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***Research paper***

# A Proposed Segmentation and Classification Algorithm of Diabetic Retinopathy Images for Exudates Disease

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**Abstract**

The retinal image diagnosis is a significant methodology for diabetic retinopathy analysis. The diabetic retinopathy is a one of the major problematic diseases that provides changes in the blood vessels of the retinal that may issue blindness if it is not properly prevented and should be treated at the early stage. The Principle Component Analysis (PCA) algorithm is proposed to improve the contrast and brightness of the image. This paper presents the novel algorithm for blood vessel segmentation using unsupervised algorithm. The normalized graph cut segmentation with Curvelet transform is applied to segment the blood vessel to determine the thickness of the blood vessel and it is considered as one of the key feature to classify the diabetic retinopathy. The multi-resolution curvelet transform is used to improve the blood vessel segmentation. The PCA algorithm is used to provide the gradient of the image for accurate segmentation of blood vessel. Optic disc is an important key feature of retinal image that is first process for analysis behavior of disease identification. The optic disc is removed by applying morphological erosion and dilation operation. The proposed localization method consists of Hough transform to detect the circular and elliptic shape of optic disc and extracts the Region of Interest (ROI) containing optic disc. The modified expectation maximization (MEM) algorithm is proposed to segment the hard exudates from the fundus image to identify the disease of diabetics. The Gray level Co-Occurrence Matrix (GLCM) and bandlet transform is applied to calculate the features for classification. The convolution neural network (CNN) is applied to classify the images into normal or abnormal.

***Keywords:*** *Diabetic retinopathy, Image segmentation, Image enhancement, Principle Component Analysis, Curvelet Transform*

## 1. Introduction

Diabetic retinopathy is selected collectively of the common diseases that is caused by diabetic and is a major explanation for blindness among working-age individuals around the world. Diabetic Retinopathy could be a progressive disease which can be prevented without losing the vision by timely diagnosing at the early stage of the disease attack. Due to its prevalence and clinical significance the researchers has attempted to progress its diagnosing and treatment by developing algorithms to perform retinal image restoration, image enhancement and segmentation. Just in case of diabetic retinopathy blood vessels get broken cause them to leak which eventually ends up with blindness. The different types of diabetes in people give several types of retinopathy after few years of this progressive disease. Diabetic retinopathy of any structure widens closely with all patients having type 1 and type 2 diabetes diseases. Diabetic Retinopathy (DR), a general condition of the attention Caused in having Diabetes Mellitus will cause many complications vision loss being the foremost at hand. Early symptoms of DR represent the prevalence of small, red dots called micro-aneurysms within the retinal surface followed by larger hemorrhages. Once the blood vessels become easily broken and area unit broken, proteins break from them into the retina, giving rise to yellowish-white exudates. Hard exudates any arise complications if they combine and extend into the macular region inflicting Diabetic Macular Edema. This ends up in fast vision loss within the patients [1]. Early detection of the symptoms of DR will immensely cut back the chances of progression of loss of vision with timely treatment.

The essential for automatic segmentation algorithms may aid in detecting these conditions by characteristics and segmenting exudates, if present, within the structure retinal image of the attention. To find out the optic disc localization morphology based approach is employed. At the start to scale back the impact of non-uniform illumination and noise, the retinal image is pre-processed. After pre-processing we have obtained the most probable location of the optic disc by evaluating bright pixels in retinal image enhancement and threshold operation. To avoid the case of exudates pathology detection as optic centre the detected optic disc centre is verified by the presence of main blood vessel. Since the blood vessel converge at the optic disc while exudates are not surrounded by blood vessels. The modified expectation maximization algorithm is applied to segment the exudates disease affected pixels from the fundus image [2].

