INDIAN JOURNAL OF SCIENCE AND TECHNOLOGY

RESEARCH ARTICLE

Relative Feature Classification Method for Diabetic Retinopathy Detection from Scanned Eye Images

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OPEN ACCESS

Received: 07-04-2024

Accepted: 04-07-2024

Published: 07-08-2024

Citation: Dhanasekar J, Sudha VK (2024) Relative Feature Classification Method for Diabetic Retinopathy Detection from Scanned Eye Images. Indian Journal of Science and Technology 17(31): 3244-3252. https://doi.org/10.17485/IJST/v17i31.1133

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Funding: None

Competing Interests: None

Published By Indian Society for Education and Environment (iSee)

ISSN
Print: 0974-6846
Electronic: 0974-5645

Abstract

Objectives: Intense/unattended Diabetic Retinopathy (DR) results in vision loss for diabetic patients for which a precise computer-aided image process is required. This article introduces a Distributive Function-Relative Feature Classification Method (DFRFCM) for identifying precise DR positive rates using scanned eye inputs. **Methods:** The proposed method performs a linear distributive assessment for the identifying features between the positive and false rate regions. This linear assessment is based on matching features between inputs and training sets for maximum classifications. **Findings:** The classification of feature relativity is the key factor used for training the neural network across various regions identified. Such a process relies on one-layered neural processing for distinguishing the distribution or closure of the features between consecutive regions. **Novelty:** The closure pixels are identified as false rates from which DR region detection and intensity are classified. This process improves the detection accuracy with fewer errors and has an accuracy of 91.817% and an error of 7.27% when compared with conventional methods.

Keywords: Diabetic Retinopathy; Distributed Function; False Rate; Linear Classification; Neural Network

1 Introduction

One eye-related consequence of diabetes is diabetic retinopathy. Damage to the blood vessels in the retina, the light-sensitive tissue at the back of the eye, is the cause of it. Any person with type 1 or type 2 diabetes has the potential to acquire the illness. The likelihood of developing this eye problem increases with the length of your diabetes and the degree of blood sugar management. Diabetic Retinopathy (DR) leads to vision loss which is detected using effective image processing systems. DR detected based on extracted features are used in medical applications [(1)]. The major challenge in diabetic retinopathy is its detection, in the early stages of diabetic retinopathy, mild symptoms are frequently present and can be difficult to identify without sophisticated imaging methods and skilled medical professionals. Small hemorrhages and microaneurysms are easily overlooked. A Multi-Label Feature Extraction and Classification (ML-FEC)

model using principal component analysis (PCA) is used. The ML-FEC extracts the features and texture of the DR from medical data [2]. The extracted features are pre-trained to identify the subset for the DR detection process. The ML-FEC model is used to reduce the computational cost and complexity of providing medical services to patients [3]. To reduce the latency, DR detection uses a Convolutional Neural Network (CNN) algorithm for Feature Extraction and Classification (FEC) processes. The extraction technique is used to extract the patterns and features from the given fundus images [4]. Feature Classification for DR detection is a complex task in every medical healthcare center [5]. False and positive rates are identified from the fundus images which provide essential data for the classification process. The Deep Learning (DL) technique analyses the features and sustains data from the images. This technique addresses the exact cause and condition of the DR disease which enhances the performance in providing services [6,7]. A CNN-based classification method is used to detect the initial stages of DR. The recognized features provide segment-level data for the feature classification process. The CNN algorithm increases the specificity and sensitivity level of the DR detection [8].

Sundar et al. [9] proposed a graph convolutional neural network (GCNN) based classification method for healthcare systems. The proposed method is mostly used to classify diabetic retinopathy diseases for the diagnosis process. Retinal images are used which produce optimal information for the detection process. It detects the topological features from the images that reduce the latency in the computation process. The proposed GCNN-based method increases the accuracy of the disease classification process.

Wong et al. [10] developed a new transfer learning approach based on parameters and weights of features. The main aim of the approach is to identify the diabetic retinopathy (DR) disease types of the patients. The actual weights and parameters of the features are evaluated to classify the exact types of the DR. An adaptive differential evolution (ADE) is used here to configure the parameters. The developed approach enhances the performance and feasibility range of the systems.

