An Efficient Meta-Heuristic-Feature Fusion Model using Deep Neuro-Fuzzy Classifier

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***Abstract*—Diabetic Retinopathy (DR) is the major cause of the loss of vision among adults worldwide. DR patients generally do not have any symptoms till they reach the final stage. The categorization of retinal images is a remarkable application in detecting DR. Due to the level of sugar available in the blood, the categorization of DR severity becomes complicated to determine the grading level of the damages caused in the retina. To rectify these challenges, a new DR severity classification model is proposed for detecting and treating the DR. The main objective of the proposed model is to classify the severity grades that occurred in the retinal region of the human eye. Initially, gathered retinal images are enhanced and the blood vessel segmentations are done by utilizing the optic disc removal and active contouring model. The abnormalities such as "microaneurysms, hemorrhages, and exudates" are segmented by utilizing Fuzzy C-Means Clustering (FCM) and adaptive thresholding. Then, the segmented images are given to "VGG16 and ResNet", in which the two different feature sets are acquired. Then, these features are added to obtain the second set of features as F2. Again, the enhanced images act as an input to the "VGG16 and ResNet", which are attained as the first feature set as F1. In the feature concatenation phase, the resultant of two features is used for feature fusion with the aid of weights parameter that is optimized by Modified Mating Probability-based Water Strider Algorithm (MMP-WSA), where the feature fusion is carried out using the mathematical expression. Finally, the multi-class severity classifications are done by using the Optimized Deep Neuro-Fuzzy Classifier (ODNFC), where the optimization of hyper-parameters is done by the proposed MMP-WSA. Thus, the experimental results of the proposed model have been acquired by the precise segment of the abnormalities and better classification results regarding the grade level.**

Keywords*—Multi-class severity classification; diabetic retinopathy; modified mating probability-based water strider algorithm; optimized deep neuro-fuzzy classifier; fuzzy clustering model; adaptive thresholding; optic disc removal; image enhancement

I. Introduction

The retinal image evaluation is a diligent investigation platform in Diabetic Retinopathy (DR). It is the major cause of serious eye difficulties or even loss of sight in developed countries [9]. The retina mainly comprises of the optic disc, fovea, and blood vessels. A few basic symptoms of DR are "sudden changes in vision, eye pain, double vision, Eye Floaters, blurred vision/fluctuating vision and Shadow in Field of View (FOV) and Spots" [11]. The DR is considered one of the deep-rooted visual problems that tend to vision loss if it is not identified on time [15]. Early detection by utilizing regular periodic evaluations is a determinative factor in declining the hazard of serious visual deterioration [16]. The major lesions present in the DR are referred to as exudates, cotton wools, hemorrhages, and Microaneurysms. Hence, the identification of "Microaneurysms and hemorrhages" plays a significant role in the automatic detection of retinopathy [19]. Furthermore, the determination of this disease needs a huge amount of experience and adequate knowledge from doctors. Also, because of the presence of inadequate ophthalmologists and the lack of resources, the screening of patients with Diabetes Mellitus (DM) is considered to be complicated [20], which leads to loss of vision [12]. The DR is broadly categorized into a couple of sections known as proliferative and non-proliferative. The non-proliferative refers to the weakening of blood vessels inside the retina, which causes "leakage of fluids and blood on the retinal surface" due to DR [13]. This leakage minimizes the retinal sensitivity, while it is wet and swollen. The proliferative refers to the developed levels of DR, which creates neovascularization, a creation of bloody vessels newly and naturally in the variety of microvascular network forms that originate on the retina internally [14].

