Communications on Applied Nonlinear Analysis
ISSN: 1074-133X
Vol 32 No. 10s (2025)

Diabetic Retinopathy Deep Learning Model for Image Class Prediction by Modified Frog Leaping Optimized Features

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Article History:

Received: 12-01-2025

Revised: 15-02-2025

Accepted: 01-03-2025

Abstract:

The healthcare sector greatly benefits from image classification, which holds immense value in medical diagnostics. One of the critical health concerns identified by the WHO is diabetic retinopathy (DR), a widespread condition that poses a serious threat to vision and has reached epidemic proportions worldwide. This paper has proposed a DRDLOFLM (Diabetic Retinopathy Deep Learning Optimized Frog Leaping Model) model that predicts the class of the DR disease. For training of machine visual content features are extracted from the image. Selected features are extract from the blocked image so cumulative prediction gives better output of image diagnosis. Block region were selected by the frog leaping algorithm for the optimization of features. Experiment is perform on read medical images of DR images. Results shows that proposed DRDLOFLM (Diabetic Retinopathy Deep Learning Optimized Frog Leaping Model) has improved the evaluation parameters values.

Index Terms: Medical image diagnosis, Frequency Feature, Clustering, DIP.

I. INTRODUCTION

In the medical domain, the effectiveness of disease treatment significantly improves when conditions are identified at an early stage. Diabetes, a metabolic disorder, leads to an excessive accumulation of glucose in the bloodstream due to insufficient insulin production [1]. This condition affects approximately 425 million adults worldwide [2] and has serious implications for multiple organs, including the retina, heart, nerves, and kidneys [1,2].

Diabetic retinopathy (DR) is one of the most prevalent retinal diseases associated with diabetes. Its early symptoms often include blurred vision and eye floaters, while prolonged and untreated progression can result in complete vision loss. The disease manifests through various retinal lesions, such as hemorrhages (HM), microaneurysms (MA), hard exudates, and soft exudates [3].

Many individuals fail to recognize the early warning signs of DR, leading to delayed diagnosis and an increased risk of vision impairment. Early detection is essential for preserving eyesight, as timely intervention allows for more effective treatment. Traditional automated DR detection systems follow a multi-stage process, beginning with fundus image analysis to detect and classify lesions. Compared to manual diagnosis, automated methods offer greater efficiency, reduce costs, and save time [4]. Manual assessments, on the other hand, are labor-intensive and susceptible to misdiagnosis. To enhance accuracy and efficiency, machine learning techniques (MLT) have been incorporated into automated DR detection systems.

This study observes that a majority of existing research has primarily focused on binary classification of DR. Furthermore, optimizing feature selection remains a critical aspect of medical diagnostics. To address these challenges, this paper outlines the following key objectives

1. Find the feature set that improves the detection accuracy.
2. Optimized the features for supporting the learning model.
3. Train a machine learning model that identifies all classes of DR class of images.

The remaining parts of the paper are divided up into a few sections. In the second section, this paper will elaborate on the research work that various scholars have done so far. Additional research has been published that details the proposed model with a block diagram and algorithm. In the fourth section of the paper, a comparison of the proposed model is carried out on a variety of evaluation parameters. The conclusion section of the paper discusses the findings.

II. Related Work

Gupta and Chhikara [7] conducted an in-depth analysis of diabetic retinopathy (DR) detection methodologies, incorporating techniques such as Adaboost, Random Forest, and Support Vector Machines (SVM). Their study underscores the constraints of these conventional models in extracting intricate disease-related features. Additionally, their comparative study emphasizes the critical role of fundus image quality, noting that several publicly accessible datasets suffer from poor contrast and suboptimal resolution, which can hinder accurate diagnosis.

Herman Khalid Omer et al. [8] introduced a computer-aided diagnostic framework called DREAM, designed to evaluate fundus images under varying lighting conditions and fields of view. This system employs a neural network-based classification model to assign severity scores to DR cases. The research methodology incorporates several key steps. Application of enhancement techniques such as histogram equalization, noise reduction, and image scaling to refine dataset images. Utilization of vSLAM for feature extraction.

Deployment of a Bilayered Neural Network with re- substitution validation to perform classification.

