Deep Identification of Micro-Aneurysms for the Detection of Diabetic Retinopathy

Praveen Modi[1], Harkaran Singh[2]

{modi.240289@gmail.com[1], harkaran1978@gmail.com[2]}

Department of Computer Engineering, SVKM's NMIMS, School of Technology Management and Engineering, Indore (M.P), India[1],

Department of Construction, Melbourne Polytechnic, Heidelberg West, Victoria-3081, Australia[2]

Abstract. The detection of diabetic retinopathy (DR), using fundus images, helps the ophthalmologist to make decision about its severity level. These images may have various significance issues like dark brightness, blurring etc. This paper is focused on the effective identification of tiny red dots-micro aneurysms and improving the quality of fundus images. WCLAHE technique has been adopted to improve the contrast. Furthermore the bi-linear interpolation method has been applied to fine the irregular boundaries in the fundus images. These images have been effectively segmented to locate the region of interest (ROI) from which the statistical features have been computed. The issues of over fitting and bias have been effectively resolved in the improved support vector machine (I-SVM) model. The proposed solution has been tested on the collected dataset from IEEE Data Port, consist of 3,200 images, encompassing both DR and non-DR cases. The performance metrics such as accuracy, F1-score, AUC have been used to analyze the results The proposed model has shown the better accuracy (96%), F1-Score (93.29%) sensitivity (92.13%), and specificity (94.49%) under 10-fold cross-validation as compared with the existing classification.

Keywords: WCLAHE, ANN, SVM, Over-Fitting, Bi-Linear

1 Introduction

Diabetic retinopathy is the result of disease such as high glucose level, high blood pressure in the working-age population worldwide [1]. A consistently high level of sugar in the blood and irregular fluctuations over time can harm blood vessels [2]. If untreated, it has severe impact on human eyes which may leads to vision loss. Opthmalogists use the retinal eye fundus images to locate the presence of DR related symptoms. The various symptoms of DR can be divided into three broad categories- red, yellow, and white color. Micro aneurysms [3] are the very tiny red dots which may be scattered in the entire image as shown in fig 1. Blood spots of different shapes and medium or large size, produced by bleeding or injury, are referred to as hemorrhages (HE's). Other symptoms like Exudates (Ex's) and Cotton wool Spots (CW's) belongs to yellow and white color respectively. DR is graded into two types- binary and multiclass [4]. Furthermore multiclass grading can be categorized into proliferative and non- proliferative based on the density of identified symptoms.

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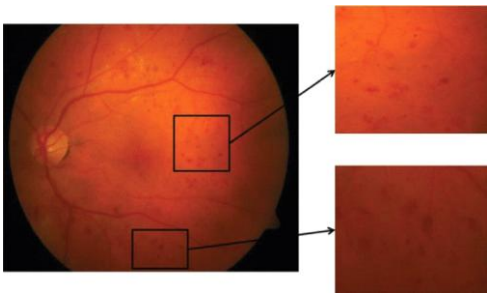


Fig 1. Tiny red dots- Micro-aneurysms [5]

It has been observed that the process of capturing the retinal fundus images suffers from irrelevant illumination, blurred, darkened candidate regions, and uneven light distribution [6]. Due to these irregularities in the images, the performance of classification model gets affected and produces the less accurate results. In the literature survey, the quality of images is improved using existing methods such as Gaussian [7], Min-Max Normalization [8], CLAHE [9] etc. Several feature extraction and selection technique such as Genetic algorithm [10], Principal component analysis[11] etc. have been reported. Various classification models like KNN, ANN, SVM, VGG16, VGG19 [12] etc have been used for the DR prediction. Several challenges still persist like non-uniform reflectance, over-fitting, oversaturation, and biased outcomes. The main aim of this paper is to resolve the issues of over-fitting and bias for improving the better prediction of DR. The rest of paper is divided into four sections. Section-II shows the related previous work, Section-III describes the proposed model, Section-IV presents the results, and Section-V concluded the whole paper.