Modified Expectation-maximization (MEM) algorithm rule is associate in unsupervised algorithm that computes maximum-likelihood estimates in an exceedingly given fundus image and this approach aims for density estimation of information points. This can be a usual approach for minimizing issues with most chance approach. It involves two stages: in E-stage we tend to calculate the chance (expectancy) and in M-stage the boosting (Maximization) of the chance estimates is finished. This method is iteratively preceded until convergence happen. The MEM algorithmic rule is employed for the exploration of the constraint accomplishing the utmost chance. The benchmarks of the method, is whichever in extreme range of repetitions to reduce the calculation time, or a minor error [3].

The most important contribution of the projected technique lies within the use of associate degree adaptive threshold for segmenting out the exudates from the structure fundus image. The mean and standard deviation of a specific retinal image has been strategically combined and to calculate the edge for segmentation of exudates. The proposed algorithm is tested on images of two completely different databases those are real time database and DRIVE database and is in a position to detect phase the exudates from the images. Another important contribution lies is that the use of geometrical options, orientation and distance from optic disc to correctly reject the false positives from the segmental images. Apart from optic disc and exudates, there are a unit several alternative pixels with similar intensities that area unit detected throughout the segmentation method. The proper rejection of such false pixels is necessary to extend the ultimate accuracy of exudates detection from the structure retinal images. So, the higher than mentioned options for individual objects are determined and area unit subjected to an automatic machine learning algorithmic program to kind them as either exudates or non-exudates pixels [2].

Figure 1 shows the fundus images with blood vessel and normal optic disc. The first procedure that determines exudates employs a gamma correction to boost distinction, the Otsu's adaptive threshold methodology is applied to binaries the segmented image, and a logic operation between the binary mask and therefore the threshold image is realized to induce the segmental exudates image.

**Figure 1:** Fundus Image

The second procedure is for blood vessels, in which we initial use the negative of the filtered image, then a anisotropic diffusion filter to remove noise and artifacts is applied, additionally a gamma correction is applied to enhance contrast and brightness, and image threshold (Otsu's method) is performed victimization international statistics to obtain the required object regions together with their edges. Segmentation of the blood vessels is obtained applying a morphological closing and a logical operation between the binary mask and therefore the threshold image [4].

## 2 Literature Survey

Balint Antal and Andras Hajdu., (2012) have proposed an ensemble based system to enhance micro aneurysm location. The reliable micro aneurysm recognizable proof in computerized fundus images about the retinal image preparing depends on the gathering structure that distinguishes the micro aneurysm. The accumulation system is broke down with the yield of different classifiers and the blend of interior component of micro aneurysm finders.

Akara Sopharak., et al, (2011) dissected the morphological method in an ideal way for successful location of micro aneurysm and optic disc detection on non-widened understudy and low-differentiate retinal images. To overcome the downside of Diabetic Retinopathy (DP) recognition, a novel approach for retinal blood vessel extraction utilizing a scientific investigation of shape and Space Subjective Fuzzy clustering Method is introduced.

Charu Sharma and Geeta Kaushik., (2014) describe that an automatic detection of retinal images can easily diagnose and screen diabetic retinopathy. Image segmentation is done using Neural Network and Fuzzy Clustering. This method becomes a failure in some noisy regions and the result regions become too bright, causing incorrect image segmentation.

The recognition of diabetic retinopathy arrange utilizing shading fundus images has been proposed by Pardeep Singh Sodhu and Kirtu Khatkar., (2014). Removing the highlights from basic retinal images, utilizing retinal image preparing procedure, at that point they are in to Support Vector Machine (SVM) utilizing Fuzzy C-implies clustering. This Fuzzy C-Means Clustering is a blend of SVM system furthermore, pre-preparing to enhance the veins and optic disc discovery. Cross breed approach is utilized to investigate and evacuate diabetic retinopathy. The issue as "k" intends to limit the neighborhood least.

## 3. Existing system

Previously, the region growing algorithm is used to segment the retinal image. Region growing-based techniques start from preliminary seed point and recover pixels of comparable behavior to divide the diabetic retinal image into homogeneous regions [5].