Nahiduzzaman et al. [11] introduced a parallel convolutional neural network (PCNN) based -DR identification method for healthcare systems. A feature extraction technique is used here to extract the important features for the DR classification method. PCNN is mainly used to minimize the time required to identify the DR types of patients. The introduced approach improves the accuracy of the DR identification process.

Mahmood et al. [12] designed a hybrid approach for DR diagnosis using fundus images. The fundus images produce optimal information which is required for the DR diagnosis process. The deep features and patterns of the DR are evaluated from fundus images. The early signs of DR are also calculated which reduces the complexity ratio in the diagnosis process. The designed approach increases the significance and effectiveness range of diagnosis systems.

Fang et al. [13] proposed a new DR classification method using a directed acyclic graph (DAG) network model based on multi-features. The multi-features are identified from fundus images that decrease the latency and energy consumption level in the classification process. The main aim of the optimized model is to classify the types of DR for healthcare centres. The proposed method improves the efficiency ratio in the DR diagnosis process.

Fang et al. [14] introduced a DAG network based on multi-feature fusion for the DR classification process. It is used as a multi-classification method that classifies the symptoms and conditions of patients via fundus images. The important features are extracted from fundus images that produce optimal information for the DR classification process. The introduced method identifies the exact grade and types of DR that enhance the lifespan of the patients.

Jadhav et al. [15] proposed an optimal feature selection-based DR detection method. The actual goal of the method is to detect the actual types of DR for the diagnosis process. The feature selection technique selects the unique features of DR from the fundus images. An optimization algorithm is implemented here to reduce the risk ratio in the detection process. Experimental results show that the proposed method increases the overall accuracy level in the DR detection process.

Dayana et al. [16] developed a deep learning (DL) enabled optimized feature selection method for DR detection using fundus images. The developed method uses an attention-based fusion network (AFU-Net) that evaluates the texture and features of the fundus images. The fundus images produce the optimal features for the DR detection process. The developed method improves the significance and feasibility range of DR detection in healthcare applications.

Mohan et al. [17] introduced an optimal hybrid feature selection technique for DR grading in healthcare systems. The main goal of the technique is to minimize the risk level in the DR diagnosis process. The introduced technique uses a whale optimization algorithm to classify the features using fundus images. The introduced technique enhances the overall performance and accuracy ratio in the DR grading process.

The methods introduced above rely on single-feature extraction as topological [9] or weighted [10], and patterns [12] or multi-feature extractions as in [13,14]. The extracted features are precise to select and to be utilized for DR detection as discussed in [15,16] or hybridized as in [17]. However, the methods fail to extract or select the least preference features from error regions. Deviating from the regions the extraction is delayed or skipped in such a process that does not ensure maximum precision. Besides, the feature replacement possibilities are also less given classification. The proposed method addresses this problem by identifying

relative features that are optimal for classification. The classification is the filtering process to utilize even the least preferred feature for DR detection in this method. The main objectives of the work are

- To design a distributive function-relative feature classification method for improving the accuracy of diabetic retinopathy detection using retinal image inputs.
- To efficiently classify positive and false feature regions using extracted feature sequences across various matching and correlating training inputs.
- To perform a metric and experimental analysis using comparative and sample dataset inputs for validating the proposed method's efficiency.

The problem of false region detection due to latency and DR stages is unclear for different pixel distributions. The feature extraction from these regions is limited due to error chances that impact precision. The proposed method is motivated by this fact to extract the least possible features from such regions that are used to train the learning paradigm in a view to improve detection precision. The linear assessments and classifications are the augmenting features of this process in this proposed method.

2 Methodology

The creation of more economical, non-invasive, and accurate screening techniques for early detection, particularly in environments with limited resources is a major research gap in identifying diabetic retinopathy which leads to a major problem in traditional methods and also large-scale investigations and meta-analyses are made easier with the integration of big data technologies and enhanced data sharing among academics.

2.1 Distributive Function-Relative Feature Classification Method

This article presents a discussion of the design, description, and performance of the novel feature classification method for DR detection. The proposed method takes retinal images as input for feature extraction and classification processes. These two processes are tuned using linear assessments for maximizing detection accuracy aided by positive rate classifications. For a precise understanding, the proposed method is depicted in Figure 1.

