How to Cite:
Vijayalakshmi, P. S., & Kumar, M. J. (2022). An improved grey wolf optimization algorithm (iGWO) for the detection of diabetic retinopathy using convnets and region based segmentation techniques. *International Journal of Health Sciences*, *6*(S1), 13100–13118. https://doi.org/10.53730/ijhs.v6nS1.8330

An improved grey wolf optimization algorithm (iGWO) for the detection of diabetic retinopathy using convnets and region based segmentation techniques

P.S. Vijayalakshmi
Research Scholar, Department of Computer Science, SNMV College of Arts and Science, Coimbatore-50, TN, India,
Email: vijips2605@gmail.com

Dr. M. Jaya Kumar
Assistant Professor, Department of Information Technology, SNMV College of Arts and Science, Coimbatore-50, TN, India,
Email: jayaku3@gmail.com

***Abstract*---**Diabetic Retinopathy is a retinal eye disease that affects people with Diabetes Mellitus. DM is metabolic disorder and it is caused by the high glucose level in blood. This leads to eye deficiency called Diabetic Retinopathy (DR). In this paper, we proposed iGWO algorithm for the detection and diagnosis of DR stages and Region growing technique is used for segmentation of the images. Various preprocessing techniques are followed for the better enhancement of the images. An improved Grey Wolf Optimization (iGWO) algorithm are proposed to obtain the global optimum. Convnets are utilized for DR categorization. The iGWO-FFOCNN model is compared with existing technologies like SVM-GSO (Support Vector Machines – Glowworm Swam Optimization), PSO-CNN (Particle Swarm Optimization-Convolutional Neural Networks), CNN (Convolutional Neural Networks), DCNN-EMFO (Deep Convolutional Neural Networks-Enhanced Moth Flame Optimization) and MACO-CNN (Modified Ant Colony Optimization–CNN). The APTOS DR Dataset utilized for the proposed metodology. The effort is made for identifying the DR stages by using iGWO. Finally, the results confirm that iGWO-FFOCNN technique yields good performance than compared to the existing techniques in relation to F-measure, precision, recall and also in DSC (Dice Similarity Coefficient), JSC (Jaccard Similarity Coefficient) and time period.

Manuscript submitted: 18 March 2022, Manuscript revised: 9 April 2022, Accepted for publication: 27 May 2022

***Keywords*---**Gray wolf optimization, improved gray wolf optimization algorithm, Convnets, Region growing, segmentation, enhanced crow search algorithm.

Introduction

Diabetic retinopathy (DR) is among the most common reasons for blindness in people of age of employment. It is one of the most recognized dreaded diabetic challenges. The primary difficulty with DR is that it is incurable once it has progressed to an advanced degree, thus early detection is critical. Many variables contribute to DR, including oxidative damage, enzymatic activation, cell osmoticlysis, rise in toxins, stimulation of Hormones, various growth hormones, and carbonic metabolites. Pods, optic neuritis, flashes and abrupt vision impairment are all frequent symptoms of DR [1]. Nonvascular pathologies, such as hypertension, diabetes, and cardiovascular disorders, are also affected [2]. All of these methods injure retinal cells, causing micro aneurysms, cotton wool patches, hemorrhages, and a variety of other abnormalities. This results in morphological alterations in the vascular system, just like changes in dimension, height, and highly branched ratios. As a result, veins of blood supply essential points that may be utilized to diagnose and evaluate circulatory and ophthalmic illness. In most other occurrences, newly formed blood vessels begin to form as in macula, resulting in depreciation of eyesight [3].

Macular Edema, Hard Exudates, Micro aneurysms, Hemorrhages, Cotton Wool Spots and Neovascularization are all symptoms of DR. DR is divided into five categories based on these five clinical characteristics. According to Wilkinson et al. [4], there are five grades of DR: Level 0 is healthy with no indications of DR, level 1 is light DR, level 2 is medium, level 3 is acute, and level 4 is described by new artery growth and vision loss concerns such as bleeding into the ocular vascular separation. Micro aneurysms arise as a result of revascularization or aberrant permeability of blood vessels in the retina are the early stages of retinal injury. Micro aneurysms are little blood vessels that are smaller than 125 microns in diameter and appear in the fundus imaging as a crimson patch with sharp borders. The leaking of lipids and other enzymes via dysfunctional arteries of blood causes hard exudates to accumulate within the retina's outer surface. White or pale yellow little patches sharpness borders appear [5]. Cotton Wool Spots [6] are an Ocular Nerve Fiber Layer has a foamy white lesion caused by debris deposition and are caused by an arteriole occlusion. Hemorrhages are red patches with an uneven edge caused by weak capillaries leaking blood, and they are larger than 125 microns. Neovascularization is the unusual development capillaries of blood in the retina's innermost layer that leak into the hollow translucent, producing impaired sight [7].

Deep Learning (DL) solutions for effective DR detection and categorization have become possible because to recent breakthroughs in Artificial Intelligence (AI) and increased computer resources and capabilities. GPUs have sparked interest in strategies for deep learning, that have demonstrated remarkable achievement in a variety of visual technology applications and even have decisively defeated classical methods based on manual. Numerous deep-learning (DL) algorithms have been developed for diverse tasks have furthermore been created to assess retinal fundus pictures in order to build automatic computer-aided diagnosis systems for DR.

The paper is ordered as the following sections: literature review in the Section 2, proposed methodology shows in the section 3 and it describes the preprocessing methods, segmentation of lesions, classification and feature extraction. The experimental outcomes are discussed in section four. Lastly, in section 5, conclusions are provided.

