Journal of Population Therapeutics & Clinical Pharmacology

RESEARCH ARTICLE
DOI: 10.53555/zm5aha16

AN AUTOMATED APPROACH FOR DETECTING DIABETIC RETINOPATHY USING WORDS GENERATION WITH UPDATED SURF AND KNN

Pradeep Kumar K.G[1*], Dr. Karunakara K[2] and Dr. Thyagaraju G. S[3]

[1*]Assistant Professor, Dept. of Computer Science & Engineering, A. J. Institute of Engineering & Technology, Mangalore. Email id- putturpradeep@gmail.com
[2]Professor & Head, Dept. of ISE, Sri Siddhartha Institute of Technology, Tumakuru, Karnataka.
[3]Professor & Head, Dept. of CSE, SDM Institute of Technology, Ujire, India.

Abstract: Human physiology study has been using image processing on various areas. On the contrary, manual study requires huge amount of time and expertise. The work presented here uses machine learning and image processing in order to diagnose the diabetic retinopathy present in the retinal image taken from the fundus camera. The dataset are being collected from various databases such as MESSIDOR, IDBDR0, and IDBDR1. The methodolgy uses the words generation technique with combination of updated SURF and KNN that classifies over 200 images taken from Fundus camera containing lesions present in the retina of the eye. The proposed technique helps in treating and early diagnosis of DR, helping clinicians in a faster mode.

Keywords: Diabetic Retinopathy (DR), Classification, Retina, Machine Learning

1. INTRODUCTION

Diabetic retinopathy (DR) is a significant and growing public health concern that stands as one of the leading causes of blindness globally, particularly among working-age adults. It is a microvascular complication of diabetes mellitus, arising due to prolonged periods of hyperglycemia and characterized by damage to the retinal blood vessels. The condition develops progressively, often asymptomatically in its early stages, which makes early detection and timely intervention critical for preventing irreversible vision loss. With the increasing prevalence of diabetes worldwide, understanding diabetic retinopathy and its implications has become more urgent than ever. Diabetic retinopathy develops when high blood sugar levels damage the tiny blood vessels in the retina, the light-sensitive tissue located at the back of the eye. Over time, this damage can result in the leakage of blood or fluid, causing swelling in the retinal tissue and impairing vision. The condition typically progresses through two main stages: non-proliferative diabetic retinopathy (NPDR) and proliferative diabetic retinopathy (PDR). NPDR is an earlier stage characterized by microaneurysms, retinal hemorrhages, and other signs of vascular compromise, while PDR marks an advanced stage with the growth of abnormal blood vessels (neovascularization) that can lead to complications such as vitreous hemorrhage and retinal detachment.

The impact of diabetic retinopathy extends beyond its direct effects on vision. It is a marker of systemic vascular damage and often correlates with other diabetes-related complications, such as nephropathy and cardiovascular disease. As such, DR not only threatens an individual's quality of life but also imposes a substantial economic burden on healthcare systems worldwide. The World Health Organization (WHO) and other organizations have highlighted diabetic retinopathy as a priority area for action, emphasizing the importance of preventive measures, early diagnosis, and effective management.

