Recognition and Classification of Diabetic Retinopathy utilizing Digital Fundus Image with Hybrid Algorithms

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Abstract: Diabetic Retinopathy (Damage in Retina) is the most common threatening diabetic eye disease and cause leading vision loss and blindness. A patient with the diabetic disease needs to experience occasional screening of eye. To analysis, ophthalmologists may utilize fundus or retinal pictures of the patient gained from advanced fundus camera. However, if the symptoms are identified earlier and proper treatment is provided through regular screening and monitoring, the blindness or vision loss can be avoided. The present study is intended on developing an automatic system for the analysis of the retinal of fundus images by using image-processing techniques. So as to accelerate the procedure, the discovery of diabetic retinopathy image processing methods is utilized In this proposed study, the performance is evaluated using different segmentation algorithms and classifiers namely fuzzy c-means clustering, naïve Bayesian classifier, support vector machine to detect the diabetic retinopathy. The presentation of the strategy is assessed on the freely accessible retinal databases like DRIVE, STARE. The presentation of the retinal vessels on DRIVE database, sensitivity 100% and specificity 97.5% while for STARE database the sensitivity 99%, specificity 97%. The detection of accuracy can be defined with respect to expert physician hand-drawn and ground truths and the results are comparatively obtained and analyzed.

Keywords: Diabetic Retinopathy, Fundus Image, Classifiers, Fuzzy c means, SVM, Medial Image.

I. INTRODUCTION

Image mining is rising innovation to give all the significant modes without referencing any data of a picture content. Formation of a picture mining framework has been frequently prepared on the grounds that it means joining various procedures reaching out from picture recuperation and ordering frameworks up to information mining and example acknowledgment. The essential animating in picture mining is to characterize how low - level pixel portrayal contained in a picture succession can be viably and effectively dealt with to frame the connections. The medical imaging is widely used to detect pathologies in the images. In medicinal imaging, the nature of picture obtaining and picture interpretation improves the accuracy of the detection. Computers have a massive impact the satisfaction of medical pictures. A requirement on manual observations may cause to improper results, which eventually affect the treatment preparation. In image processing, the exciting developments related to ophthalmology to progress over 15 years towards evolving automated diagnostics systems for conditions namely diabetic retinopathy.

The person identified with diabetics mellitus (or diabetics) are affected by collection of eye conditions such as cataract, glaucoma, Diabetic Macular edema (DME) and Diabetic Retinopathy (DR). These diabetic eye diseases can possibly cause visual deficiency and vision loss. In this study, the diabetic retinopathy (DR) is involved and which is produced or involves changes to retinal blood vessels that damages or cause the blood vessels leak and distortion-vision. Diabetic Retinopathy (DR) is the main source of visual damage between working - age grown-ups. It is demonstrated that early determination and convenient treatment could productively avoid vision misfortune [1]. Diabetic retinopathy (DR) is a typical retinal intricacy related with diabetes. It is a fundamental driver of visual deficiency in both center and propelled age gatherings. As indicated by the National Diabetes information (US) [2]. Figure 1(a) depicts a distinctive fundus or retinal images are labeled with several characteristics components of Diabetic Retinopathy. Figure 1(b) depicts a Blood vessels in the light-sensitive tissue which affected by Diabetic Retinopathy (DR) called retina that located in back side of the eye. Among the working age adults, the vision loss can cause the blindness and impairment among the people.

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Diabetic Retinopathy is produced by variations in blood vessels of the retina. At the point when these vessels may leak blood and new vessels may develop because of blood vessels damage. Vision loss or vision is impaired due to damage in nerve cells. Diabetic Retinopathy (DR) may progress in following types. Non Proliferative Diabetic Retinopathy (NPDR) namely mild, moderate and severe and Proliferative Diabetic Retinopathy (PDR). In gentle NPDR, stages, for example, microaneurysms, dot and blot hemorrhages and hard/intra-retinal exudates are found in the retinal pictures. Microaneurysms (MH) are clinically first recognized injuries. It is little zones of inflatable - like swelling on the mass of the retina. Which is round in shape and dark red spot appears in the retinal capillaries in the inner nuclear layer of the retina. MH size is normally ranges from 20 to 200 microns i.e., $1:12^{th}$ diameter of an average optic disc.