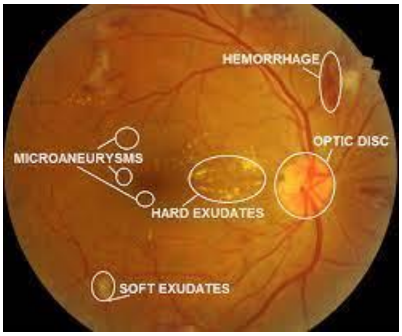


Figure 1: Retinal fundus image

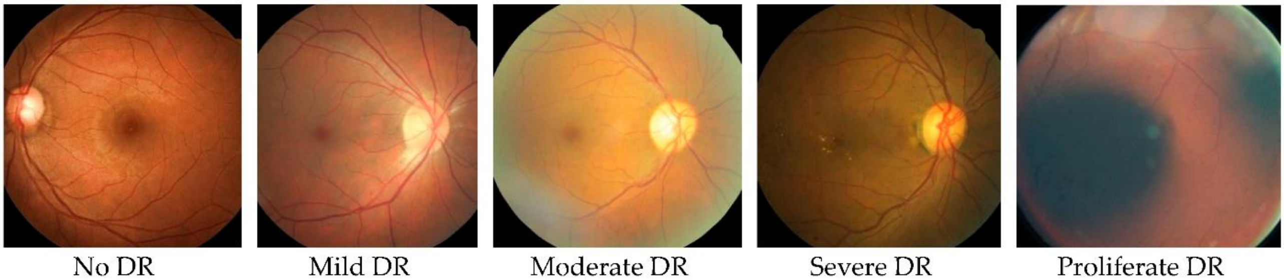


Figure 2: Stages of DR

Review of Literature

Various studies have been conducted on identifying and categorizing diabetic retinopathy, however, there are always improvements to be made in terms of accuracy and application to other types of datasets. Antal and Hajdu [8] developed a DR-levels and diagnosing abnormalities soit allows for numerous feature extraction and pre-processing approaches. Highlighted, intensity improvement, localized distribution, vessel elimination is some of the pre-processing techniques. Diameter closure techniques, tophat transformation algorithm, Inter reflect, circle Hough transformation technique, and multiple Gaussian filters fitting are among the feature extraction methods. Finally, three classifiers are tested for lesion detection: Random forests, k-nearest neighbor and SVM.

A TensorFlow framework was used to construct a smartphone application for real-time diabetic retinopathy detection. The CNN model was Mobile Nets, which include 28 convolutional layers and are tailored for mobile devices. The result is a label, such as diabetic retinopathy or no diabetic retinopathy. This concept was created with mobile devices in mind [9]. Vimala et al. presented a technique for noticing maculopathy disease in retinal pictures using morphological procedures. Contrast Limited Adaptive Histogram Equalization improves the quality of retinal pictures (CLAHE). Morphological processes are used on a regular basis to shape structures. To aid in the discovery of the illness, a Support Vector Machine (SVM) is used in the categorization process [10].

Karthikeyan et al. suggested a novel algorithm-based technique that combined association rule data mining with an upgraded FPG growth algorithm that is comparable with ACO. CACO, or Continuous Ant Colony Optimization for exudate segmentation, is the algorithm employed in this approach [11]. Naluguru et al. [12] offer EC approaches for segmentation. In automated DR, it is a form of feature extraction approach that includes blood vessel segmentation. They are extracting the blood vessels, texture, optic disc, and entropies from the retina using GA with SVM and Bacterial Foraging Algorithm (BFA). It starts with segmentation and then extracts features from pictures using bifurcation points, texture, and entropy before moving on to statistical feature extraction. After extracting statistical features, the authors employ GA and BFO with a neural network to categorize the pictures into three categories: normal, NPDR, and PDR. They then determine the best classifier for retinal lesions and grade them as mild, moderate, or severe.

Bajeta et al. [13] built a model for blood vessel segmentation in which they used ACO in fundus pictures and had ACO extract features. To extract characteristics from retinal pictures. Mateen et al. showed asymmetrically optimized result employing a Gaussian mixture model (GMM), visual geometry group network (VGGNet), singular value decomposition (SVD), principal component analysis (PCA), and softmax for region segmentation, high dimensional feature extraction, feature selection, and fundus image classification. According to the authors, the VGG-19 model outperformed AlexNet and the spatial invariant feature transform in terms of classification accuracy and processing time (SIFT) [14].

Gu et al. proposed a retinal image segmentation method. For the segmentation of medical pictures, deep learning has been used. For retinal pictures, a context encoder network performs this segmentation approach. The basic components of the context encoder network are a feature encoder, a context extractor, and a feature decoder module are all included. As a fixed feature extractor, a pre-trained ResNet is used [15].

Deep learning with transfer learning models for medical diagnosis of DR were researched by Khalifa et al.[16] The numerical experiments were carried out using the 2019 dataset from the Asia Pacific Tele-Ophthalmology Society (APTOS). GoogleNet ,Res-Net18, SqueezeNet, VGG16, AlexNet and VGG19 were the models used in this study. These models were chosen because they have a smaller number of layers than bigger models like DenseNet and InceptionResNet. A method called computer-assisted retinal vascular segmentation is used to diagnose eye disorders. They told using an establishment inter artificial bee colony algorithm, an unsupervised retinal vessel identification approach was developed. (EMOABC) [17]. The curve is utilized in this energy to discover a set of characteristics worth considering choose thresholds this will divide the vessels. while also reducing noise. The EMOABC method is basic and straightforward compared to various approaches.

According to Shankar et al. [18], using the feature extraction with Inception-ResNet v2 model and the deep learning neural network with moth search optimization (DNN-MSO) method, a successful DR classification approach has been provided. The Messidor dataset was used to validate the provided model, and the findings showed that it produced better outcomes. For diabetic retinopathy classification, Glowworm Swarm Optimization and utilized with Support Vector Machine with [19] was employed in conjunction with a Genetic Algorithm. The classifier performance of the Support Vector Machine is controlled by the parameters C and gamma. The Support Vector Machine, in combination with the GSO-GA with chromosomes, will also steer the GA's search in orbit. This GSO has no memories, and glow worms do not have any information stored in their memories. This strategy has been shown to enhance detection accuracy. SVM combined with hybrid GSO is employed to classify DR in this case. To update the location depending on the population, a hybrid GSO is employed, and that will give a superior result. Heterogeneous GSO employs a local GA search technique to find optimal values.

Proposed Methodology

The following phases make up the newly introduced work. Preprocessing comes initially, followed by localization, segmentation, classification, and prediction. Global minimum is obtained by using iGWO. CNN's Softmax Classifier performs the classification. The outcomes of these work approaches are the most effective procedure.

Selecting Dataset

The model will be trained by using the APTOS (Asia Pacific Tele-Ophthalmology Society) 2021 Blindness Detection (APTOS2019 BD) dataset [20]. The dataset includes 3662 Images of the fundus taken from a range of patients in rural India. Images are available in a range of sizes and from one of five categories: Absent DR (level 0), Slight (level 1), Medium (level 2), Extreme (level 3), and Cell proliferation DR (level 4).

Preprocessing techniques

Images of the retinal fundus in various sizes and aspect ratios are included in the dataset. Before training with Deep Convolutional Neural Networks, we performed a number of preprocessing processes on the original images in our dataset. Preprocessing is a technique for removing unwanted noises and improving image quality. There are a few visual options for image processing, as well as a variety of pre-processing approaches.

Rescaling, also known as resampling, is a process for creating a new version of an image with a certain size. Upsampling is the process of increasing the image's dimensions, whereas downsampling is the process of decreasing the image's dimensions. Every clipped picture was then scaled to a standard input image size of 256x256 pixels.

