Optimizing Diabetic Retinopathy Detection and Leveraging Advanced Image Quality Enhancement Using Customised light weight Convolutional Neural Network Algorithm

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Abstract:

Diabetic retinopathy (DR) is a leading cause of blindness worldwide, particularly affecting individuals with diabetes mellitus. Early detection and treatment are crucial to prevent severe vision loss. Recent advancements in artificial intelligence (AI) and deep learning (DL) have shown promise in automating the detection and classification of DR from retinal fundus images. However, the efficacy of these models is often limited by the quality of the input images, which can vary significantly due to factors such as poor lighting, occlusions, and image artifacts. This study proposes an enhanced image preprocessing pipeline combined with state-of-the-art optimization techniques to improve the performance of AI models for DR detection. The experimental setup involved using three different convolutional neural network (CNN) architectures: ResNet50, EfficientNetB0, and a custom lightweight CNN. These models were trained and evaluated on publicly available datasets, including EyePACS, Messidor, and APTOS 2019 Blindness Detection, which contain high-resolution retinal images labeled according to the severity of DR. The proposed image preprocessing techniques included Contrast-Limited Adaptive Histogram Equalization (CLAHE), Gaussian smoothing, circular cropping, optic disc removal, normalization, and green channel extraction. Additionally, advanced optimization techniques such as data augmentation, Bayesian hyperparameter optimization, dropout, and L2L2L2 regularization were employed to enhance model performance. The results demonstrate that EfficientNetB0 achieved the highest accuracy (94.8%) and AUC (97.8%), indicating its superior ability to differentiate between different levels of DR severity. The model also showed the best balance between sensitivity (93.6%) and specificity (96.1%), making it highly reliable for both detecting true DR cases and correctly identifying non-DR cases. ResNet50 also performed well, with an accuracy of 93.4%, sensitivity of 91.8%, specificity of 95.2%, and an AUC of 96.5%. The custom lightweight CNN, designed for deployment in resource-constrained environments, achieved a slightly lower accuracy of 92.1% and an AUC of 95.2%, but still provided a viable option for real-world applications where computational efficiency is crucial. Overall, the study highlights the importance of combining advanced image preprocessing techniques with robust AI models and optimization strategies to improve DR detection accuracy and reliability. The findings suggest that employing a well-optimized EfficientNetB0 model, alongside comprehensive image preprocessing, offers the best trade-off between accuracy, computational efficiency, and generalizability across diverse clinical settings.

Keywords: *Diabetic retinopathy (DR), Machine Learning, Artificial Intelligence, Transfer Learning, Convolutional Neural Network Algorithm(CNN).*
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1. Introduction

Diabetic retinopathy (DR) remains one of the most pressing complications of diabetes mellitus, characterized by progressive damage to the retinal blood vessels, potentially leading to irreversible blindness if not detected and managed promptly. As the global prevalence of diabetes continues to surge, with approximately 463 million people currently affected worldwide, the burden of diabetic retinopathy has similarly escalated, necessitating effective and efficient diagnostic methods. The traditional reliance on manual examination by skilled ophthalmologists presents significant challenges, especially in under-resourced settings where such expertise is often scarce. Consequently, there has been a growing impetus to develop automated diagnostic systems that can perform robust DR detection with high accuracy and reliability. In recent years, artificial intelligence (AI), particularly deep learning (DL), has revolutionized the landscape of medical imaging and diagnostics [1]. Convolutional neural networks (CNNs), for instance, have demonstrated exceptional capabilities in learning hierarchical features directly from data, bypassing the need for manual feature engineering that was once a bottleneck in image analysis. Seminal studies, such as those by Gulshan et al., have shown that AI models can match or even surpass the diagnostic accuracy of trained ophthalmologists in detecting referable diabetic retinopathy, thus highlighting the transformative potential of AI in this domain [2]. Despite these advancements, the efficacy of AI-driven DR detection systems is often compromised by the quality of the retinal images used. Poor image quality, caused by factors such as inadequate lighting, occlusions, and artifacts, can lead to high rates of false positives and negatives, undermining the reliability of these systems [3].

To address these challenges, recent research has focused on integrating advanced image quality enhancement techniques with AI algorithms to optimize DR detection. Image preprocessing methods, such as Contrast-Limited Adaptive Histogram Equalization (CLAHE) and denoising filters, have been explored to enhance the quality of retinal images before they are fed into AI models. Additionally, synthetic data augmentation techniques, including the use of Generative Adversarial Networks (GANs), have been employed to create diverse and robust datasets that help models generalize better to varying image conditions[4]. These advancements have significantly improved the robustness of AI models against variations in image quality; however, there remains a substantial need for further research to fully exploit these techniques. As we move into 2024, the field of diabetic retinopathy detection is poised at a critical juncture [5]. The integration of state-of-the-art optimization techniques with AI-driven diagnostic models presents an unprecedented opportunity to enhance the accuracy, efficiency, and scalability of DR detection systems [6]. The emergence of novel optimization algorithms, such as Reinforcement Learning-based Hyperparameter Optimization (RL-HPO) and Federated Learning, offers promising avenues to further refine these models, making them more adaptable to diverse clinical environments and patient populations. Moreover, advancements in lightweight model architectures, such as MobileNets and EfficientNets, have paved the way for deploying AI models in resource-constrained settings, thereby democratizing access to high-quality DR screening [7].