In automated DR diagnosis and segmentation, soft computing models play a remarkable role. Models for DR diagnosis and classifications are genetic algorithms, neural networks, and evolutionary algorithms [21]. Early detection of diabetic retinopathy can prevent the loss of vision in future [10]. Other than automated DR categorization, the fuzzy classifiers are modeled to be translucent with steps of categorization and logic descriptions that are detectable and understandable [22]. However, it needs a huge amount of labeled data for monitoring the training networks. The categorization of retinopathy images is considered a difficult task and so many experienced clinicians are required for the manual interpretation of a high number of retinopathy images. Because of this, Fuzzy C-Means Clustering (FCM) is considered [23]. The fuzzy methodology supports providing enhanced image representations and also in enhancing the analysis performance and providing a more dependable system for screening [24]. The screening of the DR disease at the early stage itself is complicated and so the "Neuro-Fuzzy Hybridization" provides a synergistic intellectual system that joins the human-like reasoning model of a fuzzy system with a neural network's learning structure. The Neuro-Fuzzy hybrids are broadly termed "Neuro-Fuzzy Systems (NFS) or Fuzzy Neural Networks (FNNs)" [25]. Thus, the latest investigators aim on establishing a new DR diagnosis model through deep learning approaches.

The major offerings of this paper are as follows:

- To develop a novel DR severity classification approach based on deep learning approaches for categorizing severities caused by DR, to enhance the early disease diagnosis rate, and to reduce the fatality of patients regarding vision loss.
- The image enhancement process utilizing RGB channels and processing segmentation in two stages known as "blood vessel segmentation and abnormality segmentation" by utilizing the "optic disc removal, adaptive thresholding, FCM and active contouring" model to improve the quality of segmented images.
- To establish the weighted optimal feature selection process in two models by choosing the remarkable features utilized with weight function by developing a Modified Mating Probability-based Water Strider Algorithm (MMP-WSA) for limiting the features and enhancing the performance of categorization.
- To develop an ensemble known as an Optimized Deep Neuro-Fuzzy Classifier (ODNFC), for classifying the DR severity with parameter optimization such as "hidden neurons of DNN, the learning rate of DNN, EXP-bound in fuzzy and weights" are optimized with the developed MMP-WSA for obtaining improved validity in DR categorization.
- To establish a new meta-heuristic algorithm known as MMP-WSA for mounting the weighted optimal feature selection by optimizing the weight function and enhancing the classification accuracy by optimizing the hyper-parameters of developed ODNFC.

The contribution of this research work is as follows. In Section II, the relevant works and their related difficulties are briefed. In Section III, the proposed DR diagnosis model by utilizing ODNFC and image enhancement processing is elaborated. In Section IV, the blood vessel and abnormality segmentation are discussed. In Section V, feature extraction and optimal weighted feature selection for DR diagnosis are explained. In Section VI, the developed MMP-WSA and the developed ODNFC are briefed. In Section VII, the experimental results are discussed. In Section VIII, the proposed DR diagnosis is concluded.

II. Literature Survey

A. Related Works

In 2020, Vaishnavi *et al.* [1] established a new classification approach based on segmentation to categorize the 'DR images", effectively. The proposed approach comprised three major processing known segmentation, feature selection, preprocessing, and categorization. The proposed model has undergone pre-processing utilizing "Contrast-Limited Adaptive Histogram Equalization (CLAHE)". The "AlexNet" model was utilized for feature extraction to collect the most important features. Finally, the categorization of DR images was done by utilizing the SoftMax layer. The experimentation results represented that the established approaches have achieved the maximum categorization rate.

In 2021, Bhardwaj *et al.* [2] proposed a system known as Hierarchical Severity Level Grading (HSG) for the identification and categorization of disorders in DR. The images of the retinal fundus available in the developed HCG system were classified into grades 0, 1, 2, 3 based on the count of anomalies, hemorrhages, and microaneurysms in the images of the fundus. The complications of the "landmark segmentation of retinal images, DR severity grading and DR retinal discrimination" have been notified in this paper contributing to the proposed model. For the categorization of DR and non-DR images, the developed systems have attained greater accuracy with SVM [17] and KNN [18] classifiers. The hierarchical inequities into more grades of harmfulness in disease have resulted in a certain accuracy range for the KNN classifier. The HCG system attained a remarkably minimum time for computation when compared with other state-of-art models.