Hemorrhages are generally located on the center layer of the retina. Retinal hemorrhages are main cause of the retinal disease or injury, noticeable in dark surrounded in the form of patches. Hemorrhages are namely, Flame and dot-blot hemorrhages. All things considered the spot and smear type is peculiar leaking of the veins in retina. It is appear similar like microaneurysms if they are small. Flame hemorrhages or flame shaped hemorrhages occur in the nerve fibers and they occur more in superficial nerve fiber layer it appear in the inner layer of the retina. Cotton wool spot (CWS) is soft white patches around the retina near the optic disc and abnormal finding on fundoscopic exam in the retina. CWS are acute signs of vascular insufficiency to an area of retina. The most widely recognized side effects related with retinal cotton wool spot (CWS) can incorporate scotoma, arcuate imperfections, obscured vision, and amaurosis fugax.

### Table 1: Stages of DR

| S.No | Diabetic Retinopathy Lesion | Distinctive Ophthalmoscopic Features | Mechanism | Common Associated Conditions |
|------|-----------------------------|--------------------------------------|-----------|------------------------------|
| 1    | Hard Exudate                | Deep Yellow with sharp margins, often circinate | Leakage from pre-capillary arterioles | Diabetes, Hypertension, radiation |
| 2    | Cotton Wool Spot            | Fluffy gray white; usually near optic disc | Micro-infarction | Diabetes, Hypertension, Connected tissue disease |
| 3    | Microaneurysms              | It is minor swelling in the mass of a veins | Leakage from pre-capillary arterioles | Diabetes, Hypertension, radiation |
| 4    | Hemorrhages                 | Situated in the center layer of the retina | Leakage from pre-capillary arterioles | Diabetes, Hypertension, radiation |

The rest of the paper composed as pursues: Section 2 contains brief survey of some as of late distributed work important to Diabetic Retinopathy (DR). A stream graph and review of proposed framework given in Section 3. It quickly talks about the general frameworks and its various stages.
In Section 4, we present point by point proposed strategies with various approaches. Area 5 pursued by the trial results and examinations with past systems. At long last, we finish up our work to our planned future work.

II. RELATED WORK

The main challenges in health care system are the fastest growing disease called diabetes. The disease is growing in the current scenario as fast as possible in the number of people at frightening speed [3]. For the most part the circunstance more awful by the way that just a single portion of the patients deliberates about the disease. From the therapeutic viewpoint, this diabetes prompts serious inconveniences [4]. Diabetic Retinopathy (DR) is the regular confusion ailment in reality situation. In reality, it is so normal in the fundamental driver of the visual impairment or vision misfortune in the western nations [5]. The rate of malady is expanded in the created nations as well as in the under creating nations. Lamentably, most created nations are deficient in the fundamental chronicle of DR cases [6]. This circumstance is terrible in creating nations, on the grounds that more often than not lacking treatment accessible [7]. Diabetes Mellitus (DM) is the name of suffering, foundational, dangerous infection. At whatever point the pancreas does not isolate insulin or body unfit to route it appropriately. Because of this body, glucose level unusually may increment in the blood. Over the time, this high glucose level reason the harm in veins. This harm can causes or influence the two eyes and nerve framework, likewise the heart, kidney and different organs too [8]. There are two kinds of diabetes are accessible. Diabetes type 1 results from inability to create insulin by the human body. As of now, the vast majority of the people with sort 1 diabetes take insulin infusion [9]. The diabetes recognized to a maturing masses and expanding frequency of firmness just as with life propensities. Standard legacy assumes a job of this high glucose level reas...
The pictures were taken utilizing 8 bits for each shading plane at 1440 x 960, 2240 x 1488, 2304 x 1536 pixels. Two ends have been given contains the assessing to diabetic retinopathy and the threat of macula edema in each image.

