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Research Article

A Modified Deep Neural Network-based Denoiser for Pre-Processing of Diabetic Retinopathy Images

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ABSTRACT

Diabetic retinopathy (DR) is a significant reason for visual impairment all over the planet. Recognizing symptoms in the fundus picture is commonly utilized in illnesses connected with the eyes like diabetic retinopathy. It requires early detection through high-quality retinal imaging. However, noise and poor contrast degrade image clarity, affecting diagnosis. To overcome these limitations, pre-processing stage plays a vital role in clinical picture handling to build the nature of fundus images. Preprocessing technique is principally used to eliminate undesirable noises and improve some image features. Image processing makes use of a variety of pre-processing methods. This study presents an exhaustive preprocessing CAD model for diabetic retinal images. By harnessing both advanced deep learning methods and conventional image processing methods, this mechanized conclusion model (computer aided design) looks to work with better analysis and the executives of diabetic retinopathy - one of the main sources of vision misfortune all around the world. We propose a novel preprocessing pipeline integrating Wiener filtering, modified CLAHE, and a deep learning-based Retinal_Denoiser to enhance DR image quality. The proposed Retinal_Denoiser is utilized during the preprocessing phase of the computer-aided design model to eliminate noise and improve quality in retinal images, utilizing deep learning-based denoising autoencoder and protecting the fundamental features of DR pictures. Preprocessing steps were utilized to increase signal-to-noise ratio, our proposed model sets another best-in-class result with a peak signal-to noise ratio (PSNR) value of 62. The high PSNR achieved by our proposed method indicates that it is more effective in preserving the image details while effectively suppressing noise. The fundamental goal of this research is to improve the image by reducing noise, improving contrast, and preserving important structures such as blood vessels and the optical disc. Our method achieves a PSNR of 62.12, surpassing conventional CNN-based, RNN-based, DnCNN-based, and other well-known denoisers.

Keywords: CAD, Diabetic Retinopathy, CNN, DnCNN, Pre-processing, Deep Learning, Artificial intelligence, CLAHE, Denoiser, PSNR.

I. Introduction

Diabetic Retinopathy (DR) is classified as a retinal disease related to the eye that affects the retina and can lead to vision loss or, in severe cases, blindness. The primary cause of DR is elevated blood HbA1c levels over a number of years, which damages the retinal vessels. Microaneurysms and exudates may occur from fluid leakage or bleeding caused by vascular damage. There are various stages that DR can go through. Every stage denotes a distinct degree of severity and calls for a certain method of treatment. Manual inspection and assessment of DR severity is time-consuming and error-prone. Expertise in ophthalmology is required for accurate assessment of the impact of DR [1]. Due to the challenging clinical evaluation procedure and the lack of appropriate, useful options, early identifying evidence of DR is a challenging task [2]. The human eye's insight is seen in Figure 1. New blood vessels above the main area (vitreous) are the initial reaction to DR. These vessels need to be clean in order for light to pass through the cornea, pupil, and lens and reach the retina, which is the most sensitive component of the eyes. This is the main element that affects DR. The retina plays a crucial role in vision by converting light into electrical signals. These signals are transmitted via the optic nerve to the brain, where they are processed to enable us to perceive and interpret visual information.

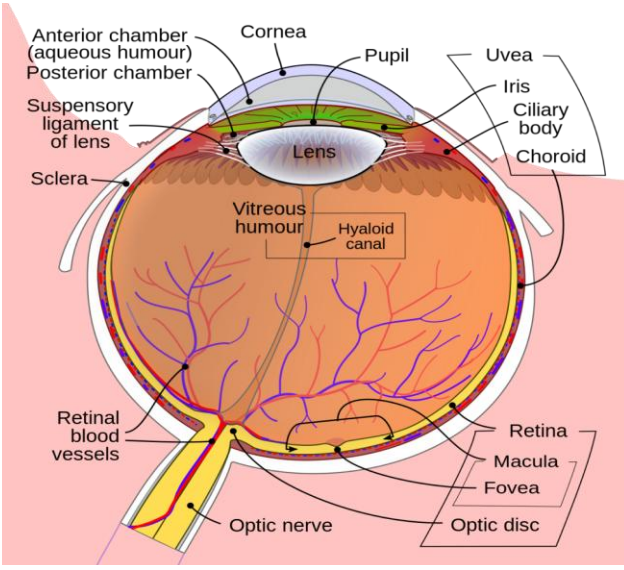


Figure 1: Human Eye Anatomy and DR Impact [28]