- **Min-MaxNormalization**

To avoid the convolutional neural network from learning the image's underlying ground noise, each image was modified using Min-Max normalization. Image normalization is a typical image processing technique that changes the intensity range of pixels. Min-Max normalization is used to scale the image values between 0 and 1. A picture's pixel intensities will be scaled within a range 0 and 1:

$X' = x - min(x) / max(x) - min(x)$ ______________________________ (1)

where x is the initial value and x0 the new value standardized.

- **Image Resolution Enhancement**

Imaging filters are used to intensify the retinal characteristics of blood vessels, optic disc, MA, HM, and exudates in the retinal fundus image. In clinical applications, medical images play an essential role. The clarity of visuals for human seeing is improved via image enhancement. Enhancement procedures include removing blur and noise from a picture, as well as increasing contrast and revealing features in the image.

- **Contrast Limited Adaptive Histogram Equalization (CLAHE)**

CLAHE works on tiles, which are tiny areas of a picture rather than the complete image. This approach may be used to boost the image's local contrast. HSV conversion of a BGR (blue, green, and red channel) images (Hue, Saturation, and Value channel). This allows us to solely use the value channel for the CLAHE algorithm. CLAHE is based on the following variables:
ClipLimit is a number in the range [0, 1] that determines the contrast enhancement limit.
NBins is a 256 positive integer value that represents the number of histogram bins required to construct a contrast enhancement transformation.

- **Median filter**

The algorithmic program's workings are as follows: median filtering determines the output value of each pixel, the pixel values are taken inside a range of spatial windows with a minimum size of 3x3, and the current values are sorted in ascending order [21]. Mathematically, things went like this:
$G(x,y) = med \{ fmg\ (x-m,y-n)\ ,\ (m,n) \in w \}$________________________(2)
where g (x, y) is an image created from the image of fmg (x, y), with w as the window in the image field and (m, n) as the window element.

- **Gaussian Filter**

The final picture is Hue Saturation Density was transformed from RGB color space then histogram equalization filtering by median. Gaussian noise is reduced from retinal pictures simply rearranging the result with distribution equalization with a Gaussian kernel for improved feature extraction. The Gaussian kernel is defined as,

$$G(x,y) = \frac{1}{2\pi\sigma 2}\ e^{\frac{-a^2+b^2}{a2}} \quad (3)$$

The variation of the picture pixel values σ is shown here. The value of is selected adaptively using the procedure below.

Algorithm 1: An algorithm is proposed for evaluating adaptively based on image intensity.

Input: fundus Image of Retina R-FIMG Result: Standard deviation σ
Step 1) Transformation of RF_IMG into HE image H-IMG
Step 2) H-IMG to HIS and is to convert RGB color space.
Step 3) RGBcolor into HSBcolor space
Step 4) Compute the mean of value of HIS-I
Step 5) Computer σ as $\sigma = \sqrt{mean\ /HIS - I}$

Figure 3: Input image

Figure 4: Grey scale image

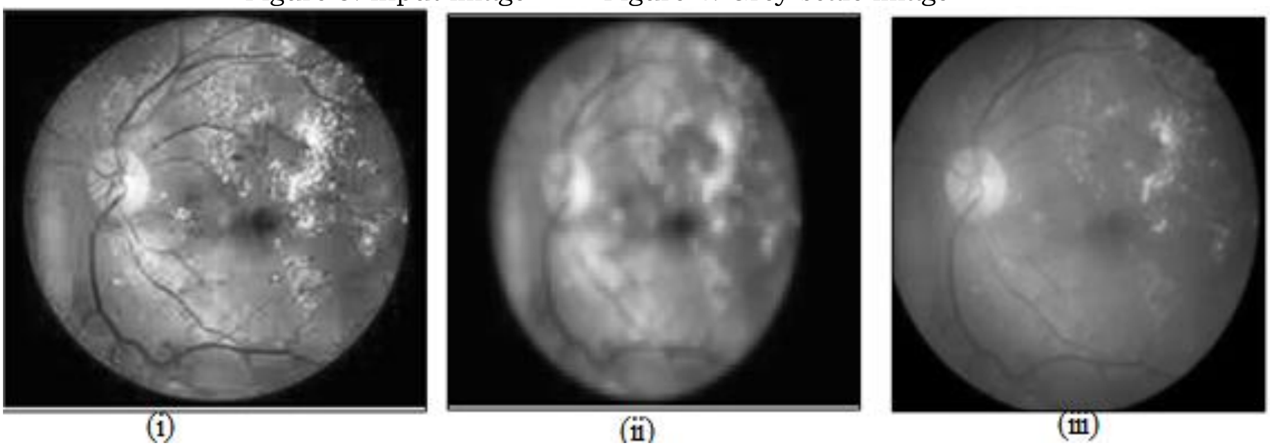


Figure 5: Preprocessed image i) CLAHE image ii) Gaussian filter iii) Median filter

Segmentation of the Image

The technique of segmenting a retinal fundus image into meaningful regions with homogenous attributes is known as image segmentation. Identifying the lesions with the appearance of Fundus ocular images on the optical disc and blood vessels looks to really be a a difficult issue. As a result, the problem is to locate and remove the and even a circle optics discs to detach the blood capillaries that follow. The following steps are involved in image segmentation for this proposed system. i) Optic disc finding, (ii) Optic disc removal, iii) Blood vessel extraction, (iv) microanurysms, Hemorrhages, and Exudate Segmentation.

Optic disc detection and Elimination

Considering one of the aims of the proposed system is to identify the lesion, it's essential to remove the optic disc before the feature extraction operation can begin. In contrasted to the rest of the fundus picture, the optic disc has consistent intensity levels, uniform contrast, and uniform color. When viewing a retinal image in colorspace, the circle optical disc appears white or pale yellowish in color. The optic disc is distinguished as a large circular area with great contrast. Entropy [22] was determined mathematically for a high intensity fundus picture for oculat disc localization as in the

$$H(M) = -\sum_{\boldsymbol{h \in IP(M)}} \boldsymbol{P_h} . log_2(P_h) \qquad (4)$$

Along with all M pixels in a patched frame IP(M), P_h refers to the quantity of units in a distribution I the patchframe and h∈IP(M).
The actions of morpo-dilation and morpo-erosion are essential in morphological image processing methids. Dilation increases the amount of pixels on the boundaries of objects in a picture, whereas erosion reduces the number of pixels on the edges of objects. The image is processed in this study using a mix of dilate-erode procedures.
The dilation of P by Q denoted P ⊕Q is denoted as,

$$P \oplus Q = \{ R | \ (\hat{Q}) \ R \cap P \neq \phi \ \} \qquad (5)$$

where Q seems to be the structuring element and ϕ represents the empty set. In these other aspects, dilatation P by Q is the set of elements the origin positions of all the structural components.
Erosion, on the other hand, diminishes boundaries and expands the size of holes. If any of the structural component does not entirely ON weighted pixels merge, it will set ON pixel to OFF [22]. P is being eroded by Q denoted P ⊖ Q, is described this way:

$$P \ominus Q = \{ R \ | \ (\widehat{Q}) R \subseteq P \} \qquad (6)$$

Blood vessels extraction

For the extraction of objects of interest, the matching filters (MF) technique convolves the picture with numerous matched filters. Thus, constructing multiple filters to identify vessels with varying orientations and sizes plays a key role in obtaining vessel outlines. The computing burden is affected by the size of the convolution kernel. Following the MF, various image processing processes such as thresholding are frequently performed to get the final vessel outlines. A thinning technique is performed first to find vessel centerlines.

