Prediction of Diabetic Retinopathy using Deep Learning with Preprocessing

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Abstract

INTRODUCTION: When Diabetic Retinopathy (DR) is not identified promptly; it frequently results in sight impairment. To properly diagnose and treat DR, preprocessing of picture methods and precise prediction models are essential. With the help of numerous well-liked filters and a Deep CNN (Convolutional Neural Network) model, the comprehensive method for DR image preparation and prognosis presented in this research is described. Using the filters that focus boundaries and contours in the ocular pictures is the first step in the initial processing stage. This procedure tries to find anomalies linked to DR. By the usage of filters, the excellence of pictures can be developed and minimize disturbances, preserving critical information. The Deep CNN algorithm has been trained to generate forecasts on the cleaned retinal pictures following the phase of preprocessing. The filters efficiently eliminate interference without sacrificing vital data. Convolutional type layers, pooling type layers, and fully associated layers are used in the CNN framework, which was created especially for image categorization tasks, to acquire data and understand the relationships associated with DR.

OBJECTIVES: Using image preprocessing techniques such as the Sobel, Wiener, Gaussian, and non-local mean filters is a promising approach for DR analysis. Then, predicting using a CNN completes the approach. These preprocessing filters enhance the images and prepare them for further examination. The pre-processed images are fed into a CNN model. The model extracts significant information from the images by identifying complex patterns. DR or classification may be predicted by the CNN model through training on a labeled dataset.

METHODS: The Method Preprocessing is employed for enhancing the clarity and difference of retina fundus picture by removing noise and fluctuation. The preprocessing stage is utilized for the normalization of the pictures and non-uniform brightness adjustment in addition to contrast augmentation and noise mitigation to remove noises and improve the rate of precision of the subsequent processing stages.

RESULTS: To improve image quality and reduce noise, preprocessing techniques including Sobel, Wiener, Gaussian, and non-local mean filters are frequently employed in image processing jobs. For a particular task, the non-local mean filter produces superior results; for enhanced performance, it may be advantageous to combine it with a CNN. Before supplying the processed images to the CNN for prediction, the non-local mean filter can assist reduce noise and improve image details.

CONCLUSION: A promising method for DR analysis entails the use of image preprocessing methods such as the Sobel, Wiener, Gaussian, and non-local mean filters, followed by prediction using a CNN. These preprocessing filters improve the photos and get them ready for analysis. After being pre-processed, the photos are sent into a CNN model, which uses its capacity to discover intricate patterns to draw out important elements from the images. The CNN model may predict DR or classification by training it on a labeled dataset. The development of computer-aided diagnosis systems for DR is facilitated by the integration of CNN prediction with image preprocessing filters. This strategy may increase the effectiveness of healthcare workers, boost patient outcomes, and lessen the burden of DR.

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1. Introduction

DR it is a vision disorder which results from a disease called Diabetes Mellitus. For the development of numerous abnormal ocular infections, DR promotes inflammation and blood vessel breaches in the layers of the retina. Individuals that have diabetes for longer, like 10–15 years, are more likely to experience it [1]. It is estimated that 73 million people in India have diabetes [2]. The fundus of the retina detects numerous DR retinal defects for annotated images and any extra therapies that may be required. The early identification of DR is a difficult endeavor due to the laborious medical evaluation process and the lack of appropriate therapeutic options. As a result, such a health problem requires sophisticated tools for precise evaluation and therapy.

Investigators have suggested smart professional systems that use DL to evaluate and detailed examination of the DR characteristics in those images that are affected by fundus to solve the difficulties of time-consuming DR identification. When compared to conventional techniques, expert models [3] are more efficient in terms of time, extraction of features, error identification, and early detection and therapy [4]. These intelligent systems use the fundus pictures as their initial input, that are then examined and argument for the identification of important characteristics [5], allowing them to classify DR as No Diabetic Retinopathy (NDR), Mild Non-Proliferative DR (Mild NPDR), Moderate NPDR, Severe NPDR, and Proliferative Diabetic Retinopathy (PDR).

