

Enhanced Optimization using Advanced Cuckoo Search Algorithm with Ensemble classification for detection of Diabetic Retinopathy

Nandeeshwar Sampigehalli Basavaraju

Research Scholar, Department of Computer science & Engineering, Presidency University, Rajanukunte, Bangalore, Karnataka-560064, India

technandy1@gmail.com

<https://presidencyuniversity.in/school/school-of-engineering/>

Dr. Shanmugarathinam Ganesarathinam

Associate Professor, Department of Computer science & Engineering, Presidency University, Rajanukunte, Bangalore, Karnataka-560064, India

shanmugarathinam@presidencyuniversity.in

<https://presidencyuniversity.in/school/school-of-engineering/>

Abstract

Diabetic Retinopathy (DR) is an eye disease which occurs due to enormous glucose level in the blood among diabetic patients. The diabetic patients are having higher chances of getting blindness if the sugar level is increased in body. An identification of landmark features present in the fundus images has to accurately find the features from the optic disc of fundus images. The existing researches used various Artificial Intelligence (AI) techniques for screening and diagnosing the DR earlier to prevent the diabetic patients from blindness which was determined based on the level of DR severity. However, the existing models were efficient that consumed time and the premature convergence was resulted with the drawback for the real world optimization approach. Thus, the proposed Dynamic weighted based Cuckoo Search Algorithm (DWCSA) is modified to improve the performances based on their basic structure. The higher convergence helped to train the model better for finding solutions. The proposed model overcomes the constraint issues occurred during feature selection process showed improvement in the accuracy. The proposed DWCSA obtained the accuracy of 97.46 % compared to the existing CNN model that obtained 98.94 % of accuracy for DIARETDB1 whereas, the e-optha dataset obtained accuracy of 98.91% for the proposed model.

Keywords: Diabetic Retinopathy; DIARETDB1, Dynamic Weighted CSA, e-optha. Ensemble classification.

1. Introduction

The diabetic retinopathy has affected for about 80 million people by the year 2020. Many expert systems collaborated for diagnosing the disease and the detection. The World Health Organization (WHO) has detected glaucoma and Diabetic Retinopathy (DR), and Macular Degeneration (MD) has shown a major cause for early detection and screening. It is also based on the regular screening for the vision impairment caused globally [1-3]. The disease is affected directly to the part of retina that should be manually diagnosed by ophthalmologist. The treatment of disease should be acknowledged for the early prediction and based on the screening the disease detection is performed [4,5]. The disease is treated regularly for early detection and the screening of the disease is done manually due to presence of large diabetic patients when the age of the people is increased. The retina assessment for DR screening includes a series of attention which has an indicative feature with blood occlusion have macula, blood vessels, and optic disk [6]. The vascular pathology is characterized based on the retinal blood vessels which plays an important role in disease analyzing such as diabetics, hypertension, stroke, and arteriosclerosis.

The retinal vessels consist of certain number of features that are extracted based on the branching pattern, width, length that provides valuable information related to analyzes the disease. The retinal image needs the valuable information which is related for analyzing the human eye with respect to the vascular condition [7]. The blood vessels and the arteries has features such as opacity, color, and diameter which are used as observable features for the DR

detection. Thus, based on the structure features present in the retina, the information related to the glaucoma is used for the detection of diabetic [8]. It takes longer for recovering by the treatment unlike other micro hemorrhages. There are many number of researches used for recognition of disease that exudation for early DR prediction [9]. An automated system is used for the detection using the clustering techniques which classifies the normal and abnormal retina. Based on the variation in the contrast values, the effectiveness of the retinal background is made in comparison with the blood vessels and other structures [10].

The present research has surveyed from past that includes imaging and ML processes that discusses all the grading tasks for DR. The clinical implementation is done with respect to all the state of the art techniques. The present research work surveys the existing methodologies under Artificial intelligence (AI) for diagnosing the system accurately in assisting the medical professionals for diagnosing and screening the DR at an earlier stage without using full the available resources. The deep learning facilitates diagnoses obtains sensitivity and specificity at higher rate. Thus the better decisions are minimally made based on the provided comprehensive description for the current technology used for DR diagnosis. The contributions of the research work are as follows:

- To utilize two datasets named DIARETDB1 and e-Ophtha for diagnosing DR
- To utilize pre-processing techniques including Normalization and hessian based frangi low light vessel enhancement for fundus image enhancement
- To develop segmentation approaches such as Multi-level Otsu thresholding approach and Morphological operations for segmenting the affected region
- To develop the Gray Level Co-occurrence Matrix (GLCM) feature extraction technique that extracted features and the proposed Dynamic Weighted Cuckoo Search Algorithm (DWCSA) is used for the selection of features.
- To develop the Ensemble classifier that includes SVM, NN, DT, RF for the purpose of classifying the retinal fundus image into micro aneurysm and hemorrhage.

The organization of the research paper is given as follows: Section 2 describes the literature review on Diabetic Retinopathy detection for fundus images using the machine learning models. Section 3 describes the proposed method and Section 4 describes results obtained by the proposed research. The conclusion and the future work of this research is shown in Section 5.

2. Literature Review

Muhammad Mateen et al. [11] detected Diabetic Retinopathy using pre-trained Convolutional Neural Networks (CNNs). The existing models noticed exudates were found to have the signs of DR anomalies and thus the detection of the lesions were important. The treatment was required immediately to prevent from the vision loss. The pre-trained CNN model detected the exudate the deep CNN model which was applied individually solved the problem. The e-Ophtha and DIARETDB1 database were used to simulate the results and the CNN model with transfer learning solved the problems of ambiguity in fundus images. However, the developed pre-trained CNN failed to diagnose hemorrhages and micro aneurysms while determining diabetic retinopathy.

