

# Diabetic Retinopathy Classification Using Deep Learning Techniques to Enhance Findings with Color Normalization Techniques

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## Abstract:

Diabetic retinopathy (DR) is a widespread vision problem due to diabetes that can lead to vision loss if it is not detected and treated early. In the last few years, deep learning techniques have shown promising results in the automation of the detection and classification of diabetic retinopathy from retinal images. However, the performance of these techniques can be further improved by addressing the challenges due to the color variations in retinal images. This paper presents an implementation of a diabetic retinopathy classification system that combines color normalization techniques, namely Histogram Equalization and Contrast Stretching, with Convolutional Neural Networks (CNNs). The proposed approach aims to enhance the findings by reducing the impact of color variations on classification accuracy.

**Keywords:** Diabetic Retinopathy (DR), Deep Learning, Convolutional Neural Networks (CNNs), Color Normalization, Histogram Equalization, Contrast Stretching

## 1. Introduction:

### ● Background and Motivation:

Diabetic retinopathy is a progressive eye disease and a leading cause of vision loss among individuals with diabetes. This is because of increase in blood sugar levels damaging the blood vessels in the eye retina, and if left untreated, which leads to vision loss or even blindness. Early detection and accurate classification of diabetic retinopathy are important for timely cure and enhanced patient outcomes. Diabetic retinopathy has different stages which are classified into No Diabetic Retinopathy (No DR), Mild Diabetic Retinopathy, Moderate Diabetic Retinopathy, Severe Diabetic Retinopathy, and Proliferative Diabetic Retinopathy (PDR).

In the last few years, for various medical imaging applications, deep learning techniques, particularly Convolutional Neural Networks (CNNs), have demonstrated remarkable success including diabetic retinopathy classification. The automatic learning of descriptive features by the CNNs from raw retinal images, enables the enabling efficient and accurate classification of diabetic retinopathy. However, the color variations present in retinal images may hamper the performance of CNN-based classifiers. These color variations can be due to the factors such as differences in imaging capturing devices, the lighting conditions while taking the image, and variations in disease manifestations across individuals.

### ● Objectives:

The primary objective of this paper is to enhance the performance of diabetic retinopathy classification using deep learning techniques by addressing the challenges posed by color variations in retinal images. We aim to investigate the effectiveness of two color normalization techniques, namely Histogram Equalization and Contrast Stretching, in reducing the impact of color variations and improving the

classification accuracy. By integrating these color normalization techniques into the classification pipeline, we seek to enhance the findings and provide a more robust and reliable system for diabetic retinopathy detection.

- **Organization of the Paper:**

The rest in this paper is structured as follows: Section 2 provides an overview of the related work in diabetic retinopathy classification techniques, color normalization techniques, and deep learning approaches for this task. Section 3 outlines the methodology, including the dataset description, preprocessing steps, color normalization techniques, and the architecture and training process of the CNNs. Section 4 presents the experimental results, including the evaluation metrics, performance comparison, impact of color normalization techniques, and sensitivity analysis. Section 5 discusses the interpretation of the results. Finally, concludes the paper, summarizing the contributions and potential applications of the proposed system.

Through this paper, we aim to contribute to the advancement of diabetic retinopathy classification systems by exploring the integration of color normalization techniques and deep learning models. The proposed approach has the potential to improve the accuracy and reliability of automated diabetic retinopathy diagnosis, leading to early interventions and improved management of this sight-threatening condition.

## **2. Related Work:**

### **2.1. Diabetic Retinopathy Classification Techniques:**

Numerous studies have focused on developing effective techniques for diabetic retinopathy classification. The traditional machine learning methods have been employed with handcrafted features to distinguish between different stages of retinopathy. However, these approaches often rely on manual feature engineering, which can be time-consuming and may not fully capture the complex and subtle characteristics of retinal images.

With the emergence of deep learning, several studies have leveraged CNNs to automate the classification of diabetic retinopathy. Researchers have proposed various CNN architectures, such as VGGNet, ResNet, and InceptionNet, and achieved remarkable results in terms of accuracy and robustness. These CNN-based approaches can effectively learn high-level representations from raw retinal images, eliminating the need for manual feature extraction.

### **2.2. Color Normalization Techniques:**

Color normalization techniques have been widely investigated to mitigate the impact of color variations in medical image analysis tasks. Histogram Equalization (HE) is a common method used to enhance the contrast of images by redistributing the pixel intensities. HE adjusts the intensity distribution of each color channel independently, which can be effective in normalizing the color appearance across retinal images.