Mutawa, A.M. et al. [9] developed a deep learning framework leveraging Convolutional Neural Networks (CNN) to accurately predict DR severity levels. The model underwent training, validation, and testing on the APTOS-DDR fundus dataset. Preprocessing techniques involved contrast-limited adaptive histogram equalization (CLAHE) to enhance image contrast, followed by discrete wavelet transform (DWT) to extract essential image coefficients. The CNN model efficiently identified and learned relevant patterns from the preprocessed images, enabling multi-class categorization of DR into five distinct stages: normal (no DR), mild, moderate, severe, and proliferative DR (PrDR).

K. Ahnaf Alavee et al. [10] employed a diverse array of image preprocessing strategies—including Random Rotation, Horizontal and Vertical Flipping, Resampling, Constant Filling, and Zooming—to refine retinal fundus images by mitigating artifacts and unwanted noise. Their study introduced a novel custom-built CNN model, achieving an impressive classification accuracy of 95.27% in distinguishing between DR and No_DR cases. Recent advancements in deep learning-driven medical imaging have substantially enhanced the precision and efficiency of DR diagnosis, leading to improved clinical outcomes.

Makala Bindu Priya et al. [11] devised a comprehensive multi-step approach for DR detection and classification. Initially, the optic disc was segmented and eliminated using Marker-Controlled Watershed Conversion, followed by blood vessel extraction through Two-Dimensional Grey Gradient-Based Multilevel Image Thresholding. The study employed Federated Fuzzy K-Means Clustering for the segmentation of DR-related abnormalities, including hard exudates, hemorrhages, microaneurysms, and soft exudates. To refine feature representation, the Force-Invariant Improved Feature Extraction technique was utilized to minimize feature vector dimensions, while the Binary Chimp Optimization Algorithm (BCOA) was applied to achieve optimal feature selection. Classification was carried out using the MHSAGGCN model, which categorized fundus images into normal, mild, moderate, and severe DR stages.

Nagachandrika Gogulamudi et al. [12] sought to create an advanced computer-assisted diagnostic system for DR classification by analyzing retinal fundus images. The proposed model was trained on an extensive dataset to detect and categorize varying degrees of blindness and DR severity. A non-uniform squash function was integrated into capsule neural networks to improve the model's ability to focus on complex images while ensuring stability during training. To assess its efficacy, the model's performance was benchmarked against pre-trained CNN architectures such as InceptionV3, VGG16, VGG19, and Xception. The redesigned capsule network was fine-tuned to address the limitations of earlier research, delivering improved accuracy and robustness in DR detection.

III. Proposed Model

Explanation of Medical Image diagnosis for Diabetic retinopathy was done in this section of paper. Whole DRDLOFLM (Diabetic Retinopathy Deep Learning Optimized Frog Leaping Model) model was detailed in fig. 1. This work takes raw image as input to extract features for the training of deep neural network. Each block of the fig. 1 is detailed while notation used in the description was list in table 1. DRDLOFLM was trained by the frog leaping algorithm optimized feature set.

Image Pre-Processing

The input is retinopathy image dataset RID contains noisy data, which must be cleaned up by applying a filter in order to get the pixel value back to normal. In order to get rid of the noise, the proposed model uses a noise removal filter [13]. The image is then converted into a particular format after it has been resized to correspond with the working environment of the model. Therefore, if image RI is the input image, then image PRID is the preprocessed images that is obtained by applying resizing, grey conversion, and the weiner filter.

I_p=Imagepreprcessing(RID)

Feature Extraction

This work has processed image pixels into two cluster first was used for the trained and other was transformed to non-train portion. For clustering Frog Leaping algorithm was used. In frog algorithm two step was done in a involved as a modification in existing frog algorithm. So modified frog algorithm applies twice memeplex operation in single iteration. This reduces the iteration count and increases the solution quality.

FLA (Frog Leaping Algorithm**)**

This genetic algorithm was proposed by Muzaffar Eusuff et. al. in [14]. Its an meta heuristic algorithm having global search ability with mathematical functions. Here natural memetics were used for searching the best set of solution from available area. In this algorithm each feature set act as 'Frog" where group of x frog is term as memeplex. Crossover operation in FLA is term as Shuffling. So after maximum number of iterations best set of features set (Frog) is identified.

Table 1 DRDLOFLM notation table.

Notation	Meaning
RID	Retinopathy Image Dataset
PRID	Processed RID
IFB	Image Feature Bins
RIB	Retinopathy Image Block
ICF	Image Cosine Features
FP	Frog Population
Ff	Frog Fitness
x	Memeplex count
SRI	Segmented Retinopathy Image
s	Stride
p	padding
w	Filter size
RDTM	Retinopathy Deep Trained Model

Generate Frogs

In this SFLA set of probable solutions act as frog, so collection of frog is term as population. Hence frog having set of pixels that may act as cluster center or probable solution. So let us understand this by assuming f number of frogs and c minimum number of cluster in a set. So Frog look like: F={P1, P2}. Hence frog generation function is shown in Eq. 2.