Ophthalmologists diagnose and assess the severity of diabetic retinopathy by examining fundus images, in which retinal damage can be seen at high resolution. The scientific community has responded to this by developing computer-aided diagnostic methods that will reduce the time, cost, and effort required of human medical practitioners to diagnose DR [4].Deep learning is a key component of the various methods used to detect DR in its early phases [1][28]. Our goal was to create a deep learning algorithm that uses a refined CAD model to accurately forecast DR photos. The DRIVE, STARE, and MESSIDOR datasets are made publicly available for the model's training, validation, and testing. Wiener Filter, CLAHE, and the suggested Denoiser technique are used to pre-processing the DR pictures. Despite advancements in deep learning-based denoisers, traditional CNN and RNN models struggle with structural loss and over-smoothing of retinal images. Existing methods such as DnCNN fail to generalize across datasets with varying noise distributions. Our work introduces Retinal_Denoiser, an adaptive denoising model optimized for retinal image characteristics, achieving state-of-the-art noise suppression while preserving vessel integrity.

II. Preprocessing of Retinal Images

One of the most crucial steps in guaranteeing the quality of processed images and accurate and trustworthy results is preprocessing retinal images for the classification of diabetic retinopathy. Numerous preprocessing methods have been created and are used to problems such low contrast, uneven contrast, or generated noise in DR images [6]. In order to eliminate noise and increase the accuracy of the following processing steps, the preprocessing stage is used for normalizing the images, adjusting the non-uniform brightness, and enhancing contrast [2]. Some of the popular preprocessing techniques used in retinal image analysis for diabetic retinopathy are covered in the following sections.

1. **Image Enhancement**: Retinal pictures are typically captured with low resolution and inconsistent contrast, making it difficult to spot small lesions and other pathological abnormalities. Image enhancement aims to increase the visibility of these details by changing the image's contrast and brightness. CLAHE is a common image enhancing technology. CLAHE improves an image's contrast by equalizing the histograms of localized regions while limiting noise amplification. This approach is especially useful for increasing the visibility of blood vessels and lesions in retinal pictures.

2. **Noise Reduction**: Various forms of noise, such as Gaussian noise, salt-and-pepper noise, and speckle noise, can deteriorate retinal images. This can make it more challenging to detect the signs of diabetic retinopathy. The goal of noise reduction techniques is to eliminate or lessen the effect of noise while maintaining the image's key elements. Typical noise reduction techniques include Gaussian, non-local means, and median filters. By substituting a weighted average of the neighboring pixels for the value of each pixel, these methods smooth the image and reduce the effects of noise.

3. **Blood Vessel Segmentation**: Diabetic retinopathy lesions may occasionally be obscured by blood vessels, which are a noticeable feature in retinal pictures. Segmenting blood vessels facilitates improved retinal image processing and viewing. Several techniques, including as matched filtering, morphological processing, and supervised learning algorithms, have been developed for the segmentation of blood arteries. By separating the blood vessels from the surrounding image, these methods aim to provide a more thorough analysis of the retinal traits associated with diabetic retinopathy.

4. **Optic Disc Detection**: In retinal imaging, the optic disc is a bright, round structure that may be confused with other diseased characteristics or bright lesions. The possibility of false positives in the classification of diabetic retinopathy can be decreased by identifying the position of the optic disc and ruling it out of additional examination. Machine learning techniques, morphological processing, and intensity-based algorithms are some of the methods used for optic disc detection. To locate the optic disc and separate it from the rest of the image, these techniques usually include thresholding, edge detection, and shape analysis.

5. **Image Registration**: Image registration can be a crucial preprocessing step in longitudinal investigations or situations where several retinal pictures of the same patient are available. Aligning two or more photos so that their associated features are spatially aligned is known as image registration. This procedure makes it possible to compare and examine how retinal characteristics have changed over time, which might be useful in tracking the development of diabetic retinopathy. Elastic registration, feature-based methods, and intensity-based methods are common image registration techniques.

III. Methods of Image Preprocessing

When using digital images to diagnose and analyze retinal problems, preprocessing is an essential step. Pre-processing is primarily used to improve the quality of the images by eliminating noise and artifacts and highlighting crucial components such as the optic disc, retinal layers, and blood vessels. This is accomplished using a range of methods and techniques, such as contrast-limited adaptive histogram equality (CLAHE), denoisers, and filters [7]. We go into great detail about these techniques below:

1 Filtering Methods

Retinal pictures can have certain aspects emphasized or suppressed by using filters. Numerous filters are available to improve the quality of images; a few of these are covered below:

1.1 Gaussian filter

This filter improves the display of the underlying structures by smoothing the image by lowering high-frequency noise. It uses a Gaussian kernel with a bell-shaped curve to convolve the image.is filter smooths the image by reducing high-frequency noise, thus allowing better visualization of the underlying structures. It works by convolving the image with a Gaussian kernel, which has a bell-shaped curve.