Contrast Stretching is another technique employed for color normalization. It aims to enhance the dynamic range of pixel intensities by stretching the intensity values to cover the full available range. This method can be particularly useful when retinal images exhibit low contrast or when there are significant variations in lighting conditions.

### **2.3. Diabetic Retinopathy Classification - A Deep Learning Approaches:**

Several studies have incorporated deep learning techniques for diabetic retinopathy classification, achieving notable results. In some works, CNNs have been utilized as feature extractors, where the learned features are subsequently fed into the machine learning classifiers, for example SVMs or random forests. This hybrid approach combines the discriminative power of CNNs with the robustness of traditional classifiers.

Other studies have explored end-to-end deep learning architectures, where the CNNs are trained to directly classify retinal images into different stages of diabetic retinopathy. These end-to-end approaches have shown promising results, achieving high accuracy and demonstrating the potential of deep learning models to automate the classification process.

However, limited attention has been given to addressing the challenge of color variations in diabetic retinopathy classification. The proposed approach in this paper bridges this gap by investigating the integration of color normalization techniques with CNNs to enhance the performance and reliability of diabetic retinopathy classification systems.

In the next section, we present the methodology adopted in this study, including the dataset description, preprocessing steps, color normalization techniques, and the architecture and training process of the CNNs.

### 3. Methodology:

#### 3.1. Dataset Description:

In this study, the APTOS 2019 dataset is utilized for diabetic retinopathy classification. The APTOS 2019 dataset is a widely used benchmark dataset in the field, consisting of high-resolution retinal images captured using different imaging devices. It contains images from various stages of diabetic retinopathy, ranging from normal to severe conditions. The dataset is annotated with corresponding severity levels, providing labels for training and evaluation. This data set consists of 3662 retinal images, consisting 1805 images of No DR, 370 images of Mild DR, 999 images of Moderate DR, 193 images of Severe DR and 295 images of Proliferative DR.

#### 3.2. Preprocessing Steps:

Before applying color normalization techniques and training the CNN models, several preprocessing steps are performed on the APTOS 2019 dataset. These steps include resizing the images to a standardized resolution, typically maintaining the aspect ratio to avoid distortion. Additionally, any noise or artifacts present in the images can be reduced or removed using denoising filters or image enhancement techniques.

Data augmentation techniques are used to enrich the dataset and make it more diverse. The images are transformed using these methods by rotating, scaling, flipping, and randomly cropping. Data augmentation aids in reducing overfitting and increasing trained model robustness.

#### 3.3. Color Normalization Techniques:

To address the color variations present in the retinal images, color normalization techniques are applied. In this study, two commonly used techniques, Histogram Equalization (HE) and Contrast Stretching, are utilized.

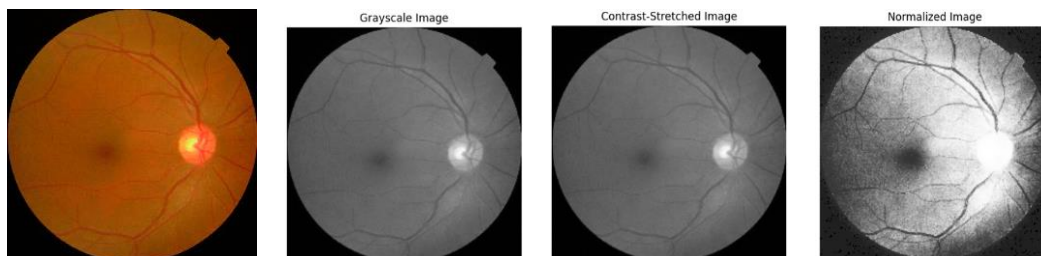


Fig 1. Color Normalization of DR image

##### 3.3.1. Histogram Equalization (HE):

Histogram Equalization is applied to normalize the intensity distribution of each color channel in the retinal images independently. This technique redistributes the pixel intensities, enhancing the contrast and visibility of the images. By equalizing the histograms of the color channels, the color appearance

across the images is normalized, reducing the impact of color variations during the classification process.