FP←GenerateFrog(f, c)-----Eq. 2

Fitness Function

Estimation of fitness value of frog depends upon the input feature training matrix as per frog F. Hence this function estimates distance from the frog where sum of minimum distance values is consider as frog fitness value Ff.

Memeplex: Estimated fitness value of each frog were sorted in descending order [15]. After sorting x set of frogs were cluster which is term as memeplex. Hence whole population FP is divide into m/x memeplex have x number of frogs.

Shuffling: In this step of genetic algorithm crossover of the algorithm was done by selecting one best parent in memeplex. So as per fitness value crossover with other set of frogs were perform. So selection of this common parent depends on fitness value. Here best fitness values frog of memeplex act as common parent in all crossover operation in a memeplex. This work done two time shuffling operation with different memeplex set of frogs.

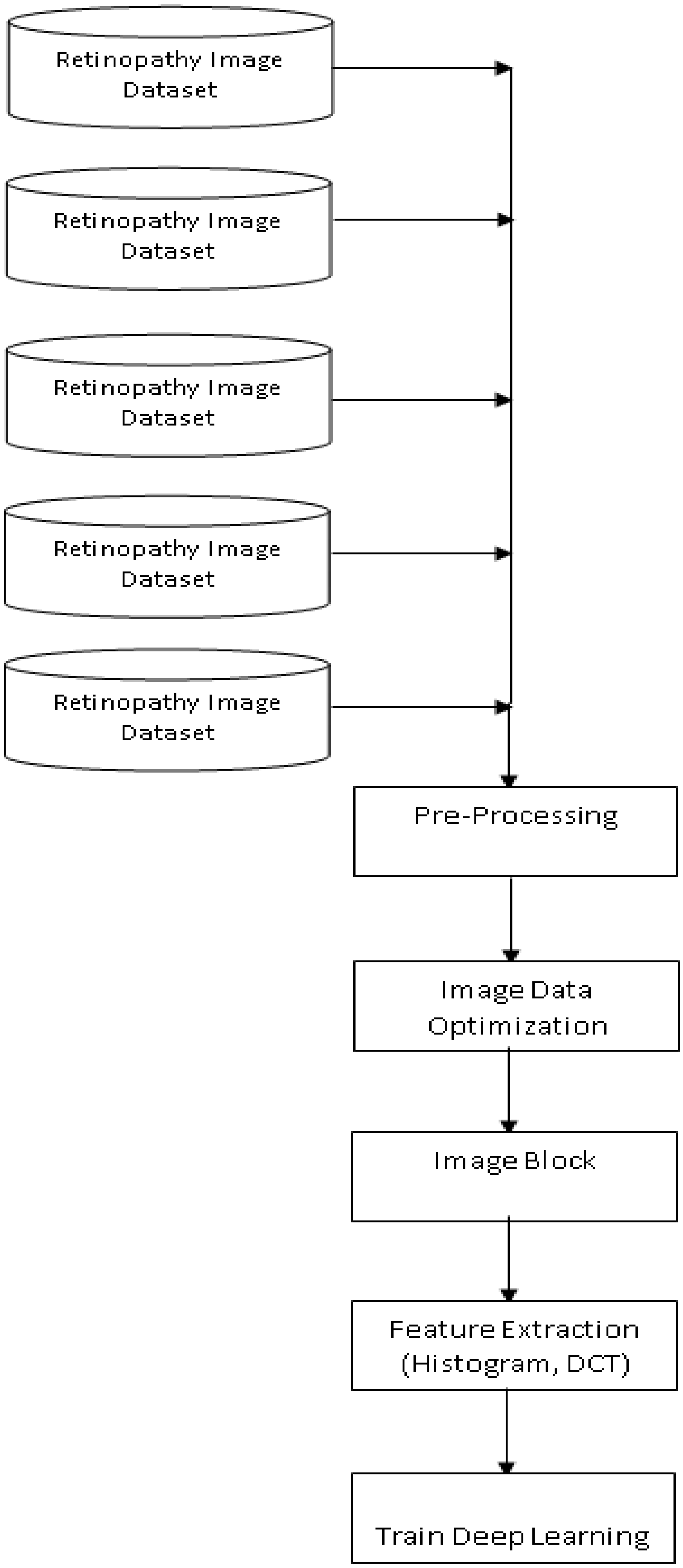


Fig. 1 DRDLOFLM block diagram.