Alaguselvi and Kalpana Murugan [12] performed an automated lesion for detecting diabetic retinopathy by performing the morphological operations. The present research work utilized differential evolution algorithm matched filter with morphological operations to detect the lesions among the fundus retinal images. The value of threshold for an image is obtained based on the iterative process based on the self-organization. It removes the optic disc and blood vessels are removed the retinal image region which was used to determine distinct lesion loss types. The detected lesions are in such a way that hemorrhage, micro-aneurysm exudates were extracted through possible ways. However, the developed model failed to determine lesions which were overlapped with the retina image from the original region lowered the performances.

Zhitao Xiao et al. [13] developed an automated non-proliferative diabetic retinopathy screening system using parabolic fitting basis of color fundus images. The structure of the fundus image includes the optic disc, blood vessels, macula which were located were extracted. The disc localization was performed using the parabolic fitting that was based on the physiological structure of the blood vessels and the optic disc characteristics. The micro aneurysms, hemorrhage, and exudates were needed to be determined based on the characteristics. Therefore, an optical model was simulated based on retina's anatomical structure from human eyes. The fundus images were failed to perform clinical diagnosis and automatic screening of patients.

Pratheeba and Nirmal Singh [14] utilized Random Forest Classifier that was used for detecting the hard exudates. The novel classification technique was applied to improve the automatic detection of hard exudates from the colored retinal images. The features from the retinal OCT images considers GLCM that provides better values and the classifier used was Random Forest. The Random Forest was used for the classification which was applied on the colored retinal image that classified the data clusters in terms of accuracy. However, less consumption of time provided during image classification.

Yanfei Guo and Yanjun Peng [15] developed Cascade Attentive Refine Net (CARNet) for multi-lesion segmentation of DR images. The segmentation of lesion showed challenge due to the various sizes and complex structures. The inter class similarity was shown and compared to other fundus images. The CARNet model was used to segment the multi lesion segmentation accurately with DR. The developed approach misclassified the noises for the MA in the fundus image which showed contrasted false-positive values lower. However, the ophthalmologists were failed to identify the inconspicuous and small lesions that would improve the performances.

Jiakun Deng et al. [16] developed a Multi-Feature Combination for Retinal Micro Aneurysm Detection for local structure awareness. The existing algorithms were focused with the target features but also targeted the local structural features and the target features. Thus, the MA detection showed efficient Local Structure Awareness Based Retinal MA Detection (LSAMFC) was used in the research work. However, the developed model was based on deep learning model which showed overfitting problems because of less amount of data.

3. Proposed method

The block diagram of the proposed research work is shown in the figure 1. The datasets such as DiaRetDB1 and e-ophta are used for the present research work evaluation. The pre-processing is performed for the DiaRetDB1 and e-ophta dataset. The dataset images are undergone for the pre-processing using Normalization and hessian based frangi low light vessel enhancement. The obtained pre-processed image is undergone for the process of segmentation using Otsu's thresholding, morphological transform. The obtained segment is undergone for the process of feature extraction using Gray Level Co-occurrence Matrix (GLCM). The extracted features are undergone for the process of feature selection using dynamic weighted cuckoo search algorithm. The selected features are undergone for the process of classification using Ensemble approach that classified into Hemorrhages and Micro aneurysms.

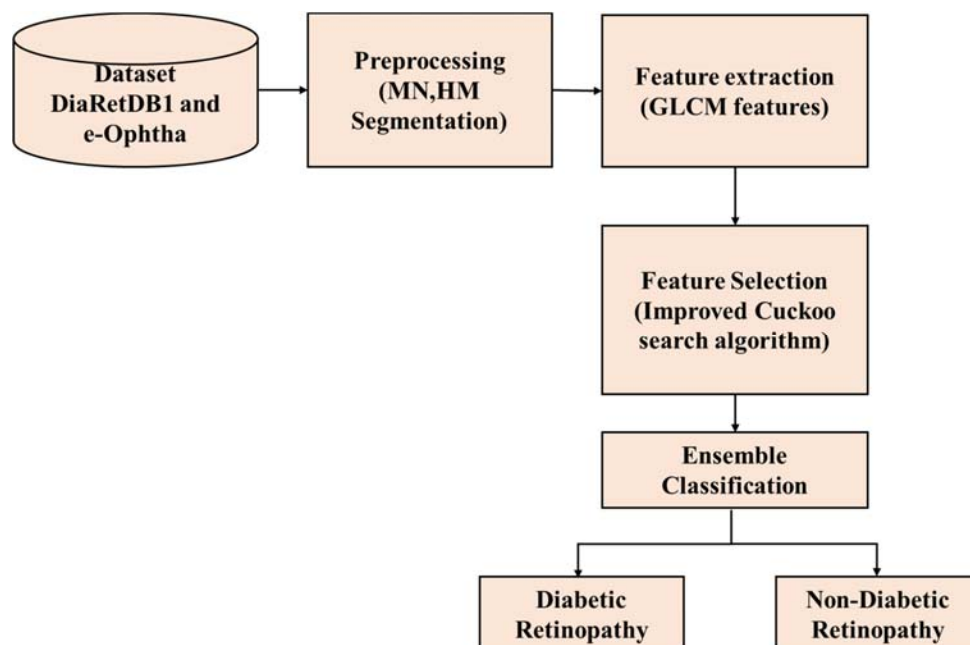


Figure 1: Block diagram of the proposed Dynamic Weighted Cuckoo Search Algorithm

3.1 Data collection

3.1.1 DiaRetDB1

The present research work consists of 89 number of color fundus images and 84 number of mild non-proliferative sign that are micro aneurysm images of diabetic retinopathy. There are 5 normal images that do not have any signs of DR as per the experts. The digital fundus camera images are taken using 50degree field of view which is having varied image settings. Therefore, the data which was corresponded obtained better accuracy for practical situations as the images are comparable and used for evaluation of performances by using diagnostic models. The calibration level 1 fundus images are used in the datasets and the input dataset images are shown in the figure 2(a) and the normalized image is shown in 2(b).