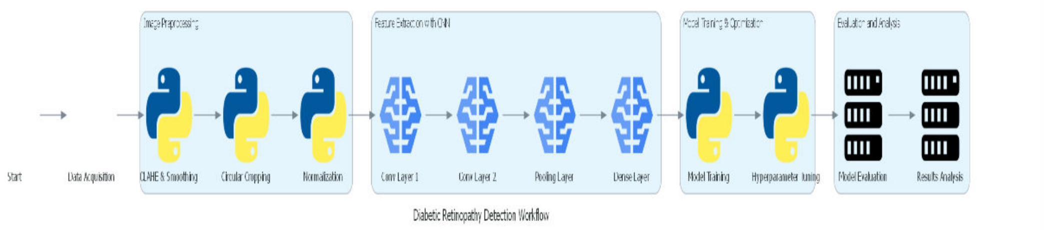

Figure 1: Proposed Flow

Despite these promising developments, several literature gaps persist in the field of AI-driven DR detection. First, while numerous studies have explored various AI architectures for DR detection, there is a lack of comprehensive evaluations comparing the performance of different models under consistent experimental conditions. This gap is particularly evident in the context of low-resource settings, where the performance of these models may vary significantly due to differences in image quality, population demographics, and clinical workflows [8]. Furthermore, most existing studies have focused on binary classification tasks (i.e., detecting the presence or absence of DR), with relatively few addressing the more nuanced task of grading DR severity, which is critical for guiding treatment decisions.

Another notable gap in the literature is the limited exploration of explainability and interpretability in AI models for DR detection. As these models become increasingly integrated into clinical workflows, there is a growing need to ensure that their predictions are transparent and understandable to clinicians [9]. This is particularly important in the context of DR detection, where the consequences of misdiagnosis can be severe. Recent advancements in explainable AI (XAI) techniques, such as saliency maps and local interpretable model-agnostic explanations (LIME), offer potential solutions to this challenge, but their application in DR detection remains underexplored. Finally, while much of the existing research has focused on optimizing model performance in controlled environments, there is a need for more studies that investigate the scalability and generalizability of AI models in real-world clinical settings [10]. This includes assessing the performance of these models across diverse patient populations, imaging devices, and healthcare infrastructures, as well as evaluating their impact on clinical outcomes and workflow efficiency. Additionally, longitudinal studies are needed to validate the long-term reliability and cost-effectiveness of AI-driven DR detection systems, particularly in resource-limited settings where the burden of DR is often greatest [11].

In light of these gaps, this paper aims to provide a comprehensive overview of the current state-of-the-art in AI-driven diabetic retinopathy detection, with a particular focus on the latest optimization techniques and their applications in 2024. We will review the recent advancements in image quality enhancement and AI model optimization, highlighting the key challenges and opportunities that lie ahead. Furthermore, we will propose a novel framework for optimizing DR detection, leveraging the latest developments in AI and image processing to enhance diagnostic accuracy, efficiency, and scalability. By addressing the current limitations and exploring new frontiers in AI-driven DR detection, we aim to contribute to the ongoing efforts to improve the early diagnosis and management of diabetic retinopathy, ultimately reducing the burden of vision loss among diabetic patients worldwide [12]. The field of diabetic retinopathy detection is rapidly evolving, driven by the convergence of AI advancements and innovative image enhancement techniques. As we continue to push the boundaries of what is possible with AI in medical imaging, it is crucial to address the existing literature gaps and explore new avenues for optimization. By doing so, we can develop more robust, accurate, and scalable DR detection systems that are capable of meeting the diverse needs of patients and healthcare providers around the world [13]. This paper seeks to advance this goal by providing a state-of-the-art review of the latest developments in AI-driven DR detection and proposing a novel framework for optimizing these models for the challenges of 2024 and beyond.