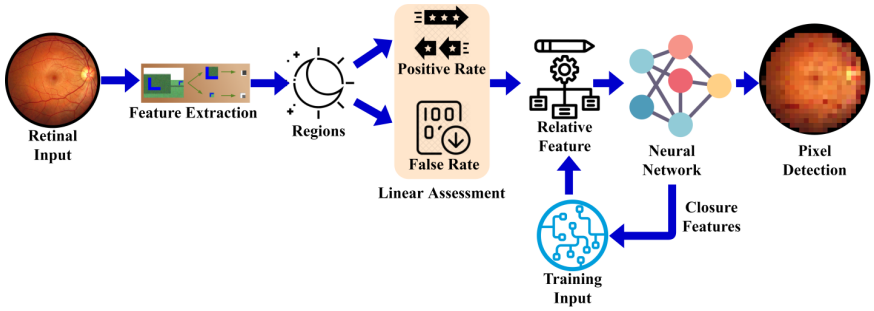

Fig 1. Proposed Method Illustration

As presented in Figure 1, the features extracted in the retinal regions are assessed linearly based on region continuity. In this proposed method, textural features such as entropy (E^o) and Variance (v^o) are considered for linear assessments. These features are computed using Equation (1).

$$\left.\begin{aligned} v^o &= \sum_{i=1}^{n} (R_i - x)^n \, p(R_i) \\ E^o &= -\sum_{i=1}^{n} p(R_i) \log_2 p(R_i) \end{aligned}\right\} \tag{1}$$

Where n is the maximum pixels, R is a random pixel in the region x and $p(R_i)$ is the maximum pixel in x such that $x < n$. These features are linearly analyzed for their distribution using the relativity metric. This relativity is analyzed using neural learning and training for the varying x in an input. The variations v^o observed in any x are identified for their false/positive rates on correlation with the training inputs (Figure 1). The extracted features are linearly analyzed based on positive and false rates across $x = n$ pixels such that $\sum p(R_i) = n$ are achieved. Based on this linearity, the derivation's false rate (f_r) and

positive rate (p_r) are defined as

$$\left.\begin{array}{c} \forall p(R_i \le n, \dfrac{\sum v^o}{x} + \dfrac{E^o}{n} = max\ value = 1 \ \forall\ v^o = 0 \\ such\ that\ p_r = \dfrac{E^o}{x_1} + \dfrac{E^o}{x_2} + \cdots + \dfrac{E^o}{x_i} \ \forall\ i \in n \\ and\ f_r = 1 - \dfrac{p_r}{n}, \dfrac{p_r}{n} = 1 \ \forall\ v^o = 0 \end{array}\right\} \tag{2}$$

The above representation is the linearity for x, n equalizing them similarly provided new variations are suppressed. The change in this sequence using the relative measure increases the false rate due to unattended v^o. This relative measure from the training inputs is correlated with v^o and E^o for detecting either of the above linearities. Based on this correlation output, single-layer neural training is performed. In this context, the relative feature measure (ρ_f) and its correlation instances $(C_1 to C_n)$ are defined as in Equation (3).

$$\left.\begin{array}{l} \rho_f = \dfrac{x_I - x_2}{E^o} + \dfrac{x_I - x_2}{v^o} \pm \dfrac{n_I - n}{n} \\ and \\ \left.\begin{array}{l} C_1 = \rho_{f_1} + \left(\dfrac{x}{x_I}\right)_1 \\ C_2 = \rho_{f_2} + \left(\dfrac{x}{x_I}\right)_2 \\ \vdots \\ C_n = \rho_{f_n} + \left(\dfrac{x}{x_I}\right)_n \end{array}\right\}, if\ x < x_I \\ (or) \\ \left.\begin{array}{l} C_1 = \rho_{f_1} + \left(\dfrac{x_I}{x}\right)_1 \\ C_2 = \rho_{f_2} + \left(\dfrac{x_I}{x}\right)_2 \\ \vdots \\ C_n = \rho_{f_n} + \left(\dfrac{x_I}{x}\right)_n \end{array}\right\}, \ if\ x > x_I \end{array}\right. \tag{3}$$

In the above Equation (3), the x_I and n_I represent the region in the input and its corresponding pixels. The correlation is amendable based on and x_I counts for which ρ_f varies accordingly. The $\pm$ in ρ_f indicates the $x < x_I$ (or) $x > x_I$ conditions. The ρ_f detection is expected to be continuous such that v^o and E^o in the training, input pursue the same x sequence as the testing input. The relative factor of highness provides $p_r > f_r$ such that accuracy is improved. In the alternating sequences of x (missing in either input/testing image) the chances of $f_r > p_r$ is high for which the learning is pursued. Therefore, the possible cases for training initialization are diagrammatically given in Figure 2.