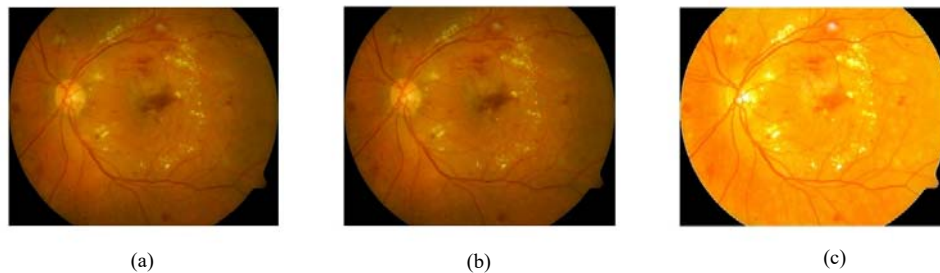


Figure 2: (a) Input image (b) Normalized image (c) Enhanced image for DiaRetDB1

3.1.2 e-Ophtha

The another dataset used is e-Ophtha consists of e-Ophtha Ex and e-Ophtha MA. The dataset consisted of 47 colored retina images are having annotated exudate with e-ophtha MA which consists of 148 colored retina images annotated with micro aneurysm. The variation in the size and the image resolution is ranging from 1440×960 to 2544×1696 pixels.

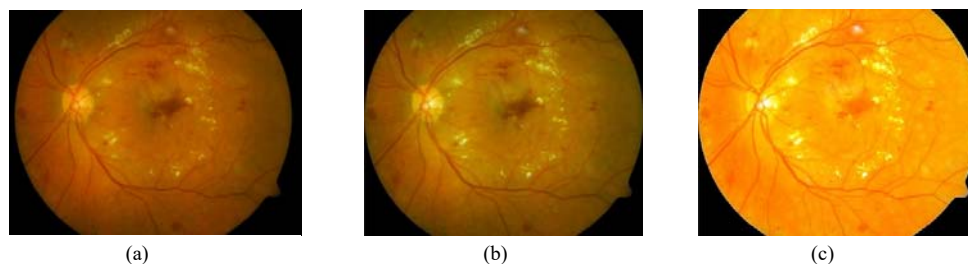


Figure 3: (a) Input image (b) Normalized image (c) Enhanced image for e-Ophtha dataset

3.2 Pre-processing using Normalization and hessian based frangi low light vessel enhancement

The collected images are undergone for pre-processing using Normalization and Hessian based Frangi Low Light illumination of retina leads to non-uniformity. The illumination is more and less at few part and in low contrast or low brightness lesions are not visible. Also, the images vary in quality and color and thus it is important to perform image pre-processing for overcoming the problems. Thus, the histogram stretching for each color channel of ice and clipping is performed in the range of $\mu \pm 3\sigma$, where σ and μ are known as the mean deviation and standard deviation of the color channel. The images are obtained with standardized color normalization is important. The histogram stretching is performed for each of the color channel of ice, clipping ranges as $\mu \pm 3\sigma$, σ and μ are called as the mean and standard deviation for the colored channel.

3.2.1 Hessian based frangi low light vessel enhancement

The obtained normalized image is undergone for the process of image enhancement using Hessian based Frangi low light vessel enhancement. The eigenvector functions are used with the Hessian for computing the likeliness of the image region as it consists of vessels or other ridges of an image. The filter scales are influenced on the basis of coverage, contrast, out-of-plane, quality of image, light fluence, gain insight which are needed for showing

performances improvement. The generation of artifactual structures are interpreted in vessels to provide recommendation appropriately for frangi usage. The filters that are used to avoid the misinterpretation process performs the post process optoacoustic images.

The camera response model is applied for light enhancement that can normalize the retinal fundus image. The camera response model can adjust the pixel value that is desired with exposure on the basis of components like camera response function and brightness transformation. The hessian based Frangi vessel enhancement model is used to enhance the visualization of blood vessels. Hessian based Frangi vessel enhancement techniques are working on the basis of eigenvalue decomposition with the local hessian matrix used for the retinal fundus image enhancement. The blood vessels contrast is enhanced which reduces the background noise and suppresses the non-vascular structures. Figure 3 consists of (a) Input image (b) Normalized image (c) Enhanced image for e-Ophtha dataset. Figure 4: Hessian based enhancement for DiaRetDB1 (left) and e-Ophtha database (right).