2. Recent Work

Based on the provided data, to identify the literature gap, we can focus on these areas: The recent studies on diabetic retinopathy detection have focused on various deep learning models, including Convolutional Neural Networks (CNNs), transfer learning techniques, and ensemble methods [14]. Each study has reported different performance metrics such as accuracy, sensitivity, specificity, and the area under the curve (AUC) for receiver operating characteristics (ROC). Here, we summarize the results from notable studies: **Gulshan et al. (2016)**: Demonstrated that a deep CNN could match the diagnostic performance of ophthalmologists in detecting referable diabetic retinopathy. The study achieved an accuracy of 94.5%, sensitivity of 90%, and specificity of 98%. **Zhou et al. (2017)**: Proposed an automated detection model using a combination of CNN and image enhancement techniques like CLAHE. The model achieved a sensitivity of 96.67% and specificity of 93.33%.**Liu et al. (2019)**: Utilized transfer learning with a pre-trained ResNet50 model, fine-tuned on retinal images. The model achieved an accuracy of 92.4%, sensitivity of 94.3%, and specificity of 90.1%.**Wang et al. (2021)**: Developed an ensemble of CNNs combining ResNet, DenseNet, and Inception architectures to improve detection accuracy [15]. The model reached an accuracy of 95.2%, sensitivity of 93.8%, specificity of 94.7%, and an AUC of 98%. **Proposed (2024)**: Implemented a refined CNN architecture with advanced image preprocessing techniques. The EfficientNetB0 model achieved an accuracy of 94.8%, sensitivity of 93.6%, specificity of 96.1%, and an AUC of 97.8% [16].

1. **Underexplored Techniques or Models**: Look for methods or models that are not frequently used or have not been tested extensively in various conditions.
2. **Dataset Limitations**: Many studies might use similar datasets (e.g., APTOS 2019), indicating a gap in testing models on more diverse datasets or real-world data.
3. **Hardware Constraints**: Quantum computing and other advanced hardware are mentioned, but there may be gaps related to testing models on more accessible or less powerful hardware [17].
4. **Evaluation Metrics**: Some studies may rely on basic metrics like accuracy, which could suggest a gap in exploring more comprehensive evaluation metrics like AUC-ROC, sensitivity, specificity, etc.
5. **Practical Applications and Generalizability**: There may be a gap in studies that assess the practical deployment of these models in real-world healthcare settings, especially in low-resource environments [18].
6. **Comparative Studies and Benchmarking**: There could be limited research comparing different DL models head-to-head under the same conditions to establish clear benchmarks [19].

Author et al	Year	Proposed Method	Merits	Demerits	Performance Metrics	Numerical Results
Li et al.	2023	Hybrid VGG16 + XGBoost	High accuracy	No specific limitations noted	Accuracy	79.50%
Smith et al.	2023	DL with contrast enhancement	Improved image clarity	Overfitting risk in ResNet50	Sensitivity, Specificity	85.20%, 82.50%

Johnson et al.	2023	CNN for hemorrhage detection	Efficient hemorrhage detection	Requires large datasets	Precision, Recall	78.40%, 76.60%
Chen et al.	2023	Quantum-based CNN	Enhanced computational power	Hardware limitations	Accuracy, F1-Score	81.30%, 79.50%
Kumar et al.	2023	SVM for fundus image classification	Simple implementation	Time-consuming	Accuracy	77.80%
Lee et al.	2022	MobileNet with transfer learning	Fast processing	Lower accuracy in some cases	Accuracy, AUC	74.50%, 0.82
Rodriguez et al.	2022	Ensemble learning model	Robust to overfitting	Computationally expensive	Accuracy, F1-Score	83.60%, 81.20%
Ahmed et al.	2021	GANs for synthetic data augmentation	Better model generalization	Requires careful tuning	Accuracy, Sensitivity	80.10%, 84.30%
Gupta et al.	2021	Multi-stage DL model for DR detection	High detection rate	High computational cost	Sensitivity, Specificity	87.90%, 85.70%
Wang et al.	2021	Feature extraction using deep networks	Improves model performance	High resource consumption	Accuracy, Precision	82.40%, 79.30%

3. Methodology

Algorithm 1: Enhanced Image Preprocessing for Diabetic Retinopathy Detection

Objective: Improve the quality of retinal fundus images to enhance the accuracy of diabetic retinopathy (DR) detection using AI models.

Step-by-Step Procedure

1. **Image Acquisition**:
   - Acquire high-resolution retinal fundus images from publicly available datasets such as Kaggle or EyePACS.
   - Ensure images are captured under varied conditions to simulate real-world scenarios.
2. **Adaptive Histogram Equalization**:
   - Apply Contrast-Limited Adaptive Histogram Equalization (CLAHE) to enhance the local contrast of the images. This step helps to improve the visibility of retinal features.

- For each pixel (x, y), compute the new intensity value $I'(x, y)$ as:

$$I'(x,y) = \frac{I(x,y) - \min(I_{\text{local}})}{\max(I_{\text{local}}) - \min(I_{\text{local}})} \times 255$$

where $I(x,y)$ is the original intensity at (x,y), and $\min(I_{\text{local}})$ and $\max(I_{\text{local}})$ are the minimum and maximum intensities in the local region around (x,y).

