International Journal of Computer Information Systems and Industrial Management Applications.
ISSN 2150-7988 Volume 13 (2021) pp. 172-181


Received: 27 Jan 2021; Accepted: 13 May 2021; Published: 6 August 2021

# The Fusion of Features for Detection of Clinical Symptoms of Diabetic Retinopathy and its Grading from Digital Fundus Images

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***Abstract*: Diabetic Retinopathy is a recurrent retinal disorder that can affect patients with both type 1 and type 2 diabetes. From a large amount of data available, it is apparent that Diabetic Retinopathy is a progressive disease that can terminate in severe vision problems or complete vision loss. The clinical symptoms of Diabetic Retinopathy include microaneurysms, haemorrhages, hard and soft exudates. They are lesions seen on the surface of the retina among diabetic patients. They indicate a pre-proliferative Diabetic Retinopathy state and needs to be treated. This paper describes a method based on morphological operations and thresholding for detection of clinical symptoms of Diabetic Retinopathy and grading them. As a part of the feature extraction stage, feature level fusion comprising LBP and HOG features is explored as it yields better accuracy in detection of affected areas in fundus images. Various classifiers namely; SVM, k-NN, Decision tree and ECOC classifiers have been tested. The average accuracy values for detection of microaneurysms and hemorrhages using fusion features yielded 95% for SVM, 97% for k-NN and 96% for Decision tree classifier respectively and the average accuracy values for detection of hard and soft exudates using fusion features yielded is 98% for SVM, 91% for k-NN and 98% for Decision tree classifier respectively. The proposed method using fusion features for grading of Diabetic Retinopathy yielded an accuracy of 32% for k-NN, 91% for Decision tree and 98% for ECOC classifier respectively. The methods and algorithms developed as a part of this research work will aid the ophthalmologists and clinicians in early detection of retinal disorders. It will also be useful for mass screening programs particularly in rural areas and developing nations.**

***Keywords*:** Microaneurysms, Hemorrhages, Hard exudates, Soft exudates, Fusion features, Diabetic Retinopathy.

## I. Introduction

In today's era of automation, image processing has become an integral part of many organizations irrespective of their area of operation. Instant information acquisition and processing are pivotal for the success of an organization. Medical imaging is steadily becoming an integral part of health care management systems. Medical image processing is an area of computation that creates visual representations to reveal the structure of tissues for medical intervention. It deals with images documenting the internal physiology and anatomy of human organs that are captured for medical diagnostics and treatment. Diabetes mellitus is a metabolic disorder caused due to the presence of high glucose levels in the blood. Diabetes mellitus can be categorised into two types, namely, type 1 and type 2 diabetes. In such a condition, the human body is incapable of effectively using the insulin produced in the body. Recent studies have found that there are about 382 million diabetic patients worldwide [1] and this number is predicted to progressively increase in the years to come. Diabetic Retinopathy is a recurrent retinal disorder that can affect patients with both type 1 and type 2 diabetes. From a large amount of data available, it is apparent that Diabetic Retinopathy is a progressive disease that can terminate in severe vision problems or complete vision loss. Diabetic Retinopathy is generally categorised into two different phases as Non-Proliferative Diabetic Retinopathy (NPDR) and Proliferative Diabetic Retinopathy (PDR), based on degradation of blood vessels and hemorrhagic changes [2]. Non Proliferative Diabetic Retinopathy is further categorized into different stages as mild NPDR, moderate NPDR, and severe NPDR, whereas Proliferative Diabetic Retinopathy is an advanced stage of the Diabetic Retinopathy disease. NPDR occurs when blood vessels are damaged and start leaking fluid. It is characterized by clinical indications such as the presence of microaneurysms, haemorrhages, hard and soft exudates. PDR on the other hand occurs when new blood vessels start abnormally growing on the surface of the retina. Microaneurysms are the earliest obvious symptoms of retinal damage and are caused by an inconsistent permeability of the vasculature. They are tiny red spots of less than 125 micron size and have sharp margins. Haemorrhages are similar to microaneurysms but greater than 125 microns in size and have irregular margins. They are caused by the leakage of feeble capillary walls. Hard exudates are irregularly shaped yellowish-white deposits caused due to leakage of lipids or other proteins on the retinal surface. They are often found in clumps or circinate rings and located in the outer layer of the retina. However, Soft exudates appear as fluffy pale yellowish white lesions that occur due to closing of arterioles reducing the flow of blood to the retina. They are also known as cotton wool spots. Figure 1. shows fundus image with clinical indications of Diabetic Retinopathy. Determining the severity of the disease is important for providing relevant treatment and relief to the patient. Currently, most ophthalmologists determine the NPDR severity grade based on symptoms using an International Clinical Diabetic Retinopathy Disease Severity Scale [44], as shown in Table 1.