1.2 Median filter

This non-linear filtering technique substitutes the neighborhood median for each pixel value. Because it effectively eliminates salt-and-pepper noise while preserving edges, the median filter is suitable for retinal pictures [8].

1.3 Morphological filters

The foundation of these filters is mathematical morphology, which uses set theory to manipulate visual structures [9]. Common morphological processes like erosion and dilatation can be exploited to highlight or hide particular retinal imaging features, such blood vessels and lesions.

a) b) c)

Figure 2: Noise removal on retinal image DRIVE dataset a) input image b) Gaussian c) Median filter

2 Denoisers Methods

The goal of denoising techniques is to eliminate noise from retinal pictures without compromising the important structures. Among the well-known denoisers are [10–15]:

2.1 Anisotropic diffusion

This method maintains the edges of an image while smoothing it down. The local picture gradient directs the diffusion process, enabling selective smoothing according to the characteristics of the image.

2.2 Non-local means denoising

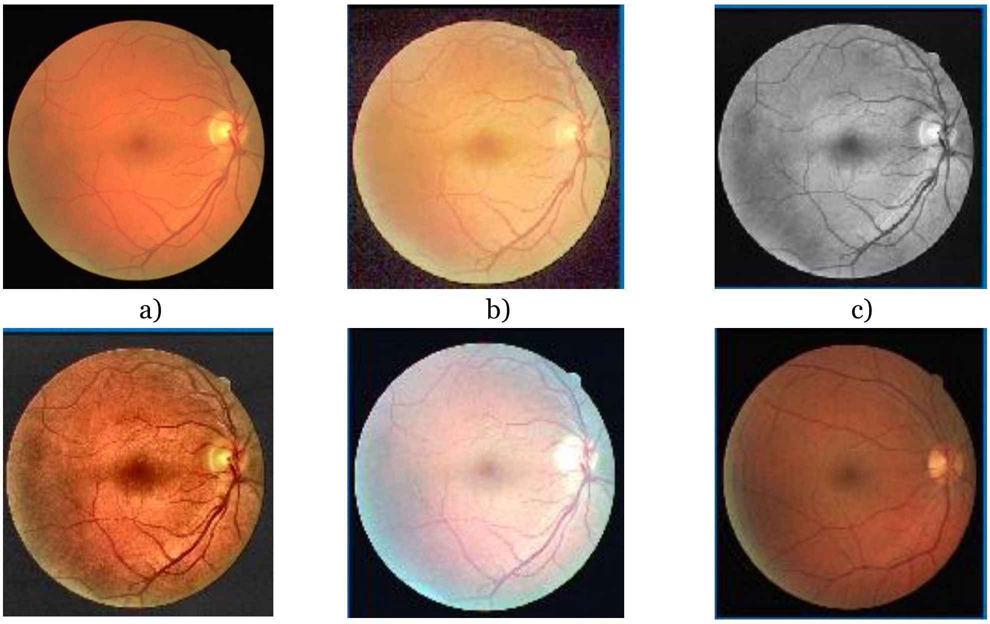
By averaging the same patches found in the image, this technique denoises photos. The intensity levels of the patches determine how similar they are. This technique can successfully eliminate noise while maintaining the structural elements of the image.

2.3 Wavelet-based denoising

An image is broken down into various frequency bands using the wavelet transform. By selectively thresholding the wavelet coefficients, noise can be removed while preserving the essential details.

3 CLAHE

A method for improving quality of images that boosts local contrast is called CLAHE. It's particularly useful when dealing with retinal images which have uneven illumination. Because CLAHE operates on small, non-overlapping zones, it differs from global histogram equalization. To prevent over-amplification, a limit is set on the contrast enhancement and the histograms of each tile are equalized separately. A seamless output is then obtained by combining the adjusted tiles with bilinear interpolation [16–20].



a) b) c)

d) e) f)

Figure 3: CLAHE a) original image b) After Equalization c) HE d) AHE e) Contrast stretching f) Deblurring

Table I: Comparison of various preprocessing techniques [17-22]