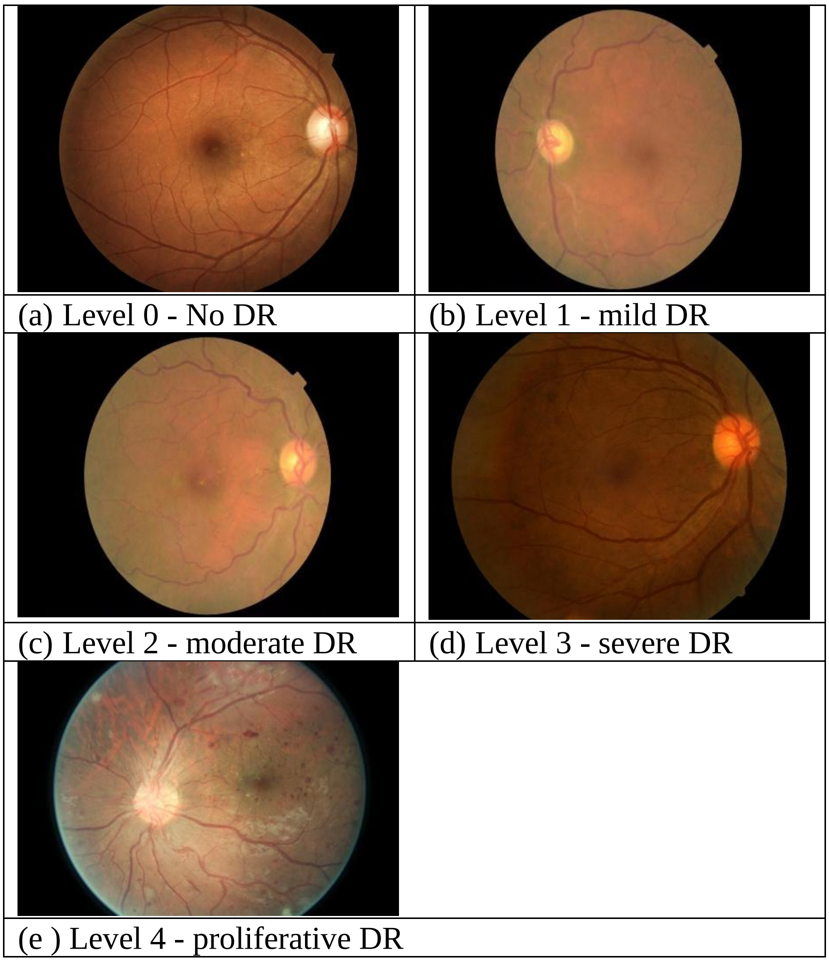
Numerous risk factors contribute to the development and progression of diabetic retinopathy. Poor glycemic control is the most significant modifiable risk factor, underscoring the importance of effective diabetes management. Other factors, such as hypertension, dyslipidemia, duration of diabetes, and genetic predisposition, also play critical roles.

Pregnancy in women with diabetes can further exacerbate the risk of DR progression. Fortunately, advancements in medical science have led to improved strategies for the detection and management of diabetic retinopathy.

Regular screening using fundus photography or optical coherence tomography (OCT) is recommended for individuals with diabetes to enable early detection of retinal changes.

Treatment options, including laser photocoagulation, intravitreal injections of anti-vascular endothelial growth factor (anti-VEGF) agents, and corticosteroids, have significantly improved outcomes for patients with DR. Additionally, patient education and lifestyle modifications, such as maintaining optimal blood sugar levels, controlling blood pressure, and adhering to a healthy diet, are essential components of comprehensive care.

According to the WHO about 422 millions of people are suffering from diabetes, the large chunk of this coming from poor and developing countries. There has been total of 1.6 million death. Of late the diabetes has been increasing rapidly which is cause of the concern. This disease lead to permanent visual impairment. The 33% of the person who suffers from the Diabetes has the symptoms of DR.



(a) Level 0 - No DR
(b) Level 1 - mild DR
(c) Level 2 - moderate DR
(d) Level 3 - severe DR
(e) Level 4 - proliferative DR

Figure 1. Ophthalmologist annotated stages of DR

Out of which 10% suffers acute vision problems. The DR forms a discharge from the retinal tissue leading to lesions and can cause haemorrhages. There is another symptom where clumps are formed around the margin of the retina which is yellow-whitish in nature. The retina with irregular red spots are haemorrhages.

The Figure 1 shows retinal images taken from fundus camera with various stages of DR. The retinal image captured from the specialized fundus camera are not easily accessible as they carry the information related to the patients which has confidentiality clause to adhere with. Although we have achieved success in attaining few images taken from the fundus camera that are being made available to the public for the research purpose. The datasets are being collected in terms of two categories one is normal and the other is DR. The database used for the images made available to the public are MESSIDOR, IDBDR0, and IDBDR1.

Diabetic retinopathy is a preventable but potentially devastating complication of diabetes. As the prevalence of diabetes continues to rise, concerted efforts in education, screening, and treatment are essential to mitigate the burden of this condition. By fostering awareness and encouraging proactive management, healthcare providers, policymakers, and individuals can work together to reduce the impact of diabetic retinopathy and preserve vision and quality of life for millions around the world.