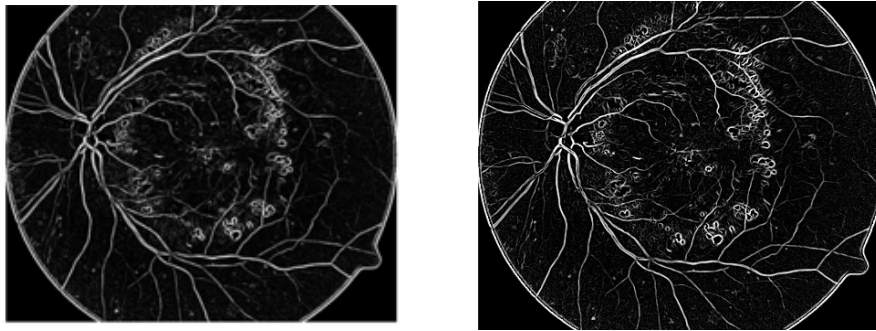


Figure 4: Hessian based enhancement for DiaRetDB1 (left) and e-Ophtha database (right)

3.3 Segmentation using Morphological operations

The obtained images from the pre-processing is undergone for the process of segmentation to binarize the images based on pixel intensities. The input image is applied to perform thresholding that is converted to the binary image. The input image pixel is more than the threshold that are evaluated in terms of intensity. The output pixel is marked white in the foreground image and the intensity of input pixel is less or equal to threshold and the pixel which is marked black that represents the background image. The important region has to be segmented using thresholding approach yet the residue part is required to be removed. To perform the function, multi-level Otsu thresholding algorithm is performed for pixel separation to distinct classes. They are separated based on the intensity values of gray levels. The threshold values are calculated based on multi Otsu thresholding which determines the desired number of classes. The main reason for utilizing multi-level Otsu thresholding and morphological operation techniques are to eliminating the unwanted image regions. The processed functions performed processes on the basis of size and shapes. The class probabilities within the class are weighted and calculated using the Eq. (1)

$$q_1(t) = \sum_{i=1}^t P(i), q_2(t) = \sum_{i=t+1}^I P(i), q_n(t) = \sum_{i=I+t+1}^n P(i) \quad (1)$$

The threshold value ranges from 1 to t

q_1, \dots, q_n are weighted class within pixel probabilities P of the foreground and background.

The class means are given as Eq. (2)

$$\mu_1(t) = \sum_{i=1}^t \frac{iP(i)}{q_1(t)}, \mu_2(t) = \sum_{i=t+1}^I \frac{iP(i)}{q_2(t)}, \dots, \mu_n(t) = \sum_{i=I+t+1}^n \frac{iP(i)}{q_n(t)} \quad (2)$$

μ_1 and μ_2 are the average gray level values

An input image having structuring element performs morphological operations to an image thereby obtains an output image having same size. The morphological operation is performed for each pixel of an input image that corresponds to the neighborhood pixels. The shape and size of an image is chosen based on the neighborhood pixels and

morphological operation is performed for constructing specific shapes for an input image. The specific pixels were not clear as the intensities of the darker pixels were difficult for distinguishing.

After image segmentation, color histogram features are extracted from the segmented regions for better classification of DR stages. The color histogram is the extensively used method to extract the color features of an image. The color histogram feature vectors denote the fundus image from a different perspective and also it states the frequency distribution of color bins in a fundus image. The color histogram method counts the similar pixel and extracts the discriminative feature vectors. The extracted feature vectors are given as the input to the ensemble classifier to classify the different stages of DR.

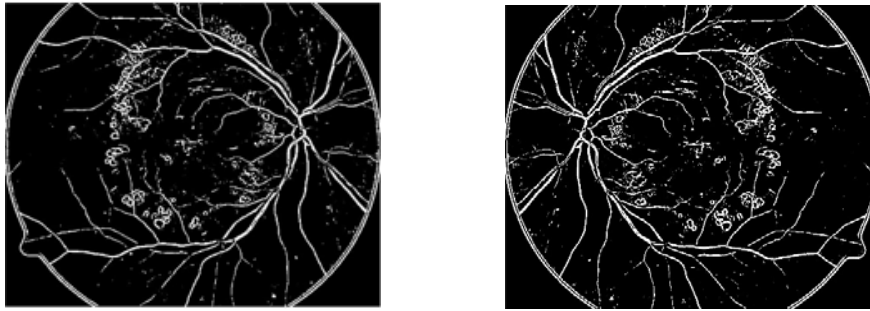


Figure 5: Segmented image for DiaRetDB1 (left) and e-Ophtha database (right)

3.4 Feature selection and optimization using Dynamic Weighted cuckoo search algorithm (DWCSA)

The process of cuckoo egg laying is mimicked in CSA. The cuckoos lay the fertilized eggs in host nests that has hope on them of spring that are raised by the proxy parents. The hosts can identify the eggs in the nests as they are not belonging to them. These circumstances are applicable to the foreign eggs that are thrown out of the nests when the whole nests were discarded. The CS optimization approach is based on the following principles.

1. The egg is laid at a time and the eggs are randomly placed in a host bird's nest.
2. The best nests consist of high quality eggs that are further carried in the next generations.
3. The available host nests are fixed in number and the host discovers the foreign eggs that are having a probability of p_α , and range of p_α is varied from 0 to 1. The best nests are selected for calculating further.

The new solution for cuckoo i is generated when the Levy flight is performed based on the below Eq. (3).

$$x_i^{t+1} = x_i^t + \alpha_0(x_i^t - x_{best}) \oplus Levy(s, \lambda) \quad (3)$$

Where α_0 is the step size, $\alpha_0 > 0$ and x_{best} is the current optimal solution. The Levy flights are drawn from the Levy distribution that is provided in the Eq. (4)

$$Levy(s, \lambda) \sim u = t^{-1}, (1 \leq \lambda \leq 3) \quad (4)$$

Where

$$Levy(s, \lambda) = \frac{\lambda \Gamma(\lambda) \sin(\frac{\pi \lambda}{2})}{\pi} \frac{1}{s^{1+\lambda}}, \quad \text{where } (s \gg s_0 > 0)$$

Where $\Gamma(\lambda)$ is known as the standard gamma functions are having λ as index.