Population Updation: As shuffling changes the frogs of the population so retention of this frog depends on fitness value. This can be understand if new frog have good fitness value as compared to parent frog fitness value than new frog was include in the population, otherwise parent frog will continue in population. Hence in all situation population size will never change from f number.

Image Blocked: The segmented image is then blocked into pixel values of a fixed nxn size. The features are extracted from the image that has been blocked. Histogram and discrete cosine transform (DCT) features are extracted from the image in the proposed model so as to increase the work efficiency.

Histogram Feature

Here work has utilized B bins of histogram values. So image feature is counting of pixels range in [(1-B), (B+1 – 2B), ………(PB-M)], where M is max pixel limit and P is (M/B – 1). This can be understand as let image have 256 type of pixel values, now bins have values in range of [(0-15), (16-31), (32-47),………………….(250-255)]. Small feature set of sixteen values are produced with the image in form of visual content so comparison takes less time [16].

DWT (Discrete Cosine Transform)

As image information is concentrated in the low-frequency DCT coefficients (top-left corner of the transformed image) [17]. Feature extraction typically involves selecting only a subset of these coefficients, usually based on their position in the frequency domain. In this work DCT frequency feature is use. DCT efficiently concentrates most of the image energy into a small set of coefficients. Hence DCT coefficients allows to understand the dominant frequencies present in an image.

Deep Learning

Convolutional Neural Network training takes input of DCT and histogram feature set of each block. As image have four class label hence each of blocked feature set is flag with same label. CNNs are designed to utilize image structural information efficiently while reusing weight parameters [18]. They achieve this through two key operations: convolution and pooling, which help maintain geometric transformation invariance in image data.

Convolution Operation: The convolution operation extracts position-invariant features, ensuring that an object (e.g., a tumor) is recognized regardless of its location in the image. This is achieved by applying a small convolution filter across the 2D input, providing two major benefits [19]:
Preserving image structure for effective feature extraction.
Parameter sharing, which reduces the number of free parameters, making the network easier to train and less prone to overfitting. Stride s and padding p control the movement and dimension adjustments in convolution operations.

Max-Pooling Operation: Pooling helps increase the receptive field of feature maps to handle objects of varying sizes. Since stacking multiple convolutions is inefficient for large receptive fields, downsampling using max-pooling or average pooling is used. Pooling reduces spatial dimensions while retaining critical features, improving efficiency in learning high-level representations.

Fully Convolutional Networks (FCNs): FCNs extend CNNs for per-pixel classification, directly segmenting entire input images instead of classifying individual pixels. They maintain image structure across hidden layers and utilize convolutional feature maps as inputs for segmentation tasks, such as tumor detection in medical imaging. FCNs enable end-to-end learning without fully connected layers, making them efficient for dense predictions.

IV. Experiment and results

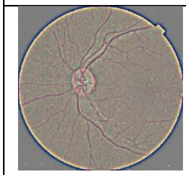
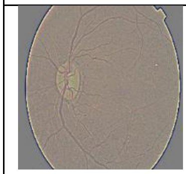
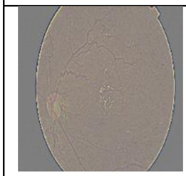
Experimental Setup: Implementation of proposed model is done on MATLAB software 2016a. Experiment is performed on machine having configuration of 4 GB RAM, i3 6th generation processor. Further validation of model is done by comparing proposed model with NSL-MHA-CNN techniques proposed in [20].

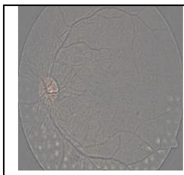
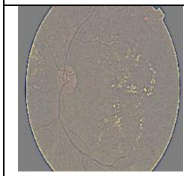
Dataset: Proposed work experimental values are obtained from real dataset. Explanations of dataset with detailed features are shown in table 2 [21].

Table 2 Diabetic Retinopathy dataset.

Dataset Feature	Values
Class	5
Total Images	2750
Size	256x256
Format	Gray

Table 3 Dataset of diabetic retinopathy images.

Images	**Class**
	**Healthy**
	**Mild DR**
	**Moderate DR**

	**Poliferate DR**
	**Severe DR**

Results

Table 4 Precision value of retinopathy image class detection models.