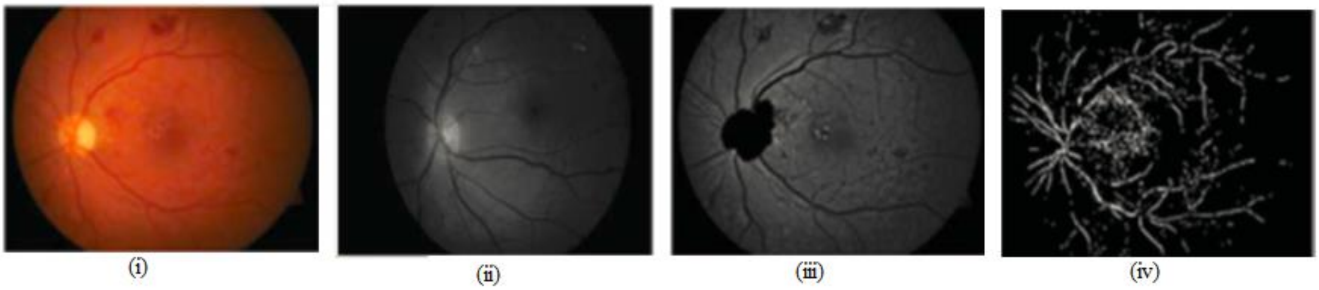


Figure 6:i) Fundus image ii) Green Channeled imaged iii) Optic disc removal iv) Blood vessel extraction

RBT for Segmentation of Lesions in DR

The Lesions of DR are Microanurysms, Hemorrhages, and Exudates are segmented by using Region Based Techniques (RBT) called Region growing. Region growing [23] is a method for extracting a linked region of an image using predetermined criteria. This criterion is based on information about intensity. A method of picture segmentation called region expanding examines nearby pixels and adds them to a section class with no boundaries discovered. This method is repeated for each pixel in the region's boundaries. If nearby areas are discovered, a region-merging algorithm is applied, wherein the weakest edges are dissolved and robust edges are preserved. This studies indicate a new region-growing depending on technique the vector angle color similarity measure. The method for expanding regions is as follows:

Step 1: Pick a few seed pixels from the sample.
Step 2: Create a region from each seed pixel.
Step 3: Change the seed pixel for the area prototype.
Step 4: Determine how similar the regional design and the selected pixel are.
Step 5: Determine the degree of similarity between the applicant and its closest regional neighbor;
Step 6: If both similarity measurements are greater than the experiment's predefined criteria, include the candidate pixel.
Step 7: Calculate the new principal constituent for the region prototype;
Step 8: Move onto another pixel to be evaluated.When there are no more pixels that meet the criteria for inclusion in that region, the region will be stopped expanding.

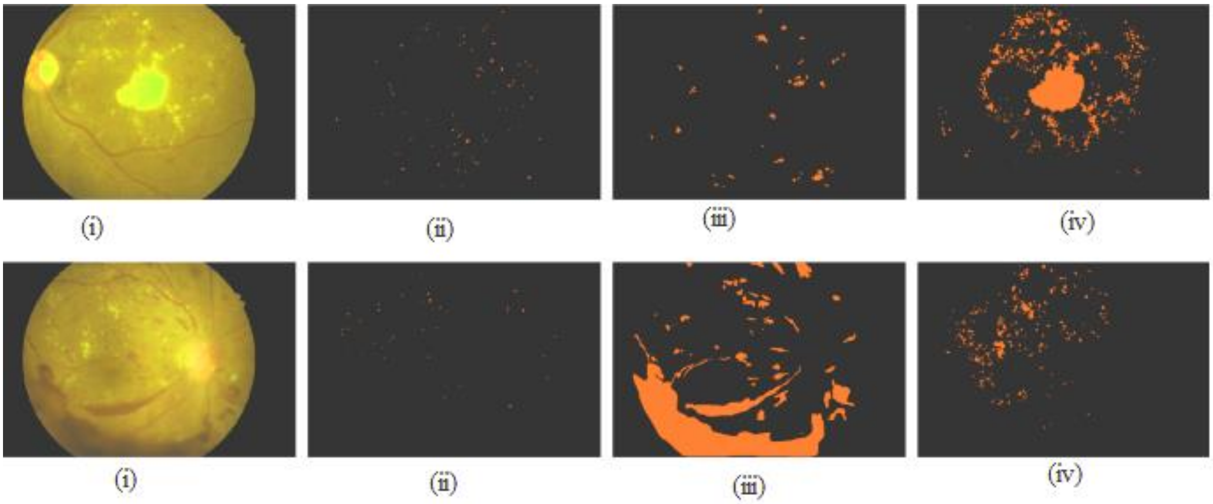


Figure 7: i) Retinal fundus image ii) Microanurysms iii) Hemorrhages iv) Exudates

Convnets for Classification

Convolutional Neural Networks (CNN) or Convnet is a viable method for categorizing retinal fundus images. It is a two-dimensional model that is built and used to recognize image datasets. Its first step is to specify all of the functions that will be used to construct the model. TensorFlow is a lovely computational graph that aids in the creation of these functions and variables by just defining their shape or size rather than putting data in them. Using a 256x256 input image, a filter is being used on all of the of the images, capturing the data. This information is transmitted to the pooling layer, which conducts a mathematical calculation and returns a specified result. The whole model, including the layers required for classification, may be used for training, testing, and classification.

Grey Wolf Optimization Algorithm (GWO)

The GWO algorithm [24] is a novel metaheuristic population-based stochastic method for picking the optimal solution from a set of solutions. The GWO algorithm is centered on how grey wolves behaved, and it replicates the social hunting mechanism in 3 stages: tracking, surrounding, and attacking. Grey wolves are four groups were formed: alpha, beta, delta, and omega. Each group has a rigorous social dominating structure. The α grey wolf is a dominating wolf who makes judgments about sleeping time and hunting.