The CS algorithm the worst nest is abandoned with p_α as the probability and the new nest is built based on the random walk using the below formula shown in Eq. (5)

$$x_i^{t+1} = x_i^t + r(x_j^t - x_k^t) \quad (5)$$

From the above Eq. (5), r is the random number and x_j^t and x_k^t are the random solutions generated for each of the iterations t .

However, the existing models was efficient that models showed drawbacks related to time consumption and premature convergence with respect to the real world optimization approach. Thus, the CS is modified for improving the performances based on their basic structure.

3.4.1 Adaptive control parameters

The control parameters show sensitive for the performances of the metaheuristic algorithms. The model consumed lot of parameter strategies for improving the performances. The control parameters include piece wise, linear, or curve that decrease with the generation known as adaptive parameter strategy. If the control parameters are changing with the fitness value, the optimization problem called as self-adaptive strategy for parameter archiving mechanism is performed. The parameters such as p_α and α_0 are utilized which helped the algorithm for determining the global and local solutions. The different problems are faced by the parameters which should be adjusted on the basis of personal experience. The value of p_α is small when the large value of α_0 is present. The performances for the algorithm is generated as poor has shown increase in iteration numbers. The value of p_α is directly proportional to α_0 as the greater value of p_α , larger is the value of α_0 . The speed of the convergence is higher, helps in finding the best solutions. The values of p_α and α_0 changes dynamically change with the number of generations and are expressed in the following Eq. (6) and Eq. (7)

$$p_\alpha = p_{ai} \cdot 2^\tau, \tau = e^{1 - \frac{G_m}{G_m + 1 - G}} \quad (6)$$

$$\alpha_0 = 0.5 \times \exp\left(-\frac{G-1}{G_m}\right) \quad (7)$$

From the above equation, p_α is known as the pre-defined constant, where G_m is called as the maximum number of iterations, G is called as the total number of iterations. The dynamic weighted random walk strategy is built with random walk has lead with the slower rate of convergence and vibration. Therefore to enhance the local search, the larger ω shows greater exploration or exploitation of host nest positions that is having solutions. The value ω is linearly decreasing relatively shows larger value because of small value throughout the course that enhances effectively with local search. The weighted coefficient is represented as ω , ω_{max} , and ω_{min} are called as the user defined constants. Thus, the below equations are corresponded to the weighted coefficient's. The evaluation method was proposed as the fitness function that overcome the constraint issues that considers the classification accuracy and takes the rate of feature reduction as an adjusting term which is represented in Eq. (8) and Eq. (9)

$$x_i^{t+1} = \omega x_i^t + r(x_j^t - x_k^t) \quad (8)$$

$$\omega = \omega_{max} - \frac{G(\omega_{max} - \omega_{min})}{G_m} \quad (9)$$

The fitness function evaluated using the below Eq. (10)

$$f = \beta \cdot \frac{d-s}{d} + (1 - \beta) \cdot acc \quad (10)$$

From the above equations, d is called as the total number of features present in the datasets. s is known as the feature numbers that are selected by the metaheuristic optimization algorithms. $1 - \beta$ is known as the average weight of the accuracy.

3.4.2 Pseudo code for the proposed Dynamic Weighted CSA

Begin

Objective function is represented as $f(x)$, $x = (x_1, x_2, \dots, x_d)$; #input

The parameters p_{ai} , ω_{max} , ω_{min} are initialized

```

The population from  $n$  host nests are initialized represented as  $x_i (i = 1, 2, \dots, n)$ ;
For  $G = 1: G_m$ 
    Generate  $p_\alpha, \alpha_0, \omega$ 
    A cuckoo ( $m$ ) is randomly evaluated by Levy flights,  $Levy(s, \lambda) \sim u = t^{-\lambda}$ ;
    Generate new nests,  $x_i^{t+1} = x_i^t + \alpha_0(x_i^t - x_{best}) \oplus Levy(s, \lambda)$ ;
    The quality or fitness  $f$  is calculated;
    Choose a nest among  $n(n)$  randomly;
    if ( $F_m > F_n$ )
        Replace  $j$  with the new solution;
    end
    if ( $r > p_\alpha$ )
        Abandon a fraction from the worst nests;
        And build new ones from their locations using  $x_i^{t+1} = \omega x_i^t + r(x_j^t - x_k^t)$ 
    end
    the best solutions are kept (or nests with quality solutions);
    the best solutions are used for finding the current best; #output
end
End

```

3.5 Classification of DR using Ensemble Classifier

The Diabetic retinopathy comes under mainly two classes: non-proliferative and proliferative. The word abnormal blood vessel growth is present in the retina and early disease detection is called non-proliferative diabetic retinopathy (NPDR).

3.5.1 Support Vector Machine

The SVM is applied to perform binary classification that assigns the data points either 1 or 0. For multiclass classification, the same principle is utilized. The multiclass problem is broken down into multiple binary classification cases that followed one-vs-one multiclass classification for all other classes.

3.5.2 K-nearest neighbor

The concept of KNN classifier depends on the calculation of the distance between the training and testing samples $W[A]$ to identify the nearest neighbour. In the KNN classifier, the nearest neighbours are considered based on the training and testing samples $W[A]$. Several distance measures are utilized to calculate the distance between training and testing samples $W[A]$ like Chebyshev distance, city-block, Euclidean, Minkowsky, etc. Among these available distance measures, Euclidean distance is used to calculate the distance between training and testing samples $W[A]$ in KNN classifier.