Here are the categorization categories for DR that is most frequently used.

No Diabetic Retinopathy (NDR): This classification denotes that the retinal pictures do not contain any indications of DR.

Mild Non-Proliferative Diabetic Retinopathy (Mild NPDR): Microaneurysms (little blood vessel bulges), minimal retinal hemorrhages (tiny bleedings), and/or mild retinal edema are the hallmarks of mild NPDR.

Moderate NPDR: Increased microaneurysms, more noticeable retinal hemorrhages, and/or moderate retinal edema are the hallmarks of mild NPDR.

Severe NPDR: Significant retinal edema, cotton wool patches, extensive retinal haemorrhages, and/or blocked blood vessels are all signs of severe NPDR.

Proliferative Diabetic Retinopathy (PDR): Improvement of the aberrant plasma vessels on retina characterizes PDR, the most severe form of DR.

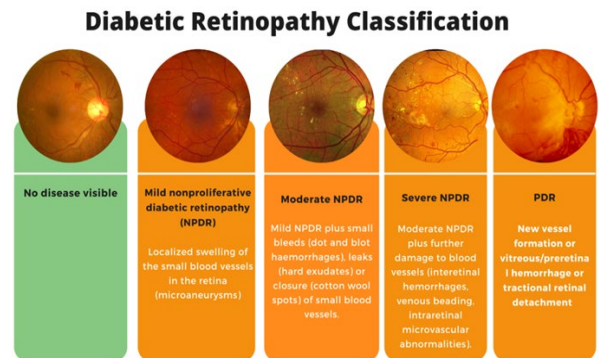The following figure 1 shows the various DR classifications.

Figure 1. Diabetic Retinopathy Classification

2. Significance of Diabetic Retinopathy Prediction

The importance of DR forecasting is multifaceted and has great value in the medical industry. Some salient features are emphasizing the need of anticipating DR.

Timely Detection: DR is an incurable illness that, if left untreated, can result in permanent impairment to the retina and cause sight loss. Diagnosing DR early on enables prompt action and suitable treatment options to avoid or slow down the development of the illness, thereby improving the likelihood of safeguarding sight and enhancing the health of patients.

Preventive Actions: By recognizing those who are at risk for getting DR, physicians can start taking measures to avoid it. People can lower their risk of getting or worsening DR with periodic monitoring along with suitable therapies, such as optimizing glucose levels and BP control. Identification of those at greatest risk who are most likely to benefit from measures to prevent harm depends heavily on forecasting.

Resource Management: DR prognosis aids in resource optimization by giving sufferers who need immediate assistance the highest priority. Medical professionals can effectively deploy resources and guarantee prompt connections for additional testing and therapy by recognizing patients who are at high risk of problems that could endanger their vision. With this preventive strategy, the pressure on medical facilities is reduced, and care for patients is improved.

Individualized Treatment Programs: Medical providers can modify methods of therapy according to the degree of seriousness and development of the disease by forecasting DR. The choice of suitable therapy options, such as laser-based photocoagulation, intravitreal administering medication, or surgical treatments, is made possible by the early detection of DR. Better results and an improvement in the standard of life among patients can result from customized therapy programs.

Tracking the growth of an Illness: Models of prediction for DR offer significant insights into how the condition develops as time passes. Medical professionals can evaluate the efficacy of medical treatments and modify their care strategy as necessary by constantly tracking retinal changes. The use of longitudinal forecasts aids in monitoring the development of diseases, making wise decisions, and assuring the best possible care for patients.

Patient Participation and Training: Educating people on their visual condition and related dangers, DR helps people take control of their health. Individuals who are conscious of their vulnerability to DR can take preventative measures to control their blood sugar levels, follow their medication regimens, and schedule routine eye exams. Participation by patients is facilitated by knowledge of the illness, which also encourages self-care.