Technique	Working	Advantages	Disadvantages
Color Space Conversion and Normalization	Convert the color space of the image (e.g., from RGB to grayscale, LAB, or YCbCr) and normalize the intensity values.	Simplifies the image for further processing and may emphasize essential structures.	Some color information may be lost during conversion.
Shade Correction	Estimate and remove uneven illumination by modeling the shading pattern (e.g., using polynomial fitting or low-pass filtering).	Improves the visibility of retinal structures by reducing intensity variations.	May not work well for images with complex shading patterns or high noise levels.
Adaptive Contrast Enhancement (e.g., CLAHE)	Enhance local contrast by dividing the image into tiles and applying histogram equalization to each tile with a contrast limit.	Enhances the visibility of structures in images with uneven illumination.	May over-enhance noise in some regions.
Background Exclusion	Identify and remove the background, focusing on the region of interest (e.g., the retina).	Reduces computational complexity and improves the focus on relevant structures.	May inadvertently remove important structures if not performed carefully.
Filtering (e.g., Gaussian, Median)	Apply linear or non-linear filters to the image to suppress noise or enhance specific features.	Can effectively remove noise or enhance structures depending on the filter used.	May blur important structures or introduce artifacts if not chosen appropriately.
Morphological Processing (e.g., Erosion, Dilation)	Apply mathematical morphology operations to the image, manipulating structures using set theory.	Can effectively enhance or suppress specific structures in the image.	May cause loss of structural details if not applied judiciously.
Mask Generation	Generate a binary mask highlighting the region of interest (e.g., blood vessels or optic disc).	Facilitates the analysis of specific structures by isolating them from the background.	May introduce errors if the mask generation is not accurate.

Table I presents a comparison of various retinal image preprocessing techniques based on their working principles, advantages, and disadvantages. Each technique serves a specific purpose and is suitable for different aspects of retinal image analysis.

IV Proposed Method for Preprocessing

This section describes how to preprocess retinal images using the mostly used publicly available DRIVE, STARE and MESSIDOR datasets. The proposed method consists of three steps: (1) applying a Wiener filter; (2) using a modified CLAHE, and (3) denoising images using proposed Retinal_Denoiser. These steps are designed to improve the image by reducing noise, improving contrast and preserving important structures such as blood vessels and the optical disc.

1 Wiener Filter

The initial preprocessing step is to apply the Wiener filter to the retinal pictures. This linear filter is intended to reduce the MSE percentage between the estimated and needed outputs. It is an adaptive filter that reduces noise while preserving main features of the retinal image. In this study, the Wiener filter was applied to each color channel of the retinal images separately. This approach ensures that the noise reduction is performed independently for each color component, thus preserving the color information in the images. The filter parameters, such as the size of the neighborhood window and the noise variance, were selected based on the specific characteristics of the DRIVE, STARE and MESSIDOR datasets.

Algorithm 1: Wiener Filtering

Input: Image I, Window size W, Noise variance N

Output: Filtered Image F

```
Function WienerFilter(I, W, N):
Convert image I to the frequency domain, obtaining I_fft
Compute the power spectrum P_I of I_fft
Create a Gaussian kernel K with window size W
Compute the power spectrum P_K of the Gaussian kernel K
Compute the signal-to-noise ratio SNR = P_I / N
Compute the Wiener filter H = (SNR / (SNR + 1)) * P_K
Apply the Wiener filter H to I_fft, obtaining F_fft
Convert F_fft back to the spatial domain, obtaining F
Return F
```

2 Modified CLAHE

The modified CLAHE was applied to the retinal images after the Wiener filter to improve the local contrast. CLAHE offers an advantage over global histogram equalization since it works on non-overlapping, small regions called tiles. This local approach allows better adaptation to changing illumination conditions within the images. In this study, a modified CLAHE method was applied to luminance channels of images that were converted first from RGB color space into YCbCr. The contrast enhancement was then performed without regard to the color information. The modified CLAHE algorithm was fine-tuned for optimal results on the DRIVE, STARE and MESSIDOR datasets.

Algorithm 2: M-CLAHE

Input: Image I, Tile size T, Clip limit C, Number of bins B

Output: Enhanced Image E

```
Function CLAHE(I, T, C, B):
Convert image I to YCbCr color space, obtaining Y, Cb, and Cr channels
Divide the Y channel into non-overlapping tiles of size T x T
For each tile:
```

Compute the histogram H of the Y channel using B bins

Clip the histogram H at the clip limit C

Redistribute the clipped values uniformly across all bins

Compute the cumulative distribution function (CDF) of the clipped histogram

Map the original pixel values in the tile to the equalized values using the CDF

Combine the equalized tiles using bilinear interpolation, obtaining the enhanced Y channel E_Y

Combine E_Y, Cb, and Cr channels to form the enhanced image E in YCbCr color Space