**Disadvantages of existing system**

The region growing algorithm required seed point selection procedure. The seed point selection varies from image to image. The automated seed point selection is not possible in the existing system due to the following reasons:

- The existing system has the pixel directionality mismatch.
- Efficient pixel segmentation is not possible.
- Vessel tracking is not implemented in the existing system.
- Inner vessel pixels cannot be segmented properly due to the low illumination and brightness.
- They are not fit for noise medical image edge detection because noise and edge belong to the scope of high frequency.
- The retinal blood vessel, optic disc and exudates segmentation are not automated and unreliable.

## 4. Proposed System

The proposed system gets input from the given dataset. Preprocessing methods are applied initially then followed by feature extractions to segment blood vessel, optic disc and exudates. Finally, to validate the image whether it is normal or abnormal, CNN classifier is applied. The block diagram showing the different stages of retinal image feature segmentation and classification of the disease is shown in figure 2.

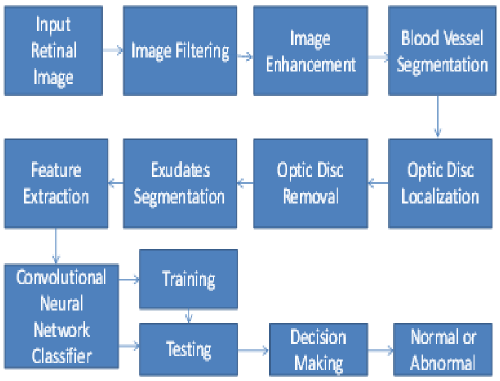



**Figure 2**: Block diagram for segmentation and classification of exudates

The following algorithms are proposed for efficient retinal image segmentation and classification with preprocessing task.

- Image Restoration – 2D Anisotropic Bilateral Filter (2D ABF)
- Image Enhancement – Principle Component Analysis (PCA)
- Blood Vessel Segmentation – Curvelet Transform based Normalized Graph Cut (NGC) Segmentation
- Optic Disc Removal – Morphological Operation
- Exudates Disease Segmentation – Modified Expectation Maximization (MEM) algorithm
- Classification – Convolution Neural Network (CNN)

### 1. Retinal Image Preprocessing

In the image preprocessing, the image filtering is an important task to eliminate the noises from the images. The input image is affect by impulse noise, the typical poverty model at point $(i, j)$ in a 2D matrix can be written as

$$y(i,j) = x(i,j) + n(i,j) \qquad (1)$$

Where $x, y$ and $n$ represent an input image, the noisy image, and the impulse noise, respectively. For successful filtering, it is popular to get a reliable degradation estimation function that can find the degree of the noise as well as the noise's pixels. The adaptive filter reflects on all pixels in the image in revolve and seems at its close by adjacent pixels to choose whether or not it is representative of its background. Instead of restore the pixel value with the mean of neighbor's pixel values, it is restored with the median of those values [6, 7]. The proposed 2D ABF filter differs from the existing median filter. The 2D ABF performs spatial functioning to find which pixels in an image have been degraded by noise. The 2D ABF organize pixels as noise by evaluating each pixel in the image to its neighbor pixels. Figure 3 shows the 2D anisotropic bilateral filtered image taken as the output for the preprocessing first step. The anisotropic diffusion filter is applied to the noisy input image. The noises are completely eliminated in the restoration process [8, 9].

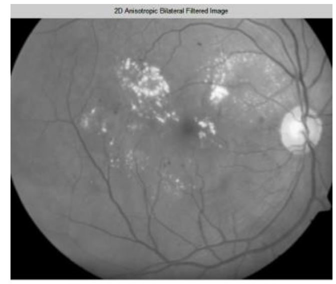



**Figure 3**: 2D Anisotropic Bilateral Filtered Image

### 4.1 Retinal Image Enhancement

Image enhancement is the process of adjusting digital image so that the results are most suitable for display. It is used to improve the quality of the image. The PCA is used to enhance the image. Adaptive Mean Adjustment is a computer image processing technique used to improve contrast in images. It modifies the allocation of the pixels to become more consistent and improves the pixels intensity in terms of brightness and contrast. In histogram equalization, a histogram displays the sharing of the pixel intensity values. Dark image will have low pixel values whereas a bright image will have high pixel values [10]. The histogram formula is given by,