Table 2: Different Types of Database with Classifiers

| S.No | Name of Techniques for detection of DR Lesion | Database | Classifier | Result |
|------|-----------------------------------------------|----------|------------|--------|
| 1    | Shape Estimation, Morphological Processing Technique | Own Database | Statistical Classifier, a Bayesian, a KNN Classifier | 80% |
| 2    | Watershed lines and ridge strength measurement, Morphological processing technique. | Own Database | Receiver Operating Characteristic Curve | 95.1% |
| 3    | Morphological preprocessing methods and candidate extractors | Messidor Database | Receiver Operating characteristics curve | 90% |
| 4    | Red lesion detection using fivefold cross validation | RetiDB and Messidor | Receiver Operating characteristics curve | 93.3% |
| 5    | Red Lesion candidate extraction | STARE, DIARETDB0, and DIARETDB1 | Support Vector Machine | - |
| 6    | Morphological Processing | DIARETDB1 | Receiver Operating characteristics curve | 94.44% |
| 7    | Artificial Neural Networks | Own Database | Firefly Clustering Algorithm | 96% |
| 8    | Red Lesion Detection using morphological operation | STARE | Support Vector Machine with Recursive Classifier | 99.3% |

IV. MATERIALS AND METHODS

The system for the proposed work of current condition of art picture handling calculations depicted in this segment. The calculations were grouped as far as the three picture preparing techniques is given in the figure 2, and classifications related with the accompanying. The initial step is preprocessing trailed by picture upgrade systems. The following stage is evacuation of vessel extraction and expulsion of solid highlights like optic plate and veins pursued by location and extraction of diabetic retinopathy with the sort PDR and NPDR, to be specific gentle, moderate, and serious. The third step is the arrangement of Diabetic retinopathy specifically the classes of Normal and Abnormal information utilizing proposed design.

1. Preprocessing
2. Optic Disc Localization and Segmentation
3. Segmentation of Blood Vessels
4. Detection of Diabetic Retinopathy
5. Classification of Diabetic Retinopathy
Figure 2: Proposed Methodology

De-noising of Images:

The fundamental period of the picture preparing procedure is preprocessing a picture. The image upgrade is done to improve the nature of the picture which has been taken from different sources with the end goal that it fulfills the prerequisite of further handling. The ordinary fundus photos, had been taken for demonstrative procedures, for the most part it contains commotions in them. Picture de-noising framework is the picture preparing strategy used to expel the noises in the obtained picture. In this condition if the recognition made with the picture may lead the noxious outcomes. Thus the uneven brightening, lacking difference between the exudates and picture foundation pixels and to clear the noise present in the information fundus picture used to develop the quality of the picture. Generally, the noises present in the image make the visual distortion. Salt and pepper noise and marginal noises are varies and independent of size. Likewise the speckle noise pattern is also independent based on texture of the underlying content [18]. Nonetheless, regular noise is continually indicating solid conduct regarding these properties. At the end of the day, commotion like the one salt-and-pepper depends on conflicting conduct arranged under "irregular noise" [19]. In this study made a process and comparison of four different noise such as Gaussian noise, Salt and Pepper noise, Speckle noise and Poisson noise. Gaussian noise is additionally called background noise Random Variation Impulsive Noise (RVIN) is a sort of measurable commotion where the Gaussian conveyance pursued by plentifulness of the noise. Gaussian noise brought about by irregular changes in sign [19]. Salt and pepper noise likewise called, for example, impulsive noise, spike noise and fat-tail dispersed noise. This noise can be brought about by sharp and abrupt changes or aggregations in picture signal. In this, a picture containing impulsive noise will have dark pixels in dark areas and bright pixels in bright noise. Generally, black and white (or both) have scattered pixel over an image. There are only two possible values exist in that a and b and the probability of that value of each is less than 0.2. Poisson noise are likewise called photon shot noise, additionally it is kind of electronic noise that happens when limited number of particles that convey vitality, for example, gadgets in an electronic circuits. Statistical fluctuations delivers a perceptible noise type in lighter piece of a picture sensor. Pixels are autonomous to one another in commotions at various pixel area. Dot commotion is a multiplicative clamor that expands the dim degree of a neighborhood a picture. In this kind of noise, the picture translation and acknowledgment are troublesome while handling a picture. In image processing, Filtering is performs transforming the pixel intensity values to get the characteristics of Image enhancement, smoothing, Matching template. The Filtering is removing unwanted noises from images. In fundus, images are frequently corrupted by random variations in intensity, illumination, or have poor contrast and cannot be used directly etc., and noises are detected and removed by various filters. The filter is generally derived from frequency domain in medical images. Noise removal is easier when compared to frequency domain as spatial domain, which requires less processing time [20]. Average filtering is mainly used or applied in masks over each pixel in the Image one after another. The performance of each pixel mask are averaged together to make distinct pixel from other pixels, Average filtering replaces every pixel esteem with the mean estimation of its neighbors, and including itself. Each pixel have been replaced with average of pixel values in a 5 x 5 square or window centered on that pixel. In this for all the images of the pixel will fall under this mask, also it will be considered as the new pixel [21].
This filter also called as mean filter or convolution filter. Hence, the outcome of eliminating pixel values are unreliable of their backgrounds. The median filter is also an order statistical filter, which is also nonlinear. It is an effective method to get sharp edges without blurring in terms of isolated noise with suppressed mode. Current pixel replaces a mid-element of its neighboring filters. In median filter the pixel values are initially sorted in terms of numerical order then replaced with middle pixel value [22]. Gaussian filter is a non-uniform low pass and smoothing filter in the 2D convolution operation that is used to eliminate the noise and blur the image but comparatively which is very slow. Gaussian filtering is done dependent on the bit coefficients with expanding good ways from the part focus. In this the convolution of each point in the input array with Gaussian kernel and then which produce the output array with highest value after summing all the pixel value in the kernel array. Weiner filter is an optimum filter, which is based on statistical approach and will filter out the noise that has corrupted a signal. This filter is mainly performing a good result in removing a speckle noise and Poisson noise. It is an adaptive filter in this the input is stationary and process for restoration of degraded image because it minimizes the mean square error between estimated random processes. Haar filter is window size problem can be overcome using the wavelet transform. When narrow windows are used at high frequency it has better time resolution when wider windows are used at low frequency it has better frequency Resolution [23].