3. Related Works

In the industrialized world, where the prevalence of myopia is over 50%, DR constitutes one of the main causes. Initial recognition of DR lessens the hazard of serious loss of eyesight. The manual recovery of the attributes is the main focus of the existing analysis. However, Bilal, G et al, 2021 makes an effort to instinctively recognize DR in their various groups using a novel strategy centered over the DNN of Grey Wolf optimization (GWO). Size and reliability of the dataset are improved using the theory of generic and Gaussian space databases to address issues with unbalanced datasets. The optional method is trained and examined by utilizing both the original and newly added data sets. When this study, CNN's model accuracy for a larger data set is 0.9691, which is excellent in comparison to the given data and other methods. [6]

The group of eye issues known as DED (Diabetic Eye Disease) impacts patients with diabetes. Finding DED in retinal fundus imaging is important because prompt diagnosis and therapy can eventually reduce the risk of vision loss. Preliminary DED detection and categorization heavily rely on the retinal fundus picture. The construction of an appropriate diagnosis model from a retina fundus picture is strongly dependent on the amount and standard of the images. This Rubina Sarki et al., 2021 offer a systematic investigation into the value of image analysis for DED categorization. The outcomes of the investigations carried out demonstrated sufficient accuracy rate, specificity value, and sensitivity information, and the best accomplishment with reliability for DED categorization issues was achieved using conventional image processing techniques with a newly established CNN design [7].

Excessive levels of glucose in the blood may cause diabetes, a condition that can damage the retina and lead to diabetic retinopathy, which can result in loss of sight which is irreversible. The fundus oculi procedure entails locating the eyes so that a pathological examination can be done. Hanan A. Hosni Mahmoud 2022 uses a technique in this investigation to forecast how DR would develop. For the identification of DR progression using DL (Deep Learning) models, there is an analysis needed. To anticipate the advancement of DR, propose an R-CNN (Recurrent CNN) model in this study to identify an impending field of vision examinations. In this study, a standard set of 7000 eye images from individuals without DR development cases across time is used. The training phase uses about 80% of the given dataset's ocular scenarios, followed by testing and validation using 10% and 10% of the actual cases, respectively. The seventh test will be assessed with R-CNN results after input from the first six visual field experiments is used. Regression modeling and the HMM (Hidden Markov), approach are contrasted in terms of efficiency with the R-CNN. Regression and HMM both have significantly lower average forecast precision than suggested R-CNN. R-CNN has the lowest categorization MSE (Mean Square Error) between the two competing methods in the majority of examinations for point wise categorization. Additionally, it is discovered that R-CNN is the model least negatively impacted by the seriousness of DR and declining consistency. Professionals can make recommendations on DR by the support of the R-CNN method's accurate prediction of a continuous field of vision test [8].

Plasma vessels in retina of eye of a person can develop visual vascular consequences from diabetes, including DR and macular edema, pictures of which are being employed for physical disease identification and detection. DL-based automated identification for this costly task might prove quite helpful. Even though they only employ a small portion of photos (1/4) in training, Jaakko Sahlsten et al., 2019 offer a DL system that detects accessible DR comparable to or better than those reported in the prior studies. They also benefit from improved image quality. They also offer innovative findings for correctly categorizing images based on medical five-grade DR and the initial findings for the four-grade diabetes-related macular edema scales, as well as new findings for various examination and medical grading methods for DR and macular edema categorization. These findings imply that a DL method could improve assessment and diagnosis efficiency while achieving outcomes that are above suggested levels and that the equipment could be used in clinical evaluations demanding higher grading [9].

DR is an extremely prevalent retinal eye condition that affects millions of people worldwide. Depending on how severe it is, it can cause total blindness. Both the blood

vessels examined in retina and tiny internal layers of the eyes are harmed. Timely identification of DR is crucial when combined with routine screening techniques to find moderate causes in manual commencement to prevent such problems. However, these methods of diagnosis are quite pricy and complex. The study by Posham Uppamma et al., 2023 makes several original contributions: first, giving a thorough history of the DR condition and conventional methods of diagnostics. The many imaging methods and DL applications in DR are then described. Third, many DR-detecting use cases and real-world situations are investigated, including those where DL approaches have been used. The paper concludes by highlighting prospective study avenues that can be investigated and have a positive impact on DR diagnosis [10].