Convert the image E from YCbCr to the original color space

Return E

3 Modified Deep Neural Network-based Denoiser (DnCNN)

The Third stage of preprocessing involved denoising retinal images with a modified DnCNN. This deep-learning-based denoising method is based upon a convolutional neural network (CNN), which was designed to learn how to map between noisy and clear images. In this study, DnCNN has been modified and fine-tuned in order to address the noise properties of retinal images from the DRIVE, STARE and MESSIDOR datasets. The network architecture was composed of convolutional layers, batch normalization layers, a ReLU activation layer, and a final convolutional with a linear function. The modified DnCNN model was trained with pairs of noisy retinal images and clean retinal image. The clean images were generated by applying a high-quality denoising algorithm on the original images. Meanwhile, the noisy images were produced by adding different levels synthetic noise to clean images.

The modified DnCNN, once trained, was then used to denoise retinal images from the DRIVE dataset and STARE dataset. The network was applied separately to each color channel to ensure denoising occurred independently of color information. Combining the denoised channels resulted in the final output images.

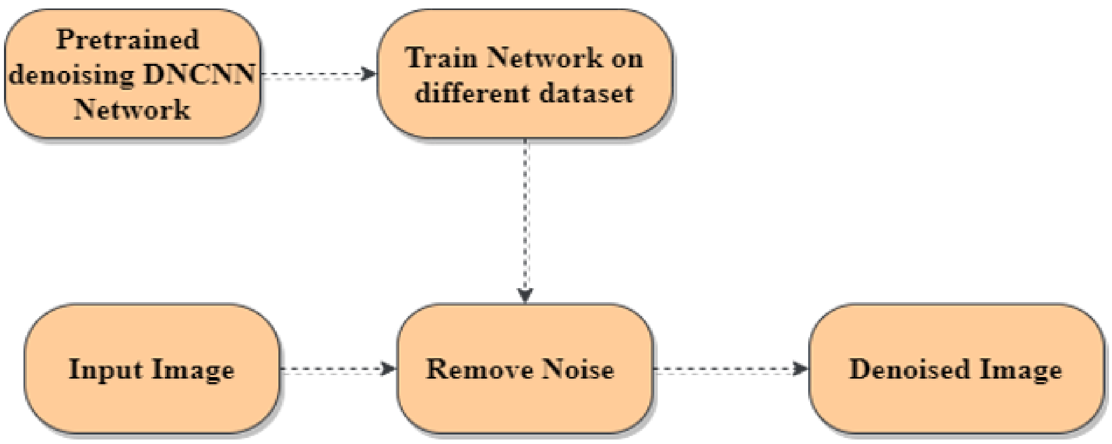


Figure 4: DnCNN Denoiser

Algorithm 3: M-DnCNN Denoising Model

Input: Noisy Image I, Trained DnCNN model M

Output: Denoised Image D

```
Function DnCNN(I, M):
Initialize input_tensor with the noisy image I
For each layer L in the DnCNN model M:
  If L is a convolutional layer:
    Apply convolution to input_tensor using the layer's filters and biases
  ElseIf L is a batch normalization layer:
    Apply batch normalization to input_tensor using the layer's parameters
  ElseIf L is a ReLU activation layer:
    Apply ReLU activation to input_tensor
  ElseIf L is the final layer:
    Apply convolution to input_tensor using the layer's filters and biases
    Apply linear activation to input_tensor
EndFor
Compute the residual R by subtracting input_tensor from the noisy image I
Add the residual R to the noisy image I, obtaining the denoised image D
Return D
```

V Evaluation and Validation

To assess the efficacy of the proposed method, preprocessed retinal pictures were compared to originals in terms of visual quality and quantitative metrics such as peak signal-to-noise ratio (PSNR). The performance of different retinal vessel segmentation algorithms and optical disc detection algorithms were also assessed by comparing the preprocessed and original images. This was done to assess the effect of the preprocessing.