Other subservient grey wolves have accepted him. The β grey wolf, who aids in decision-making, is regarded to be at the second rung of the hierarchy. It obeys and dominates the instructions of other grey wolves. When gets too old or dies, the following most qualified grey wolf to flourish is β. δ is the next third tier in a grey wolf hierarchical order that either listens to and submits to wolves or dominates ω wolves.If the wolf is α/ β/ δ/ω, ω is the lowest level in the grey wolf hierarchy that submits to other powerful grey wolves [26]. Team hunting is an intriguing social activity of grey wolves, which includes the social hierarchy of wolves. The main hunting techniques used by grey wolves are listed below.

i. Getting close to the prey
ii. Surrounding and pestering it until it stops moving.
iii. Striking out the prey

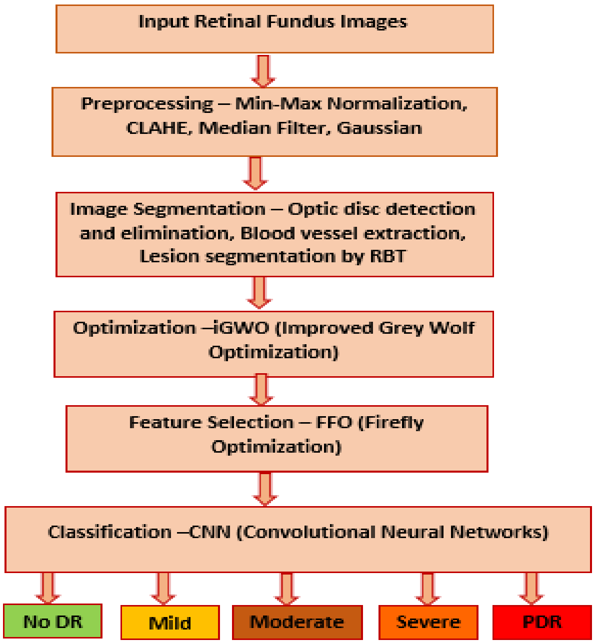


Figure 8: Workflow of proposed method

Improved Grey Wolf Optimization (iGWO)

For the better value of global minimum, the Improved Grey Wolf Optimization Algorithm (iGWO) is chosen. The improved global minimum is found using this population-based optimization strategy. The exploration entails looking into a potential area in order to find a better solution amongst some of the available options, whereas exploitation entails using the solutions found during the exploration phase. Exploration and exploitation stability aids convergence to the global optimum. The trade-off system for exploration and exploitation has to be enhanced. Therefore, in addition to address the shortcomings of the existing GWO method, the improved Grey Wolf Optimization (iGWO) approach is presented.

Different developments are made in the suggested iGWO algorithm in order to come up with solutions to the efficiency and convergence rate difficulties. vectors and they might also be used to change the algorithm's convergence rate. With the goal of simulating grey wolf hunting behavior, it is assumed that the fittest wolf has a better understanding of the probable position of prey, and hence only such fittest solution is archived. The iGWO method is suggested to improve performance in terms of avoiding convergence speed, convergence rate, and accuracy by avoiding premature convergence.

The search agents are activated and dispersed throughout the search space. Local minima are used to classify the whole search space. Finally, the data is used by the people, who identify the global minimum. The convergence speed is determined in this method, so each individual fitness(optimal) is calculated for the local optimum solution. This approach achieves population-based fitness estimations. Eventually, the exploitation goes off without a hitch. Locally, possible solutions are investigated, and metaheuristic optimization is used to obtain exact optimization.

Algorithm 2: iGWO Algorithm

Restore and Initialize the grey wolves(search agents) population X_i (i=0,1,2,....,n)
generate randomly position of each search agent
Restore and Initialize a,A,C
Computer the fitness value of each search agent in the pack
Set X_α,X_β,X_δ according to the fitness
X_α= the best search agent
X_β = the second best search agent
X_δ = the third best search agent
t=1
while(t< Max_Number_Iterations)
    for each search agent
        update the position of each search agent
    end for
    update a,A,C
    Compute the fitness value of each search agents
    Update X_α,X_β,X_δ and X_ω
t=t+1
end while
return X_α

This iGWO yields the 94% accuracy. We think this performs will be better from the existing algorithms.

Feature Extraction Using Firefly Optimization (FFO)

The Firefly algorithm is a swarm-based metaheuristic algorithm that imitate the way fireflies communicate by flashing their lights [25]. The method assumes that almost all fireflies are unisex, meaning that another firefly can be attracted to another firefly; a firefly's appeal is proportionate to its brightness, which is determined by the objective function. A brighter firefly will attract another firefly. In addition, the brightness diminishes with distance according to the inverse square rule. Basis of performance mostly in objective function, a randomly generated viable solution termed firefly will be assigned a light intensity. The brightness of the firefly, which itself is directly proportional to its light intensity, will be calculated using this intensity. For minimization tasks, the maximum light intensity will be awarded to the solution with the least functional value. Each firefly will follow fireflies with higher light intensity that once intensity or brightness of the solution has been assigned. The brightest firefly will conduct a local search by travelling about randomly in its neighborhood. As a result, if firefly x is brighter than firefly y, firefly x will use the update to migrate towards firefly y.

Results and Discussion

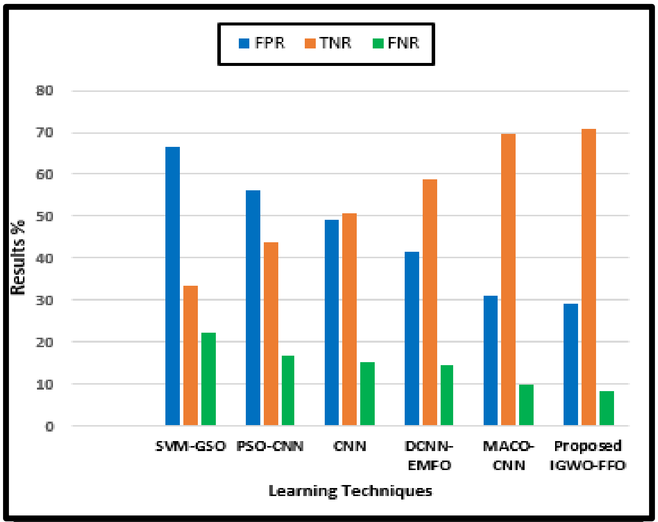
Five distinct phases of DR pictures were taken from the APTOS dataset for this suggested experiment [20]. Diabetic Retinopathy is divided into five categorizations: NPDR normal, NPDR mild, NPDR moderate, NPDR severe, and Proliferative DR. The collection is made up of 3662 photographs taken from patients in rural India. The whole dataset is separated into training and testing sets with a 70:30 ratio and images with No DR 1805, mild 370, moderate 999, severe 193, and PDR 295. This suggested iGWO-based DR detection is implemented in Python using the Google Colob tools Keras and Tensorflow. Various standard metrics like that as f1 measure, recall, accuracy and precision were computed, as well as segmentation measures such as DSC, JSC, and time period.