When analyzing a face image for studies, preprocessing the image is necessary due to the variations in lighting conditions, poses, head orientations, and facial expressions considering the image quality is largely dependent on the efficiency of the recording device, such as a CCTV or webcam. Edge recognition, noise elimination, color normalization, and histogram equalization are prominent methods for preprocessing. The purpose of preparation is to raise the image's quality and increase its attributes in preparation for the next step. The Median filter is used in this study by G. Hemalatha et al., 2016 to normalize the colors and reduce noise. Enhancing the edge is achieved using a Gabor filter, and image contrast light is achieved using histogram equalization. Therefore, applying hybrid filters results in an increased quality picture, which aids in the effectiveness of generating results for any study procedure [11].

According to a review of medical reports, other than 10% of diabetic persons had a significant chance of developing issues in the eye. Eighty to eighty-five percent of persons with diabetes for over ten years also have DR, an eye condition. In clinics, DR disease is frequently seen and assessed using retinal fundus imaging. ML (Machine Learning) algorithms have a very difficult time processing the initial fundus images of the retina.

Pre-processing of the original retinal fundus pictures is done in this article by Dilip Singh Sisodia et al., 2017 using methods such as removal of green channel, histogram equalization, enhancement of images, and also resizing. Additionally, fourteen characteristics are taken out for quantitative evaluation from pre-processed photos. The Kaggle DR dataset is used for the tests, and the outcomes are assessed by taking into account the derived feature's average and SD (Standard Deviation). With a mean difference of 1029.7, the capillary area was the parameter that received the highest ranking in the analysis. The outcome has been attributed to its synchronous appearance in all three stages of DR pictures, namely mild, normal, and severe, and its total absence in typical diabetic images [12]. DR develops as an outcome of diabetes' damaging impacts on the eyes. Another condition that needs to be identified early is DR. Loss of vision could result if it is not addressed quickly. By the year 2200, as predicted that 1/3 of a million diabetes individuals have DR. DL has been recommended

as one of many efficient strategies for illness diagnosis. Abdüssamed Erciyas et al., 2021 proposed a DL-based technique that completely and consistently detects DR lesions and classifies the discovered lesions. The initial step of the suggested strategy entails gathering DR data from several sources to establish a data pool. Disorders are predicted and ROI (Region of Interest) is defined by utilizing Faster RCNN. Transfer learning and model of attention is utilized for the classification of images generated in the following phase. Using the Kaggle and MESSIDOR datasets as testing grounds, the approach achieved 99.1% and 100% ACC and 99.9% and 100% AUC accordingly. It can be shown that the acquired results are more effective when compared to previous findings that have been published [13].

4. Materials and Methods

4.1 Image Pre-processing

The Method Preprocessing is employed for enhancing the clarity and difference of retina fundus picture by removing noise and fluctuation. The preprocessing stage is utilized for the normalization of the pictures and non-uniform brightness adjustment in addition to contrast augmentation and noise mitigation to remove noises and improve the rate of precision of the subsequent processing stages. DED characteristics are also confined, retrieved, separated from fundus pictures for additional categorization in the pre-trained methods. Following figure 2 demonstrates the structure of the proposed DR classification system.
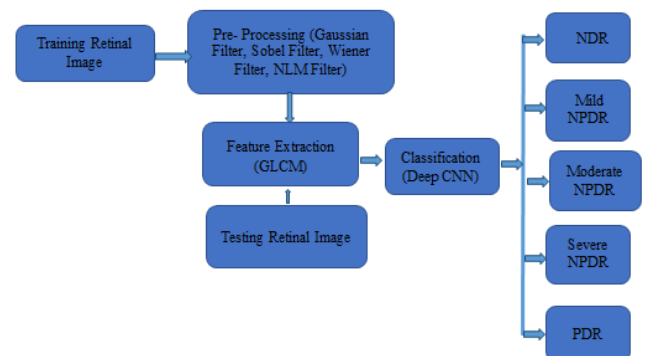

Figure 2. Diabetic Retinopathy Classification Systems

This part provides a quick overview of the preprocessing methods used in the study.