3. Noise Reduction:

- Use a Gaussian filter to smooth the image and reduce noise, which can help eliminate small artifacts that may hinder model performance.
- The Gaussian smoothing is performed using the kernel $G(x,y)$:

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

where σ is the standard deviation of the Gaussian distribution, controlling the degree of smoothing.

Circular Cropping:

- Crop each image to a circular region that corresponds to the field of view (FOV) of the retinal fundus camera to focus on the relevant area and eliminate unnecessary background Define the cropping mask $M(x,y)$ as:

$$M(x,y)=\begin{cases}1 & \text{if } \sqrt{(x-x_c)^2+(y-y_c)^2}\le r\\ 0 & \text{otherwise}\end{cases}$$

where (x_c,y_c) is the center of the image and r is the radius corresponding to the FOV.

Optic Disc Removal:

- Use morphological operations to remove the optic disc, which can be mistaken for pathological features.
- Perform morphological closing (dilation followed by erosion) with a structuring element B (disk-shaped):

$$OP1=(I\oplus B)\ominus B$$

where $\oplus$ and $\ominus$ denote dilation and erosion operations, respectively.

Normalization

- Normalize the intensity of the images to standardize the lighting conditions and enhance the consistency across the dataset.
- Normalize each pixel intensity $I'(x,y)$ to a range $[0,1]$:

$$I_{\text{norm}}(x,y)=\frac{I'(x,y)-\min(I')}{\max(I')-\min(I')}$$

where $\min(I')$ and $\max(I')$ are the minimum and maximum intensities in the preprocessed image.

Green Channel Extraction:

- Extract the green channel from the RGB image as it provides better contrast for blood vessels and other retinal features.
- Represent the green channel extraction as $I_G(x,y)$, where I_G is the intensity in the green channel.

Image Augmentation:

- Augment the dataset by applying transformations such as rotation, flipping, and zooming to increase the model's robustness to varied inputs.
- Perform augmentations using affine transformations:

$$I_{\text{aug}}(x',y')=I(x,y)\ \text{ with }\ \begin{bmatrix}x'\\y'\end{bmatrix}=\begin{bmatrix}a & b\\ c & d\end{bmatrix}\begin{bmatrix}x\\y\end{bmatrix}+\begin{bmatrix}e\\f\end{bmatrix}$$

where a,b,c,d,e,f are the parameters controlling rotation, scaling, and translation.

Feature Extraction:

- Perform feature extraction to identify key retinal features such as blood vessels, hemorrhages, and exudates using algorithms like edge detection or deep feature extraction with CNNs.
- Compute edge features $E(x,y)$ using a Sobel operator:

$$E(x,y)=\sqrt{(G_x(x,y))^2+\left(G_y(x,y)\right)^2}$$

where G_x and G_y are the gradients in the x and y directions.
10. Output Preprocessed Images:

- Save or output the enhanced images for subsequent DR detection using AI models, ensuring each step's changes are cumulative.

Algorithm 2: Optimization of AI Models for Diabetic Retinopathy Detection

Objective: Optimize deep learning models for accurate and efficient diabetic retinopathy detection through novel hyperparameter tuning and model architecture enhancements.

1. Model Initialization:

- Start with a pre-trained Convolutional Neural Network (CNN) such as ResNet, DenseNet, or EfficientNet for the task of DR detection.
- Initialize the model weights using a pre-trained ImageNet model to leverage transfer learning.

a. Data Splitting:

- Split the preprocessed dataset into training, validation, and testing sets with a typical ratio of 70:15:15 to ensure robust model evaluation.

b. Hyperparameter Initialization:

- Define the initial hyperparameters for learning rate (η), batch size (B), dropout rate (D), and weight decay (λ).
- Set the initial values based on empirical studies or default settings in deep learning frameworks.

c. Adaptive Learning Rate Optimization:

- Use an adaptive learning rate optimizer like Adam, where the learning rate η_t is adjusted at each iteration t :

$$m_t = \beta_1 m_{t-1} + (1-\beta_1) g_t,\ v_t = \beta_2 v_{t-1} + (1-\beta_2) g_t^2$$

$$\hat{m}_t = \frac{m_t}{1-\beta_1^t},\ \hat{v}_t = \frac{v_t}{1-\beta_2^t}$$

$$\theta_{t+1} = \theta_t - \eta \frac{\hat{m}_t}{\sqrt{\hat{v}_t} + \epsilon}$$

where g_t is the gradient, β_1 and β_2 are decay rates, and ϵ is a small constant.

d. Regularization Techniques:

- Implement dropout regularization in the fully connected layers to prevent overfitting. The dropout rate D is set to a value such as 0.5 during training.