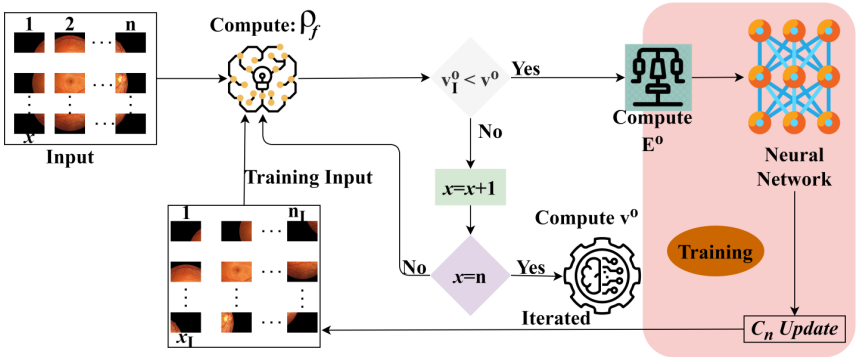

Fig 2. Training Initialization case

The training initialization case is validated for identifying f_r in any x due to $p(R_i)$. First, the p_f is estimated for the $(n, x) \in$ Training and testing inputs. From this computation, if $v_I^o > v^o$(V_I^o is the variation observed in the training input),

then E^o is the p_r or f_r or both deciding factors. This case requires neural network training for $\sum x$ from Z to n pixels for regions encountered. The contrary case of $v_I^o < v^o = false$ increases the x estimation to the consecutive pixel for v^o computation. The final case of C_n is updated for such consecutive pixels from 2 to $x \leq n$ for p_f detection (Figure 2). This case encounters the problem of region switch over (i.e.) x to $(x+1)$ to $(x+2)$ to …to (n) where either p_r or f_r is high which reduces the classification. Therefore, intense repeated one-layer neural network is employed for identifying v^o and f^r in any continuous sequence of $i \in n$. The entire process is used to finalize v^o in any consecutive sequence of (x_1, x_2) or (x_2, x_3) or… (x_{n-1}, x_n). Therefore, the entire training is performed for p_r and f_r variation (high/low) between successive x. The neural network is represented in Figure 3 for the variation (high/low) classification of x. Such a network is used for identifying f_r or providing training iteratively.

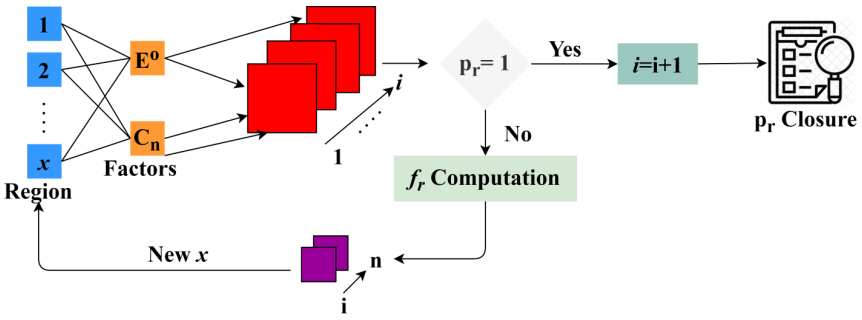

Fig 3. Neural Network Representation

The neural network validates the $p_r = 1$ condition for v^o detection and $f_r = 1$ for training. Depending on the improvement i.e., $i = i+1$ from any consecutive $x \in n$ sequences. As described before, the variation (high/low) of the one-layer neural network (Figure 3) is computed in Equation (4).

$$\left.\begin{array}{l} \underbrace{\begin{array}{c} v_1^o = pr_1 \\ v_2^o = \left(pr_2 - f_{r_1}\right) + \left(\dfrac{\rho_f}{C_n}\right)_1 \\ \vdots \\ v_n^o = \left(pr_n - f_{r_{n-1}}\right) + \left(\dfrac{\rho_f}{C_n}\right)_{n-1} \end{array}}_{Low\ variation} \\ \underbrace{\begin{array}{c} v_2^o = \left(\dfrac{\rho_f}{C_n}\right)_2 + fr_1 \\ v_3^o = \left(\dfrac{\rho_f}{C_n}\right)_3 + fr_2 \\ \vdots \\ v_n^o = \left(\dfrac{\rho_f}{C_n}\right)_n + fr_{n-1} \end{array}}_{High\ Variation} \end{array}\right\} \tag{4}$$