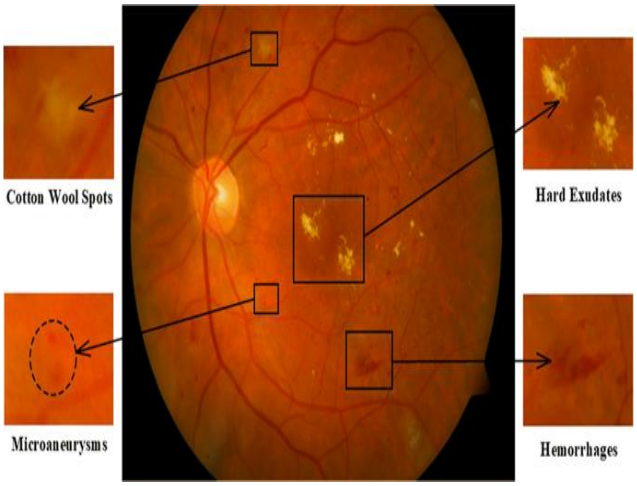



**Figure 1.** Fundus image with clinical indications of Diabetic Retinopathy

| NPDR Grade | Symptoms |
|---|---|
| Normal | No abnormalities |
| Mild | Microaneurysms only |
| Moderate | Microaneurysms, dot bolt haemorrhages, few exudates |
| Severe | All of the abnormalities in the above two grades in large numbers |

*Table 1.* NPDR severity grades based on symptoms using International Clinical Diabetic Retinopathy Disease Severity Scale.

From the literature, it can be observed that different methodologies have been proposed for segmentation and classification of Diabetic Retinopathy lesions. A multi-agent based system model for segmentation of microaneurysms has been proposed in [3]. This model comprises of multiple independent agents that operate based on local knowledge but are capable of providing global results. A region-based approach has been adopted by [4] for detecting abnormal structures present in the retina such as exudates and red lesions with reference to its distance from the macula. A unique motion pattern generation algorithm along with the utilization of a descriptor from the Radon space was proposed in [5] for detection of haemorrhages. In [6], a neural network based approach for detection of exudates was proposed. They combined pre-processing methods based on luminosity and contrast normalization along with global and adaptive thresholding methods for segmentation of exudates. This was further extended with colour and shape feature extraction for accurate detection of exudates. A multi-resolution analysis using symlet wavelet and k-Means clustering algorithm for extraction of soft exudates from digital fundus images was explored in [7]. In [8] colour transfer to pre-process retinal images was used and they created a supervised learning method based on the multilayer perceptron to find the initial seeds that predict hard exudates regions. A method based on morphological operations and thresholding for identification of soft exudates from digital fundus images was explored [9]. An automated method for microaneurysms based on Spencer and Cree system was proposed in [10]. The images in which microaneurysms and dot haemorrhages are present are graded as "DR" otherwise "Normal". A study to understand the efficiency of the automated grading system was taken up in [11]. This system assessed the quality of fundus images and checked the presence of dot haemorrhages and microaneurysms. It also graded the fundus images as belonging to “disease” or “no disease” grades. A SVM and k-NN classifier was used to establish a hierarchical severity grading system consisting of grade 0 (Non-DR class) and grades 1, 2, 3 based on the presence of microaneurysms and haemorrhages in [45]. A hybrid descriptor set that combines speeded up robust features (SURF) and spatial local binary pattern along with a dimensionality reduction approach for automated grading of Diabetic Retinopathy into four categories viz, normal, mild, moderate and PDR was generated in [46]. This paper focuses on the extraction of clinical symptoms of Diabetic Retinopathy comprising microaneurysms, hemorrhages, hard and soft exudates and exploring the use of a fusion of HOG and LBP features to distinguish between diseased and healthy images. It further grades the images according to the presence of clinical symptoms as Normal, Mild, Moderate and Severe Diabetic Retinopathy.

## II. Materials and Methods

The proposed experiment has been conducted in three different phases, during the first phase, algorithms were developed for the detection of early symptoms of Diabetic Retinopathy such as microaneurysms and hemorrhages. In the second phase, algorithms were developed for detection of advanced symptoms such as hard and soft exudates. In the third phase, the digital fundus images were graded as belonging to Normal, Mild, Moderate and Severe Diabetic Retinopathy. The algorithms were tested on a number of fundus databases that are available online. To implement the proposed methodology for detection of microaneurysms and hemorrhages, fundus images from some of the standard publicly available databases were chosen viz, STARE [12], e-Ophtha [13], DIARETDB1 [14], High Resolution Fundus (HRF) [15] and Messidor[16] were considered. In all, 608 digital fundus images from these databases have been tested. To implement the proposed methodology for detection of hard and soft exudates, the digital fundus images were chosen from, Messidor [16] e-Ophtha-Ex[13], DIARETDB0 [17] and DIARETDB1 [14]. In all, 359 digital fundus images from these databases have been tested. The choice of these databases was based on the fact that the fundus images have been annotated for yellow lesions by medical experts. Finally, Grading of Diabetic Retinopathy was implemented on all these databases. The following Table 2 provides the dataset description of the images used for implementation of the proposed method for detection of microaneurysms and hemorrhages and Table 3 provides the dataset description of the images used for implementation of the proposed method for detection of hard and soft exudates.

| Database | FOV | Image size | H | D | T |
|---|---|---|---|---|---|
| MESSIDOR | 45° | 1488X2240 | 06 | 68 | 74 |
| e-Ophtha-Ex | $50^0$ | 1696X2544 | 14 | 68 | 82 |
| DIARETDB0 | 50° | 1152X1500 | 04 | 110 | 114 |
| DIARETDB1 | 50° | 1152X1500 | 05 | 84 | 89 |

H-Number of healthy images, D-Number of diseased images, T-Total images, FOV-Field-of-View

*Table 2.* Dataset Description of the images used for implementation of the proposed method for detection of microaneurysms and hemorrhages.

| Database | FOV | Image size | H | D | T |
|---|---|---|---|---|---|
| e-Ophtha | $50^0$ | 1696X2544 | 233 | 148 | 381 |
| HRF | 45° | 2336x3504 | 00 | 18 | 18 |
| DIARETDB1 | 50° | 1152X1500 | 05 | 84 | 89 |
| MESSIDOR | 45° | 1488X2240 | 32 | 68 | 100 |
| STARE | 45° | 700 X605 | 10 | 10 | 20 |

H-Number of healthy images, D-Number of diseased images, T-Total images, FOV-Field-of-View

*Table 3.* Dataset Description of the images used for implementation of the proposed method for detection of Hard and Soft exudates.