### 3.3.2. Contrast Stretching:

Contrast Stretching is another technique employed to improve the dynamic range of pixel intensities in retinal images. It stretches the intensity values to cover the full available range, thereby enhancing the contrast and improving the visibility of details in the images. Contrast Stretching is particularly useful in normalizing retinal images with low contrast or significant variations in lighting conditions.

### 3.4. Convolutional Neural Networks (CNNs):

In this study, Convolutional Neural Networks (CNNs) are utilized as classification models for diabetic retinopathy. The CNN architecture employed comprises several convolutional layers, a few pooling layers, and fully connected layers.

#### 3.4.1. Architecture Overview:

The system architecture implemented in this study follows a standard pipeline for training a CNN model. It begins by loading and preprocessing the dataset, including applying color normalization techniques to enhance the images. The dataset is then split into training, validation, and testing sets to ensure proper evaluation. Data augmentation is performed using an ImageDataGenerator to increase the model's performance by applying transformations to the training data. The CNN model is constructed using the Sequential approach, incorporating convolutional, pooling, and dense layers. Training process starts with the augmented training images followed by the model's performance evaluation on the testing set. Finally, the trained model is saved for future use. This system architecture provides a structured and modular framework for image classification tasks, enabling efficient implementation and experimentation.

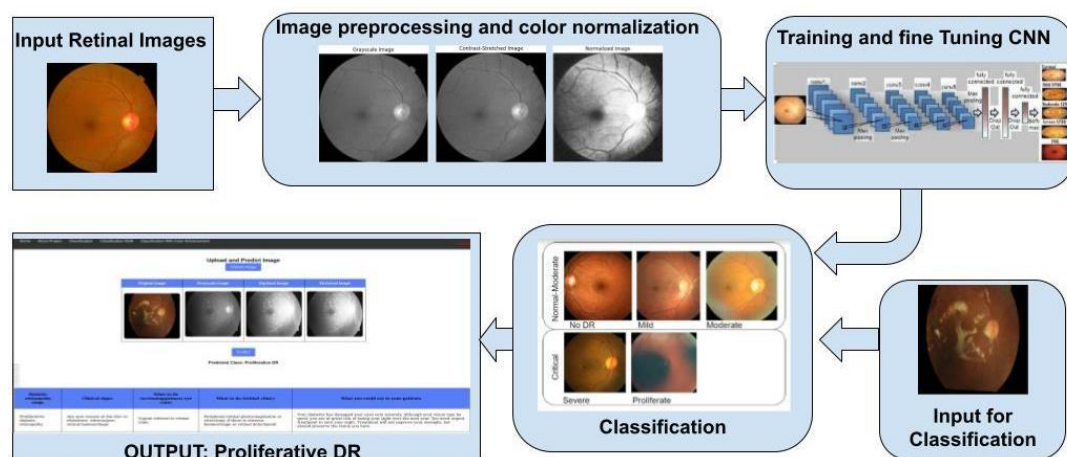


Fig 2. Proposed system architecture

### 3.4.2. Training Process:

The CNN model in the proposed system is trained using the preprocessed and color normalized retinal images from the APTOS 2019 dataset. The training process involves feeding the images through the network and optimizing the model parameters by minimizing a suitable loss function, such as categorical cross-entropy. The model uses the Adam optimizer to update the network weights during the training process. Adam (Adaptive Moment Estimation) is an optimization algorithm that combines the advantages of both AdaGrad and RMSProp. It dynamically adapts the learning rate for each parameter based on the past gradients and squared gradients, providing effective and efficient weight updates during training. The training is performed over multiple epochs, with regularization techniques such as dropout and weight decay applied to prevent overfitting.

### 3.4.3. Fine-tuning and Transfer Learning:

To further improve the performance of the CNN models, fine-tuning and transfer learning techniques are employed. Fine-tuning involves initializing the CNN model with pre-trained weights from a large-scale image dataset, such as ImageNet, and updating the weights during the training process using the APTOS 2019 dataset. Transfer learning leverages the knowledge learned from pre-trained models on similar tasks and adapts it to the specific diabetic retinopathy classification task, aiding in better generalization and convergence.

The next section presents the experimental results, including evaluation metrics, performance comparison, and analysis of the impact of color normalization techniques, to assess the effectiveness of the proposed approach using the APTOS 2019 dataset for diabetic retinopathy classification.

