical decision-making, this lack of transparency hinders

trust, adoption, and integration of AI tools into real-world diagnostic workflows.

This paper presents a novel diagnostic framework that not only delivers high predictive accuracy but also prioritizes transparency and usability. The proposed system employs a hybrid deep learning architecture that combines the strengths of EfficientNet and MobileNet for robust feature extraction, enhanced by a Random Forest ensemble classifier to improve classification performance on imbalanced datasets. Importantly, the model integrates Explainable AI (XAI) techniques, such as Grad-CAM, to provide visual justifications for each prediction, making the system both accurate and interpretable.

To facilitate real-world applicability, the system is deployed as a web-based diagnostic platform, enabling users—clinicians or otherwise—to upload retinal fundus images and receive real-time predictions along with heatmap-based visual explanations. This design supports scalable screening and has the potential to bridge the gap

between AI-driven diagnostics and trustworthy clinical decision support, particularly in resource-limited settings.

II. Literature Survey

The intersection of artificial intelligence (AI) and ophthalmology has witnessed substantial progress, particularly in the early detection of Diabetic Retinopathy (DR) through automated image classification. Early systems predominantly relied on traditional machine learning algorithms, which required manual feature extraction. For instance, Haloi [1] utilized Local Ternary Pattern (LTP) features in combination with a Support Vector Machine (SVM) classifier, achieving over 90% accuracy on the MESSIDOR dataset. While commendable at the time, this approach was heavily dependent on handcrafted features and struggled to generalize across diverse imaging conditions due to the absence of end-to-end learning capabilities.

Subsequent studies introduced custom Convolutional Neural Networks (CNNs) trained on datasets like FUNDUS. Although such models showed improved performance over traditional methods, they lacked architectural depth and failed to utilize transfer learning, which limited their ability to extract high-level semantic features. Additionally, these models were often vulnerable to overfitting and underperformed on complex cases, such as severe or proliferative DR stages.

To address these limitations, the research community turned toward transfer learning with pre-trained CNN architectures such as VGG16, ResNet50, InceptionV3, and more recently, EfficientNet. These models, originally trained on large-scale datasets like ImageNet, offer the ability to transfer rich and generalized features to the medical domain. In particular, EfficientNet, introduced by Tan and Le [3], employs a compound scaling strategy to balance network depth, width, and resolution, achieving state-of-the-art accuracy with relatively low computational costs. MobileNet, another widely adopted architecture, is optimized for mobile and embedded applications due to its lightweight nature and efficient depth wise separable convolutions [4].

Despite these advances in accuracy, a critical limitation remains lack of interpretability. Most of these high-performing models function as opaque black boxes, providing predictions without insight into their decision-making process. In the context of medical diagnostics, such opacity is a significant barrier to clinical adoption.

To bridge this gap, recent studies have explored ensemble models and Explainable AI (XAI) techniques. Ensemble models combine multiple neural architectures or learning algorithms to enhance robustness and generalization. These include soft voting, feature-level fusion, or hybrid classifier ensembles. However, while they often improve prediction metrics, ensemble systems tend to increase model complexity and inference time.

Parallel to these developments, researchers have begun integrating XAI methods such as Gradient-weighted Class Activation Mapping (Grad-CAM) and Local Interpretable Model-Agnostic Explanations (LIME). These techniques provide visual or textual explanations by highlighting which regions of the input image influenced the model's decision. Although promising, most implementations of XAI in DR detection remain experimental and are rarely coupled with real-time or user-facing applications, limiting their real-world utility.

A synthesis of the existing literature reveals several persistent gaps. Many systems lack clinical interpretability, which is crucial for trust and accountability in healthcare. Others struggle with dataset imbalance, particularly in underrepresented DR stages. Very few offer deployment-ready solutions, and even fewer support real-time user interaction via accessible platforms.

This project is motivated by these gaps. By combining state-of-the-art feature extraction, robust ensemble classification, and visual explainability within a web-deployable interface, our proposed system seeks to offer a holistic and clinically viable solution for diabetic retinopathy diagnosis.

III. Methodology

The development of the proposed diabetic retinopathy (DR) detection system follows a structured, end-to-end machine learning pipeline designed to ensure accuracy, transparency, and real-world deploy ability. The methodology comprises five core phases: data acquisition and preprocessing, data augmentation and class balancing, model architecture design, integration of explainable AI techniques, and system deployment via a web application interface.

A. Dataset Collection and Exploration

The dataset utilized in this study is sourced from Kaggle's Diabetic Retinopathy Detection Challenge, which comprises high-resolution retinal fundus images captured under various imaging conditions. Each image is labeled into one of five categories:

- 0 – No DR
- 1 – Mild
- 2 – Moderate
- 3 – Severe
- 4 – Proliferative DR

Prior to model development, the dataset undergoes exploratory analysis to assess image quality, identify potential artifacts, and determine the degree of class imbalance. Metadata is parsed to prevent data leakage, ensuring that images from the same patient are not split across training and test sets.