Table 1: Performance results of various models

S.No	Techniques	Results %							
		FALSE PR	TRUE NR	FALSE NR	PRECISION VALUE	RECALL VALUE	F-measure VALUE	Accuracy VALUE	Error%
1	SVM-GSO	66.66	33.34	22.21	77.77	77.77	77.77	66.66	33.34
2	PSO-CNN	56.13	43.87	16.76	84.56	82.77	83.65	75.00	25
3	CNN	49.20	50.80	15.32	85.21	88.87	87.00	80.00	20
4	DCNN-EMFO	41.35	58.65	14.42	87.11	89.11	88.09	82.00	18
5	MACO-CNN	31.22	69.78	9.83	93.43	92.21	92.81	91.32	8.68
6	**Proposed iGWO-FFO**	**29.12**	**70.88**	**8.45**	**94.11**	**93.02**	**92.05**	**94.11**	**6**

Table 2: Experimental results of DSC, JSC and time period

S.No	Techniques	DSC	JSC	Time period
1	SVM-GSO	0.51	0.56	4.8
2	PSO-CNN	0.56	0.61	4.5
3	CNN	0.64	0.68	3.5
4	DCNN-EMFO	0.68	0.73	2.8
5	MACO-CNN	0.78	0.78	2.4
6	**Proposed IGWO-FFO**	**0.89**	**0.89**	**1.9**



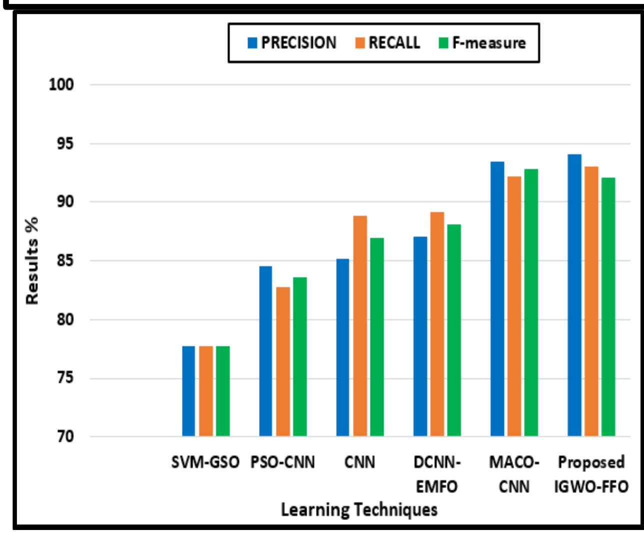


Figure 9: Learning system Models with comparisons of outcomes (False PR,True NR, False NR)

Figure10: Learning system Models with outcomes (precision values, recall and F-measure values)

The performance of six different classifiers, SVM-GSO [26], PSO-CNN [27], CNN [28], DCNN-EMFO [29], MACO-CNN [30], and the suggested IGWO-FFOCNN, is shown in the figure9. It shows that the suggested IGWO-FFOCNN has a higher TNR outcome percentage and a lower FPR, FNR. The SVM-GSO approach yields percentages of 66.66 %, 33.34 %, and 22.21 % for those criteria, respectively. The result percentages for the PSO-CNN classifier are 56.13 %, 43.87 %, and 16.76 %, respectively. According to CNN, the results are 49.20 %, 50.80 %, and 15.32 %. The DCNN-EMFO model yields values of 41.35 %, 58.65 %, and 14.42 %, respectively. The outputs of a deep learning model MACO-CNN are 31.22 %, 69.78 %, and 9.83 %, respectively. The outcomes of the suggested IGWO-FFOCNN model are 29.12 %, 70.88 %, and 8.45 %, respectively. When compared to existing methodologies, it indicates that the proposed IGWO-FFOCNN has a higher TPR.

In addition to accuracy, recall, and F-measure, the figure 10 depicts the additional performance measures of various classifiers' outputs. It is demonstrated that the suggested IGWO-FFOCNN has a higher F-measure, accuracy, and recall. The 77.77 %, 77.77 %, and 77.77 %, respectively, are obtained using the SVM-GSO approach. 84.56 %, 82.77 %, and 83.65 % for the PSO-CNN classifier, respectively. According to the CNN model, 85.21 %, 88.87 %, and 87.00 % are correct. The DCNN-EMFO approach produces results of 87.11 %, 89.11 %, and 88.09 %. Accordingly, the MACO-CNN model receives 93.43 %, 92.21 %, and 92.81 %. The outcomes of the suggested model IGWO-FFOCNN are 94.11 %, 93.02 %, and 92.05 %, respectively.

The additional performance measures Accuracy and error outcomes of those classifiers SVM-GSO, PSO-CNN, CNN, DCNN-EMFO, MACO-CNN, and proposed IGWO-FFOCNN are shown in the figure 11. It reveals that the projected IGWO-FFOCNN has a 94.11 % accuracy rate and a 6% error rate, indicating that it leads to better outcomes.

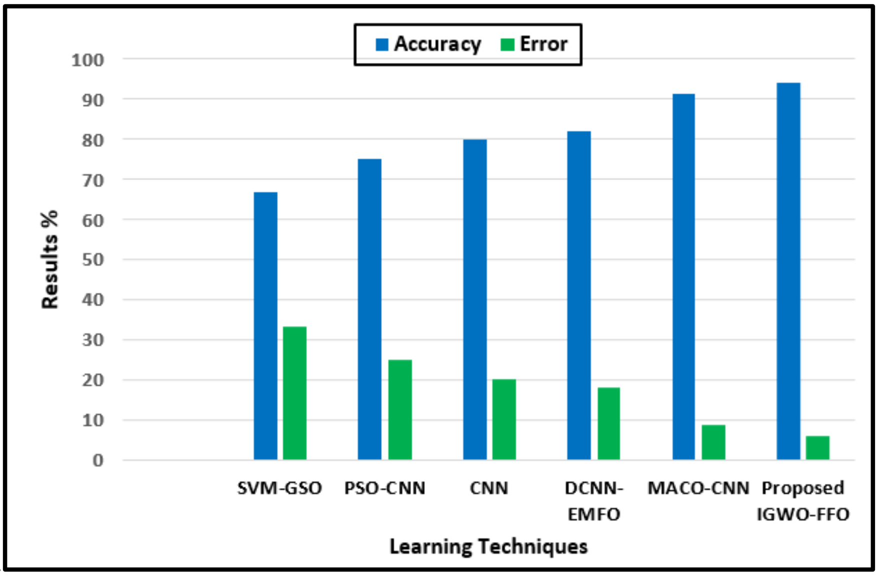


Figure 11: Learning Techniques and outcomes (Accuracy and Error)