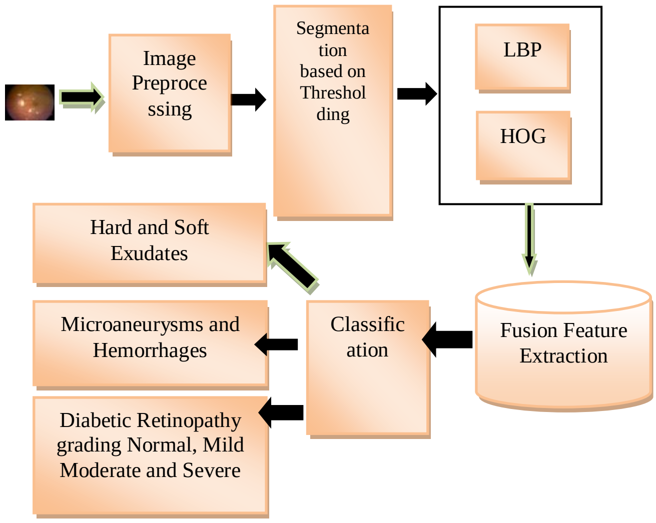
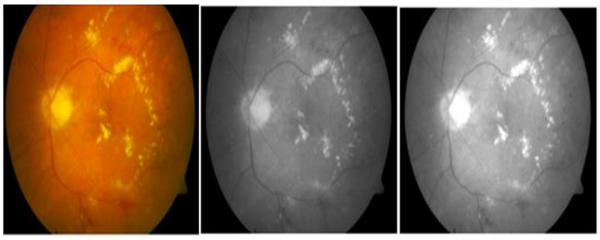



**Figure 2.** Flow diagram of the proposed method



(a) (b) (c)

**Figure 3.** (a) Sample RGB fundus image (b) Grayscale image (c) Image after contrast adjustment

## III. Proposed Methodology

The proposed methodology for detection of clinical symptoms of Diabetic Retinopathy comprising microaneurysms and hemorrhages, hard and soft exudates is based on image processing techniques that include fundus image preprocessing, segmentation, feature extraction and classification. These steps are commonly executed in both phase 1 and phase 2. The flow of steps in the proposed method is presented in the flow diagram as shown in Figure 2.

### A. Preprocessing

The initial step in most image processing applications is preprocessing. It is particularly essential for fundus images because of differences in illumination, field-of-view, resolution and quality of images. Hence, during this step, each of the fundus images from experimental datasets is normalized for accurate segmentation and feature extraction. In the proposed technique, the fundus images are resized to 576 x 720 pixels and the image is converted from RGB to grayscale [23]. Further, Contrast Limited Adaptive Histogram Equalization [18] is applied to highlight the clinical symptoms present on retina surface. This is followed by mean and Gaussian filtering in order to reduce noise. The original fundus image is shown in Figure 3 (a), Figure 3(b) shows the grayscale image and Figure 3(c) shows image after contrast enhancement.

### B. Segmentation

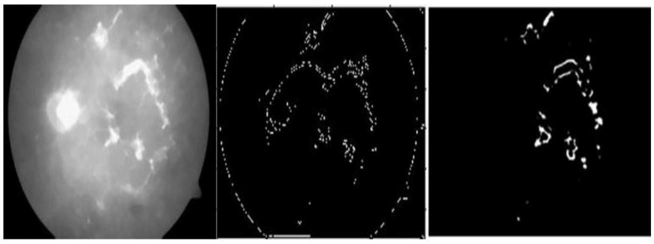
Proposed method for segmentation of clinical symptoms of Diabetic Retinopathy from digital fundus images is based on morphological operations and thresholding [18]. However, to accurately detect the lesions regions, it is necessary to detect and eliminate the vasculature comprising blood vessels and capillaries as well as the optic disc present on the retinal surface. The blood vessels are removed from the fundus image initially by applying canny edge detection followed by morphological opening and closing operations [21], whereas, the optic disc is eliminated by computing a circular mask and subtracting it from the segmented image [22]. The clinical symptoms of Diabetic Retinopathy such as microaneurysms, hemorrhages, hard and soft exudates are present on the surface of the retinal image. Since digital fundus images exhibit dissimilarities in intensity and texture, segmentation based on local thresholding [19] is proposed in this paper.

$$f(x,y) = \begin{cases} 1 & \text{if } g(x,y) > T \\ 0 & \text{if } g(x,y) <= T \end{cases} \quad (1)$$

where f(x,y) is the fundus image, g(x,y) represents the intensity of a pixel and T indicates the threshold. Figure 4(a) shows the image after canny edge detection, Figure 4(b) indicates the image after optic disc and blood vessel elimination, Figure 4(c) depicts the segmented image after microaneurysms and hemorrhages are detected. Figure 5(a) shows image after blood vessels are eliminated, Figure 5(b) presents the image after canny edge detection and Figure 5(c) shows the segmented image with exudates.