B. Image Preprocessing

Preprocessing is a critical step in enhancing model performance by improving input image quality and standardization. All images are resized to 224×224 pixels to ensure compatibility with deep learning models. Gaussian filtering is applied to remove high-frequency noise while preserving essential anatomical structures. Canny edge detection enhances retinal vessel boundaries and microaneurysms, which are key indicators of DR. Additionally, images are transformed to the HSV color space to accentuate hue-based abnormalities such as hemorrhages or exudates. Pixel values are normalized to a [0,1] range to stabilize model training, and in certain cases, Contrast

Limited Adaptive Histogram Equalization (CLAHE) is used to improve local contrast, particularly in low-light images.

C. Data Augmentation and Class Balancing

To mitigate the pronounced class imbalance in the dataset and improve model generalization, a variety of augmentation techniques are applied using the Keras and Albumentations libraries. These include random rotations, horizontal and vertical flipping, zooming, brightness and contrast modulation, and affine transformations such as shearing and translation. Through targeted augmentation, each DR category is expanded to include approximately 2000 images, ensuring a balanced dataset that represents all severity levels equally during training.

D. Model Architecture and Training Strategy

The proposed architecture employs a hybrid deep learning approach combining two pre-trained models: EfficientNet-B0 and MobileNetV2. EfficientNet is selected for its compound scaling capability, which provides state-of-the-art performance with fewer parameters, while MobileNet offers computational efficiency, making the system suitable for real-time applications. Intermediate feature representations from both models are extracted and concatenated into a single composite feature vector.

This joint feature vector is then passed to a Random Forest classifier, chosen for its ability to model complex, non-linear decision boundaries and handle imbalanced data effectively. The hybrid ensemble thus leverages both deep, learned features and classical robustness to noise and overfitting. The models are trained using categorical cross-entropy loss and optimized using Adam optimizer. Evaluation is conducted using metrics such as accuracy, precision, recall, F1-score, and AUC-ROC to ensure a comprehensive understanding of model performance across all classes.

E. Integration of Explainable AI

Given the need for clinical trust and transparency, Explainable AI (XAI) is a critical part of the methodology. We incorporate Grad-CAM (Gradient-weighted Class Activation Mapping) to produce class-specific heatmaps that highlight the regions of the retina most influential in the model's decision. This allows clinicians to visually verify and interpret the AI's output. Additionally, LIME (Local Interpretable Model-Agnostic Explanations) is considered for further experimentation in generating local, pixel-level explanations, though Grad-CAM remains the primary method in our deployed model.

F. System Development and Deployment

To make the system accessible to end-users, the trained model is deployed through a web-based application. The frontend is developed using HTML5, CSS3, and JavaScript, providing a clean and intuitive interface for users to upload images. The backend is implemented using Flask, a lightweight Python web framework, which handles image preprocessing, model inference, and explanation generation. Upon image upload, the user receives the predicted DR class, the model's confidence score, and a corresponding Grad-CAM visualization, all rendered within seconds.

G. Testing and Validation

The complete pipeline undergoes rigorous testing. Unit testing ensures the reliability of each functional component—from preprocessing to inference. Additionally, the system is validated using a hold-out test set and external images from other publicly available datasets to test its generalization. Informal user feedback from medical professionals is collected to evaluate the system's interpretability and usability.

IV. Existing System

Over the past decade, automated diabetic retinopathy (DR) detection systems have evolved from traditional machine learning classifiers to modern deep learning architectures. While these systems have demonstrated promising performance in research settings, they continue to face limitations that restrict their effectiveness in real-world clinical environments. Broadly, the existing systems can be categorized into three groups: traditional machine learning approaches, early deep learning models, and more advanced transfer learning or ensemble-based methods.

Traditional machine learning systems were among the earliest to attempt automated DR detection. These systems relied on handcrafted features such as texture patterns, blood vessel segmentation, and statistical measurements, which were then fed into classifiers like Support Vector Machines (SVM), K-Nearest Neighbors (KNN), or Decision Trees. For example, Haloi's work using Local Ternary Pattern (LTP) features combined with an RBF-SVM classifier achieved reasonable accuracy on the MESSIDOR dataset. However, these models struggled to generalize across diverse datasets and imaging conditions. Their reliance on domain-specific feature engineering limited scalability and failed to capture the complex patterns necessary for diagnosing various stages of DR.