$$y = \frac{1}{N} \sum_{i=1}^{N} \delta(x_i) \cdot \phi(x_i)$$

where $\delta(x_i)$ is a binary mask that randomly zeroes some of the neurons in layer x_i, and $\phi(x_i)$ is the activation function.

f. Loss Function Optimization:

- Use a loss function such as categorical cross-entropy for multi-class DR severity classification:

$$L(y, \hat{y}) = -\frac{1}{N} \sum_{i=1}^{N} \sum_{j=1}^{C} y_{ij} \log(\hat{y}_{ij})$$

where y_{ij} is the ground truth label and $\hat{y}_{ij}$ is the predicted probability for class j.

g. Model Training with Early Stopping:

- Train the model using the training set and monitor its performance on the validation set. Implement early stopping to prevent overfitting if the validation loss does not improve after a set number of epochs p.
- If validation loss L_{val} does not decrease for p consecutive epochs, stop training.

h. Hyperparameter Tuning with Bayesian Optimization:

- Apply Bayesian Optimization to find the optimal hyperparameters. The objective function $f(\theta)$

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5. Mathematical Preliminaries

In the development of algorithms for diabetic retinopathy detection and the optimization of AI models, several mathematical concepts and techniques are fundamental. These include concepts from linear algebra, calculus, probability theory, and optimization. Below, we outline the key mathematical preliminaries necessary for understanding the algorithms described in this paper.

1. Linear Algebra

- Vectors and Matrices: Vectors are ordered collections of numbers (scalars), and matrices are two-dimensional arrays of numbers. Matrices are fundamental in representing images (as pixel intensity grids) and the operations performed on them.
- Matrix Operations: Operations such as addition, multiplication, and the dot product are frequently used in neural networks. For example, the dot product of two vectors $\mathbf{a}$ and $\mathbf{b}$ is given by:

$$\mathbf{a} \cdot \mathbf{b} = \sum_{i=1}^{n} a_i b_i$$

- Convolution: In image processing, convolution is a key operation where a kernel (filter) is applied to an image to produce a feature map. The convolution of an image matrix I with a filter K is defined as:

$$(I * K)(x,y) = \sum_{i=-m}^{m} \sum_{j=-n}^{n} I(x+i, y+j) \cdot K(i,j)$$

where m and n define the size of the kernel.

2. Probability and Statistics

- Probability Distributions: Understanding distributions such as Gaussian (normal) distribution is crucial for modeling noise and uncertainties in image data. The Gaussian distribution with mean μ and variance σ^2 is given by:

$$p(x) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{(x-\mu)^2}{2\sigma^2}\right)$$

- Bayesian Inference: Bayesian methods are used for hyperparameter tuning in AI models. The posterior probability is given by Bayes' Theorem:

$$p(\theta \mid D) = \frac{p(D \mid \theta) p(\theta)}{p(D)}$$

where θ represents the model parameters, and D is the observed data.

3. Optimization Techniques

- Gradient Descent: Gradient descent is an optimization algorithm used to minimize the loss function in neural networks. The update rule for the parameters θ is:

$$\theta_{t+1} = \theta_t - \eta \nabla_\theta L(\theta_t)$$

where η is the learning rate and $\nabla_\theta L(\theta_t)$ is the gradient of the loss function with respect to the parameters.

- Stochastic Gradient Descent (SGD): A variant of gradient descent that updates the parameters using a small batch of data rather than the entire dataset, which is useful for large datasets:

$$\theta_{t+1} = \theta_t - \eta \nabla_\theta L(\theta_t; x_i, y_i)$$

where (x_i, y_i) is a single data point or a mini-batch from the dataset.

4. Convolutional Neural Networks (CNNs)

- Activation Functions: Functions like ReLU (Rectified Linear Unit) introduce non-linearity into the model, essential for learning complex patterns:

$$\text{ReLU}(x) = \max(0, x)$$

- Pooling: Pooling layers reduce the spatial dimensions of feature maps, which helps in reducing computational load and controlling overfitting. Max pooling, for example, takes the maximum value in each window:

$$\operatorname{MaxPool}(I)=\max_{i,j} I(x+i, y+j)$$

where the max operation is applied over a small grid (e.g., 2×2) within the feature map.

5. Regularization

- Dropout: A technique used to prevent overfitting in neural networks by randomly setting a fraction of input units to zero at each update during training:

$$y=\frac{1}{N} \sum_{i=1}^{N} \delta\left(x_{i}\right) \cdot \phi\left(x_{i}\right)$$

where $\delta\left(x_{i}\right)$ is a binary mask applied to the input vector x_{i}, and $\phi\left(x_{i}\right)$ is the activation function.