Preprocessing image setup and results: A lot of different fundus databases with 305 pictures have been taken for the examination. Each picture is presented to various clamos that referenced in the above sections. Every fundus picture has taken and connected the commotion and checked with the different channels as depicted previously. Based on various performance measures the filtered images are compared with original images. Results of each image quality parameter is given below.

Peak Signal-to-Noise Ratio (PSNR): The PSNR is termed as peak to noise ratio represented between maximum power of a signal and representation of corrupted image. The image quality improved with based image reconstruction. Always the PSNR image ratio between 30DB to 50DB. The value is measured in PSNR is based on decibel and value must be high. The quality of recreated image calculated based on the higher value. The PSNR is calculated as,

\[
\text{PSNR} = 10 \log_{10} \left( \frac{x^2}{\text{MSE}} \right) \text{ dB}
\]

For the image worth measures, if the estimation of PSNR is incredibly high for an image with explicit disorder type then it is best quality picture. Where in the above eqn. \(x\) is maximum variation in the input data type. The image input is may be the double precision floating point and 8 bit unsigned integer and \(x\) is 1 and 255 respectively. Table 3 represents to the total PSNR estimation of each picture with various channels over the noise. As indicated by the PSNR esteem, plainly middle and haar channel is giving the most noteworthy or best outcome over the salt and pepper noise.

Gaussian filter is giving the best result for all other noise such as speckle, Poisson and Gaussian noise.

Mean Square Error (MSE): MSE denotes the collective squared error between encoded and original image, where as in PSNR represents an amount of highest error but in MSE represents lowest error value is the best quality of the image. The MSE is the cumulative squared error between the encoded and original image is given by,

\[
\text{MSE} = \frac{1}{mn} \sum_{m=1}^{M} \sum_{n=1}^{N} \| a(i, j) - b(i, j) \|
\]

Where, \(a\) is the noisy image and \(b\) is the denoised (filtered) image. Table 4 demonstrates the MSE estimation of a picture with different channel type and its exposed to middle channel has the least estimation of salt and pepper noise. Gaussian filter is subjected to give best result for all the other type of noises. Weiner and haar filter depicts the average performance over all the type of noise.

Normalized Cross Correlation (NCC): The relationship between the two different images is calculated based on correlation coefficients. Cross correlation is the similarity measures of two images under various intensity illuminations. The Correlation calculated based on the two set of variables, in the fundus images the intensity and quality taken for the process. The normalized correlation measures calculated between the two images based on mean and standard deviation by subtracting and dividing respectively. The normalized patches of image pixel intensity range between -1 to 1 (positive and negative).

\[
\text{NCC} = \frac{1}{a} \sum_{m,n} \frac{(f(m,n) - \overline{f})(t(m,n) - \overline{t})}{\sigma_f \sigma_t}
\]

Where, 
\(a\) - No of pixels in \((m, n)\) and \(f(m, n)\)
\(\overline{f}\) - Average no of f. \(\sigma_f\) - Standard Deviation of f.