$$Histogram = X(I,j) - \frac{Xmin(I,j)}{Xmax(I,j)} - Xmin(I,j) \qquad (2)$$

Where, X is the image, Xmin-Minima of the image, Xmax-maxima of the image. The contrast of the image is calculated as follows [11],

$$WCON = \frac{DN\max(window) - DN\min(window)}{DN\max(image) - DN\min(image)} \qquad (3)$$

An algorithm has been developed for image enhancement adaptive mean adjustment using principle component analysis. In PCA analysis, the lower and upper thresholding values are assigned for normalization. The normalization is used to minimize the difference between input image and processed image in terms of brightness. The proposed system has the capability to give adaptively enhanced image output in contrast. Figure 4 shows the enhanced image by applying the Principle Component Analysis, the contrast and brightness are improved.

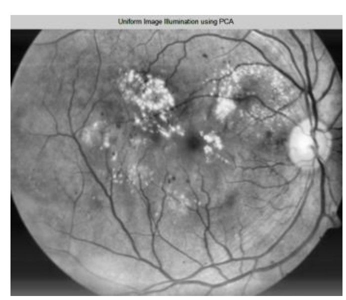



**Figure 4** : Image enhancement using Principle Component Analysis.

**Algorithm 1: PCA based Adaptive Mean Adjustment for Image Enhancement**

Step1: Input Image to be filtered

Step2: **Case 1**: For 3 channel image (RGB)

Step3: Set the threshold values (Median)

Step4: Set lower and upper threshold values to calculate the Minima and Maxima.

Step5: Apply the double Precision to the Image

Step6: Apply Normalization

Step7: Calculate the Mean of the Gray Scale Value

Step8: Adjust the Mean Value

Step9: **Case 2:** 1 Channel Image (Gray)

Step10: Set lower and upper threshold values to calculate the Minima and Maxima

Step11: Color Image Threshold (Image Bandwidth)

Step12: Convert from RGB Image to NTSC Color format (to adjust Luminance, the intensity of light emitted from a surface per unit area in a given direction)

Step13: Calculate the Mean adjust value for Green layer using Color Image Upper Threshold

Step14: Calculate the Mean adjust value for Blue layer using Color Image Lower Threshold

Step15: For Case 1 and Case 2:Mean Adjustment for First Layer, Calculate Minima and Maxima

Step16: Apply formula (Image-Minima/Maxima-Minima)

Step17: Enhanced Image Output.

**2. Retinal Image Blood vessel**

The blood vessels generally show a coarse to fine centrifugal distribution and appear as a mesh-like structure or tree-like structure [12]. Their morphological features, such as length, width and branching, play an important role in diagnosis, screening, early detection and treatment of various cardiovascular and ophthalmologic diseases such as stroke, vein occlusions, diabetes and arteriosclerosis. The investigation of morphological highlights of retinal veins can segment a favorable location and treatment of a disease when it is still in its beginning period. Besides, the examination of retinal veins can aid assessment of retinal image enrollment [13].

## 4.1 Blood Vessel Segmentation

The Curvelet transform based blood vessel segmentation is proposed to segment the blood vessel to estimate the thickness of the blood vessel. The proposed algorithm is intended for retinal vessel segmentation. Contribution to the framework is a shading fundus image of human retina obtained by a fundus camera and the output is a binary segmented image which contains just the vessels. The differentiation of the fundus image has a tendency to be splendid in the middle and decrease along the edge, thus pre-preparing is basic to limit this impact and have a more uniform image. From visual perception, vessels by and large show the best complexity from the foundation in the green layer and along these lines the green layer is chosen from the difference upgraded images for additionally preparing. The difference between the blood vessel (foreground) and the background is by and generally poor in the fundus images [14].