3.5.3 Random forest

The values obtained from the feature selection process is optimum and are fed for RF classifier for classification. The RF is an ensemble classifier which is used for improving the model accuracy and the decision trees present in it perform lower classification errors when compared with the existing models. The trees present are having size for minimum node which is considered to split the node on the basis of features. The tree is constructed individually on the basis of bootstrap sample that has original data in it. The forest formed has an object and each of the objects is known as tree. The decision making is performed based tree. Therefore, best decision for tree is performed to class objects of each of them to perform voting. The class is selected from the forest that receives the votes for the number of objects. The RF uses both the process of bagging and boosting for the selection of random variables to build the tree. The features from RF is as follows:

3.5.4 Decision tree

Decision tree method partitions the feature space into similar set of exclusive regions. Consider K observation and each observation has p input related to response variable $(y_i, x_{i1}, x_{i2}, \dots, x_{ij}, \dots, x_{ip})$ for $i = 1, 2, \dots, K$; $j = 1, 2, \dots, p$. Prediction label y_i for input features i ; $(x_{i1}, x_{i2}, \dots, x_{ij}, \dots, x_{ip})$ are input features.

Classification tree splits the input into categories based on input explanatory variables. Each partitioned sub-region has less observations. Until stopping criteria is reached, the process is continuing. The feature space is partition into Q regions $\{R_1, R_2, \dots, R_Q\}$. The best splitting point for each splitting variables is found based on scanning possible values. Feasible splitting point and splitting variables pair are obtained by scanning input variables. Random Forest is based on decision tree.

3.5.5 Neural Network

The ANN is a popular machine learning technique, which is growing rapidly in the recent years. The ANN has been applied in the non-linear analysis and achieved the significant performance. The multi-layer neural architecture is the parallel computation model consists of many neurons connected in the previous layer. The ANN is inspired by the process of the human being nervous system. This is based on the process of learning from patterns and analysis the networks. The neural network process two computational procedures forward process and back propagation. In the forward process, all input signals are processed in the forward direction in the activated network layers, i.e. input to output. For better understanding of the Artificial Neural Network, the three-layered feed-forwarded network is discussed in this section. The outputs are weighted based on the error value and then summed up in the output neuron. Based on the aforementioned process, the input and output layers are explained below. The non-negative matrix factorization D_F is given as input as y in ANN.

All the aforementioned classifiers are ensemble to obtain the classification output. The ensemble classifiers classified the fundus images into NDR or DR.

4. Results and Discussions

In DR detection, the proposed k-means based ensemble model performance is simulated by Python 3.7.3 environment on a computer with 8 GB RAM, Intel Core i5 processor, and Windows 10 (64 bit) operating system. In medical image classification, accuracy is determined as the ratio of correctly predicted observations to the entire observations. Further, sensitivity computes the number of true positives, and specificity finds the number of true negatives that are precisely recognized. The mathematical representation of accuracy, specificity, sensitivity, and F-score is denoted in the Eq. (11-14).

$$Accuracy = \frac{TP+TN}{TN+TP+FN+FP} \times 100 \quad (11)$$

$$Specificity = \frac{TN}{TN+FP} \times 100 \quad (12)$$

$$Sensitivity = \frac{TP}{TP+FN} \times 100 \quad (13)$$

$$F - score = \frac{2TP}{2TP+FP+FN} \times 100 \quad (14)$$

where, TP indicates true positive, FP states false positive, TN denotes true negative, and FN states false negative.

4.1 Quantitative Analysis

The table 1 shows the results obtained by the proposed method without using feature selection algorithms. The performances evaluated for the proposed method without feature selection algorithm for various classifiers such as Support Vector Machine (SVM), K-Nearest Neighbour (K-NN), Random Forest (RF), Decision Tree (DT), Neural Network (NN), Ensemble classifier. Without the use of proposed dynamic weighted CSA obtained accuracy if 97.73%, sensitivity of 97.32%, specificity of 95.46%, F-score of 96.93%, and precision of 96.54%. The present research work uses SVM for the classification that was not suited for large datasets. The SVM failed not to perform well as the target classes are overlapped

Without feature selection					
Classifiers	Accuracy (%)	Sensitivity (%)	Specificity (%)	F1_score (%)	Precision (%)
SVM	46.45	43.64	46.07	46.05	47.09
KNN	93.18	92.63	93.48	92.54	92.45
RF	94.36	95.15	93.38	94.59	94.05
DE	93.42	92.38	93.49	93.42	94.49
NN	96.91	95.78	94.87	94.92	94.07
Ensemble	97.73	97.32	95.46	96.93	96.54

Table 1: Results obtained by the proposed method without using feature selection algorithms

Table 2 shows the results obtained by the proposed method with feature selection algorithm. The SVM classifier has obtained 94.79% of accuracy, KNN of 94.77%, RF of 96.36 %, DT of 95.03, ANN of 98.16%. Similarly, the accuracy value obtained by the ensemble approach is 99.35% of accuracy.

When the number of features at each of the data point exceeded, the training data samples underperformed. The KNN classifier failed to work well as it was high dimensional showed complication in calculating the distance. The existing RF model showed improvement in the Prediction accuracy for overcoming the complex problems that are usually inferior to gradient-boosted trees obtained accuracy of 93.18%. The RF was less interpretable compared with the Decision trees that obtained accuracy of 94.36% of accuracy. The decision tree with small change in the data can cause a large change in the structure of the decision tree causing instability that obtained accuracy of 93.42%. The Artificial Neural Networks (ANN) failed to immediately corrode that made decisions on similar events. The results obtained by the ANN classifier showed 96.91% of accuracy and without the feature selection algorithm, the models showed moderate accuracy values.