Gaussian Filter (GF)
The three bands in the fundus picture are red, green, and blue. Exudates are more visible in the green layer than they are in the red and blue channels. The green layer of the fundus picture likewise has a wider optic disc. Depending on the Gaussian operation, the Gaussian Smoothing computes the mean rate of nearby pixels. Impact of

disturbance and other lights is eliminated by this operator. It removes the high-frequency elements from the image by acting as a Gaussian low-pass filter [14].

$$Is(x,y) = Ig(x,y) * g(x,y) - - - - - (1)$$

Where $g(x,y)$ is a Gaussian method and $**$ stands for convolution. $Is(x,y)$ is the Gaussian-type noise and $Ig(x,y)$ is the element of the green stream [15].

Wiener Filter (WF)

The wiener filter [16] technique is a method that uses statistics to remove distortion from every pixel in a picture. It transmits the best possible exchange among reduction noise and reverses filtering. It is the ideal filter to use for reducing the total MSE during the noise flattening process. By placing an MSE restriction on the approximated and the initial image, it attempts to construct an image. Filter of the Wiener analyze the frequency domain data, but it fails for rebuild components of frequency that have been damaged by noise. Smallest wiener filter function in the domain of frequency is shown by Equation (2), and the minimal error is shown by Equation (3). The inversions of fading and noisy additives are instantly removed by the Wiener filter.

$$e^2 = E\{J(x,y) - \hat{j}(x,y)\} - - - - - (2)$$

$$(u,v) = \left[\frac{1}{D(u,v)} \frac{|D(u,V)|^2}{|D(u,V)|^2 + \frac{P_\eta(u,v)}{P_j(u,v)}} \right] K(u,v) - - - - $$

$$- (3)$$

Here $D(u,v)$ is called as degradation method; $|D(u,V)^2|, D^*(u,v) = D(u,v)D^*(u,v); D^*(u,v)$, the complex conjugate value of $D(u,v); P_\eta(u,v)$ noise power spectrum; $P_j(u,v)$, under graded picture power spectrum. Following figure 3 shows the innovative picture and the clarified retina image.
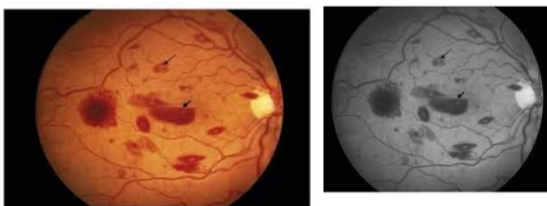

Figure 3. a) Original Image   b) Wiener Filter

Sobel Filter (SF)

The filter created by Sobel is used for recognizing boundaries. To figure out the way it works, it determines the changing level of image intensity at each of the pixels in the image. It establishes a change in the greatest increase in dark form light as well as the course and rate of that change. Based on how fast or slowly the image changes at each of the pixels, the result shows that the border is more inclined to be properly expressed in a pixel. It also shows how that edge is most likely to be oriented. When an image

filter is placed to a single pixel in a region of consistent luminosity, a vector with zero values is created. When utilized by something on a border, it creates a vector that points across the edge from lower to higher values.

To determine the gradient amplitude at each of the pixels in the picture, the gradient approximations provided by G_x and G_y are combined.

$$G = \sqrt{G_x^2 + G_y^2} - - - - - (4)$$

The direction of the gradients is measured using:

$$\theta = \arctan\left(\frac{G_y}{G_x}\right) - - - - - (5)$$

A θ value of 0 will represent a left side darker vertical border.

Non-local means Filter (NLM)

The nonlocal evaluation of pixels takes the role of the local comparing of patches in this kind of filter. For de-noise an existing pixel, this filter makes no expectations around where to place the best pertinent pixels. The geometric harmony in an entire neighborhood as well as the grey values at a single spot is related by the NLM filter [17]. The weight given to a pixel in NLM is independent of both spatial and intensity disparities [18].