The above equation describes the variation observed between consecutive x until n is reached. A low or high variation is required to suppress $f_r = 1$ such that the iteration closes p_r at any instance. Therefore, the iteration for $f_{r_{n-1}}$ is pursued under differential occurrences between x. Therefore, the above variations are observed in an either-or classification such that detection is improved for high variation. However, the variations-based detection from the iterations is defined as in Equation (5).

$$\rho(f_r) = \left\{ \begin{array}{l} \dfrac{E^o - \left(\dfrac{\rho_f}{C_n}\right) \pm \dfrac{x_I}{x}}{n}, \ \forall\ Low\ variation \\ E^o - \dfrac{C_n}{n} \pm \dfrac{p_r}{f_r}\ \forall\ High\ variation \end{array} \right\} \tag{5}$$

The variable $\rho(f_r)$ refers to the x detection with low/high variations. In this process variation suppression is performed by maximizing E^o for the available pixels. The difference between consecutive x is validated for defining multiple regions. Therefore, the feature s v^o and E^o are classified under low/high demands for new training or p_r closures in detecting false rates. The features that consecutively rely on high variation for $(i+1)$ to n generate more false rates compared to that of the C_n. Therefore, the training is pursued from $(i+1)$ to $n \in n$ for the high variation features for f_r mitigation.

3 Results and Discussion

3.1 Experimental Outputs

The experimental outputs are validated and verified using MATLAB simulations using the retinal inputs from [18]. This source provides 86 training and 53 testing images for identifying DR acquired at 60fps. The neural network is trained for 800 iterations to achieve maximum accuracy of relativity=1. Based on this information, a sample input analysis and its corresponding output are presented in Figure 4.

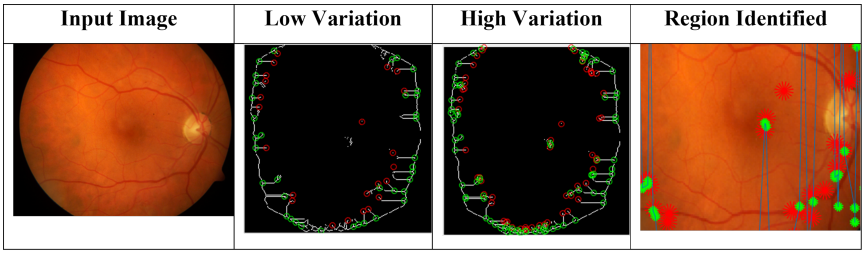

Fig 4. Input and Output Analysis

3.2 Comparative Analysis

The comparative analysis is pursued using accuracy ratio, precision, error, and classification time. The number of features is varied between 1 and 10 and the classification rate is modeled between 0.1 and 1 for metric analysis. Along with the proposed method, the MGS-ROA [15] and GCNN [9] are considered for the comparative analysis.

3.3 Accuracy Ratio

The proposed method achieves high accuracy in detecting retinopathy-infected regions from $x \leq n$. This is facilitated by classifying the $\rho(f_r)$ using high/low variation. In the single neural network-based learning process, p_r closures are inevitable in identifying new $(1\ to\ i)$ or $(i+1\ to\ n)$ sequences. The training process is performed for multiple $(i=i+1)\ \forall\ i \in x$ and $p(R_i)$ satisfying $\exists^o$. The alternating instances of v_1^o to v_n^o respond with low/high variation in classifying $x \leq n$. Therefore, the recurrent iterated training $\forall\ x_I$ and n_I interference encourages the precise x detection. This augments the accuracy factor for different features and classification rates (Refer Figure 5).