4.2 Time Efficiency

The Elapsed time for one iteration with respect to ensemble model is 0.455093 seconds. The Elapsed time for 50 iterations consumed 22.7547 seconds. The Elapsed time taken for a feature selection model is 23.894415 seconds.

With feature selection & optimization using DWCSA					
Classifiers	Accuracy(%)	Sensitivity(%)	Specificity(%)	F1_score(%)	Precision(%)
SVM	94.79	93.24	94.94	95.23	97.31
KNN	94.77	96.73	94.84	96.01	95.30
RF	96.36	94.18	96.41	93.65	93.11
DE	95.03	95.70	95.09	94.92	94.15
NN	98.16	96.65	97.35	96.31	95.98
Ensemble	99.35	98.89	98.01	98.72	98.54

Table 2: Results obtained by the proposed method with feature selection algorithms

Different optimization algorithms	Accuracy	Sensitivity	Specificity	F1_score	Precision
PSO	90.02	89.06	89.90	90.36	91.70
ACO	91.25	92.60	91.57	91.49	90.40
FOA	93.78	92.36	94.16	92.94	93.52
SSA	96.61	95.90	94.30	95.58	95.26
Proposed	99.35	98.89	98.01	98.72	98.54

Table 3: Results obtained by various optimization approaches

4.3 Comparative Analysis

The table 4 shows the comparative analysis of the proposed and the existing models that are evaluated in terms of accuracy, precision, F-score, sensitivity, and specificity. The existing CNN model vanished the features as it has to pass long path from input to the output layers. The features were vanished and thus obtained an accuracy of 98.91%. However, the overlapped lesions on an original retinal image showed accuracy of 98.68 %. The existed model used SVM that was not suited for large datasets showed an accuracy of 93%. The Random Forest failed to overcome the complex problems that showed precision of 95.90. The developed model showed difficulty for ophthalmologists to identify such small and inconspicuous lesions with eyes in clinical practice that obtained accuracy of 96.36 % for e-ophta dataset. Then, a combination of RGD with the salience and texture features is used by a Gradient Boosting Decision Tree (GBDT) for candidate classification. MA detection methods based on deep learning may lead to the existence of over-fitting due to the small amount of data.

Authors	Dataset	Method	Accuracy (%)	Precision (%)	Sensitivity (%)	Specificity (%)	F-score (%)
Muhammad Mateen [11]	DIARETDB1	Convolutional Neural Networks	98.91	95	-	-	95
R. Alaguselvi Kalpana Murugan [12]		morphology operation	98.68	-	-	-	-
Zhitao Xiao [13]		K-means clustering and SVM	93	-	89	80	-
C. Pratheeba and N. Nirmal Singh [14]		Random Forest	-	95.90	73.93	-	-
Yanfei Guo [15]	E-ophta	Cascade attentive Refine Net	97.46	-	96.52	98.45	-
Jiakun Deng [16]		Multi-Feature Combination	-	-	72	-	54.7
Proposed	DIARETDB1 and E-ophta	Proposed Improved CSA	98.94	98.54	98.89	98.01	98.72

Table 4: Comparative Analysis

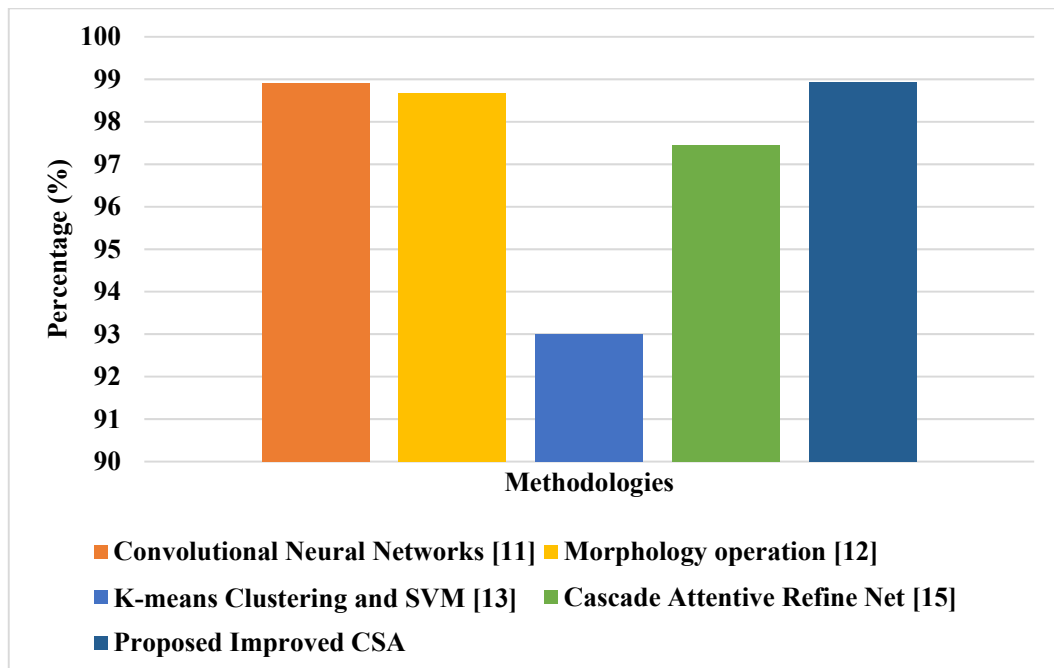


Figure 6: Comparative Analysis of the proposed and the existing

5. Conclusion

The proposed research used segmentation approaches such as Multi-level Otsu thresholding approach and Morphological operations for segmenting the affected region. From the obtained segmented regions, the Gray Level Co-occurrence Matrix (GLCM) feature extraction technique was used for extracting the features and the proposed Dynamic Weighted Cuckoo Search Algorithm (DWCSA) is used for the selection of features. The random walk strategy for the dynamic weighted was built has lead with the slower rate of convergence and vibration. Thus, to enhance the local search, the greater exploration or exploitation is shown for the host nest positions that obtained solutions. The proposed DWCSA obtained an accuracy of 97.46 % compared to the existing CNN model that obtained 98.94 % of accuracy for DIARETDB1. Whereas, the e-optha dataset obtained accuracy of 98.91%. In future, the effectiveness of interventions tailored should improve the health outcomes for reducing the cost for overcoming the progression risk.