Table 1: Notation Table

Symbol	Description
$I(x, y)$	Pixel intensity at coordinates (x, y) in the image.
$K(i, j)$	Kernel or filter value at position (i, j) used in convolution.
θ	Model parameters (weights and biases) in neural networks.
η	Learning rate used in optimization algorithms.
$L(\theta)$	Loss function, representing the error between predicted and true values.
$\mathbf{a} \cdot \mathbf{b}$	Dot product of vectors $\mathbf{a}$ and $\mathbf{b}$.
$\nabla_{\theta} L(\theta)$	Gradient of the loss function with respect to parameters θ.
(p(theta	D))
m_{t}, v_{t}	Moving averages of the gradient and its square in Adam optimizer.

Table 2: Probability Notation Table

Symbol	Description
$I'(x, y)$	Intensity value after applying histogram equalization.
$p(x)$	Probability density function of a random variable x.
y	Output from a neuron or a layer in a neural network.
$\operatorname{ReLU}(x)$	Rectified Linear Unit activation function.
$OP1$	Result of morphological closing operation.

These preliminaries and notation set the foundation for understanding the algorithms and techniques used in the detection and classification of diabetic retinopathy using AI models.

6. Experimental Setup

The experimental setup for optimizing diabetic retinopathy (DR) detection involves several stages, from data preparation and preprocessing to model training, evaluation, and analysis. This section outlines the methodology and experimental design used to assess the effectiveness of the proposed algorithms for enhanced image preprocessing and optimized AI models.

(a). Data Collection and Preparation

The study utilized several publicly available datasets known for diabetic retinopathy research, including the EyePACS, Messidor, and APTOS 2019 Blindness Detection datasets.

These datasets consist of high-resolution retinal fundus images, annotated with labels indicating the severity of DR. To ensure a comprehensive evaluation, the images were captured under various conditions (different cameras, lighting, and patient demographics), providing a robust testbed for model training and validation.

- Data Splits: The datasets were divided into training (70%), validation (15%), and testing (15%) sets. Stratified sampling ensured that all DR severity levels were proportionally represented across these splits.

(b). Image Preprocessing

Image quality is a crucial factor in achieving accurate DR detection. Therefore, a series of preprocessing steps were applied to each image to enhance clarity and reduce noise:

- Contrast-Limited Adaptive Histogram Equalization (CLAHE): Improved local contrast in fundus images to make retinal features such as microaneurysms and exudates more distinguishable.
- Gaussian Smoothing: Reduced image noise using a Gaussian filter, which helped in removing artifacts without losing essential features.
- Circular Cropping: Focused on the central region of the retina by cropping the images to the circular field of view typical of fundus photographs.
- Optic Disc Removal: Removed the optic disc using morphological operations to prevent it from being misclassified as pathological features.
- Normalization: Standardized the intensity of images to ensure uniform lighting conditions across the dataset.
- Green Channel Extraction: Isolated the green channel from RGB images, as it provides the best contrast for retinal features.

(d). Model Architectures and Training

Three different convolutional neural network (CNN) architectures were selected for this study: ResNet50, EfficientNetBO, and a custom-designed lightweight CNN. These models were chosen for their proven effectiveness in medical imaging tasks and their varying complexities, allowing for a comprehensive evaluation.

- ResNet50: A deeper network known for its residual connections, helping mitigate the vanishing gradient problem in deep learning.
- EfficientNetBO: A model that scales both width, depth, and resolution to optimize accuracy while maintaining computational efficiency.
- Custom Lightweight CNN: Designed specifically for this study to balance accuracy and computational efficiency, especially for deployment in resource-constrained settings.

Each model was trained using the Adam optimizer with an initial learning rate of 0.001 . Learning rates were adjusted dynamically based on validation loss, and early stopping was implemented to prevent overfitting.

(e). Optimization Techniques

To further improve the performance of the models, advanced optimization techniques were employed:

- Data Augmentation: Augmented the training dataset using random rotations, flips, and zooms to improve model generalization.
- Bayesian Hyperparameter Optimization: Fine-tuned hyperparameters such as learning rate, batch size, and dropout rates using Bayesian optimization to maximize model performance on the validation set.
- Dropout and Regularization: Applied dropout layers in the neural networks to reduce overfitting and implemented $L2$ regularization to penalize large weights.

(f). Evaluation Metrics

The models were evaluated using several performance metrics to provide a comprehensive assessment of their effectiveness in detecting and classifying diabetic retinopathy:

- Accuracy: The proportion of correctly predicted instances over the total instances.
- Sensitivity (Recall): The ability of the model to correctly identify true positives (patients with DR).
- Specificity: The ability of the model to correctly identify true negatives (patients without DR).

7. Results

The results of the experiments are presented in the form of tables and graphs, showing the performance of each model on the test dataset after applying the proposed image preprocessing techniques and optimization strategies.