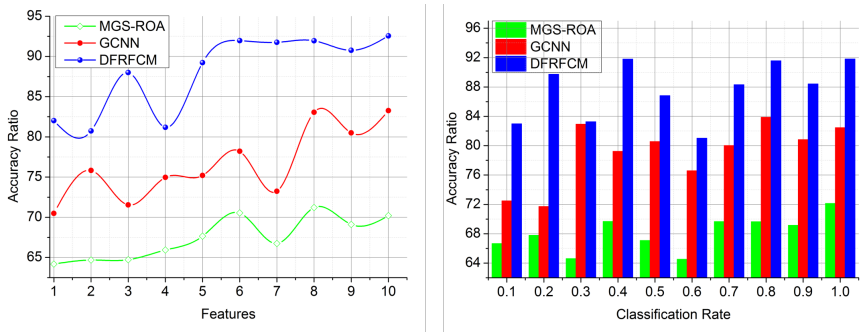

Fig 5. Accuracy Ratio

3.4 Precision

In the proposed method, two flexible computing instances are vibrant in sustaining precision. The first process is the C_n estimation using x_I and x for the consecutive sequences defined in Equation (2). Based on the interfering features between

successive x, the $\rho(f_r)$ is the second computation classified. Hence, the number of direct and indirect x identified through $v^o \forall (1\ to\ n)$ and $(2\ to\ n)$ (interfering) sequences are then computed. In any of the sequences, the $p_r = 1$ is verified for f_r identification. Such identified sequences are suppressed under recurrent f_{r_1} to $f_{r_{n-1}}$ training using C_n. Therefore, the consecutive x that identifies low variations are suppressed in the consecutive p_r closures. If the closures are high the precision is retained under various features (Figure 6).

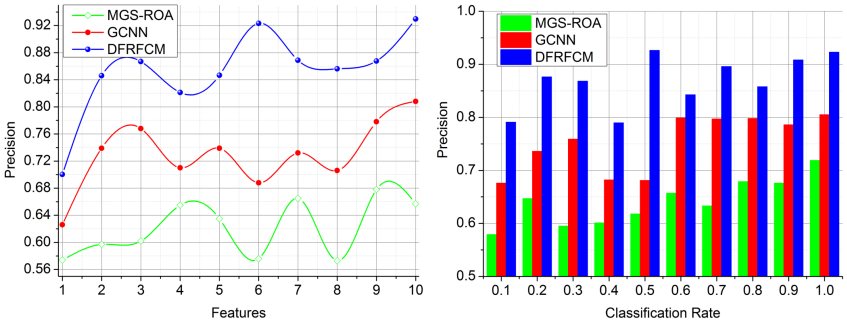

Fig 6. Precision

3.5 Error

The cumulative distribution of the interrupted sequences of x is used for error detection. The v^o occurred in distinguishable i and $(i+1)$ instances are invariable for low and high classifications. The layers of neural network processing differentiate $\rho(f_r)$ for error detection. This relies on x_I and n_I for $p_r = 1$ achievement; the fluctuations are suppressed using E^o improvements. Therefore, the second sequence of $(i+1)$ to n is used for $f_{r_{n-1}}$ suppression for high variations. In the contrary case, the errors are distinguished for $\frac{x_I}{x}$ and x/x_I independently. Therefore, the training is permitted for high variations under the distinguishable classification of v_n^o. The unclassified sequences generate $\rho(f_r)$ that are detected across various features (Figure 7).

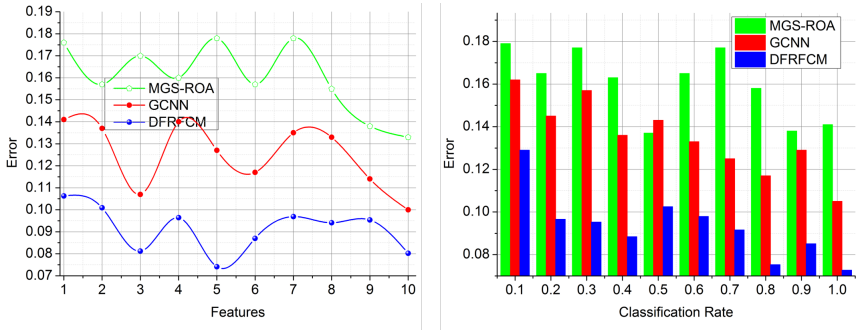

Fig 7. Error

3.6 Classification Time

The $\rho(f_r)$ classification requires ample time for identifying $\left[E^o - \left(\frac{\rho_f}{C_n}\right)\right]$ or $\left[E^o - \left(\frac{C_n}{n}\right)\right]$ differentiations. The initial classification requires $(1\ to\ i \in x)$ and $(i+1\ to\ x \in n)$ detection across incurring features. The features identified are used for detecting new missing sequences for preventing interfering sequences. Based on the variations in $C_1\ to\ C_n$ differentiation, the linearity check is performed for either of $\rho(f_r)$ defined in Equation (5). Therefore, further classifications are handled from $[(i+1)\ to\ x]$ with limited iterations. In the optimal case of feature misleads alone the classification time increases (Figure 8). The above comparative analysis is summarized in Table 1 and Table 2 for the features and classification rates.