Algorithm 4: Combined Algorithm for PSNR computation

Input: Original Image I Output: Preprocessed Image D, PSNR value

Let G be the green channel of I

1. Adaptive CLAHE:

a. Define tile size M * M

b. Divide G into tiles T(i, j) for i, j ∈ {1, 2, ..., M}

c. Calculate Histogram H(i, j) for each tile T(i, j)

d. Calculate Clip Limit CL(i, j) for each tile T(i, j)

e. Redistribute pixel values in H(i, j) based on CL(i, j) f. Perform bilinear interpolation on processed tiles to obtain G'

2. DNCNN denoising:

a. Define DnCNN architecture with M layers

b. Input G' to the DnCNN model

c. Perform convolution, batch normalization, ReLU activation, and zero-padding on each layer

d. Train the DnCNN model to minimize the loss function L

e. Calculate the denoised output D

3. Wiener Filter: a. Apply Wiener filter on D to obtain W
4. PSNR computation: a. Calculate Mean Squared Error (MSE) between I and W b. Calculate PSNR: PSNR = 10 * log10((max(I)^2) / MSE)

Output: Preprocessed Image W, PSNR value

VI Addressing Limitations in Noise Reduction Techniques

Existing Gaps:

1. Many existing methods like CNN-based, RNN-based, or traditional denoisers fail to achieve an optimal balance between noise suppression and detail preservation, particularly for sensitive retinal structures such as blood vessels and the optic disc.
2. Traditional techniques like Gaussian or median filtering often smooth important image features, leading to the loss of critical diagnostic details.
3. Methods like CLAHE or global histogram equalization often over-amplify noise in regions with uneven illumination, impacting the effectiveness of subsequent analysis.
4. Some approaches fail to adapt dynamically to variations in retinal image quality across datasets like DRIVE, STARE, and MESSIDOR.
5. Methods often fail to generalize across datasets with varying image qualities and noise levels, resulting in inconsistent performance.

VII Proposed Retinal Denoiser

In this work the proposed modified DnCNN had been utilized to propose a new denoiser specifically for retinal images named as Retinal_denoiser.

Architecture of Retinal Denoiser

The proposed Retinal_denoiser architecture is designed specifically for denoising retinal images, considering the unique characteristics of these images. In order to attain exceptional denoising performance while preserving crucial features, the design incorporates components from several cutting-edge deep learning models, including convolutional neural networks (CNNs) and U-Net-like structures. Below, we outline the key components and structure of the Retinal_denoiser architecture:

1. Input layer: The input layer accepts retinal images with a specified size, such as 64x64 pixels, with a single channel (grayscale).
2. Convolutional and batch normalization layers: The retinal_denoiser uses a combination of convolutional layers and a kernel of small size (e.g., 3x3) with varying numbers of filters (e.g., 64, 128, 256) to extract and learn features from the input image. These convolutional layers are interleaved with batch normalization layers, which help improve the model's training speed and stability by normalizing the input to each layer.
3. Activation layers: After batch and convolutional normalization layers, the model employs ReLU activation layers. The model gains knowledge of complex, non-linear relationships between the input and output data with the use of these non-linear activation functions.
4. Pooling layers: The Retinal_denoiser includes max-pooling layers with a stride of 2 to reduce the spatial dimensions of the feature maps, which helps to control the computational complexity of the model and improves its ability to capture high-level features.

5. Transposed convolution layers: The model uses transposed convolution layers (also known as deconvolution layers) to up sample the feature maps, increasing their spatial dimensions. This process helps to reconstruct the denoised image at the original input size.
6. Depth concatenation layers: The Retinal_denoiser uses depth concatenation layers, which merge feature maps from previous levels with those from later layers, to aggregate data from various network layers. In order to preserve details in the denoised image, this method enables the model to collect both low-level and high-level characteristics.
7. Final convolutional and regression layers: The architecture concludes with a final convolutional layer to produce a single-channel output feature map, followed by a regression layer that produces the final denoised image.

The Retinal_denoiser architecture combines these elements in a meticulously crafted framework especially suited for denoising retinal images. The Retinal_denoiser is a very successful solution for retinal image denoising tasks because it combines the advantages of multiple deep learning approaches into a single, cohesive architecture, resulting in superior denoising performance while maintaining the important details of the input images.