(a) (b) (c)

**Figure 4.** (a) Image after canny edge detection (b) Image after optic disc and blood vessel elimination (c) Segmented image with microaneurysms



(a) (b) (c)

**Figure 5.** (a) Blood vessels eliminated (b) Canny edge detection (c) segmented image with exudates

## IV. Feature Extraction and Classification

### *A. LBP features*

This work is based upon extracting two important features set namely, Local Binary Pattern (LBP) and Histogram of Oriented Gradients (HOG). LBP feature set was first introduced in 1994 by Ojala et al. [19]. They are texture-based features used commonly for object recognition in computer vision. LBP operates by dividing an image into cells. For instance, each cell can be of 3x3 size. Each pixel has intensity between 0-255. Now, the central value of the matrix under consideration is treated as a threshold. Each of the neighboring pixels is set 1 if its intensity is greater than or equal to the threshold, else it is set to 0. The matrix hence produced contains only binary values. This binary pattern is now converted into its corresponding decimal value. Once all the new gray values have thus been computed, a histogram is constructed that represents the feature set. The process of LBP feature computation is shown in Figure 6.

$$LBP_{P,R}(x_c, y_c) = \sum_{P=0}^{P=1} S(i_p - i_c)\, 2^P \qquad (2)$$

where $x_p$ represents the sample, $x_c$ represents the central pixel and p denotes the neighboring pixels.

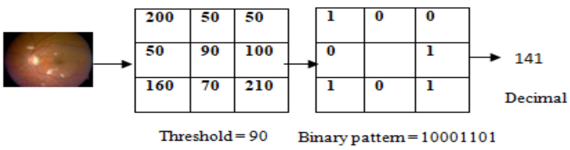



**Figure 6.** Process of LBP feature computation

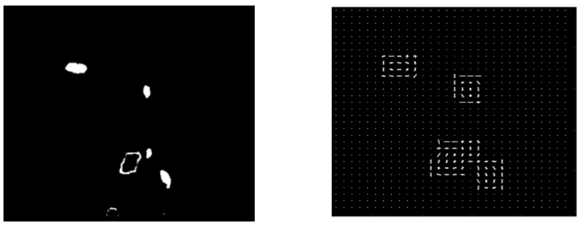
### *B. HOG features*

Image processing applications and computer vision algorithms often use Histogram of Oriented Gradients (HOG) [20] features for object detection. The main concept in HOG revolves around the idea that the appearance and shape of an object can be represented by understanding the gradients of intensity or directions of edges. It divides an image into square regions containing cells and calculates Histogram of Oriented Gradients for every cell. This computation is normalized with the help of a block-wise pattern that generates a descriptor for every cell. Every pixel gradient has magnitude and direction. These are computed as follows:

$$g = \sqrt{g^2\, x + g^2\, y} \qquad (3)$$

$$\theta = \arctan \frac{gy}{gx} \qquad (4)$$

The x-gradient works on vertical lines and y-gradient on horizontal lines. The magnitude of gradient triggers when there is any sudden change in intensity and it remains the same when the region is uniform. The HOG descriptor represents an image patch that extracts necessary information and disposes unwanted information. By looking at the gradient image it is possible to visualize the object being segmented. Figure 7(a) shows the segmented image and Figure 7(b) depicts its HOG visualization.



(a) (b)

**Figure 7.** (a) Segmented image (b) HOG visualization

### *C. Fusion features*

Feature level fusion is a technique used in image processing and pattern recognition that can improve the accuracy of object recognition and computer vision. One of the advantages of fusion of features is that it can build a compact set of correlated features that can greatly aid the process of classification. Fusion at feature level can be implemented by simply concatenating the features obtained from different sources. Let A = $\{a_1, a_2, a_3, \ldots\ldots, a_n\}$ and B = $\{b_1, b_2, b_3, \ldots\ldots, b_n\}$ represent feature vectors that have been extracted from two different sources. The aim is to combine these sets into a new set C that can represent the image characteristics in a better manner. In this experiment, LBP and HOG features have been combined as it improves the ability to detect affected areas in a retinal image considerably. Further, a database of this feature set is used to train and test the system.

### *D. Classification*

This experiment was conducted on digital fundus images from Messidor, e-ophtha, e-Ophtha-Ex, DIARETDB0, DIARETDB1, HRF and STARE databases. Various classifiers namely; SVM, k-NN, Decision tree and ECOC classifiers were used. Support Vector Machine (SVM) is a supervised non-parametric machine learning algorithm that can not only be used for classification but also regression and detection of outliers. These algorithms are versatile and use training points (also known as support vectors) in decision making. k-Nearest Neighbour (k-NN) is an instance-based non-parametric supervised machine learning algorithm that allots a class membership to a data item depending on the class that is most common among its neighbours. In machine learning and pattern recognition systems, tree-based learning algorithms are based on the structure of a tree and belong to supervised learning algorithm class. In the decision tree, the result is shown in terms of the leaf node while the non-leaf node represents the condition. Each branch of the tree symbolises the observation of the database object, and the leaves signify the outcome of the predicted values. The Error Correcting Output Code (ECOC) algorithm is a machine learning algorithm that reframes a multi-class classification problem into multiple binary classification problems, allowing the basic binary classification model to be used directly. It was particularly used for grading the digital fundus images.