Image sets	NSL-MHA-CNN	DRDLOFLM
100	0.6364	0.6362
150	0.56	0.6798
200	0.5714	0.7141
300	0.5738	0.7376
400	0.5309	0.7042

Table 4 shows the retinopathy precision value of DRDLOFLM for different testing dataset. It was found that use of moth flame optimization algorithm has remove the low informative image portion. Further paper has enhanced the precision value by 17.26% as compared to existing model.

Table 5 Recall value of retinopathy image class detection models.

Image sets	NSL-MHA-CNN	DRDLOFLM
100	0.875	0.9333
150	0.875	0.8947
200	0.8889	0.9524
300	0.8333	0.8654
400	0.8431	0.7809

Retinopathy classification models recall values shown in table 5. Proposed model DRDLOFLM has shown that use of block based feature extraction and training has increased the work efficiency.

Average DRDLOFLM model has improved the recall values by 2.516% as compared to NSL-MHA-CNN.

Table 6 F-measure value of retinopathy image class detection models.

Image sets	NSL-MHA-CNN	DRDLOFLM
100	0.7368	0.7566
150	0.6829	0.7726
200	0.6957	0.8162
300	0.6796	0.7964
400	0.6515	0.7406

F-measure values of retinopathy image classification models shown in table 6. Use of histogram and DCT feature has increased the testing efficiency. Further it was found that frog leaping genetic algorithm has increased the work f-measure value by 11.22%.

Table 7 Accuracy value of retinopathy image class detection models.

Image sets	NSL-MHA-CNN	DRDLOFLM
100	90.4762	91.5845
150	89.4309	91.9964
200	90.7285	94.1148
300	89.1089	92.4575
400	88.8078	90.324

Accuracy value of Table 7 shows that DRDLOFLM model has more efficiently classify the retinopathy images as compared to existing model [20]. Table 7 shows that use of image segmentation for feature selection has increase the learning accuracy of work.

Table 8 Precision value of retinopathy image class detection models.

Image sets	NSL-MHA-CNN	DRDLOFLM
100	0.1905	0.5714
150	0.2	0.64
200	0.2	0.7

300	0.1475	0.6885
400	0.1529	0.5294

Table 9 Precision value of retinopathy image class detection models.

Image sets	NSL-MHA-CNN	DRDLOFLM
100	0.55	0.5
150	0.56	0.6
200	0.6333	0.6667
300	0.6393	0.6393
400	0.6118	0.5176

Table 10 Precision value of retinopathy image class detection models.

Image sets	NSL-MHA-CNN	DRDLOFLM
100	0.4091	1
150	0.48	0.52
200	0.5152	1
300	0.5246	0.8033
400	0.4815	0.7160

Table 11 Precision value of retinopathy image class detection models.

Image sets	NSL-MHA-CNN	DRDLOFLM
100	0.05	0.5453
150	0.0435	0.5999
200	0.0333	0.6874
300	0.0169	0.4919
400	0.0253	0.6173

Table 8, 9, 10 and 11 shows the different retinopathy image classification accuracy values of comparing models. Proposed DRDLOFLM has high accuracy value for each class detection. Result shows that use of frog leaping and histogram, DCT feature set has trained the deep learning model effectively.

V. Conclusion

Diabetic retinopathy (DR) is one of the most prevalent retinal diseases associated with diabetes, often manifesting through early symptoms such as blurred vision and eye floaters. If left untreated, its progression can lead to severe complications, including complete vision loss. This paper has introduced the DRDLOFLM (Diabetic Retinopathy Deep Learning Optimized Frog Leaping Model), a novel approach for DR classification that leverages deep learning and optimization techniques to enhance diagnostic accuracy. The model extracts machine vision-based features from medical images, selecting the most informative regions using the frog leaping algorithm to optimize feature representation. The cumulative prediction strategy further refines diagnostic performance by focusing on critical image blocks. Experimental results on real DR datasets confirm that the proposed model significantly improves evaluation metrics. The integration of histogram and Discrete Cosine Transform (DCT) features enhances testing efficiency, while the frog leaping genetic algorithm boosts the F-measure by 11.22%. Additionally, the incorporation of the moth flame optimization algorithm effectively eliminates low-informative image portions, leading to a 17.26% improvement in precision compared to existing models. These findings demonstrate the effectiveness of DRDLOFLM in DR diagnosis, highlighting its potential to aid early detection and improve clinical decision-making for diabetic retinopathy management. In future scholar can incorporate same in hardware for instant analysis.

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