The weighted mean value of all strengths of the pixels (X_a) in picture J serves as the restored intensity $v(i,j)$ of pixel X_a.

$$NLv(i,j) = \sum_{Xb \in J} W(Xa, Xb)u(Xa) - - - - - - - (6)$$

Here $W(Xa, Xb)$ indicates the average weight value assigned to $u(Xa)$ for restoring the Xa pixel [19].

Feature Extraction

The second-order statistics-based action that the GLCM performs in the images establishes the texture connection among pixels. Two pixels are typically utilized for this procedure. The generation of pixel-pair occurrences is represented by the occurrence determined by the differences in values of pixel intensity that are calculated by GLCM [20]. A medium with same count of columns and rows as the grey elements in picture is how the GLCM characteristics are presented. All pixel pairings can differ dependent where they are. Those matrix elements comprise second-order probability of statistical rates dependent on grey color of the rows and columns. If the intensity values are high the brief matrix is very huge. The grey level values that an image retains determine the GLCM size [21].

Instead of counting, GLCM is predicted to maintain the likelihood that any two intensities will occur together. And probabilities are displayed using the translated GLCM values [22]. To calculate estimates, the entire number of possible outcomes is multiplied by the amount of times assumed blend of intensities happens. The following are approximate probabilities that are converted from a GLCM:

$$P(i,j) = \frac{coInten_{i,j}}{\sum_{i=1}^{gr}\sum_{j=1}^{gr} coInten_{i,j}} ------ (7)$$

Here, ii and jj stand for column and row, $coInten_{i,j}$ $coInten_{i,j}$ is the number of times that ii and jj's intensity values have occurred together, and $grgr$ is overall amount of the rate of intensity.

Deep CNN

Automated detection and grading of the severity levels of diabetic retinopathy have demonstrated encouraging results when employing DR classification using CNNs. Due to their capacity to learn and extract useful information from visual data, CNNs are especially adept at analyzing retinal pictures. To analyze images, convolutional neural networks often use a feed-forward process. It is quite helpful for classifying and detecting objects. Every image on CNN is shown as an array of pixels. The convolutional neural network's foundation is created by the primary operation, which is convolution. The following is a description of each layer in a deep CNN network.

Convolutional Layer

Every CNN model's foundation is this layer. Each of the MxM-sized filters in a convolution layer performs a convolution operation. By touching the filter over the input image, the dot product is obtained among the filter and areas it has covered. The finished product is referred to as the feature map. It was possible to identify nook and corner through approach. This feature map is kept and given to additional layers afterward to study more intricate.

Pooling Layer

The pooling layer comes after the convolution layer. To make the feature map smaller, this layer is added. This in turn lowers the cost of computing. Numerous pooling operations exist. Max pooling chooses the major component from the region of feature map where the filter overlaps. The average pooling method computes the mean of the components that the filter overlapped. Among the layer of convolution and the completely linked layers, this layer serves as a link.

Fully Connected (FC) Layer

Bulks, biases, and neurons make up the FC layer of the network. The neurons that reside across the unseen layers and the output layers are connected by this structure, which serves as a bridge. These layers are positioned quite close to the output layer. A single lengthy feature vector is produced by flattening the feature map from the previous layer. Other fully linked layers get the flattened vector and conduct numerous mathematical calculations on it.

Dropout Layer

When all of the attributes are linked to the completely connected layers, we come across over fitting results. When a model is trained effectively but fails terribly on the test data, it is said to be overfit. A dropout layer is used to address the over fitting problem. Neurons are eliminated according to the parameter passed for the number of dropouts to decrease the overall complexity and size of the model.

Activation Function

One requirement for CNN method is thought to be the activation function. They are employed to comprehend the relationship among the network's input parameters. The process of activation decides which pieces of learned data should be used going forward and separates it from the ones which are not very helpful [23].

5. Results and Discussion

To improve image quality and reduce noise, preprocessing techniques including Sobel, Wiener, Gaussian, and non-local mean filters are frequently employed in image processing jobs. For a particular task, the non-local mean filter produces superior results; for enhanced performance, it may be advantageous to combine it with a CNN. Before supplying the processed images to the CNN for prediction, the non-local mean filter can assist reduce noise and improve image details.