## V. Experimental Results and Discussions

The proposed algorithm is coded in MATLAB R2015b with Intel i3 processor and 4GB RAM. During the first phase of the experiment the proposed methodology was tested for detection of microaneurysms and haemorrhages. The sample original fundus images from e-Ophtha, HRF, DIARETDB1, Messidor and STARE are shown in Figure 8(a), Figure 8(c), Figure 8(e), Figure 8(g), Figure 8(i) and their corresponding segmented images using the proposed method are depicted in Figure 8(b), Figure 8(d) and Figure 8 (f), Figure 8(h), Figure 8(j) respectively. The confusion matrix obtained after classification of the images is shown in Table 4. From the Table 4, it can be observed that the True Positive rate is higher for all the classifiers and False Positive rate is low. The algorithm was tested for its performance using various performance evaluation measures namely, accuracy, precision and recall. Accuracy represents a measure of the proportion of the sum of True Positives and True Negatives to the total population. Precision provides the proportion of results that are relevant while recall represents the total relevant results correctly classified by a classification method. It is the harmonic mean of Precision and Recall. The performance evaluation measures computed for each of the databases are depicted in Table 5. The average accuracy values yielded using fusion features is 95% for SVM, 97% for k-NN and 96% for Decision tree classifier respectively. The comparative results of the proposed algorithm using fusion features with other methods suggested by various researchers in the literature are given in the Table 6. During the second phase of the experiment the proposed methodology was tested for detection hard and soft exudates. The sample digital fundus images from DIARETDB0, DIARETDB1, e-OPHTHA-Ex and Messidor are shown in Figure 9(a), Figure 9(c), Figure 9(e) and Figure 9(g) and their corresponding segmented images are shown in Figure 9(b), Figure 9(d), Figure 9(f) and Figure 9(h) respectively. From the Table 7, it can be observed that True Positive rate is higher for all the classifiers and False Positive rate is low. The algorithm was tested for its performance using various performance evaluation measures namely, accuracy, precision and recall. The performance evaluation measures computed for each of the databases are depicted in Table 8.

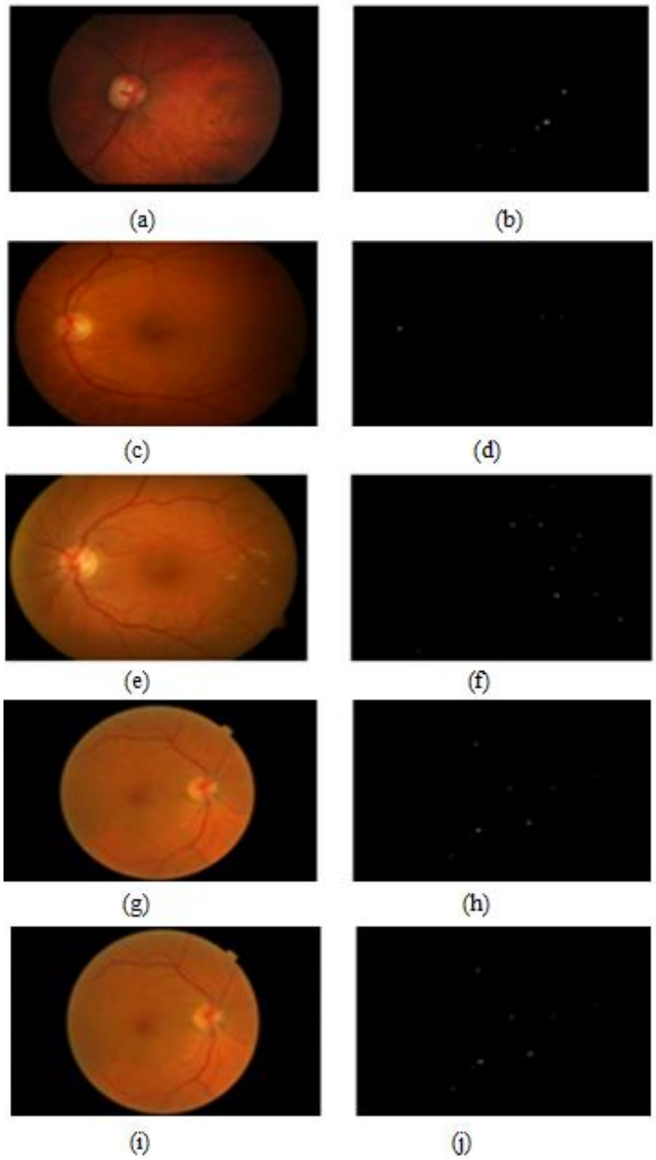



**Figure 8. (**a) Sample original fundus image from e-Ophtha database (b) Segmented image of (a), (c) Sample original fundus image from HRF database (d) Segmented image of (c), (e) Sample original fundus image from DIARETDB1 database (f) Segmented image of (e), (g) Sample original fundus image from MESSIDOR database (h) Segmented image of (g), (i) Sample original fundus image from STARE database (j) Segmented image of (i)

The average accuracy values yielded using fusion features is 98% for SVM, 91% for k-NN and 98% for Decision tree classifier respectively. The comparative results of the proposed algorithm using fusion features with other methods suggested by various researchers in the literature are given in the Table 9. The experimental dataset included 90 images belonging to each Diabetic Retinopathy grade, namely; "NORMAL", "MILD", "MODERATE" and "SEVERE". The experimental dataset included 90 images belonging to each Diabetic Retinopathy grade, namely; "NORMAL", "MILD", "MODERATE" and "SEVERE". The normal fundus image is shown in Figure 10 (a) and its corresponding segmented image is shown in Figure 10(e).. Similarly, the symptoms of mild