## 4.3 Curvelet transform

The Curvelet transform has better presentation in edges like wavelets for its directionality and anisotropy, and is therefore suggestable for multi-scale edge segmentation of blood vessel of retinal images. The Curvelet coefficients in related to sub-bands are verified through objective function and take the unnecessary pixels other than blood vessel into account for more exact restoration and better segmentation [15].

## 4.4 Normalized Graph Cut Segmentation

After applying the Curvelet transformation, the image edges become sharpen to exact segmentation of blood vessels. The normalized graph cut method is utilized for the retinal blood vessel segmentation. It introduces an unsupervised process, gradient matrix to select a candidate window which may have retinal blood vessels. The normalized slice is used to separate the blood vessels on the chose window. Vessel following is utilized for post-processing to enhance results. Graph cut is a broadly utilized procedure for retinal images segmentation in computer vision and medical image analysis. It limits the vitality work comprising of regional (processing on foreground and background) limit terms (computed by pixel, surface, shading, and so on). A graph G(ν, E) is explained as a position of nodes ν and edges E linking adjacent nodes. There are two particular nodes called terminals, *S* source (foreground) and *T* sink (background). Edges among pixels are called n-links, while t-links are calculated to the edges linking pixels to terminals. All graph edges $e \in E$ counting n-links and t-links are associated some non-negative weight (cost) [16]. Graph cut is a subset of edges $C \in E$ that divide the graph as 2 classifications: those are foreground and background. G(c) = (ν, E\C) each cut has a charge which is distinct as the amount of the charges of the edges that it gives. A globally minimum cut on a graph with two terminals can be estimated accurately in low order polynomial time optimization using normalized graph cut segmentation. Figure 5 shows the Blood Vessel Segmentation using Curvelet transform based normalized graph cut segmentation.

**Algorithm 2: Blood Vessel Segmentation**

Step 1: The Gaussian Pyramid of the input retinal image is estimated.

Step 2: For various resolution regions, the gradient vector is estimated for every pixel by applying Canny Operator.

Step 3: The gradient matrix of the image is estimated by sliding window with respect to the size of the image.

Step 4: The Eigen values of gradient matrix should satisfy the conditions as the window size of image with candidate window should be same, and do search the intensity thresholding in the candidate window by the segmentation of blood vessel.

Step 5: The seed point of blood vessel is segmented, then follow the blood vessel o the direction generated by the eigenvector of gradient matrix.

Step 6: Rearrange the segmented pixels to form the graph cut of the blood vessel.


**Figure 5**: Blood Vessel Segmentation using Curvelet transform based normalized graph cut segmentation

### 3. Retinal Image Optic Disc

The optic disc contains the comparable attributes and impressive characteristics of hard exudates, the optic disc is recognized and removes to segment the exudates pixels accurately. The pixels characteristics of optic disc are same as exudates. When we segment the disease like exudates, the pixels contains in the optic disc will give false segmentation of exudates by segmenting the optic disc. To avoid this problem, we have to segment the optic entirely using morphological operation [17].