Evaluation Metrics
MSE (Mean Square Error)
The MSE is widely used for measuring error sensitivity and the distinction between dual signals. MSE is described as the four-sided of the discrepancies between relevant pixels in the two pictures' pixel values. The signal for error $e_i = a_i - b_i$ $e_i = a_i - b_i$ in MSE is represented by the variation among two discrete image signals of a certain length NN, aa and bb, where a_i a_i and b_i b_i represent the magnitudes of the ith i^{th} pixel in aa and bb, respectively, and NN denotes the total quantity of pixel in the given pictures. The MSE of these dual signals is,

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(a_i - b_i)^2 -------- (8)$$

The gray image is represented as II and the JJ denotes the filtered picture. MSE among the two pictures $IandJ$ $IandJ$ is

$$MSE(I,J) = \frac{1}{M*N}\sum_{c=1}^{M}\sum_{d=1}^{N}(I(c,d) - J(c,d))^2 ----$$
$$-- (9)$$

Here $M*N$ $M*N$ represents the image size, $I(c,d) - J(c,d)$ $I(c,d) - J(c,d)$ describes the intensity of the unique and recreated picture pixel.

Table 1. MSE Analysis of NLM Filter with Other Existing Filters.

No.of Images	Gaussian Filter	Wiener Filter	Sobel Filter	NLM Filter
1	0.000148	0.000157	0.001192	0.0001118
2	0.0004522	0.000503	0.000973	0.000242
3	0.000589	0.000544	0.001069	0.000503
4	0.000158	0.000161	0.001084	0.000141

Table 2. PSNR Analysis of NLM Filter with Other Existing Filters

No.of Images	Gaussian Filter (dB)	Wiener Filter (dB)	Sobel Filter (dB)	NLM Filter (dB)
1	18.26	27.32	30.52	42.37
2	16.51	25.47	32.61	41.82
3	17.58	20.62	31.72	40.62
4	20.72	24.71	29.42	39.07

Figure 5. PSNR Analysis of NLM Filter with Other Existing Filters

The above Table 2 and Fig 5 represent the PSNR Analysis of NLM Filter with other existing filters obtained from four different retina images. From the results we can prove that PSNR of NLM Filter is very high that other filters. Higher PSNR means higher the performance.

SSIM (Structural Similarity Index Measure)
SSIM is a tool for calculating how similar two photos are to one another. On various windows inside an image, the SSIM index is calculated. The distance [21] between two windows with common sizes $N \times N$ is between x and y.

$$SSIM(x,y) = \frac{(2\mu_x\mu_y + c_1)(2\sigma_{xy} + c_2)}{(\mu_x^2 + \mu_y^2 + c_1)(\sigma_x^2 + \sigma_y^2 + c_2)} - - - -$$
$$- - - (12)$$

From the above equation, μ_x denotes the average value of x, μ_y represents the mean value of y, σ_x^2 describes the modification value of x, σ_y^2 indicates the modification value of y, and σ_{xy} represents the covariance value of x and y.
$c_1 = (k_1L)^2, c_2 = (k_2L)^2$ Two identifiers to steady the separation by a pathetic denominator, anywhere L denotes the rate of active pixel.
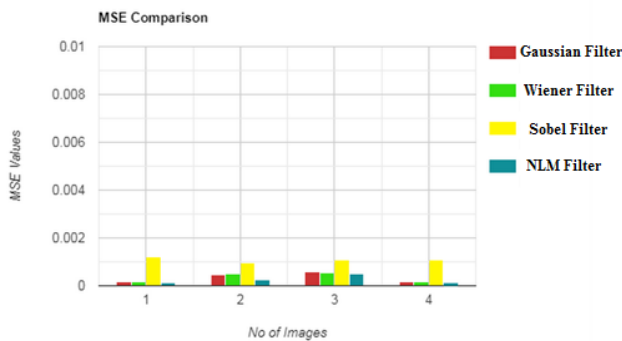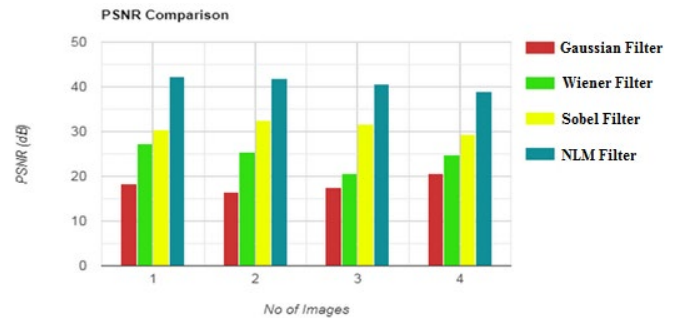