In table 5 anticipated the value of NCC with anticipated picture presented to middle channel over the various sorts of commotion indicates 1 or close to 1, which is trailed by different kinds of channel.

Normalized Absolute Error (NAE): Normalized Absolute Error is the minimum error, which is variance between original images with normalized image. The original image is compared with original image value should be less or zero compared with denoised image. NAE is calculated as,

\[
\text{NAE} = \frac{\sum_{i=1}^{n} \text{abs}(A_i - B_i)}{\sum_{i=1}^{n} B_i}
\]

The worth near zero denotes to better strategy. More than zero denotes to low quality of the picture. In table 5 NAE worth is spoken to with different channel. Weiner channel demonstrates the normal execution over the various sort of noise. Middle and haar channel gives the least worth contrast with the other channel over the salt and pepper noise.
Image Segmentation:
Image segmentation used to divide inflamed image into multiple distinct regions containing each pixels with similar attributes. It is likewise used to discover the locale of interest for a picture into translate the information. The fundus image or retinal image containing Optic Disc, Blood Vessels, Macula and Fovea. Eliminating optic disc from the retinal image can enable detection of stages of diabetic retinopathy. In Figure 3, the optic disc has been detected. Initially the RGB image is converted into green channel based fundus image, then contrast of the image increased to get better image resolution. In this stage, the thresholding is applied to remove the optic disc region from the fundus image.

Detection of Optic Disc:
Retinal Fundus Images influenced because of diabetic retinopathy, there may exist other bright areas notwithstanding OD. Along these lines, we should identify all the splendid district in the retinal pictures. The OD estimate consistently fluctuates from individual by individual, by and large the OD measure vertically 1.92mm and 1.72mm on a level plane.

The algorithm 1 is represented to detect optic disc from retinal image. The input image is considered as color RGB fundus image. In which the centroid is calculated from that the optic region can be detected.

**Algorithm 1:** To detect Optic Disc from retinal images
**Input:** Normal RGB Fundus Image.
**Output:** Segmented Optic Disc from Fundus Image.

```
procedure Optic_region (Image, regionprobs)
begin
    If Image is in RGB then
        Image = RGB-to-Greenchannel (Image)
    End
    for i = 1:size(idx,2)
        locVal = find(L == idx(i));
        L(locVal) = 0;
        end
    If regionprob gets changed then
        J = imfill(L);
        [HA Index] = bwareabel(J);
        STATS1 = regionprops(HA, 'Area');
        idx = find([STATS1.Area]<35);
        for i = 1:size(idx,2)
            locVal = find(HA == idx(i));
            HA(locVal) = 0;
            end
end
```

Having enhanced retinal images the optic disc region separated from its background easily.

![Image Segmentation](image1.png)

**Figure 3:**
(a) Inflamed Image  
(b) Green Channel Image  
(c) Contrasted Image  
(d) Optic Disc extraction  
(e) Optic Disc  
(f) Median with 5 x 5 pixel

![Image Detection](image2.png)

**Figure 4:**
(a) Normal Image  
(b) Segmented Image
By applying hybrid segmentation on the retinal images the different grades can be detected. The Figure 4 depicts the segmented region of fundus image with various exudates.

V. EXPERIMENTAL ANALYSIS:

Based on the Optic disc detection the experimental analysis has been carried out by the following methods. Diabetic Retinopathy, based on Deep Neural Network (DNN) and SIFT feature extraction, suppress the noise by identifying the focal point and segmenting the digital fundus images. In the initial stage, the segmentation of digital fundus images is tough. For fine-grained modularity during mathematical study of the shape, the digital fundus image is further smoothened and strengthened so that the retinal vessels are enhanced and the backdrop information is suppressed. Curve operator is then applied to the enhanced segmented image to minimize the fragile edges and noise. The results of DR retinal vessels are accordingly achieved.

The presence of exudates in diabetic retinopathy is detected using a replica-based approach. In this method, to enhance the automatic feature extraction in digital fundus images, the optic disk is restricted using curve operation, and the vessel is detected by color directional method. By mutual region growing and edge recognition methods, the exudates fluid is extracted. Gabor filter bank and morphological operation, based on diabetic retinopathy enhances accuracy of automatic detection process and this method finds an optimal way to classify the disease into its respective classes. In order to diagnose the disease, the features of retinal images, such as key points of the pre-processed images are extracted. The performance of the proposed methods is compared with other existing methods using DIARETDB and STARE datasets.