2 Related works

This section presents the related works previously done for the prediction of DR and its severity grading into binary and multiclass. Saeed et al.[13] designed a two-stage pre-trained-CNN transfer learning model for DR prediction. In addition, PCA method was employed for high level feature extraction. The performance of the model was analyzed over messidor & Eye-PACS dataset. It was observed that the bias result came into picture. Modi et al. [14] designed a three layer model consisting of VGG-16, SPP, and NN layer for multi-grading of DR. In this Ne-vascular vessel was created to detect the micro-aneurysms near to vessels. The performance of the model was analyzed over IEEE dataport fundus image dataset. It shows the accuracy (91.25%), specificity (94.87%) under 10-fold cross validation method. Yang [15] was designed a GCA-Efficient Net (GENet) model to predict the DR. A cosine annealing learning rate method was employed to converge the model as early. The model was trained on fundus image dataset collected from KAGGLE and analyzes the performance. The results showed that it gains the accuracy (95.6%) and specificity (98.9%). Modi et al. [16] used a MLP-CNN model for the multi-grading of DR. MAX-RGB algorithm was applied to enhance the contrast of fundus image dataset collected from IEEE data port. It was shown that the model achieved the good kappa score (0.81) result. In the continuation of previous work done by Modi et al. [17], used a deep-belied net model to address the issue of contrastive divergence during binary classification of fundus images. The images were segmented using k-means clustering and spatial feature were extracted from the identified ROIs. It was shown that, the model achieved the better accuracy (91.28%), Sensitivity (93.46%), specificity (94.84%) and F1-score (94.14%) result under 10-fold cross

validation method. In the continuation of work further done by Modi et al. [18], used a deep-forest cascaded model to improve the slower convergence rate for the binary classification of DR. in this BAT algorithm was applied for feature selection from the extracted features using multi-grained scanning technique. The performance of the model was tested over the same dataset and compares its results with the existing classification model like SVM, ANN etc. The model achieved the better specificity (94.65%), accuracy (92.94%), Sensitivity (95.67%) and F1-score (95.31%) under 10-fold cross validation method. Alavee et al. [19], integrated the CNN model with xplainable artificial intelligence (XAN) for the binary classification of DR. They applied image pre-processing operations like rotation, flipping, constant filling etc to generate the augmented dataset. They analyzed the performance of the proposed model over fundus image dataset collected from KAGGLE and IDRID. The authors claimed that the better accuracy (95.27%) result was achieved.

3. Proposed Model

This section describes the working of the proposed model as shown in fig. 2. The proposed model consisting of retinal fundus image pre-processing, improve profuse clustering, classification model, and model validation. The quality of retinal fundus images have been improved against irrelevant illumination, blurred, darkened candidate regions, and uneven light distribution. The phase of image pre-processing including the steps such as pixel intensity, WCLAHE, and Bilinear interpolation method. The phase of improve profuse clustering method consisting of steps such as edge detection and image segmentation technique based on similar pixel to identify the ROI's. In the phase of binary grading of DR, improved SVM [20] model has been used to work on the statistical feature set. These above phases are further described into subsections (a), (b), and (c) respectively. All these phases are performed over the fundus image dataset which was collected from IEEE data-port repository. This dataset consists of 3,200 images and has dimension of 1440x960. The images are transformed to gray scale using rgb2gray () function.

(a) Image Pre-Processing: This phase enhances the quality of images against irrelevant illumination, blurred, darkened candidate regions, and uneven light distribution. Pixel intensity method is used to remove the noise and inconsistent pixels. WCLAHE [21] divides the image into tiles and compute the histogram for each tile. It controls the over enhancement by clipping it using threshold limit and assign the weights to each surrounding tile based on the similarity. Finally all the tiles get stitched together using bi-linear interpolation method as shown in fig 3.

(b) Improve Profuse Clustering Method: In this phase, initially the edges of the blood vessels are identified using canny edge detection filter and are removed to identify the red dots- micro-aneurysms. Furthermore, the images are segmented using improve profuse clustering technique with augmenting the k-median, to identify the ROI's with objective of pixel similarity as shown in fig 4. Similarity has been computed using pixel eigen values and spectrum [22].

(c) Binary grading of DR: In this phase, initially the statistical features mentioned in table 1, have been computed from the identified ROI's. These features get feeded in the improved

version of support vector machine (SVM) model called least square SVM (LS-SVM) to handle the issue of bias.