Figure 4. MSE Analysis of NLM Filter with Other Existing Filters Graph

The above Table 1 and Fig 4 represent the MSE Analysis of NLM Filter with other existing filters obtained from four different retina images. From the results we can prove that MSE of NLM Filter is very low that other filters. Lower MSE means higher the performance.

PSNR (Peak Signal to Noise Ratio)
The SNR is the relation of the signal-to-noise control in a picture signal that has been collected. SNR said that

$$SNR = = 10\, log_{10} \left(\frac{P_s}{P_n}\right)^2$$
$$= 10\, log_{10} \left(\frac{A_{signal}}{A_{noise}}\right)^2 - - - - - (10)$$

Where $P_s, P_n, A_{signal}, and\ A_{noise}$ stand for, respectively, signal power, power of the noise, amplitude of the signal, and noise power. For PSNR, equation (10)'s numerator is the square of the signal's peak value, and the denominator is equivalent to the MSE. In terms of PSNR, the peak change between the original and filtered image is calculated. The PSNR is a common way for image processing to express the MSE. The PSNR of the reconstructed picture J and the original image I is

$$PSNR\,(I,J) = 10\, log_{10} \frac{R^2}{MSE(I,J)} - - - - - - - (11)$$

R Denotes the highest applicable pixel data.

Table 3. SSIM Analysis of NLM Filter with Other Existing Filters

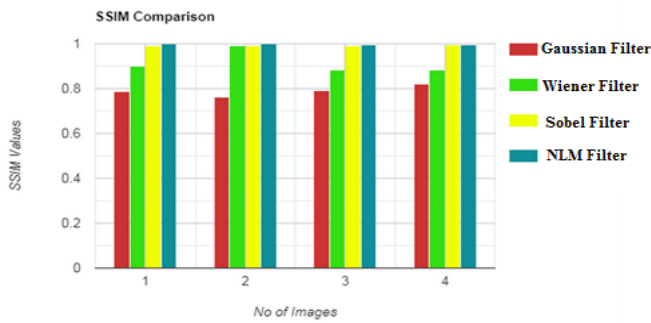| No.of Images	Gaussian Filter	Wiener Filter	Sobel Filter	NLM Filter
1	0.787	0.898	0.992	0.998
2	0.763	0.991	0.992	0.997
3	0.791	0.886	0.992	0.996
4	0.823	0.883	0.994	0.996

Figure 6. SSIM Analysis of NLM Filter with Other Existing Filters

The above Table 3 and Fig 6 represent the SSIM Analysis of NLM Filter with other existing filters obtained from four different retina images. From the results we can prove that SSIM of NLM Filter is very high that other filters. Higher SSIM means higher the performance.

6. Conclusion

A promising method for DR analysis entails the use of image preprocessing methods such as the Sobel, Wiener, Gaussian, and non-local mean filters, followed by prediction using a CNN. These preprocessing filters improve the photos and get them ready for analysis. After being pre-processed, the photos are sent into a CNN model, which uses its capacity to discover intricate patterns to draw out important elements from the images. The CNN model may predict DR or classification by training it on a labeled dataset. The development of computer-aided diagnosis systems for DR is facilitated by the integration of CNN prediction with image preprocessing filters. This strategy may increase the effectiveness of healthcare workers, boost patient outcomes, and lessen the burden of DR.

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