## 4.5 Optic Disc Removal Using Morphological Operation

The image acquired after the threshold contains the exudates, optical disc and the microaneurysms. It very well may be seen from the retina image that the optical disc is constantly situated at the left half or the correct portion of the image in the focal region, depends upon whether the left eye or the correct eye is imaged. A sub-image containing the optical disc can be shaped by extract the central row and the adjacent rows [17, 18]. Initially, the center line from the image is removed by finding the span of the image and the center esteem. Another 10% of the columns from the best and base region of the center line are added to the center column to shape a sub-image. The sub-image alone is sufficient to identify the optical disc and the exudates. In the sub-image, the quantity of articles is found by utilizing network between the adjoining pixels. After recognizing the articles, the border of each image is found. Since the micro-aneurysms are little spots, morphological activities are utilized to expel them from the sub-image. A square molded organizing component is utilized for the disintegration activity. Once the little images are evacuated, the sub image will contain the optical disc also, the exudates. The edge data is utilized to recognize the quantity of pixels in the various protests in the sub-image. It can be seen that the optical disc is typically the question with the biggest region. Henceforth, it is conceivable to expel the optical disc by looking at the region of various articles. Rather than finding the real territory, the quantity of pixels in the border of each protest is found. The question with the biggest number of pixels is the optical disc. All together to bar the likelihood of bogus recognition of exudates as the optical disc, shape data is additionally taken into account. Figures 6, 7 and 8 shows the optic disc segmentation, optic disc localization and optic disc removal.

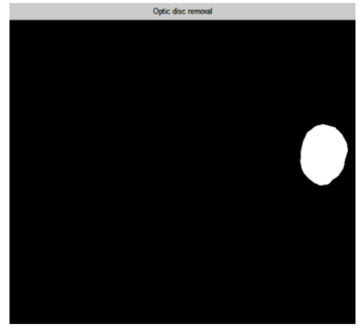



**Figure 6:** Optic Disc Segmentation


**Figure 7:** Optic Disc Localization


**Figure 8:** Optic Disc Removal

**Algorithm 3: Optic Disc removal**

Step 1: The optic disc of the retinal image is the high intensity region and has circular shape or elliptic shape.
Step 2: The optic disc pixels are characterized by a fast disparity in the intensity of adjacent pixels.
Step 3: The mask matrix for retinal image is calculated with zero values for background pixels using morphological operation.
Step 4: The mask matrix is used to differentiate the foreground and background pixels.
Step 5: The maximum intensity pixels with Hough transform shape of optic disc is searched using morphology search method of high contrast pixels in the optic disc.
Step 6: The center of mass of the high intensity region was taken as our initial point. Starting from this initial point eight 'directions' is considered: one direction for each 45 degrees in counter-clockwise. In each direction three points of interest are chosen (the ones for which there is a rapid variation in intensity with the adjacent pixel in that direction).
Step 7: All the eight directional pixels are reconstructed to form the optic disc.

### 4. Exudates

The segmentation of exudates is one of the key fact in the timely detection of diabetic retinopathy. The retina which look like as yellowish regions in fundus image is called exudates. Automatic detection of exudates is difficult because of considerable variation in brightness. Segmentation is the process of splitting a digital image into multiple segments. It is used to locate objects and boundaries in the image. So the exudates affected area is clearly shown. The segmented image is clustered and the gray scale image is converted into binary image using threshold. The soft clustering technique MEM clustering is used. In MEM each pixel of the image belongs to more than one cluster. In the clustering process the exudates is grouped accurately. To improve the accuracy in the image the Otsu threshold method is used to automatically perform clustering-based image threshold or reduction of a gray level image to a binary image. After removal of optic disc the exudates is detected in the image using modified Expectation Maximization segmentation algorithm. The hybrid version of fuzzy c means clustering and expectation maximization algorithm gives the modified expectation maximization (MEM) algorithm that have more accurate than other previous algorithms [18]. Figure 9 shows the exudates segmentation using proposed MEM algorithm.

**Algorithm 4: MEM algorithm to segment the exudates**

Step 1: Optic disc removed input image for exudates segmentation.

Step 2: Apply MEM algorithm.

Step 3: In MEM algorithm, the exudates pixels are expectation.

Step 4: Apply clustering technique to group only the expected pixels

Step 5: The grouping of the pixels is based on intensity

Step 6: The high intensity pixels are grouped as expected pixels.

Step 7: Apply Otsu thresholding technique to maximize only the exudates.

Step 8: Suppress other pixels than exudates.

Step 9: Output is the segmentation of exudates disease.