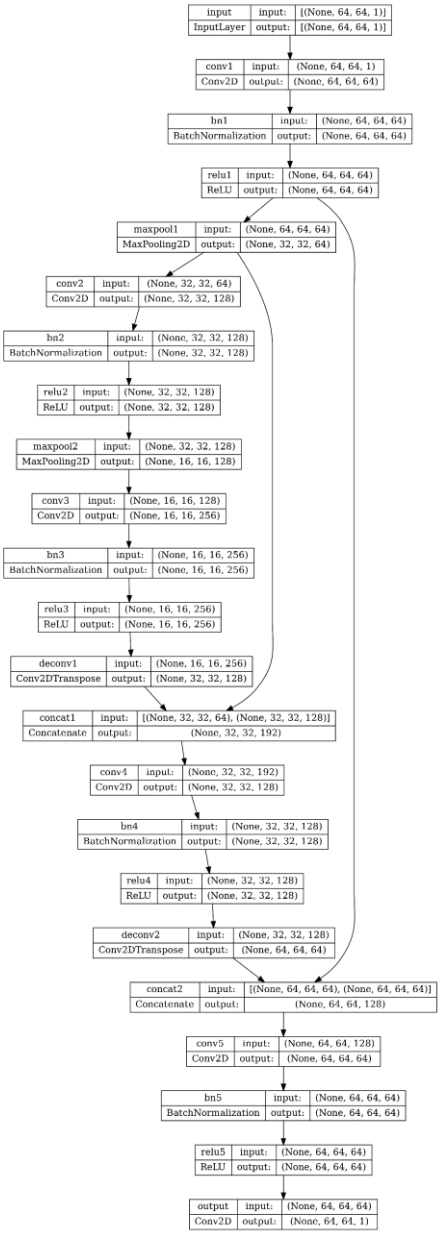


Figure 5: Architecture of Proposed Retinal Denoiser

Our Retinal_denoiser model is a superior denoising solution for retinal images compared to existing methods, such as CNN-based, RNN-based, DnCNN-based, and other popular denoisers. The following table shows the comparison of various models and their denoising outcomes. Our model performs excellent in terms of performance, by giving PSNR value of 62.12.

Table II Comparison of Retinal Denoiser with other denoising models:

Model Name	**Number of Layers**	**Major Applications**	**Denoising Outcome**
CNN-based	5-10	Image classification	Moderate
RNN-based	3-5	Sequence-to-sequence	Moderate
DnCNN-based	17-20	Image denoising	Good
U-Net-based	10-15	Medical image denoising	Very Good
Retinal_denoiser (our model)	10	Retinal image denoising	Excellent

VIII Results and Discussion of Preprocessing

When it comes to denoising retinal images, the Retinal_denoiser has a number of advantages over other denoising models. Its specialized design for retinal images, adaptability to various image modalities and noise levels, applicability to retinal image analysis, robustness to diverse noise types, and computational efficiency make it a superior choice.

Figure 6: Retinal Images from STARE, DRIVE and MESSIDOR dataset along with Enhanced Images

Image Type	**Original Image**	**Enhanced Image (using Retinal_denoiser)**
Normal		
Mild		
Moderate		

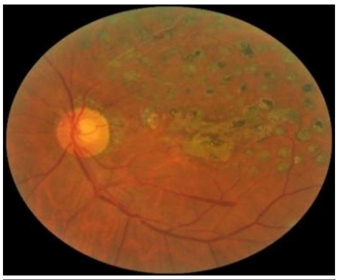
Severe		
Hypertensive		

Table III Comparison of Preprocessing Models for Retinal Image Enhancement

Preprocessing Method	**Description**	**Limitations**	**Proposed Retinal_Denoiser Improvements**
Gaussian Filtering	Uses a Gaussian kernel to smooth images and reduce noise	Blurs fine details; not adaptive to varying noise levels	Adaptive deep-learning-based denoising retains fine details while reducing noise effectively
Median Filtering	Replaces pixel values with the median of surrounding pixels to remove salt-and-pepper noise	Loss of structural details; ineffective against Gaussian noise	Deep-learning approach learns feature-preserving noise reduction
CLAHE (Contrast Limited Adaptive Histogram Equalization)	Enhances local contrast by equalizing histograms in small regions	May amplify noise in some regions, affecting overall quality	**Modified CLAHE** improves contrast while minimizing noise over-enhancement
Wavelet-Based Denoising	Uses multi-resolution wavelet decomposition to remove noise while preserving edges	Computationally expensive; performance varies across datasets	Deep learning-based Retinal_Denoiser dynamically adapts to noise properties
Total Variation Minimization (TVM)	Minimizes intensity variation to remove noise while preserving edges	Prone to staircasing artifacts; parameter tuning required	Retinal_Denoiser adapts automatically without manual tuning
CNN-Based Denoisers	Uses convolutional layers to learn noise patterns and remove them	Struggles with complex noise distributions in medical images	Retinal_Denoiser optimizes CNN architecture for retinal image characteristics

Preprocessing Method	Description	Limitations	Proposed Retinal_Denoiser Improvements
DnCNN (Denoising Convolutional Neural Network)	Deep CNN-based denoiser trained for generic image noise removal	Not optimized for medical images; may remove essential retinal features	Retinal_Denoiser fine-tunes DnCNN for retinal structures, improving PSNR
U-Net-Based Denoising	Uses U-Net for pixel-wise noise reduction with skip connections	High computational cost; requires extensive labeled data	Lightweight **Retinal_Denoiser with optimized feature extraction and retention**