Diabetic Retinopathy consisting of microaneurysms are shown in Figure 10(b) and its corresponding segmented image is shown in Figure 10(f). The fundus image having symptoms of moderate Diabetic Retinopathy comprising hemorrhages and exudates is shown in Figure 10(c) and its corresponding segmented image is shown in Figure 10(g). Figure 10(d) shows a fundus image with severe Diabetic Retinopathy and its corresponding segmented image is depicted in Figure 10(h). The confusion matrix obtained after classification of the images is shown in Table 7.

| **Classifiers** | **Databases** | **Classification results** | | | |
|---|---|---|---|---|---|
| | | **TP** | **FP** | **FN** | **TN** |
| SVM classifier | STARE | 09 | 01 | 02 | 08 |
| | e-Ophtha | 125 | 23 | 00 | 233 |
| | DIARETDB1 | 84 | 00 | 00 | 05 |
| | HRF | 14 | 00 | 00 | 04 |
| | Messidor | 68 | 00 | 01 | 31 |
| k-NN Classifier | STARE | 09 | 01 | 02 | 08 |
| | e-Ophtha | 141 | 07 | 154 | 79 |
| | DIARETDB1 | 84 | 00 | 05 | 00 |
| | HRF | 14 | 00 | 04 | 00 |
| | Messidor | 68 | 00 | 26 | 06 |
| Decision tree Classifier | STARE | 09 | 01 | 00 | 10 |
| | e-Ophtha | 123 | 25 | 04 | 229 |
| | DIARETDB1 | 84 | 00 | 00 | 05 |
| | HRF | 14 | 00 | 00 | 04 |
| | Messidor | 66 | 02 | 01 | 31 |

TP – True Positives, FP – False Positives, FN – False Negatives, TN – True Negatives

*Table 4.* Classification results of the fundus images for the detection of microaneurysms and hemorrhages from STARE, e-Ophtha, DIARETDB1, HRF and Messidor databases using fusion features with various classifiers.

| **Digital Fundus Image Database** | **SVM classifier** | | |
|---|---|---|---|
| | **Ac** | **Re** | **Pr** |
| STARE | 0.85 | 0.90 | 0.81 |
| e-Ophtha | 0.93 | 1.0 | 0.84 |
| DIARETDB1 | 1.0 | 1.0 | 1.0 |
| HRF | 1.0 | 1.0 | 1.0 |
| Messidor | 0.98 | 0.99 | 1.0 |
| | **k-NN Classifier** | | |
| STARE | 0.85 | 0.90 | 0.8 |
| e-Ophtha | 0.57 | 0.47 | 0.95 |
| DIARETDB1 | 0.94 | 0.94 | 0.94 |
| HRF | 0.77 | 0.77 | 1.0 |
| Messidor | 0.74 | 0.72 | 1.0 |
| | **Decision Tree Classifier** | | |
| STARE | 0.95 | 1.0 | 0.90 |
| e-Ophtha | 0.92 | 0.83 | 0.95 |
| DIARETDB1 | 0.94 | 0.94 | 1.0 |
| HRF | 1.0 | 1.0 | 1.0 |
| Messidor | 0.98 | 0.98 | 0.97 |

Ac-Accuracy, Re-Recall, Pr-Precision

*Table 5.* Results of performance evaluation measures of the proposed method with fusion features.

| **Databases** | **Author** | **Accuracy** |
|---|---|---|
| STARE | Arati et al. [24] | 0.84 |
| | **Proposed Method** | **0.95** |
| e-Ophtha | Ren F. et al.[25] | AUC 0.84 |
| | Parham Khojasteh et al. [26] | 0.86 |
| | **Proposed Method** | **0.92** |
| DIARETDB1 | Sreng S. et al. [27] | 0.90 |
| | Rosas-Romero R. et al. [28] | 0.95 |
| | Arati et al. [24] | 0.88 |
| | Parham Khojasteh et al.[26] | 0.97 |
| | **Proposed Method** | **0.94** |
| HRF | Priyakshi Bharali et al. [29] | 1.0 |
| | **Proposed Method** | **1.0** |
| Messidor | Priyakshi Bharali et al.[29] | 0.98 |
| | B. Antal and A. Hajdu [30] | 0.90 |
| | **Proposed Method** | **0.98** |

*Table 6.* Comparative results of the proposed method using fusion features on STARE, e-Ophtha, DIARETDB1, HRF and Messidor databases with other methods suggested by various researchers in the literature.

| **Classifiers** | **Databases** | **Classification results** | | | |
|---|---|---|---|---|---|
| | | **TP** | **FP** | **FN** | **TN** |
| SVM classifier | Messidor | 68 | 00 | 00 | 06 |
| | e-Ophtha Ex | 68 | 00 | 05 | 09 |
| | DiARETDB0 | 110 | 00 | 00 | 04 |
| | DIARETDB1 | 85 | 00 | 00 | 04 |
| k-NN Classifier | Messidor | 68 | 00 | 06 | 00 |
| | e-Ophtha Ex | 68 | 00 | 14 | 00 |
| | DiARETDB0 | 110 | 00 | 04 | 00 |
| | DIARETDB1 | 85 | 00 | 04 | 00 |
| Decision Tree Classifier | Messidor | 68 | 00 | 00 | 06 |
| | e-Ophtha Ex | 67 | 01 | 05 | 09 |
| | DiARETDB0 | 110 | 00 | 00 | 04 |
| | DIARETDB1 | 85 | 00 | 00 | 04 |

TP – True Positives, FP – False Positives, FN – False Negatives, TN – True Negatives

*Table 7.* Classification results for detection of hard and soft exudates from fundus images of Messidor, e-Ophtha-EX, DIARETDB0 and DIARETDB1 databases using fusion features with various classifiers.