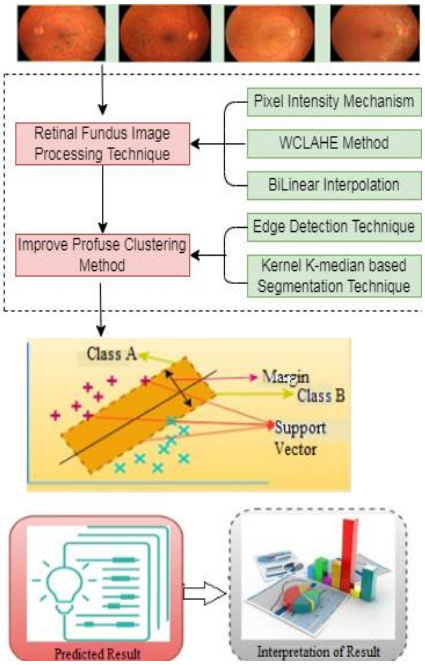


Fig. 2. Proposed DR detection Model

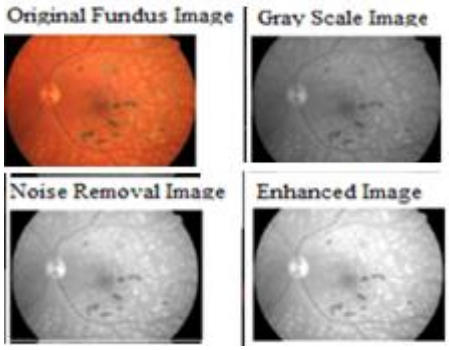


Fig 3. Enhanced Images

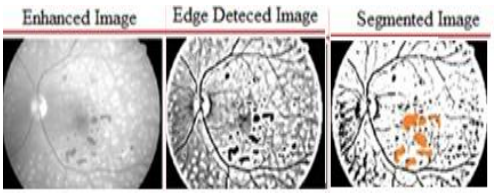


Fig. 4. Edge Detected and Segmented Image

Table 1. Statistical Feature

Feature	Formula
Mean	$\mathrm{Mu} = \frac{1}{\mathrm{M}}\sum_{\mathrm{i}=1}^{\mathrm{M}} \mathrm{A_i}$
Median	$\mathrm{Median(P)} = \begin{cases} \mathrm{A}\left(\frac{\mathrm{M}}{2}\right) & \text{if, M is even} \\ \left(\mathrm{A}\left(\frac{\mathrm{M}-1}{2}\right) + \mathrm{A}\left(\frac{\mathrm{M}+1}{2}\right)\right) & \text{if, M is odd} \end{cases}$
SD	$\sigma = \sqrt{\frac{1}{\mathrm{M}}\sum_{\mathrm{i}=1}^{\mathrm{M}} (\mathrm{A_i} - \mathrm{Mu})^2}$
Skewness	$\mathrm{sk} = \left(\frac{1}{\mathrm{M} \times \sigma^3} \times \sum_{\mathrm{i}=1}^{\mathrm{M}} (\mathrm{A_i} - \mathrm{Mu})^3\right)^{1/3}$

4. Results and Discussion

This section illustrates the achieved results for the binary classification of DR. The experiment is performed on MATLAB software with Intel core-i8 CPU and 32GB RAM. The image

dataset has been divided into training and testing subset using 10-fold cross validation [23]. In a particular iteration, a subset is used for testing and rest of the subsets are used for training purpose. To evaluate the performance of model, the performance metrics such as accuracy (Acc), F1-score (F1), Specificity (Spec) and Sensitivity (Sens) have been used. The model performance has been competitive with other models such as KNN, ANN, VGG16, and SVM model. The confusion matrix of the proposed model and other comparative models is showing in fig.5 (a)-(f). Using the confusion matrix, the performance has been computed which is showing in table 2. It can be easily seen that, the proposed model achieving the better accuracy (90.06%) and F1-score (93.29%) results as compared to other classification techniques. In a similar manner, the model the better sensitivity (92.13%) and specificity (94.49%) results as compared to other classification techniques.