Machine learning, particularly deep learning, has been extensively employed in the past decade to improve the accuracy and efficiency of DR diagnosis. Below is a comparative analysis of key studies prior to 2020.

Table 1. Key studies

Study	**ML Techniques Used**	**Dataset**	**Key Findings**	**Limitations**
Gulshan et al. (2016)	Convolutional Neural Networks (CNNs)	EyePACS, Messidor-2	Achieved over 90% sensitivity and specificity for DR detection. Demonstrated potential for real-world deployment.	High computational cost and dependency on labeled data.
Kaggle Diabetic Retinopathy (2015)	CNNs, Transfer Learning	Kaggle DR dataset	Encouraged adoption of pre-trained models (e.g., InceptionNet, ResNet) for DR classification tasks.	Variability in image quality affected performance; required further validation.
Abràmoff et al. (2018)	Ensemble-based ML	EyePACS	Validated autonomous AI for DR screening, achieving sensitivity of 87.2% and specificity of 90.7%.	Primarily focused on binary classification (referral vs. non-referral).
Quellec et al. (2017)	Recurrent Neural Networks (RNNs), Deep Features	Messidor	Combined image-level features and temporal data for staging; showed improvements in progression prediction.	Lacked scalability for larger datasets.
Lam et al. (2018)	Support Vector Machines (SVM), Handcrafted Features	Retinopathy Online Challenge Dataset	Demonstrated strong results with traditional ML on smaller datasets when combining texture-based features.	Limited performance on larger datasets compared to deep learning approaches.

2. METHODOLOGY

The methodology proposes the updated bag-of-words technique to categorize between the normal and DR fundus images automatically. In every image captured through fundus camera there is a local patch or area of high dimensional space. In the proposed work, SURF (Speeded Up Robust Features) are used to extract the images that are pre-processed. Figure 2 shows the SURF detection technique used in the retinal image. Those images are then clustered by K-means algorithm. The cluster indicates visual words known as bag-of-words. The individual image is compared to the nearest word. The no. of bins in the resultant histogram is same as the word in the vocabulary. The histogram is encoded in 1D array that are fed to the classifier. The experimental study starts with the images coming from the different databases containing varied resolution and sizes. Hence it is necessary to resize it to 512 x 512 dimension. In the next step these images are then contrasted with Histogram Equalizer to differentiate diabetic and non-diabetic retinas. After these the images are localized with feature detection technique. Next is SURF technique to scale up the images for faster computation.

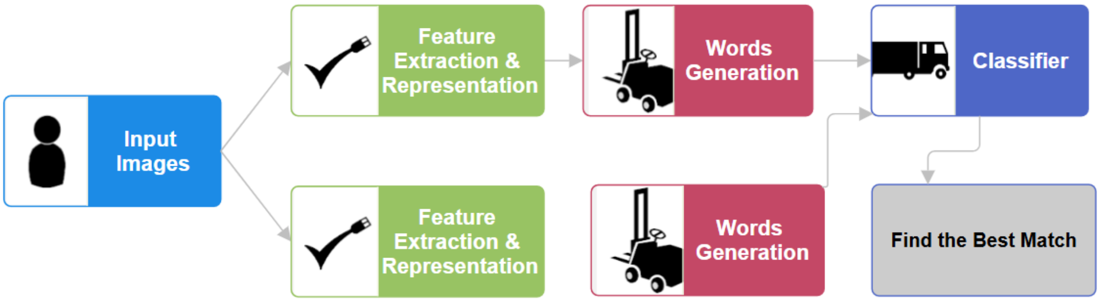


Figure 2. The Process

Words (codebook) generation involves systematically documenting the codes, variables, or categories used in a study or dataset. Initially, the data collected from various sources have been annotated and verified after data cleansing job. Based on next stage the input data may be converted during preprocesing. The next step focuses on determining the codes and organizing them. This involves, listing of variables, metadata, labeling and also handling of missing data if any will be performed. Refinement ensures consistency and clarity across codes by removing duplicate variables or unnecessary codes, this ensures consistent naming conventions After validating, variable coding follows logical order, iterative refinement may be added for ensuring reliability. At the later stage by systematically organizing the information into a clear, usable format. This is verified and validated by experienced ophthalmologist. This helps in keeping the codebook up-to-date till the end for final comparison. An image is typically represented as a matrix of pixel intensities Im(p,q,r), where p.q represents spatial coordinates image matrix, r represents color channel comprising R,G,B for color and r=1 for grayscale.