Conflicts of interest

The authors declare no conflict of interest.

Author contributions

The paper background work, conceptualization, methodology, dataset collection, implementation, result analysis and comparison, preparing and editing draft, visualization have been done by first author. The supervision, review of work and project administration, have been done by second author.

References

- [1] Gangwar, A.K. and Ravi, V., 2021. Diabetic retinopathy detection using transfer learning and deep learning. In *Evolution in Computational Intelligence* (pp. 679-689). Springer, Singapore.
- [2] Sarathi, M.P., Dutta, M.K., Singh, A. and Travieso, C.M., 2016. Blood vessel inpainting based technique for efficient localization and segmentation of optic disc in digital fundus images. *Biomedical Signal Processing and Control*, 25, pp.108-117.
- [3] Hemanth, D.J., Deperlioglu, O. and Kose, U., 2020. An enhanced diabetic retinopathy detection and classification approach using deep convolutional neural network. *Neural Computing and Applications*, 32(3), pp.707-721.
- [4] Zahoor, M.N. and Fraz, M.M., 2017. Fast optic disc segmentation in retina using polar transform. *IEEE Access*, 5, pp.12293-12300.
- [5] Rehman, Z.U., Naqvi, S.S., Khan, T.M., Arsalan, M., Khan, M.A. and Khalil, M.A., 2019. Multi-parametric optic disc segmentation using superpixel based feature classification. *Expert Systems with Applications*, 120, pp.461-473.

- [6] Saman, G., Gohar, N., Noor, S., Shahnaz, A., Idress, S., Jehan, N., Rashid, R. and Khattak, S.S., 2020. Automatic detection and severity classification of diabetic retinopathy. *Multimedia Tools and Applications*, pp.1-15.
- [7] Kumar, S., Adarsh, A., Kumar, B. and Singh, A.K., 2020. An automated early diabetic retinopathy detection through improved blood vessel and optic disc segmentation. *Optics & Laser Technology*, 121, p.105815.
- [8] Washburn, P.S., 2020. Investigation of severity level of diabetic retinopathy using Adaboost classifier algorithm. *Materials Today: Proceedings*.
- [9] Dhal, P. and Azad, C., 2020, January. A novel approach for blood vessel segmentation with exudate detection in diabetic retinopathy. In *2020 International Conference on Artificial Intelligence and Signal Processing (AISIP)* (pp. 1-6). IEEE.
- [10] Romero-Oraá, R., García, M., Oraá-Pérez, J., López, M.I. and Hornero, R., 2020. A robust method for the automatic location of the optic disc and the fovea in fundus images. *Computer methods and programs in biomedicine*, 196, p.105599.
- [11] Mateen, M., Wen, J., Nasrullah, N., Sun, S. and Hayat, S., 2020. Exudate detection for diabetic retinopathy using pretrained convolutional neural networks. *Complexity*, 2020.
- [12] Alaguselvi, R. and Murugan, K., 2021. Performance analysis of automated lesion detection of diabetic retinopathy using morphological operation. *Signal, Image and Video Processing*, 15(4), pp.797-805.
- [13] Xiao, Z., Zhang, X., Geng, L., Zhang, F., Wu, J., Tong, J., Ogunbona, P.O. and Shan, C., 2017. Automatic non-proliferative diabetic retinopathy screening system based on color fundus image. *Biomedical engineering online*, 16(1), pp.1-19.
- [14] Pratheeba, C. and Singh, N.N., 2019. A novel approach for detection of hard exudates using random forest classifier. *Journal of medical systems*, 43(7), pp.1-16.
- [15] Guo, Y. and Peng, Y., 2022. CARNet: Cascade attentive RefineNet for multi-lesion segmentation of diabetic retinopathy images. *Complex & Intelligent Systems*, pp.1-21.
- [16] Deng, J., Tang, P., Zhao, X., Pu, T., Qu, C. and Peng, Z., 2022. Local Structure Awareness-Based Retinal Microaneurysm Detection with Multi-Feature Combination. *Biomedicines*, 10(1), p.124.

Authors Profile



Author 1: Nandeewar Sampigehalli Basavaraju

Completed B.E in Computer Science and Engineering from Bangalore University & and M.Tech in Computer Science and Engineering from Visvesvaraya Technological University. Pursuing Ph.D in Computer Science and Engineering at Presidency University, Bangalore, India.

Currently working as Associate Professor in Computer Science & Engineering with over 17 years of experience in teaching for UG and PG courses.

Areas of scientific interests: Image Processing, Computer Networking, Design and Development of Intelligent computing process, AI and Machine Learning



Author 2: Dr. Shanmugarathinam Ganesarathinam

Ph.D in Computer Science & Engineering 2015, Bharathiar University, India

Currently working as Associate Professor with over 18 years' experience in teaching of undergraduate and postgraduate courses in the Department of Computer Science and Engineering, Presidency University, Bangalore.

Areas of scientific interests: Computer Networking, Machine Learning and AI, Image Processing and Block chain technology