With the emergence of deep learning, especially Convolutional Neural Networks (CNNs), more sophisticated models began to replace manual feature extraction. Architectures like VGG16, ResNet, and InceptionV3 were repurposed for medical image classification tasks. VGG16, though simple and widely used, was computationally expensive and prone to overfitting when trained on small or imbalanced datasets. ResNet introduced residual connections to enable deeper networks and performed better on medical imaging benchmarks. Despite their improved accuracy, these models operated as black boxes, offering no transparency in how decisions were made—a significant drawback in medical diagnostics where explainability is crucial.

To enhance performance further, ensemble learning approaches have also been explored. In these systems, outputs from multiple CNN architectures are combined either through soft voting or feature-level fusion. While ensemble models often improve classification robustness and accuracy, they introduce additional computational complexity and typically lack real-time capability. Moreover, most existing solutions remain confined to academic research. They are rarely deployed in accessible platforms like web or mobile applications, making them impractical for use in under-resourced or rural settings where DR screening is urgently needed.

Another major challenge in existing systems is the imbalance of retinal datasets, where non-DR images significantly outnumber severe or proliferative DR cases. Many current models fail to address this imbalance, leading to biased predictions and reduced sensitivity in detecting advanced

stages of the disease. Additionally, even models trained on large and diverse datasets still fail to generalize effectively when tested on images from different sources or devices due to variations in illumination, contrast, and camera settings.

Perhaps the most persistent limitation across these systems is the lack of interpretability. While prediction accuracy has improved significantly over the years, the inability of most models to provide rationale or visual cues behind their decisions prevents clinicians from trusting and adopting these systems in diagnostic workflows.

V. Proposed System

To address the critical limitations observed in current diabetic retinopathy (DR) detection models—such as the black-box nature of deep learning, overfitting on imbalanced datasets, and the lack of real-world deployment—this paper proposes a comprehensive, hybrid AI-based system designed for transparency, accuracy, and scalability. The proposed system integrates deep learning models with classical ensemble techniques and explainable AI, deployed via a lightweight web interface for real-time clinical use.

At the core of the architecture lies a hybrid feature extraction pipeline combining EfficientNet-B0 and MobileNetV2, two convolutional neural networks pre-trained on the ImageNet dataset. EfficientNet is employed for its high performance and balanced scaling strategy, which ensures strong feature representation with minimal parameter overhead. MobileNetV2 complements this with its lightweight structure and efficient depthwise separable convolutions, making it suitable for environments where computational resources are limited. These models independently extract feature embeddings from input retinal images, which are then fused into a single, high-dimensional vector.

Rather than relying solely on deep networks for classification, the system employs a Random Forest classifier on top of the fused features. This ensemble method is chosen for its ability to model complex non-linear relationships while reducing overfitting, especially in the presence of class imbalance. The hybridization of CNN-based deep features with a decision-tree-based classifier results in a model that combines the strengths of both paradigms—deep representational learning and classical ensemble robustness.

A distinguishing feature of the proposed system is its integration of Explainable AI (XAI) to enhance interpretability. Using Gradient-weighted Class Activation Mapping (Grad-CAM), the model generates heatmaps over the input images, highlighting the specific retinal regions that influenced the predicted outcome. These visual explanations provide clinicians with valuable context for decision-making and establish trust in AI-driven diagnostics. While LIME is explored as a supplementary explanation technique, Grad-CAM remains the primary interpretability method due to its spatial relevance to image-based tasks.

To ensure clinical applicability, the model is deployed through a web-based interface developed using the Flask framework. The front end is designed with HTML5, CSS3, and JavaScript to allow users to easily upload retinal images and receive diagnostic feedback. Once an image is submitted, the system performs preprocessing, inference, and Grad-CAM visualization, returning the predicted DR stage, a model confidence score, and a corresponding heatmap—all in real time. This deployment strategy makes the system accessible to users without technical expertise and suitable for use in remote or resource-constrained healthcare environments.

Furthermore, the system includes robust handling of class imbalance through targeted data augmentation. Each DR class is balanced with approximately 2000 image samples, synthesized through controlled transformations such as rotation, flipping, zooming, brightness modulation, and contrast adjustment. This ensures fair representation during training and reduces the likelihood of bias toward more common classes.

Compared to existing systems, the proposed model offers clear advantages. It demonstrates high diagnostic accuracy, achieving a 97.4% accuracy on validation data, while maintaining transparency and low latency in inference. Its lightweight nature allows for deployment even on modest hardware, and its user-centered design bridges the gap between academic AI research and real-world clinical utility.

VI. Conclusion

To address the critical limitations observed in current diabetic retinopathy (DR) detection models—such as the black-box nature of deep learning, overfitting on imbalanced datasets, and the lack of real-world deployment—this paper proposes a comprehensive, hybrid AI-based system designed for transparency, accuracy, and scalability. The proposed system integrates deep learning models with classical ensemble techniques and explainable AI, deployed via a lightweight web interface for real-time clinical use.

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