5. Conclusion and Future Scope

This section concludes the whole work presented in this paper for the binary classification of DR. The Images are transformed to handle the issues of over fitting against irregular illumination and noise. Furthermore the bias issue has been handled using LS-SVM model through which the better outcomes have been achieved. The proposed model shows the better performance in comparison to other classification techniques under 10-fold cross validation

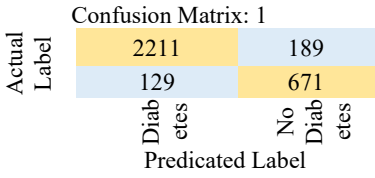


Figure 5(a). Proposed Model

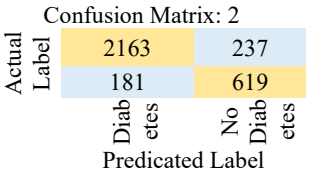


Figure 5(b). VGG19

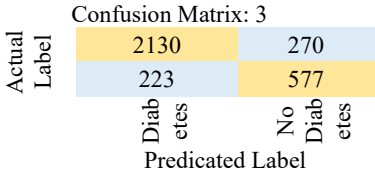


Figure 5(c). VGG16

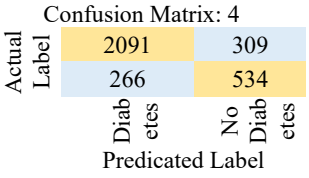


Figure 5(d). SVM

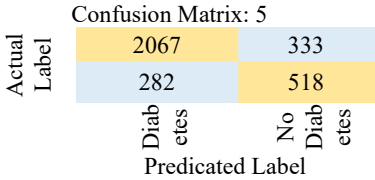


Figure 5(e). ANN

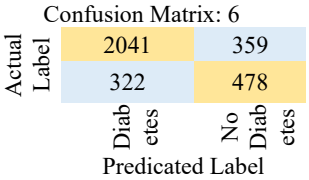


Figure 5(f). KNN

method. The image processing methods have been applied in this paper can be extended for 3-d fundus images to visualize the micro-aneurysms.

Table 2. Performance Results

Technique	Acc	F1	Sens	Spec
KNN	78.72	85.72	85.04	86.37
VGG16	84.59	89.63	88.75	90.52
ANN	80.78	87.08	86.12	87.99
SVM	82.03	87.91	87.13	88.71
VGG19	86.94	91.19	90.13	92.28
Proposed Model	90.06	93.29	92.13	94.49

References

[1] N. Cho, "IDF diabetes atlas: Global estimates of diabetes prevalence for 2017 and projections for 2045," Diabetes Res. Clin. Pract., vol. 138, pp. 271–281, Apr. 2018.

[2] Welikala, R. A., Dehmeshki, J., Hoppe, A., Tah, V., Mann, S., Williamson, T. H., & Barman, S. A. (2014). "Automated detection of proliferative diabetic retinopathy using a modified line operator and dual classification". Computer methods and programs in biomedicine, 114(3), 247-261.

[3] Hendrick AM, Gibson MV, Kulshreshtha A. "Diabetic Retinopathy". Prim Care. 2015;42(3):451-464. doi:10.1016/j.pop.2015.05.005.

[4] Sebastian, Anila, et al. "A survey on deep-learning-based diabetic retinopathy classification." Diagnostics 13.3 (2023): 345.

[5] L. Qiao, Y. Zhu and H. Zhou, "Diabetic Retinopathy Detection Using Prognosis of Microaneurysm and Early Diagnosis System for Non-Proliferative Diabetic Retinopathy Based on Deep Learning Algorithms," in IEEE Access, vol. 8, pp. 104292-104302, 2020, doi: 10.1109/ACCESS.2020.2993937.

[6] Zhou, M., Jin, K., Wang, S., Ye, J., &Qian, D. (2017). Color retinal image enhancement based on luminosity and contrast adjustment. IEEE Transactions on Biomedical engineering, 65(3), 521-527.

[7] Li, H., He, X., Tao, D., Tang, Y., & Wang, R. (2018). Joint medical image fusion, denoising and enhancement via discriminative low-rank sparse dictionaries learning. Pattern Recognition, 79, 130-146.

[8] Tian, Q., Wu, Y., Ren, X., &Razmjooy, N. (2021). "A new optimized sequential method for lung tumor diagnosis based on deep learning and converged search and rescue algorithm". Biomedical Signal Processing and Control, 68, 102761.