Feature extraction involves transforming the image from its raw pixel space to a higher-level feature space. This process edge detection through gradient calculation and gradient magnitude.The gradient of the image is computed using convolution with Sobel or Prewitt operators:

$$G_p = Im * S_p \ , \ G_q = Im * S_q \quad \text{- - - - - (1)}$$

The gradient magnitude is calculated

$$G = \sqrt{G_p^2} + \sqrt{G_q^2} \quad \text{- - - - - (2)}$$

Feature maps are applied to the image to extract patterns like edges, textures, or object shapes:

$$F_{i,j,k} = \sum_{m=1}^{K} \sum_{n=1}^{K} \mathbf{I}_{i+m,j+n} \cdot \mathbf{W}_{m,n,k} + b_k \quad \text{- - - - - (3)}$$

where $F_{i,j,k}$: Feature map value at spatial location (i,j) for filter k.
$W_{m,n,k}$: Convolutional filter weights for filter k.
b_k: Bias term for filter k.
K: Size of the filter kernel
After feature extraction, dimensionality reduction techniques like PCA or SVD can be used to reduce the size of the feature space:
$X=U \Sigma V$ - - - - - (4)
Here X is matrix of extracted features, and U,Σ,V are matrices from singular value decomposition. The extracted features can now be represented in vectorized form as
$f=[f_1,f_2,\ldots,f_d]$ - - - - - (5)
d is the number of extracted features.
SURF (Speeded-Up Robust Feature) was introduced as a more efficient alternative to the SIFT (Scale-Invariant Feature Transform) algorithm, focusing on speed while maintaining robust performance. It identifies keypoints in an image and computes descriptors that represent the local neighborhood of each keypoint.
The key steps are:

- Keypoint Detection: Identify locations in the image that are distinctive and stable across scales.
- Keypoint Description: Generate a compact representation of the local image region around each keypoint.
- Keypoint Matching: Match features across images for tasks like image stitching or object recognition.

The use of integral images helps to speed up the computation of image convolutions. An integral image Iint(x,y) is defined as:

$$I_{\text{int}}(x,y) = \sum_{i=0}^{x} \sum_{j=0}^{y} I(i,j) \quad \text{- - - - - (6)}$$

where I(i,j) is the intensity of the pixel at (i,j). The sum of intensities over any rectangular region can then be computed in constant time using:

$$\text{Sum} = I_{\text{int}}(x_2,y_2) - I_{\text{int}}(x_1-1,y_2) - I_{\text{int}}(x_2,y_1-1) + I_{\text{int}}(x_1-1,y_1-1) \quad \text{- - - - - (7)}$$

This dramatically accelerates the computation of convolution filters. The keypoints are detected by finding local extrema in the Hessian matrix determinant, which measures the local variation of pixel intensities. For a pixel (x,y), the Hessian matrix H(x,y,σ) at scale σis defined as:

$$H(x,y,\sigma) = \begin{bmatrix} L_{xx}(x,y,\sigma) & L_{xy}(x,y,\sigma) \\ L_{xy}(x,y,\sigma) & L_{yy}(x,y,\sigma) \end{bmatrix} \quad \text{- - - - - (8)}$$

where L_{xx},L_{xy},L_{yy} are second-order Gaussian derivatives of the image at scale σ, approximated using box filters in SURF. To achieve rotation invariance, it assigns an orientation to each keypoint by analyzing the Haar wavelet responses in a circular neighborhood around the keypoint. Later it generates a compact descriptor by summarizing the local neighborhood of a keypoint. For each grid cell, compute sums of Haar wavelet responses: $\sum R_x,\sum R_y,\sum|R_x|$,and $\sum|R_y|$, these values form a descriptor of length 64 (4×4×4)times. To make invariant to illumination changes descriptor can be normalized. The keypoints generated later combined and compromised with KNN through distance measurements for final decision.