The proposed method improves the accuracy and precision by 7.92% and 9.87% respectively. This method also reduces the error and classification time by 7.26% and 8.73% respectively.

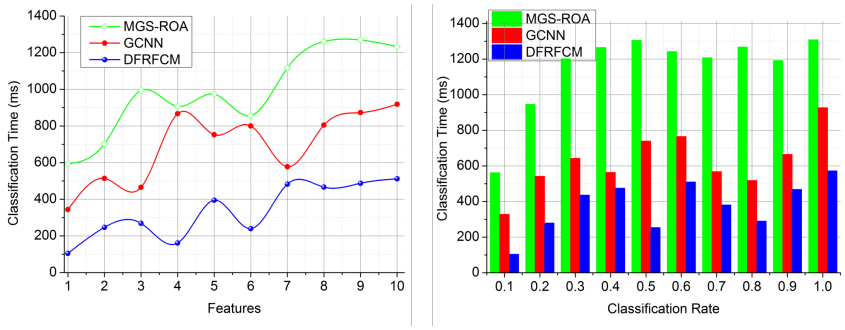

Fig 8. Classification Time

Table 1. Comparative Analysis Summary for Features

Metrics	MGS-ROA	GCNN	DFRFCM
Accuracy Ratio	70.2	83.26	92.564
Precision	0.657	0.808	0.9298
Error	0.133	0.1	0.0802
Classification Time (ms)	1233.12	918.56	512.411

Table 2. Comparative Analysis Summary for Classification Rate

Metrics	MGS-ROA	GCNN	DFRFCM
Accuracy Ratio	72.14	82.45	91.817
Precision	0.719	0.805	0.9228
Error	0.141	0.105	0.0727
Classification Time (ms)	1308.82	926.97	572.436

The proposed method improves the accuracy and precision by 7.26% and 8.04% respectively. This method also reduces the error and classification time by 7.03% and 8.13% respectively.

4 Conclusion

This article discussed the working and performance of the novel distributive function-relative feature classification method for improving the DR detection accuracy from retinal image inputs. For this purpose, the feature classification aided by the one-layer neural network is introduced. Based on the linear relativity feature observed for both false and positive pixel rates, the classification is planned to be recurrent using the neural training network. Therefore, linear computations are performed between the testing and training inputs to verify maximum matching rates. This process is thus optimal in identifying consecutive regions across different variations between alternating pixel sequences for reducing false rates. From the comparative analysis, the proposed method achieves 7.92% high DR detection accuracy, 9.87% high precision, 7.26% less error, and 8.73% less classification time for the varying features. The Relative Feature Classification Method has a wide and promising future potential for the identification of diabetic retinopathy. This strategy has the potential to greatly enhance diabetic retinopathy identification, monitoring, and management by utilizing technological improvements, integrating with clinical workflows, and emphasising patient-centric methods.

References

1) Asia AO, Zhu CZ, Althubiti SA, Al-Alimi D, Xiao YL, Ouyang PB, et al. Detection of diabetic retinopathy in retinal fundus images using CNN classification models. *Electronics*. 2022;11:2740–2740. Available from: https://doi.org/10.3390/electronics11172740.
2) Usman TM, Saheed YK, Ignace D, Nsang A. Diabetic retinopathy detection using principal component analysis multi-label feature extraction and classification. *International Journal of Cognitive Computing in Engineering*. 2023;4:78–88. Available from: https://doi.org/10.1016/j.ijcce.2023.02.002.
3) Mukherjee N, Sengupta S. Comparing deep feature extraction strategies for diabetic retinopathy stage classification from fundus images. *Arabian Journal for Science and Engineering*. 2023;48(8):10335–54. Available from: https://doi.org/10.1007/s13369-022-07547-1.
4) Das D, Biswas SK, Bandyopadhyay S. Detection of diabetic retinopathy using convolutional neural networks for feature extraction and classification (DRFEC). . *Multimedia Tools and Applications*. 2019;82:29943–30001. Available from: https://doi.org/10.1007/s11042-022-14165-4.