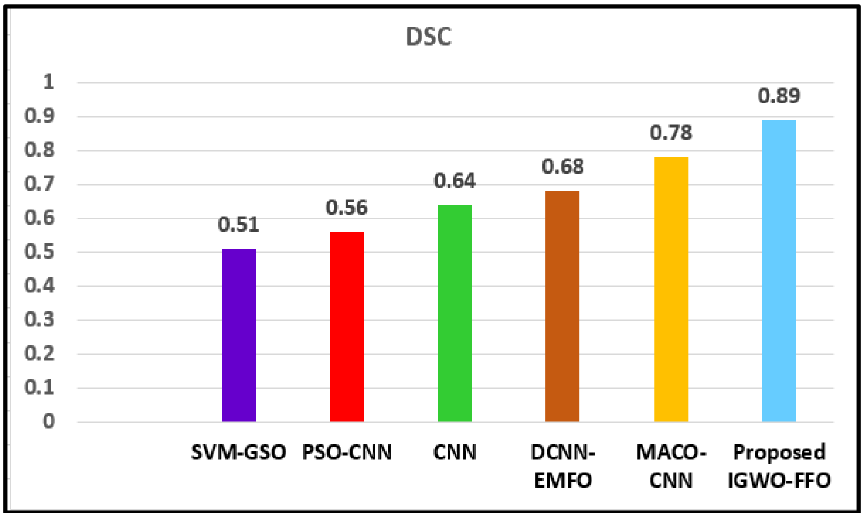


Figure 12: DSC of various learning models

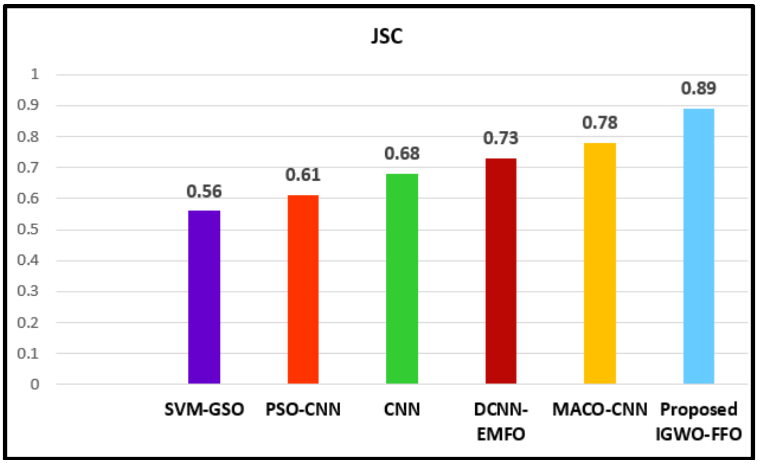


Figure 13: JSC of various learning models

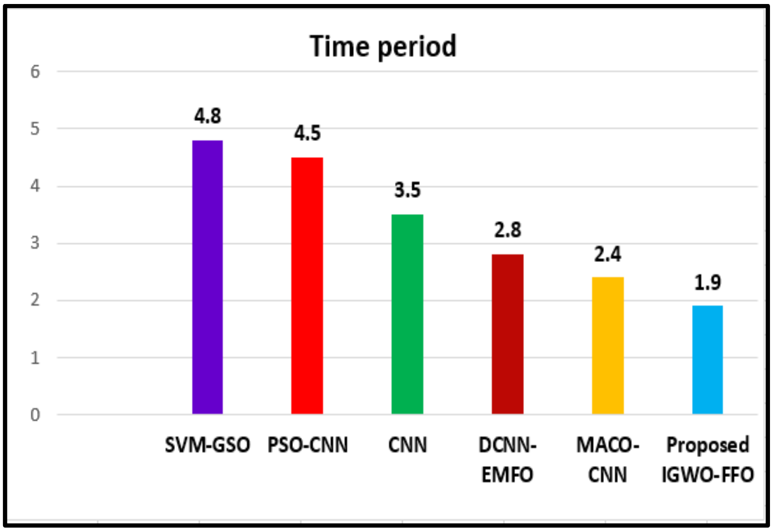


Figure 14: Time period of various learning models

The DSC, JSC, and time period of classifiers SVM-GSO, PSO-CNN, CNN, DCNN-EMFO, MACO-CNN, and proposed IGWO-FFOCNN are shown in the figures 12-14. It demonstrates that the presented IGWO-FFOCNN achieves superior DSC and JSC outcomes of 89 % and 89 percent, respectively, with a time period of just 1.9 percent.

Conclusion

Improved Grey Wolf Optimization with Firefly-based Convolution Neural Networks (iGWO-FFOCNN) is used to classify retinal fundus images in this research. Min-Max normalization, CLAHE, Median, and Gaussian filters are used for preprocessing. All of the samples came from APTOS patients in rural India. Five distinct classifiers are used to analyze performance: SVM-GSO, PSO-CNN, CNN, DCNN-EMFO, MACO-CNN, and iGWO –FFOCNN. In this case, the iGWO-FFOCNN classifier has a higher accuracy and error rate. It reveals that the suggested iGWO –FFOCNN approach achieves a higher accuracy of 94.11 % to existing technologies. The detection performance is increased in the future by utilizing hybrid embedded with cloud-based approaches such as the Hadoop cluster integrated smart algorithm for DR detection.

References

[1] Melville A, Richardson R, Mason J, McIntosh A, O'Keeffe C, Peters J. Complications of diabetes: screening for retinopathy and management of foot ulcers. Qual Health Care 2000;9(2):137–41.

[2] Faliagka E, Syrimpeis VN, Tsakalidis A, Matsopoulos GK, Tsaknakis J, Diagnosis - a global alignment and fusion medical system. Proceedings of the Third International Conference on Health Informatics - Volume 1: HEALTHINF. 2010. p. 21–8.

[3] Klein Ronald, Klein Barbara EK, Moss Scot E. Visual impairment in diabetes. Ophthalmology 1984;91(1):1–9.

[4] Wilkinson, C.P.; Ferris, F.L.; Klein, R.E.; Lee, P.P.; Agardh, C.D.; Davis, M.; Dills, D.; Kampik, A.; Pararajasegaram, R.; Verdaguer, J.T. Proposed international clinical diabetic retinopathy and diabetic macular edema disease severity scales. Ophthalmology 2003, 110, 1677–1682.