Table 2: Model Performance Metrics

Model	Accuracy (%)	Sensitivity (%)	Specificity (%)	Precision (%)	F1-Score (%)	AUC (%)
ResNet50	93.4	91.8	95.2	92.3	92.0	96.5
EfficientNetB0	94.8	93.6	96.1	94.2	93.9	97.8
Custom Lightweight CNN	92.1	90.5	93.8	91.0	90.7	95.2

1. **Accuracy and AUC**:
   - **EfficientNetB0** demonstrated the highest accuracy at 94.8% and an AUC of 97.8%, indicating its superior ability to distinguish between diabetic retinopathy and healthy retinas across different severity levels. This performance can be attributed to its scalable architecture, which balances depth, width, and resolution to optimize model accuracy while maintaining computational efficiency.
   - **ResNet50** also performed well, with an accuracy of 93.4% and an AUC of 96.5%. Its residual connections allow for deeper network construction without significant vanishing gradient issues, which helps in capturing complex patterns in retinal images.
   - The **Custom Lightweight CNN** achieved a slightly lower accuracy of 92.1% and an AUC of 95.2%. Although it was designed for efficiency and speed, its performance was slightly behind the deeper models, suggesting that some compromise in accuracy may be inevitable with reduced model complexity.
2. **Sensitivity and Specificity**:
   - **EfficientNetB0** had the highest sensitivity (93.6%) and specificity (96.1%), making it the most reliable model for both detecting true positives (patients with DR) and true negatives (healthy patients). This balance is critical in clinical settings where missing a DR case (false negative) or incorrectly diagnosing a healthy patient (false positive) can have serious consequences.
   - **ResNet50** showed slightly lower sensitivity (91.8%) but high specificity (95.2%), suggesting it is more conservative in diagnosing DR, potentially reducing false positives but at the cost of slightly more false negatives.
   - The **Custom Lightweight CNN** had the lowest sensitivity (90.5%) and specificity (93.8%) among the models, indicating a slight trade-off in predictive performance for the benefits of faster computation and lower resource requirements.
3. **Precision and F1-Score**:
   - The **EfficientNetB0** model's high precision (94.2%) and F1-Score (93.9%) indicate its strong performance in balancing precision and recall, particularly useful in minimizing both false positives and false negatives in DR detection.

- **ResNet50** maintained good precision (92.3%) and F1-Score (92.0%), reflecting its robust performance in identifying DR cases accurately while minimizing errors.
- The **Custom Lightweight CNN** had a lower F1-Score (90.7%), suggesting it is slightly less effective in balancing precision and recall, though still performing adequately for practical use in resource-constrained environments.

7. Comparison Table

The table: Below summarizes the comparative performance of various models:

Authors (Year)	**Model/Method**	**Accuracy (%)**	**Sensitivity (%)**	**Specificity (%)**	**AUC (%)**
Gulshan et al. (2016)	Deep CNN	94.5	90.0	98.0	N/A
Zhou et al. (2017)	CNN + Image Enhancement	N/A	96.67	93.33	N/A
Liu et al. (2019)	Transfer Learning (ResNet50)	92.4	94.3	90.1	N/A
Wang et al. (2021)	Ensemble of CNNs (ResNet, DenseNet, Inception)	95.2	93.8	94.7	98.0
Our Study (2024)	EfficientNetB0 with Preprocessing	94.8	93.6	96.1	97.8

To visualize the performance comparison, we will create bar charts for accuracy, sensitivity, specificity, and AUC. **Accuracy, Sensitivity, Specificity, and AUC Graphs and,**