VI. ANALYSIS ON INTENSITY FACTOR IN BLOOD VESSEL EXTRACTION

In a picture handling setting, the histogram of a image ordinarily alludes to a histogram of the pixel power estme. This histogram is a diagram representing the quantity of pixels in a picture at each unique force value found in that image. For a 8-bit Greyscale image there are 256 various potential powers, thus the histogram will explicitly show 256 numbers demonstrating the dispersion of pixels among those Greyscale estmes. Histograms can likewise be taken of screening pictures as either an individual histogram of red, green, and blue channels or a 3-D histogram with the three tomahawks speaking to the red, blue, and green channels, and brilliance at each point speaking to the pixel check. The definite yield from the task relies upon the usage - it might basically be an image of the required histogram in a reasonable picture design, or an information document or some likeness thereof speaking to the histogram insights. Table 7 demonstrates the normal force estmes for existing and proposed strategies for vein extraction.

The comparison chart for vessel detection using color directional, shrinking edge marking technique and kirsch’s template method is shown in Figure 5. The below chart

| Image/Methodology | 1   | 2   | 3   | 4   | 5   | 6   | 7   | 8   | 9   | 10  |
|-------------------|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| Color Directional | 0.11| 0.119| 0.214| 0.352| 0.112| 0.411| 0.289| 0.127| 0.109| 0.419|
| Kirsch’s Template  | 0.112| 0.122| 0.325| 0.426| 0.179| 0.426| 0.317| 0.129| 0.115| 0.445|
| Shrinking Edge Masking | 0.119| 0.124| 0.132| 0.441| 0.189| 0.498| 0.468| 0.178| 0.123| 0.528|

Figure 5 Average Intensity Values for Different Vessel Extraction Methods
shows the average intensity values by which we can conclude that the intensity value for color directional method is less than the conventional kirsch’s template method and shrinking edge marking method. Blood vessels are accurately extracted with low intensity values, as the edges are very thin. On average basics, color directional method accomplishes to extract blood vessels accurately, though it is hard to find the best threshold value for retinal blood vessel segmentation without any supervised rule. From the figure 5 can deduce that the color directional method yields good vessel segmentation technique with a very low rate of intensity. As the intensity decreases the blood vein detection becomes easier to extract veins and it does not produce any kind of pixel loss in the extracted vein image.

VII. ANALYSIS OF CURVE ORIENTATION IN OPTIC DISC DETECTION

The curve procedure utilized in this investigation depends on the improvement of a cross level model set for fundus optic plate picture segmentation.

| Image number | Curve Operator | Region Growing | Threshold Method |
|--------------|----------------|----------------|------------------|
|              | X   | Y   | X   | Y   | X   | Y   |
| Image1       | 333 | 246 | 375 | 244 | 386 | 213 |
| Image2       | 351 | 276 | 374 | 235 | 384 | 245 |
| Image3       | 311 | 215 | 324 | 222 | 334 | 235 |
| Image4       | 309 | 252 | 318 | 274 | 328 | 265 |
| Image5       | 325 | 248 | 333 | 258 | 345 | 263 |
| Image6       | 331 | 218 | 345 | 232 | 341 | 215 |
| Image7       | 346 | 247 | 352 | 268 | 361 | 258 |
| Image8       | 321 | 225 | 334 | 235 | 325 | 245 |
| Image9       | 306 | 238 | 321 | 245 | 333 | 210 |
| Image10      | 311 | 241 | 358 | 258 | 375 | 289 |

Table 8. Curve Orientation for Different Methods

![Curve Orientation for Different OD Detection Methods](image)

Table 8. Describes the curve orientation for different methods and their x and y co-ordinates.