The results of classification of fundus images for Diabetic Retinopathy grading from e-Ophtha, e-Ophtha-Ex, DIARETDB0, DIARETDB1, MESSIDOR, HRF and STARE databases using fusion features with k-NN classifier, Decision tree and ECOC classifiers are shown in Table 10, Table 11 and Table 12 respectively. The proposed method using fusion (combination of both HOG and LBP) features for grading of Diabetic Retinopathy yielded an accuracy of 32% for k-NN, 91% for Decision tree and 98% for ECOC classifier respectively.

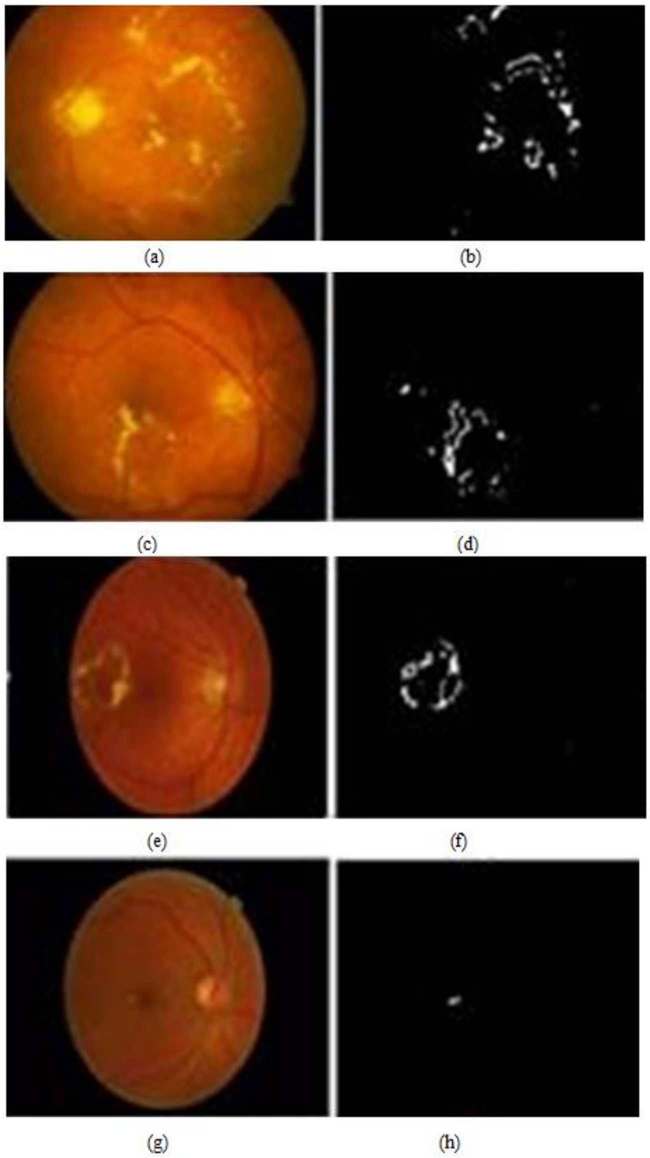



**Figure 9.** (a) Sample original fundus image from DIARETDB0 database (b) Segmented image of (a), (c) Sample original fundus image from DIARETDB1 database (d) Segmented image of (c), (e) Sample original fundus image from e-Ophtha-EX database (f) Segmented image of (e), (g) Sample original fundus image from Messidor database (h) Segmented image of (g)

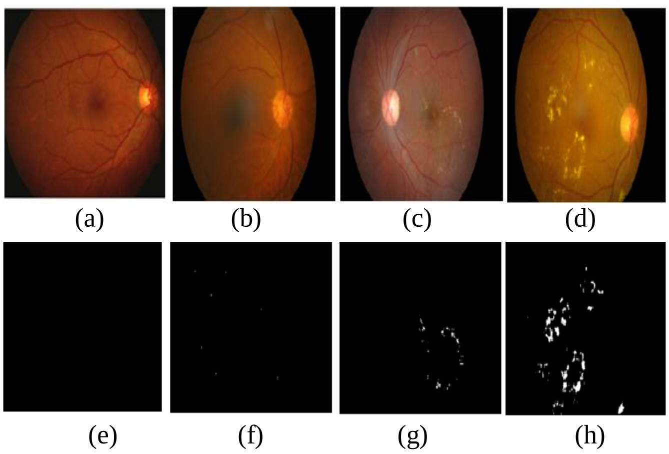



**Figure 10.** Gradewise Diabetic Retinopathy images (a) Normal (b) Mild (c) Moderate (d) Severe. Segmented Images (e) Normal (f) Mild (g) Moderate (h) Severe

| Database | SVM classifier | | |
|---|---|---|---|
| | Ac | Re | Pr |
| Messidor | 1.0 | 1.0 | 1.0 |
| e-Ophtha Ex | 0.94 | 0.93 | 1.0 |
| DIARETDB0 | 1.0 | 1.0 | 1.0 |
| DIARETDB1 | 1.0 | 1.0 | 1.0 |
| | **k-NN Classifier** | | |
| Messidor | 0.91 | 0.91 | 1.0 |
| e-Ophtha Ex | 0.82 | 0.82 | 1.0 |
| DIARETDB0 | 0.96 | 0.96 | 1.0 |
| DIARETDB1 | 0.95 | 0.95 | 1.0 |
| | **Decision Tree Classifier** | | |
| Messidor | 1.0 | 1.0 | 1.0 |
| e-Ophtha Ex | 0.93 | 0.93 | 1.0 |
| DIARETDB0 | 1.0 | 1.0 | 1.0 |
| DIARETDB1 | 1.0 | 1.0 | 1.0 |