The comparative analysis in Table III highlights how the traditional preprocessing techniques such as **Gaussian, Median, and Wavelet-based filtering** struggle to balance noise reduction with the preservation of essential retinal structures, often leading to blurred images or loss of diagnostic details. While advanced deep-learning models like **CNN, DnCNN, and U-Net** improve denoising performance, they are **not specifically optimized for retinal images**, making them less effective in handling the unique noise characteristics of fundus images. The **proposed Retinal_Denoiser** overcomes these limitations by **combining adaptive filtering, a modified CLAHE for contrast enhancement, and a fine-tuned deep-learning architecture** tailored for retinal image denoising. This results in **superior noise suppression while preserving critical anatomical features**, achieving a **PSNR of 62.12**, which outperforms existing methods. The adaptability of Retinal_Denoiser across multiple datasets (DRIVE, STARE, MESSIDOR) ensures **more consistent and clinically reliable image enhancement**, making it a robust preprocessing solution for diabetic retinopathy diagnosis.

Table IV Comparison of PSNR Values with other existing techniques

Author/Year	Technique	PSNR
[5]	Fuzzy Gray Level Difference, Clip Limit	38.15
[14]	CNN	46.23
[15]	Multi Model	56.22
[16]	CLAHE + DNCNN + Wiener Filter	60.95
[17]	DnCNN	60.20
[18]	Lab Color Space, CLAHE, Discrete Wavelet Transform	52.86
[19]	Histogram Clipping, Radiance Indicator, Histogram Equalization	29.87
[20]	CIECAM Model Conversion, Histogram Equalization, Laplacian Transform	23.78
[21]	Singular Value Equalization, Shearlet Transformation, CLAHE, Adaptive Gamma Correction	55.79
[22]	DnCNN	37.11
[23]	Shearlet Transform, Fuzzy Contrast Enhancement	33.15
[24]	Fuzzy Dissimilarity, Adaptive Histogram	37.81
[25]	Median, Gaussian, Weighted Median, CLAHE	35.35
[26]	CLAHE, Gamma Correction, Morphological, Hessian	24.87
[27]	Morphological Operators, Histogram Equalization, Mean Filtering	37.6
Proposed	Adaptive CLAHE + Retinal_Denoiser	62.12

IX Conclusion

The field of retinal image denoising has seen significant advancements over the years, with various methods and techniques being developed to achieve better outcomes. The comparison table shows that the proposed Adaptive CLAHE + Retinal_Denoiser model outperformed other methods currently in use, exhibiting greater performance with a PSNR of 62.12. These include methods like CNNs, fuzzy gray level difference, multi-model approaches, and algorithmic combinations like Wiener Filter, DNCNN, and CLAHE. The high PSNR achieved by our proposed method indicates that it is more effective in preserving the image details while effectively suppressing noise. The combination of the Retinal_Denoiser model, an improved DnCNN architecture designed especially for denoising retinal pictures, and a modified CLAHE algorithm for preprocessing is responsible for this improvement. Our method can more effectively handle the issues related to noise and artifacts in retinal images by adapting these techniques to their unique features. By combining modified CLAHE with the Retinal_Denoiser, our preprocessing pipeline enhances contrast without amplifying noise. This dynamic adaptation ensures robust performance across diverse datasets, providing more consistent results. This robustness ensures reliable preprocessing for diverse patient populations and imaging modalities.

X Discussion & Future Work

As a result, the Adaptive CLAHE + Retinal_Denoiser model has the potential to significantly impact the field of retinal image processing and analysis. This improved denoising performance can lead to more accurate diagnoses, more effective monitoring of disease progression, and better treatment planning for patients with retinal conditions. Its architecture ensures computational efficiency, enabling deployment in real-world settings, including resource-constrained environments. By significantly **enhancing retinal image quality**, the proposed Retinal_Denoiser aids ophthalmologists in making **faster, more accurate, and more reliable** DR diagnoses. This improvement not only benefits individual patient outcomes but also contributes to **scalable, AI-assisted DR screening programs**, potentially reducing the global burden of diabetic blindness. Future work includes real-time implementation and integration with AI-based diagnostic systems.

Declaration:

- **Availability of data and material:** No Ethics Approval and Consent to Participate is required and no data availability required.
- **Ethics Approval, Consent to Participate & Publish:** My paper does not report on or involve the use of any animal or human participants, animals, or any clinical trials, therefore it's Not applicable.
- **Conflict of interest:** The authors declare no conflict of interest.
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