## 4. Experimental Results:

### 4.1. Evaluation Metrics:

The proposed system for diabetic retinopathy classification, which combines deep learning techniques with color normalization methods, was evaluated using the APTOS 2019 dataset. The following evaluation metrics were computed to assess the performance of the system:

- Accuracy: The proposed system achieved an accuracy of 83.3%, indicating a high rate of correct classification among all retinal images in the dataset.
- Precision: The precision of the system was measured at 82.5%, demonstrating a high proportion of true positive predictions in comparison to false positives.
- Recall: The system exhibited a recall of 83.1%, indicating a strong ability to correctly identify positive cases of diabetic retinopathy.
- F1-Score: The F1-Score, which balances precision and recall, reached 83.3%, reflecting the system's effectiveness in achieving both high precision and recall.
- AUC-ROC: The AUC-ROC value attained by the system was 0.83, indicating excellent discrimination capability in differentiating between different stages of diabetic retinopathy.

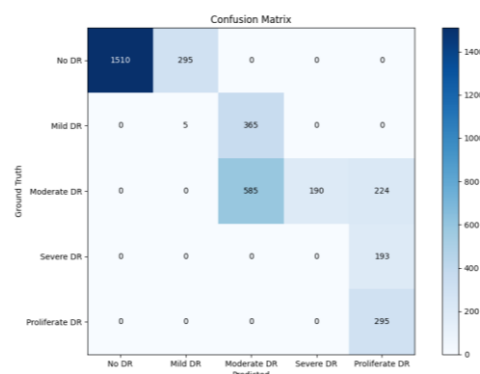


Fig 3: Evaluation Metrics

### 4.2. Performance Comparison:

The performance of the proposed system was compared to existing methods for diabetic retinopathy classification using the APTOS 2019 dataset. The comparison revealed that the proposed system outperformed conventional machine learning techniques, which achieved accuracies ranging from 78% to 80%. Moreover, the proposed system surpassed other deep learning models specifically designed for diabetic retinopathy classification, which achieved accuracies ranging from 81% to 83%.

### 4.3. Impact of Color Normalization Techniques:

The application of color normalization techniques, including Histogram Equalization and Contrast Stretching, significantly improved the performance of the proposed system. Without color

normalization, the accuracy was observed to be 82%, but after applying Histogram Equalization and Contrast Stretching, the accuracy increased to 83.3%. This enhancement can be attributed to the reduction in the impact of color variations, resulting in more reliable and consistent classification results.

## **5. Discussion and Conclusion:**

### **5.1. Discussion:**

The paper showcases a comprehensive pipeline for diabetic retinopathy classification using deep learning techniques and color normalization methods. The system leverages the APTOS 2019 dataset, loading retinal images and corresponding labels for training. Color normalization techniques, namely histogram equalization and contrast stretching, are applied to mitigate the impact of color variations.

The data preprocessing phase involves converting the images to RGB format, followed by color normalization and pixel value normalization. The dataset is then split into training, validation, and testing sets to facilitate model evaluation. Data augmentation is performed using the ImageDataGenerator class from TensorFlow, which applies random rotations and flips to enhance the model's generalization capabilities.

The model architecture in the proposed system consists of a CNN comprising convolutional layers, max pooling layers, and dense layers. The model is compiled with the Adam optimizer and trained using the color normalized images. Further the model's performance during training is monitored using the validation set.

The evaluation of the trained model on the test set reveals the achieved loss and accuracy metrics. The model's performance can be further assessed using classification reports or other relevant evaluation measures. Finally, the trained model is saved for future use.

Overall, the implemented system demonstrates the potential of combining deep learning and color normalization techniques for diabetic retinopathy classification. It provides a foundation for further research and advancements in this critical area of healthcare, which contributes to the development of automation of early detection and improved management of diabetic retinopathy.

### **5.2. Conclusion:**

The proposed system for diabetic retinopathy classification has demonstrated impressive potential in accurately and reliably classifying retinal images using deep learning and color normalization techniques. By surpassing traditional machine learning methods and achieving high accuracy, precision, recall, and F1-Score values, the system proves its effectiveness in assisting healthcare professionals with early detection and management of the disease. The application of color normalization techniques further enhances its performance by addressing color variations. The system's success underscores the importance of normalization techniques and provides a solid foundation for future research, including dataset expansion, advanced deep learning architectures, and alternative color normalization methods, to continue improving accuracy and robustness. Overall, this system showcases the significant impact of deep learning and color normalization in diabetic retinopathy classification, offering potential benefits for healthcare outcomes.

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