**Figure 9**: Exudates segmentation

### 5. Classification Method

The proposed system for class of retinal image data is built primarily based on Gray Level Co-occurrence Matrix (GLCM) by making use of unique classifiers. The system is split into 5 levels to categories retinal image data. First step is the statistics set collection, second is ROI extraction system, third is the pre-processing steps that's again divided into two steps filtering and enhancement, fourth is the feature extraction from GLCM and ultimate degree is class. Authentic retinal image data have one-of-a-kind types of noises, artifacts of their heritage, pectoral muscle tissue and many others that are unwanted for feature extraction and classification. For this reason a cropping operation has been applied on retinal image data to extract the ROIs which includes the abnormalities, other than the unwanted portions of the retinal image data. Image database offers all of the details about every retinal imagery through length in pixels, individual of history tissue, magnificence of abnormality, Xc and Yc coordinate fee of centre of abnormality, 'r' radius of circle enclosing the abnormality by the radiologists. This option vector contains relevant information and is used as input vector for classification. Capabilities may be labeled primarily based on color, texture and shape. In this proposed system, we are particularly involved about texture features and for extraction of functions; gray level Co-occurrence Matrix (GLCM) is used because it has been demonstrated as an effective tool for image data extraction. On this proposed system texture of the image data features specifically contrast, correlation, Energy, homogeneity is estimated.

### 6. Convolution Neural Networks Classification

The Convolution Neural Network (CNN) is applied to classify image into normal or abnormal. The Convolution Neural Networks has emerged as one of the most powerful tool-gaining knowledge of medical image classification, the accuracy of virtually all different conventional classification strategies or even medical imaging. The convolution system can simplify a retinal image containing millions of pixels to a set of small characteristic maps, thereby decreasing the measurement of input information at the same time as maintaining the maximum-critical differential features. The Most of the work is aware at the classification of small patches, known as Region of interest (ROI). An ROI is the region that is possibly to comprise exudates. That is commonly carved out of the complete image based on either clinical data or automatic segmentation. Figure 10 depicts the convolutional neural network classification.

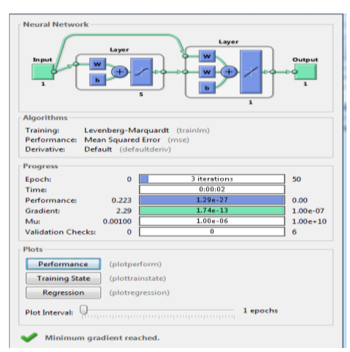
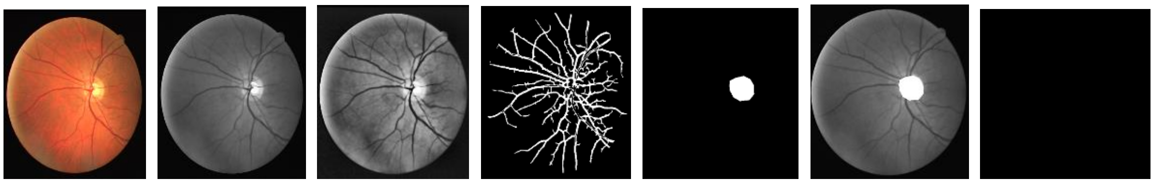