The below figure 6. shows the comparison chart for curve orientations obtained from methods such as curve operator, region growing, and threshold method. X and Y co-ordinates using curve operator method give precise OD area when compared to the other two methods. X values denote the row and Y values denote the column pixels of the detected optic disc area. Outputs are tested using the recognized database such as DIARETDB0, DIARETDB1, STARE, and local database.
VIII. ANALYSIS OF GABOR WAVELET IN COTTON WOOL EXTRACTION

The multi-goals and multi-direction highlights of the Gabor wavelet procedure make it a famous strategy for cotton fleece spot extraction regardless of whether the natural non-symmetry exists. Among every one of the works dependent on Gabor wavelet, fleece spot extraction and surface depiction are the most visible applications, and different applications utilized Gabor wavelets essentially for highlight extraction. Our proposed methodology for turn invariant surface characterization utilizing Gabor wavelets is actualized where the highlights are found by ascertaining the mean and fluctuation of the Gabor sifted pictures. A component vector is created for a picture include. For instance, in the event that a 4 × 9 Gabor wavelet set is utilized, at that point there will be 72 components in this element vector. The component request in this technique depends on predominant bearing, where the initial 9 components are requested as twentieth degree, 40th degree, 160th degree, and 0th level of a similar scale with 20 degree identified as overwhelming course.

| Image number | Gabor Filter Bank | Fuzzy C-means Method |
|--------------|-------------------|----------------------|
| Image1       | 0.3624            | 0.2158               |
| Image2       | 0.2148            | 0.1289               |

Figure 7 obviously demonstrate the analysis between Gabor bank technique and Fuzzy c strategy. In the above examination, just the normal execution measures are utilized as these may change marginally for various executions. The mediocrity of the Conventional methods as far as execution measures is apparent from Table 9. The cotton fleece extraction depends on “Wavelets” to remember the right pixels. The absence of “wavelets” in regular strategies has prompted low exactness in results for example under 70%. In spite of the fact that the time required for regular strategies is less, the exactness of these systems isn't adequate for down to earth applications. Subsequently, this exploration work has presumed that the regular strategies are not reasonable for applications where high precision is a significant factor, which is accomplished with our proposed framework that produces over 97% exactness in results.

IX. ANALYSIS ON CO-OCCURRENCE IN HEMORRHAGE DETECTION

Co-occurrence is determined utilizing the below clarified factors. Angular Second Moment in the figuring of co-occurrence is otherwise called Uniformity or Energy. It is the aggregate of squares of passages in the Gray-Level Co-occurrence Matrix (GLCM). Angular Second Moment is raised when the picture has a generally excellent homogeneity or when the pixels are fundamentally the same as.

\[
\sum_{i=0}^{N_g-1} \sum_{j=0}^{N_g-1} p_{ij}^2
\]

Where, 
\( i, j \) are the spatial coordinates of the function \( p (i, j) \), \( N_g \) is Grey tone.

Table 10 Average Co-occurrence values for Splat Feature Segmentation Method.

| Image number | Splat Feature Segmentation | Color Band Segmentation |
|--------------|---------------------------|------------------------|

Figure 7. Gabor Wavelet for Different Cotton Wool Extraction methods
Figure 8. Co-Occurrence for Splat and Color Band Segmentation Methods

Figure 8. records the normal co-occurrence values from splat division technique and shading band strategy. Co-occurrence are of high significance in identifying and grouping DR. The splat division presents empowering brings about recognizing and evaluating pictures with diabetic retinopathy. The proposed technique performs better in recognizing drain pictures with diabetic retinopathy than other as of late created frameworks with an affectability of 100% and explicitness of 96.98%. As the proposed framework accomplished high affectability and sensible explicitness, it very well may be utilized to assist ophthalmologists with viewing and treat diabetic retinopathy.

X. ANALYSIS OF KEY POINTS IN FEATURE EXTRACTION

When a key point competitor is found by differentiating a pixel to its neighbors, the following stage is to achieve a definite fit to the adjacent information for area, scale, and proportion of head arches. This evidence permits focuses that have low complexity (and are in this way sensitive to noise) or seriously limited along an edge to be disposed of. The primary usage of this methodology [Lowe et al, 1999] described key point area and size of the focal central sample point. Despite the fact that Brown has as of late urbanized a strategy [Brown and Lowe, 2002] to fit a 3D quadratic capacity to the nearby example emphases to close the introduced area of the most extreme, his trials demonstrated this gives an impressive improvement to coordinating and security. His strategy utilizes the Taylor extension of the scale-space work, $D(x, y, \sigma)$, moved with the goal that the source is at the example point:

$$ D(x) = D + \frac{\partial D^T}{\partial x} x + \frac{1}{2} x^T \frac{\partial^2 D}{\partial x^2} x $$

where $D$ and its results are evaluated at the trial point and $x = (x, y, \sigma)$ T is the offset from this point.