*Ac-Accuracy, Re-Recall, Pr-Precision*

*Table 8***.** Performance Evaluation Measures.

| Databases | Authors | Pr | Re | Ac |
|---|---|---|---|---|
| DIARETDB0 | Mohammed Omar et. al. [31] | | 0.98 | |
| | Garcia et. al. [32] | 0.85 | 0.95 | |
| | Lin P., Bing-Kun Z [33] | 0.87 | 0.84 | |
| | M. Usman Akram et. al. [34] | 0.97 | 0.93 | |
| | **Proposed Method** | **1.0** | **1.0** | **1.0** |
| DIARETDB1 | Shilpa and Nagbhushan [35] | 0.89 | 1.00 | |
| | Kemal AKYOL et.al. [36] | 0.88 | 0.93 | |
| | Chen et.al. [37] | 0.99 | 0.94 | |
| | **Proposed Method** | **1.0** | **1.0** | **1.0** |
| e-Ophtha EX | Xewei Zhang et. al. [38] | 0.95 | | |
| | Qing Liu et.al. [39] | | 0.76 | 0.75 |
| | Somkuwar et. al. [40] | | | 0.96 |
| | **Proposed Method** | **1.0** | **0.93** | **0.93** |
| Messidor | N.B Prakash et. al. [41] | | 0.96 | |
| | Ravitej Rekhi et.al. [42] | | 0.76 | 0.90 |
| | Gupta and Karandikar [43] | | 0.87 | 088 |
| | **Proposed Method** | **1.0** | **1.0** | **1.0** |

*Table 9.* Comparative results of the proposed method using fusion features on Messidor, e-Ophtha-EX, DIARETDB0, DIARETDB1 databases with other methods suggested by various researchers in the literature**.**

| Class | Normal | Mild | Moderate | Severe |
|---|---|---|---|---|
| Normal | 00 | 00 | 00 | 00 |
| Mild | 90 | 88 | 70 | 78 |
| Moderate | 00 | 02 | 20 | 02 |
| Severe | 00 | 00 | 00 | 10 |

*Table 10.* Results of classification of fundus images for Diabetic Retinopathy using fusion features and k-NN classifier.

| Class | Normal | Mild | Moderate | Severe |
|---|---|---|---|---|
| Normal | 90 | 03 | 02 | 00 |
| Mild | 00 | 84 | 09 | 06 |
| Moderate | 00 | 03 | 79 | 08 |
| Severe | 00 | 00 | 00 | 76 |

*Table 11.* Results of classification of fundus images for Diabetic Retinopathy grading using fusion features and Decision tree classifier

| Class | Normal | Mild | Moderate | Severe |
|---|---|---|---|---|
| Normal | 90 | 03 | 02 | 00 |
| Mild | 00 | 87 | 00 | 00 |
| Moderate | 00 | 00 | 88 | 02 |
| Severe | 00 | 00 | 00 | 88 |

*Table 12.* Results of classification of fundus images for Diabetic Retinopathy grading databases using fusion features and ECOC classifier

## VI. Conclusion

Diabetic Retinopathy is a recurrent retinal disorder that can affect patients with both type 1 and type 2 diabetes. The clinical symptoms of Diabetic Retinopathy include microaneurysms, haemorrhages, hard and soft exudates. They are lesions seen on the surface of the retina among diabetic patients. They indicate a pre-proliferative Diabetic Retinopathy state and needs to be treated. This paper describes a method based on morphological operations and thresholding for detection of clinical symptoms of Diabetic Retinopathy. As a part of the feature extraction stage, feature level fusion comprising LBP and HOG features is explored as it yields better accuracy in detection of affected areas in fundus images. Various classifiers namely; SVM, k-NN, decision tree and ECOC classifiers have been tested. The average accuracy values for detection of microaneurysms and Hemorrhages using fusion features yielded 95% for SVM, 97% for k-NN and 96% for Decision tree classifier respectively and the average accuracy values for detection of hard and soft exudates using fusion features yielded is 98% for SVM, 91% for k-NN and 98% for Decision tree classifier respectively. The proposed method using fusion features for grading of Diabetic Retinopathy yielded an accuracy of 32% for k-NN, 91% for Decision tree and 98% for ECOC classifier respectively. The higher accuracy values on fundus images of various databases indicate robustness of the algorithm. The outcome of this research work is a software tool that can not only detect the clinical symptoms but also grade the severity of Diabetic Retinopathy. It will aid the ophthalmologists and clinicians in early detection of retinal disorders. It will also be useful for mass screening programs particularly in rural areas and developing nations.

## Acknowledgement

The authors wish to thank the developers of Messidor, e-Ophtha, e-ophtha-Ex, DIARETDB0, DIARETDB1, STARE and HRF databases for making available digital fundus images publicly and freely to the research community.

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