**Figure 10**: Convolutional Neural Network Classi**fication**

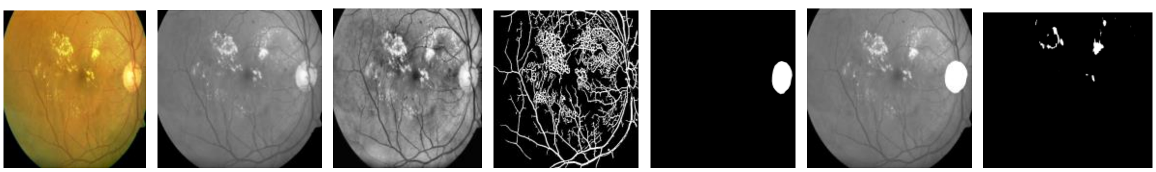
## 5. Result and Discussion

This section defines the performance analysis facts of proposed segmentation algorithm of blood vessel, optic disc and exudates. The proposed segmentation algorithm achieves better average sensitivity and specificity in both normal and abnormal retinal images. The retinal images are taken from DRIVE dataset. The obtained results are tabulated in table 1, 2 and 3. The table 1 shows the performance analysis of normal and abnormal images. The table 2 shows the accuracy testing using confusion matrix. Table 3 describes the tested image is normal or abnormal using convolution neural network classification. Figure 11 and figure 12 depicts the proposed algorithms are tested on retinal images from DRIVE dataset and result is obtained as normal, abnormal respectively.



(a) (b) (c) (d) (e) (f) (g)

**Figure 11**: (a). Input Image, (b) Filtered Image , (c) Enhanced Image using Adaptive Mean Adjustment, (d) Blood Vessel Segmentation, (e) Optic Disc segmentation, (f) Optic disc localization, (g). Exudates segmentation – Normal



(a) (b) (c) (d) (e) (f) (g)

**Figure 12:** (a). Input Image, (b) Filtered Image , (c) Enhanced Image using Adaptive Mean Adjustment, (d) Blood Vessel Segmentation, (e) Optic Disc segmentation, (f) Optic disc localization, (g). Exudates segmentation - Abnormal

**Table 1**: Performance Analysis

| Database | PSNR (Existing Median Filter) | MSE (Existing Median Filter) | PSNR (Proposed 2D anisotropic bilateral filter ) | MSE ((Proposed 2D anisotropic bilateral filter ) |
|---|---|---|---|---|
| Image 1 – Normal | 38.837 | 10.3879 | 48.8937 | .0899 |
| Image 2 – Normal | 37.3878 | 9.8378 | 49.9378 | .0937 |
| Image 3 - Abnormal | 36.8378 | 10.9378 | 43.8378 | 0.037 |
| Image 4 – Abnormal | 34.838 | 11.9378 | 42.9388 | 0.938 |

**Table 2**: Accuracy testing using confusion matrix

| Proposed Algorithm | Accuracy in % | Sensitivity in % | Speficity in % |
|---|---|---|---|
| CNN Classification | 96 | 96 | 94 |

**Table 3**: Classification of images into normal or abnormal

| Database Image | Normal/Abnormal | Reason |
|---|---|---|
| Image 1 | Normal | Exudates pixels not found |
| Image 2 | Normal | Exudates pixels not found |
| Image 3 | Abnormal | Exudates pixels found |
| Image 4 | Abnormal | Exudates pixels found |

## 6. Conclusion

This paper presents a novel approach for segmentation and classification of retinal image for diabetic retinopathy. The retinal image analysis is processed using different algorithms to improve its performance. The retinal image is preprocessed using 2D Anisotropic Bilateral Filter to eliminate all the noise content in the image. The Principle Component Analysis enhancement algorithm is used to improve its brightness and contrast. The Curvelet transform based Normalized Graph Cut segmentation algorithm is applied to estimate its thickness of the vessel to conclude the characteristics of the retinal image. The optic disc is entirely removed using Morphological operation to avoid disease segmentation incorrect. Modified Expectation Maximization algorithm is used to segment the hard exudates from the retinal image. The CNN classifier is applied to classify retinal image into normal or abnormal. The performance analysis is tabulated to prove the high accuracy classification of disease detection of real time database. The proposed system is suitable for exudates disease segmentation and classification. For exudate detection, optical disc and blood vessels are segmented for avoiding false problem to ophthalmologist. The diabetics lead to many diseases in retinal images. Those different disease cannot be segmented and classified. In future, the proposed system can be extended to detect various diseases in the diabetic retinopathy. It is concluded that this work can be used by ophthalmologist to identify the exudates diseases from diabetic retinopathy and also it helps to save the patient from vision loss.

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