[5] A. Benzamin and C. Chakraborty. (2018). "Detection of hard exudates in retinal fundus images using deep learning," in Proc. ICIEV & iclVPR, Kitakyushu, Japan, pp. 465–469.

[6] T. Y. P. Chui, L. N. Thibos, A. Bradley and S. A. Burns. (2009). "The mechanisms of vision loss associated with a cotton wool spot," Vision Research, vol. 49, no. 23, pp. 2826–2834.

[7] A. Patz. (1980). "Studies on retinal neovascularization. friedenwald lecture," Investigative Ophthalmology & Visual Science, vol. 19, no. 10, pp. 1133–1138.

[8] Antal, B., Hajdu, A.: 'An ensemble-based system for microaneurysm detection and diabetic retinopathy grading', IEEE Trans. Biomed. Eng., 2012, 59, (6), pp. 1720–1726

[9] Mookiah, M.R.K.; Acharya, U.R.; Chua, C.K.; Lim, C.M.; Ng, E.Y.K.; Laude, ―A. Computer-aided diagnosis of diabetic retinopathy: A review‖. Comput.Biol. Med. 2013.

[10] Vimala, A. G. G. S., & Kajamohideen, S. (2014). Detection of diabetic Maculopathy in human retinal images using morphological operations. Online Journal of Biological Sciences, 14(3), 175–180.

[11] Karthikeyan, T., & Vembandasamy, K. (2014). A refined continuous antcolony optimization based FP-growth association rule technique on type 2diabetes. International Review on Computers and Software (IRECOS), 9,1476–1483.

[12] Naluguru. U. Kumar and R. Tirumala, "A cross layer approach for feature extraction with accurate detection through blood vessel segmentation in automatic diabetic retinopathy," Aust. J. Basic Appl. Sci., vol. 9, no. 36, pp. 524–534, Dec. 2015.

[13] Bajčeta, M., Sekulić, P., Djukanović, S., Popovic, T., & Popović-Bugarin, V. (2016, November). Retinal blood vessels segmentation using ant colony optimization. In 2016 13th Symposium on Neural Networks and Applications(NEUREL)(pp. 1–6). IEEE.

[14] Mateen, M., Wen, J., Song, S., & Huang, Z. (2018). Fundus image classification using VGG-19 architecture with PCA and SVD. *Symmetry*, *11*(1), 1. https://doi.org/10.3390/sym11010001

[15] Gu, Z., Cheng, J., Fu, H., Zhou, K., Hao, H., Zhao, Y., … Liu, J. (2019). CEnet: Context encoder network for 2D medical image segmentation. IEEE Transactions on Medical Imaging, 38(10), 2281–2292.

[16] Khalifa, N. E. M., Loey, M., Taha, M. H. N., & Mohamed, H. N. E. T. (2019). Deep transfer learning models for medical diabetic retinopathy detection. *Acta Informatica Medica*, *27*(5), 327. https://doi.org/10.5455/aim.2019.27.327-332

[17] Memari, N., Saripan, M. I. B., Mashohor, S., &Moghbel, M. (2019). Retinal blood vessel segmentation by using matched filtering and fuzzy c-means clustering with integrated level set method for diabetic retinopathy assessment. Journal of Medical and Biological Engineering, 39(5), 713-731

[18] K. Shankar, E. Perumal, and R. M. Vidhyavathi, ``Deep neural network with moth search optimization algorithm based detection and classification of

diabetic retinopathy images,'' *Social Netw. Appl. Sci.*, vol. 2, no. 4, p. 748, Mar. 2020.
[19] Sheshathri, V., & Sukumaran, S. A Hybrid Clustering Method for Segmentation of Blood Vessel in Retinal Images.
[20] APTOS. 2019. APTOS 2019 blindness detection. https://www.kaggle.com/c/aptos 2019-blindness-detectionLast. accessed October 25, 2020
[21] Sakthivel, N., & Prabhu, L. (2014). Mean–Median Filtering For Impulsive Noise Removal. International Journal of Basic and Applied Science, 2(4), 47-57.
[22] N. Jamil, S. Tengku Mohd Tengku, and Z. A. Bakar, "Noise removal and enhancement of binary images using morphological operations," in Information Technology, 2008. ITSim 2008. International Symposium on, 2008, pp. 1-6.
[23] S. Angelina, L. Padma Suresh and S. H. Krishna Veni, "Image Segmentation Based On Genetic Algorithm for Region Growth and Region Merging",International Conference on Computing, Electronics and Electrical Technologies (ICCEET), 2012
[24] Mirjalili S, Mirjalili SM, Lewis A. Grey wolf optimizer. Advances in Engineering Software, 2014;69:46–61. URL https://doi.org/10.1016/j.advengsoft.2013.12.007.
[25] X.S. Yang, "Firefly Algorithm, Levy Flights and Global Optimization", *Research and Development in Intelligent Systems XXVI*, doi 10.1007/978-1-84882-983-1_15, 2010.
[26] Karthikeyan, R., Alli, P. Feature Selection and Parameters Optimization of Support Vector Machines Based on Hybrid Glowworm Swarm Optimization for Classification of Diabetic Retinopathy. J Med Syst 42, 195 (2018). https://doi.org/10.1007/s10916-018-1055-x
[27] Jayanthi, J. Jayasankar, T. Krishnaraj, N. Prakash, N. B. Sagai Francis Britto, Vinoth Kumar, K.,JAn Intelligent Particle Swarm Optimization with Convolutional Neural Network for Diabetic Retinopathy Classification Model,Journal of Medical Imaging and Health Informatics, Volume 11, Number 3, March 2021, pp. 803-809(7) American Scientific Publishers DOI: https://doi.org/10.1166/jmihi.2021.3362
[28] S. Sridhar, J. PradeepKandhasamy, M. Sinthuja, T.N. Sterlin Minish,Diabetic retinopathy detection using convolutional nueral networks algorithm,Materials Today: Proceedings,2021,ISSN 2214-7853,https://doi.org/10.1016/j.matpr.2021.01.059.(https://www.sciencedirect.com/science/article/pii/S2214785321000821)
[29] Arun T Nair, K. Muthuvel Automated Screening Of Diabetic Retinopathywith Optimized Deep Convolutionalneural Network: Enhanced Mothflame Model, Journal of Mechanics in Medicine and BiologyVol. 21, No. 1 (2021) 2150005 (29 pages)World Scientific Publishing Company DOI:10.1142/S02195194215000562150005-1
[30] P.S.Vijayalakshmi, Dr.M.Jayakumar, An Efficient Deep Intelligent Based MACO-CNN Algorithm for Classification of Diabetic Retinopathy Disease from Retinal Fundus Images,ISSN: 0011-9342 | Year 2021