[9] Hemanth, D. J., Deperlioglu, O., &Kose, U. (2020). "An enhanced diabetic retinopathy detection and classification approach using deep convolutional neural network". Neural Computing and Applications, 32(3), 707-721.

[10] Ponnusamy, S., Samikannu, R., Venkatachary, S. K., Sukumar, S., & Ravi, R. (2021). Computer aided innovation method for detection and classification of cervical cancer using ANFIS classifier. Journal of Ambient Intelligence and Humanized Computing, 12(6), 6231-6240.

[11] Kadan, A. B., &Subbian, P. S. (2021). "Optimized hybrid classifier for diagnosing diabetic retinopathy: Iterative blood vessel segmentation process". International Journal of Imaging Systems and Technology, 31(2), 1009-1033

[12] Chandran, V., Sumithra, M. G., Karthick, A., George, T., Deivakani, M., Elakkiya, B., .&Manoharan, S. (2021). "Diagnosis of cervical cancer based on ensemble deep learning network using colposcopy images." BioMed Research International, 2021.

[13] Saeed, F., Hussain, M., &Aboalsamh, H. A. (2021). Automatic diabetic retinopathy diagnosis using adaptive fine-tuned convolutional neural network. IEEE Access, 9, 41344-41359
[14] Modi, Praveen, and Yugal Kumar. "Augmentation Based Diabetic Retinopathy System Using Fundus Images." 2022 Seventh International Conference on Parallel, Distributed and Grid Computing (PDGC). ssIEEE, 2022.
[15] B. Yang, T. Li, H. Xie, Y. Liao and Y. -P. P. Chen, "Classification of Diabetic Retinopathy Severity Based on GCA Attention Mechanism," in IEEE Access, vol. 10, pp. 2729-2739, 2022, doi: 10.1109/ACCESS.2021.3139129.
[16] Modi, Praveen, and Yugal Kumar. "CNN-MLP Based Prediction Model for Grading of Diabetic Retinopathy." 2022 Seventh International Conference on Parallel, Distributed and Grid Computing (PDGC). IEEE, 2022.
[17] Modi, Praveen, and Yugal Kumar. "An Effective Diabetic Retinopathy Detection System using Deep Belief Nets and Adaptive Learning in Cloud Environment." Scalable Computing: Practice and Experience 24.2 (2023): 97-114.
[18] Modi, Praveen, and Yugal Kumar. "Smart detection and diagnosis of diabetic retinopathy using bat based feature selection algorithm and deep forest technique." Computers & Industrial Engineering 182 (2023): 109364.
[19] K. AhnafAlavee et al., "Enhancing Early Detection of Diabetic Retinopathy Through the Integration of Deep Learning Models and Explainable Artificial Intelligence," in IEEE Access, vol. 12, pp. 73950-73969, 2024, doi: 10.1109/ACCESS.2024.3405570.
[20] Li, H., He, X., Tao, D., Tang, Y., & Wang, R. (2018). Joint medical image fusion, denoising and enhancement via discriminative low-rank sparse dictionaries learning. Pattern Recognition, 79, 130-146.
[21] G. Rajarajeshwari and G. C. Selvi, "Application of Artificial Intelligence for Classification, Segmentation, Early Detection, Early Diagnosis, and Grading of Diabetic Retinopathy From Fundus Retinal Images: A Comprehensive Review," in IEEE Access, vol. 12, pp. 172499-172536, 2024, doi: 10.1109/ACCESS.2024.3494840.
[22] H. Muhammad AwaisRiaz, M. Nouman Noor, A. A. Safi and A. RazaShahid, "Improving Inference Time in Diabetic Retinopathy—Recent Trends and Future Directions," in IEEE Access, vol. 13, pp. 159178-159195, 2025, doi: 10.1109/ACCESS.2025.3607992.
[23] D. K. Salluri, M. Sai Surya Chandra Atthuluri, V. Sistla and V. Krishna Kishore Kolli, "A Synergistic Stacked Ensemble Deep Learning Model for Predicting Diabetic Retinopathy Severity," in IEEE Access, vol. 13, pp. 202454-202466, 2025, doi: 10.1109/ACCESS.2025.3637311