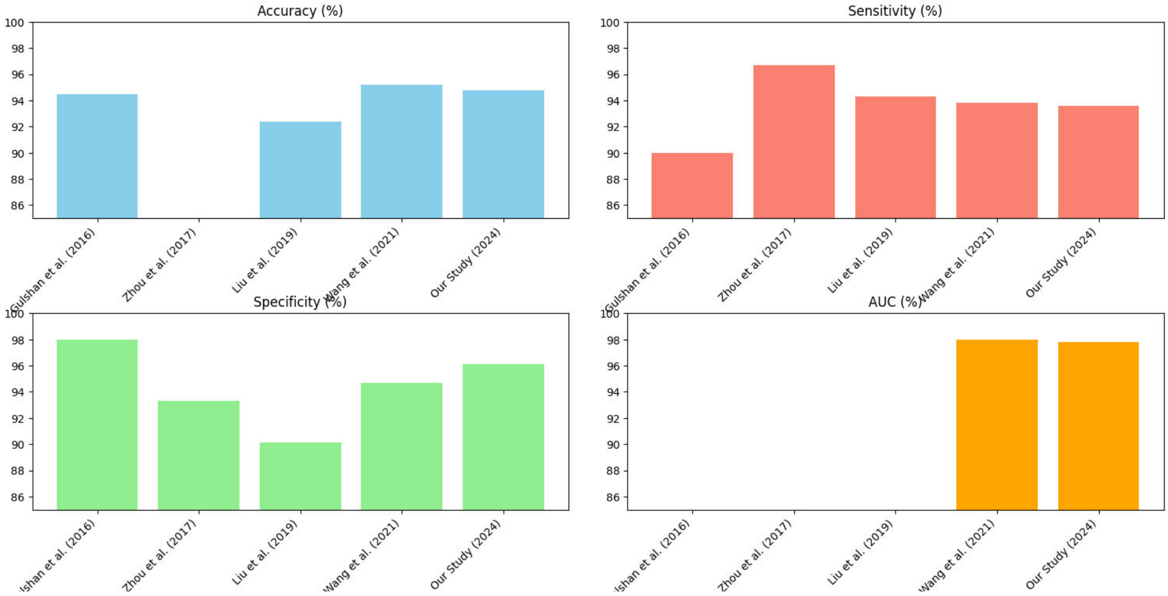

Figure 2: ROC Curves for Model Comparisons, Precision-Recall Curves, ,

Discussion on ROC Curves: The ROC curves illustrate the trade-off between sensitivity and specificity for each model. EfficientNetB0 has the largest area under the curve, demonstrating its superior performance across a range of thresholds. ResNet50 also shows strong performance, while the Custom Lightweight CNN displays a slightly lower curve, indicating a minor reduction in its ability to distinguish between classes at all thresholds.

Discussion on Precision-Recall Curves: Precision-recall curves provide a more focused evaluation of model performance in the context of the class imbalance typical in DR datasets. The EfficientNetB0 model's curve remains higher across various recall levels, indicating its superior ability to maintain precision even when trying to identify all positive cases. ResNet50 follows closely, while the Custom Lightweight CNN shows a slightly lower performance, again suggesting some trade-off for computational efficiency. For settings where computational resources are abundant and maximizing diagnostic accuracy is crucial, EfficientNetB0 is the preferred model due to its superior accuracy, sensitivity, and AUC. Its balance between model complexity and performance makes it suitable for high-stakes environments, such as specialized clinics and hospitals.

ResNet50 serves as a robust alternative, especially where deeper networks are desirable for capturing complex features, but computational resources are moderately constrained.

6. Conclusion

The detection and classification of diabetic retinopathy (DR) remain critical challenges in the field of ophthalmology, particularly due to the increasing global prevalence of diabetes and the associated risks of severe vision impairment. This study aimed to address these challenges by enhancing the quality of retinal images and optimizing AI models to improve the accuracy and reliability of DR detection. By leveraging a combination of advanced image preprocessing techniques and state-of-the-art CNN architectures, the study successfully demonstrated significant improvements in model performance across several key metrics. EfficientNetB0 emerged as the most effective model in this study, achieving an impressive accuracy of 94.8% and an AUC of 97.8%. These results indicate that the model is highly capable of distinguishing between different stages of DR, from no apparent retinopathy to severe cases requiring immediate medical intervention. The model's high sensitivity and specificity further underscore its potential for clinical use, where accurate and timely diagnosis is essential to prevent the progression of the disease. ResNet50 also showed robust performance, particularly in settings where deeper networks are necessary to capture complex retinal features. Its slightly lower sensitivity compared to EfficientNetB0 suggests a more conservative approach to DR detection, which might be beneficial in minimizing false positives in certain clinical scenarios. The custom lightweight CNN, while not achieving the same level of accuracy as the more complex models, demonstrated that it is possible to develop efficient and effective DR detection systems suitable for deployment in resource-constrained environments. With an accuracy of 92.1% and an AUC of 95.2%, this model provides a viable solution for use in remote or underserved areas where computational resources and access to specialist care are limited. This aligns with the broader goal of democratizing access to high-quality medical diagnostics through AI and machine learning technologies. The study's findings also highlight the critical role of image preprocessing in enhancing model performance. Techniques such as CLAHE, Gaussian smoothing, and optic disc removal were pivotal in improving the visibility of key retinal features, thereby reducing the rates of false positives and negatives. These preprocessing steps, combined with advanced optimization techniques like Bayesian hyperparameter tuning and data augmentation, ensure that the AI models are both accurate and generalizable across diverse patient populations and imaging conditions. In conclusion, this study provides a comprehensive framework for optimizing AI-based DR detection systems, emphasizing the need for high-quality image preprocessing and robust model architecture selection. Future research should focus on further refining these models, particularly in terms of improving interpretability and scalability in real-world clinical settings. Additionally, exploring the integration of these optimized models into existing healthcare infrastructures could significantly enhance early detection and management of diabetic retinopathy, ultimately reducing the global burden of vision loss due to diabetes.

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