5) Hemanth SV, Alagarsamy S. Hybrid adaptive deep learning classifier for early detection of diabetic retinopathy using optimal feature extraction and classification. *Journal of Diabetes & Metabolic Disorders*. 2023;22(1):881–95. Available from: https://doi.org/10.1007/s40200-023-01220-6.
6) Atwany MZ, Sahyoun AH, Yaqub M. Deep learning techniques for diabetic retinopathy classification: A survey. *IEEE Access*. 2022;10:28642–55. Available from: https://doi.org/10.1109/access.2022.3157632.
7) Homayouni A, Liu T, Thieu T. Diabetic retinopathy prediction using Progressive Ablation Feature Selection: A comprehensive classifier evaluation. . *Smart Health*. 2022;26:100343–100343. Available from: https://doi.org/10.1016/j.smhl.2022.100343.
8) Math L, Fatima R. Adaptive machine learning classification for diabetic retinopathy. . *Multimedia Tools and Applications*. 2021;80:5173–86. Available from: https://doi.org/10.1109/mysurucon55714.2022.9972593.
9) Sundar S, Sumathy S. Classification of Diabetic Retinopathy disease levels by extracting topological features using Graph Neural Networks. *IEEE Access*. 2023;11:51435–51444. Available from: https://doi.org/10.1109/access.2023.3279393.
10) Wong WK, Juwono FH, Capriono C. Diabetic Retinopathy Detection and Grading: A Transfer Learning Approach Using Simultaneous Parameter Optimization and Feature-Weighted ECOC Ensemble. *IEEE Access*. 2023;11:83004–83016. Available from: https://doi.org/10.1109/access.2023.3301618.
11) Nahiduzzaman M, Islam MR, Goni MO, Anower MS, Ahsan M, Haider J, et al. Diabetic retinopathy identification using parallel convolutional neural network based feature extractor and ELM classifier. *Expert Systems with Applications*. 2023;217:119557–119557. Available from: https://doi.org/10.1016/j.eswa.2023.119557.
12) Mahmood MA, Aktar N, Kader MF. A hybrid approach for diagnosing diabetic retinopathy from fundus image exploiting deep features. . *Heliyon*. 2023;9. Available from: https://doi.org/10.1016/j.heliyon.2023.e19625.
13) Fang L, Qiao H. Diabetic retinopathy classification using a novel DAG network based on multi-feature of fundus images. *Biomedical Signal Processing and Control*. 2022;77:103810–103810. Available from: https://doi.org/10.1016/j.bspc.2022.103810.
14) Fang L, Qiao H. A novel DAG network based on multi-feature fusion of fundus images for multi-classification of diabetic retinopathy. *Multimedia Tools and Applications*. 2023;82:47669–93. Available from: https://doi.org/10.1007/s11042-023-15296-y.
15) Jadhav AS, Patil PB, Biradar S. Optimal feature selection-based diabetic retinopathy detection using improved rider optimization algorithm enabled with deep learning. *Evolutionary intelligence*. 2021;14:1431–1479. Available from: https://doi.org/10.1007/s12065-020-00400-0.
16) Dayana AM, Emmanuel WS. Deep learning enabled optimized feature selection and classification for grading diabetic retinopathy severity in the fundus image. . *Neural Computing and Applications*. 2022;34:18663–83. Available from: https://doi.org/10.1007/s00521-022-07471-3.
17) Mohan NJ, Murugan R, Goel T, Mirjalili S, Singh YK, Deb D, et al. Optimal hybrid feature selection technique for diabetic retinopathy grading using fundus images. *Sādhanā*. 2023;48(3):2023–2023. Available from: https://dx.doi.org/10.1007/s12046-023-02175-3.
18) Hai Z, Zou B, Xiao X, Peng Q, Yan J, Zhang W, et al. A novel approach for intelligent diagnosis and grading of diabetic retinopathy. *Computers in Biology and Medicine*. 2024;172:108246–108246. Available from: https://doi.org/10.1016/j.compbiomed.2024.108246.