$$\hat{y}_q = \arg\max_{y \in \mathcal{Y}} \sum_{(\mathbf{x}_i, y_i) \in \mathcal{N}_k(\mathbf{x}_q)} \frac{\mathbb{I}(y_i = y)}{d(\mathbf{x}_q, \mathbf{x}_i) + \epsilon} \quad ----- (9)$$

where $\epsilon>0$ is a small constant to avoid division by zero.
The majority voting among neighbors was compared with generated points for the classification.

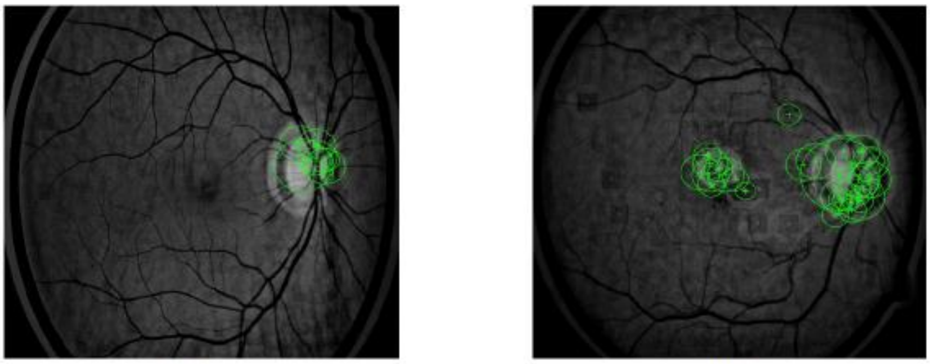
The mean value of the k nearest neighbors are considered for the regression process.

$$\hat{y}_q = \frac{\sum_{(\mathbf{x}_i, y_i) \in \mathcal{N}_k(\mathbf{x}_q)} \frac{y_i}{d(\mathbf{x}_q, \mathbf{x}_i) + \epsilon}}{\sum_{(\mathbf{x}_i, y_i) \in \mathcal{N}_k(\mathbf{x}_q)} \frac{1}{d(\mathbf{x}_q, \mathbf{x}_i) + \epsilon}} \quad ----- (10)$$

The combination of KNN with updated SURF technique, provided with satisfying results in faster mode but complexity is more in comparison with other methodologies.

3. RESULTS

The methodology is tested against MESSIDOR, IDBDR0, and IDBDR1 databases. During the experiment, the database was divided as the training set containing 70% of overall images from each repositories, and remaining 30% used for testing. During the classification took the help of experienced Ophthalmologist for final decision, resulting in 95.1% of graded DR. Every image of the repository is verified and annotated initially, later the results were also discussed and shown to ophthalmologist. The diagram in figure 3 shows the final trace for affected and non-affected retinal images.



(a) (b)

Figure 3. (a) and (b) shows the final outcome for normal retina and DR affected retina

Following table summerises performance of the proposed algorithm against affected retinal images and non affected images. For few images the algorithm over-fit due to filtering technique used. It may corrected in the upcoming research by the use of other useful filtering during final classification.

Table 2. Performance

Classification	**Performance**
Normal Retina	92
DR Retina	98.2
Average	95.1

Table 3 shows classification done on the different algorithm implemented by various researchers for performances.

Table 3: Differentiation on different algorithms

Approach Used	**Technique Used**	**Accuracy**
The Mentioned Approach	Words generation, SURF with KNN	95.1%
Morales et. al	Local Pattern (Binary)	87.65%
Seoud et. al	Dynamic Shape technique	89.9%
Selvarani et. al	Min Intensity and Max Solidity	82%
Gulshan et al	Convolutional Neural Networks (CNNs)	90%
Abràmoff et al.	Ensemble-based ML	87.2%

4. CONCLUSION

In the proposed technique, the word generation technique is merged with updated SURF and KNN is used to detect the retinopathy affected eyes. The leading reason of loss of vision among adults is detected by screening with computational technique. The algorithm used will help eye specialist in terms of feasibility, efficacy and less time consumption way of detected DR. The data repository plays a major role and various dimensions of each data will consume more time to normalize before getting into experimentation. The annotation of each data takes time, but the final result gives satisfaction. The proposed approach has the accuracy of 95.1%. For further, research work has to be done on automated estimation of DR severity on other repositories.