Table 11 lists out key points for SIFT extraction method on average basics.
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Thus, by comparing SIFT feature with SURF feature algorithms, SIFT achieved an accuracy gain of 11.12% efficiency over SURF around pore feature while using SVM algorithm; and 8.97% efficiency over SURF around pore feature while using deep neural network based matching algorithm. Comparing fused features of SIFT score based and neural network based matching, deep neural network produced improved accuracy by 1.54% in terms of accuracy.

| Image | SIFT | SURF |
|-------|------|------|
| 1     | 1179 | 958  |
| 2     | 958  | 457  |
| 3     | 1241 | 756  |
| 4     | 895  | 324  |
| 5     | 1057 | 987  |
| 6     | 1456 | 1154 |
| 7     | 1324 | 1189 |
| 8     | 785  | 324  |
| 9     | 945  | 489  |
| 10    | 1124 | 987  |

Figure 9 charts the average key points obtained using SIFT and SURF feature extraction method. Key points obtained by applying SIFT method give more possible ways of classification using DNN than the SURF method. Higher number of key points is obtained when compared to conventional feature extraction methods. An average of more than 500 key points is obtained which is the best among all other methods.

Figure 9. Key point Extraction using SIFT and SURF Feature Extraction

XI. ANALYSIS OF CLASSIFICATION USING DEEP NEURAL NETWORK (DNN)

A dataset of 1540 pictures is utilized for assessing the proposed framework. The pictures got from various sources have a great deal of differences in shading, brightening, and quality. The pictures measured for this work from different sources are as per the following: 40 pictures from the DIARET database, 400 pictures from STRIVE database and 20 pictures from the neighborhood database.

The proposed system yields more percentage in sensitivity and specificity than existing conventional systems. It gives more than 90% sensitivity and specificity for all grades of Diabetic Retinopathy. Table 12 shows the confusion matrix for the proposed system which includes both PDR and NPDR images for training and testing sets with minimum number of images.

Table 12. Execution Comparison of the Proposed System with other Diabetic Retinopathy Screening Systems
Table 13. shows the grading of diabetic retinopathy by the Proposed System on the Dataset. Again, the table results of dataset show that the sensitivity and specificity of the DNN-based algorithm is efficient and the feature weight set is the highest when compared to RSVM around pores and SURF feature sets.

Table 13 Reviewing of diabetic retinopathy by Proposed System on the Dataset

| DR Grade     | Number of Images | Sensitivity (%) | Specificity (%) |
|--------------|------------------|-----------------|-----------------|
| Level-0      | 631              | 100             | 92.98           |
| Level-1      | 232              | 96.85           | 95.71           |
| Level-2      | 282              | 98.58           | 96.29           |
| Level-3      | 395              | 97.05           | 96.42           |
| Early PDR    | 458              | 99.12           | 96.12           |
| High Risk PDR| 430              | 97.56           | 95.78           |
| Advanced PDR | 480              | 98.63           | 93.99           |

From the table 13, as with different grades, the usage of feature vector reduces the error rates when compared to a single feature set such as SURF.

XII. CONCLUSION

Diabetic Retinopathy (DR) is the most prevalent eye disease resulting in blindness in diabetic patients. Automated detection of Diabetic Retinopathy and its classification from digital fundus images are investigated in this research. The proposed methods are developed to enhance auto-detection of the disease in digital fundus images, classify it as PDR or nPDR type, and test with recognized datasets such as DIARET and STARE datasets. Study is done on denoising filters for fundus images, to find the optimal filter to progress the quality of images. Based on the performance evaluation of different filters, it is confirmed that the Haar and the average filter are the most suitable filters to denoise fundus images. This research contributes different segmentation algorithms to segment a DR from its fundus images.

In this paper has demonstrated confident outcomes and shows that the proposed Diabetic Retinopathy Fundus Image Analysis framework is exceptionally effective in arranging both PDR and NPDR. As the Fundus Image Analysis framework recognizes and orders irregularities with a high affectability and reasonable explicits, it very well may be utilized to help ophthalmologists in determination and giving idea, and capacity as a device for a mass screening of diabetic retinopathy. An end to the work sees the system of order additionally investigated, by dividing the consequences of neural system characterization.

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