REFERENCES

[1] Ding, J. and Wong, T.Y., “Current Epidemiology of Diabetic Retinopathy and Diabetic Macular Edema”. Curr. Diabetes Rep., vol, 12, pp. 346-354, 2011.

[2] Yau, J.W.Y., et al., “Global Prevalence and Major Risk Factors of Diabetic Retinopathy”, Diabetes Care, vol. 35, pp. 556-564, 2012.

[3] Larsen, M., Godt, J., Larsen, N., Lund-Andersen, H., Sjolie, A.K., Agardh, E., Kalm, H., Grunkin, M. and Owens, D.R., “Automated Detection of Fundus Photographic Red Lesions in Diabetic Retinopathy”, Invest. Ophthalmol. Vis. Sci., 44, 761-766, 2003.

[4] Usher, D., Dumskyj, M., Himaga, M., Williamson, T.H., Nussey, S. and Boyce, J., “Automated Detection of Diabetic Retinopathy in Digital Retinal Images: A Tool for Diabetic Retinopathy Screening”, Diabetic Med., 21, 84-90, 2004.

[5] Zhang, X. and Chutatape, A., “Detection and Classification of Bright Lesions in Color Fundus Images”, ICIP’04, 2004 International Conference on Image Processing, vol. 131, pp. 139-142, 2004.

[6] Morales, S., Engan, K., Naranjo, V. and Colomer, A., “Retinal Disease Screening through Local Binary Patterns”, IEEE Journal of Biomedical and Health Informatics, vol. 21, pp. 184-192, 2017.

[7] Seoud, L., Hurtut, T., Chelbi, J., Cheriet, F. and Langlois, J.M.P., “Red Lesion Detection Using Dynamic Shape Features for Diabetic Retinopathy Screening”, IEEE Transactions on Medical Imaging, vol. 35, pp. 1116-1126, 2016.

[8] Saranya, M., and Grace Selvarani, A., “Fundus Image Screening for Diabetic Retinopathy”, Indian Journal of Science and Technology, vol. 9, 2016.

[9] Cheung N, Mitchell P, Wong TY, “Diabetic retinopathy”, Lancet, vol. 10, no. 376, pp. 124–136, 2010.

[10] Yau JW, Rogers SL, Kawasaki R, et al., “Global prevalence and major risk factors of diabetic retinopathy”, Diabetes Care., A meta-analysis of individual participant data on the prevalence and major risk factors of diabetic retinopathy, vol. 35, pp. 556–564, 2012.

[11] Simó R, Hernández C., “Advances in the medical treatment of diabetic retinopathy”, Diabetes Care, vol. 32, pp. 1556–1562, 2009.

[12] Gulshan, V., et al. (2016). "Development and Validation of a Deep Learning Algorithm for Detection of Diabetic Retinopathy in Retinal Fundus Photographs." JAMA, 316(22), 2402–2410. DOI: 10.1001/jama.2016.17216

[13]Kaggle. (2015). "Diabetic Retinopathy Detection." Retrieved from https://www.kaggle.com/c/diabetic-retinopathy-detection
[14]Abràmoff, M. D., et al. (2018). "Pivotal Trial of an Autonomous AI-Based Diagnostic System for Detection of Diabetic Retinopathy in Primary Care Offices." NPJ Digital Medicine, 1(1), 39. DOI: 10.1038/s41746-018-0040-6
[15]Quellec, G., et al. (2017). "Deep Image Mining for Diabetic Retinopathy Screening." Medical Image Analysis, 39, 178–193. DOI: 10.1016/j.media.2017.03.004
[16]Lam, C., et al. (2018). "A Level-Set Based Approach for Automated Segmentation of Retinal Images." IEEE Transactions on Medical Imaging, 37(10), 2264–2271. DOI: 10.1109/TMI.2018.2843372