In 2022, Vasireddi *et al.* [3] established an automated DR identification screening model that was needed to enhance the detection speed and accuracy of the diagnosis. Proper treatments have been given to patients to prevent blindness when the complication levels of DR were detected in earlier stages accurately. The utilization of the optimization algorithm along with the required parameters for tuning enhanced the model's performance. The experimentation results have indicated that the proposed model attains superior accuracy.

In 2020, Gharaibeh *et al.* [4] proposed soft computing models for the diagnosis of Hemorrhages and microaneurysms in fundus images. This process comprised of several steps "such as i) pre-processing, ii) blood vessel segmentation, iii) blood vessel removal, iv) fovea localization, v) fovea elimination, vi) feature extraction, vii) feature selection and finally viii) detection of Diabetic Retinopathy disease" known as Hemorrhages and microaneurysms. It enhanced the performance of precision, accuracy, specificity, and sensitivity and the diagnosis of the DR easier and faster and the results were efficient and provided effective outcomes in categorization models.

In 2022, Kuna Sri Laxmi et al [5] employed various CNN architectures used to classify the severity levels of Diabetic Retinopathy. In 2022, Das and Saha [6] proposed a technique on the basis of a genetic algorithm to detect the CNN parameter automatically and further classification of DR. This approach has comprised a series of "pooling and convolution layers" for the feature extraction. The hyper-parameters in the pooling layer, convolution layer, kernel count, and size of the kernel were analyzed by utilizing the genetic algorithm. The proposed model was validated on a normally available dataset known as "The Messidor dataset". Finally, the SVM utilized for DR categorization has attained greater accuracy than other available models on the basis of a genetic algorithm.

In 2020, Luo *et al.* [7] aimed on embedding a self-monitored model into an un-monitored deep learning approach. Remarkably, it has developed a "Self-supervised Fuzzy Clustering Network (SFCN)" along with a module for feature learning, fuzzy self-monitoring, and reconstruction. The reconstruction approach and feature learning have assured the capacity of the network and the fuzzy self-monitoring module was in charge of giving more training paths for the entire network. To analyze the efficiency of the proposed model, it has established the network on three datasets, in which the results described the good performance of the un-monitored image categorization task.

In 2020, Wang *et al.* [8] proposed a hierarchical architecture to consolidate the common inter-relationship in-between the features and severity levels of DR. The proposed model was analyzed on two individual testing elements by utilizing the "receiver operating characteristic analysis, quadratic weighted Cohen's kappa coefficient and precision-recall analysis". The experimentation outcomes have demonstrated that the proposed model has enhanced the performance of DR severity in comparison with other deep-learning approaches and attained a performance close to the experienced ophthalmologists during the detection of DR severity level.

B. Problem Statement

Diabetic Retinopathy is one of the major diseases in humans, which affects the retinal region of the eye. In the medical industry, there is no early predicted symptom for retinopathy. This disease is caused in two ways: the initial stage is NPDR and the most affected phase is PDR. The remarkable symptoms are leaking blood vessels, swelling of the retina, exudates, damage to nerves, and so on. Hence, the detection and diagnosis of retinopathy become the most challenging task. The screening is targeted at an affected individual that is highly unpredictable. CLAHE and AlexNet [1] enhance the performance in terms of accuracy, sensitivity, and specificity. But, the last layer of AlexNet produces a multiclass classification problem. Gray Level Co-Occurrence Matrix and Support Vector Machine [2] yield the accurate classification of the severity grade level and increase the accuracy. However, it does not consider blood vessel bleeding and neovascularisation problem. Also, due to retinal detachment, acute blindness occurs. Deep Fuzzy Neural Network (DFNN) and Lion Optimization Algorithm (LOA) [3] provide a better severity classification. But it has more time computation complexity. PSO and fuzzy membership [4] obtains higher accuracy and extracts the blood vessels precisely. However, it mitigates the performance since it has fewer quality data. Fuzzy Neural Network [5] improves the classification rate. Moreover, the limitation is to need more numbers of rules to perform in a better way. The Genetic Algorithm and SVM [6] provide higher accuracy for different datasets. But it possesses structural and computational burdens. Fuzzy Clustering [7] yields a higher accuracy value and does not contain most qualitative criteria. However, it has an imprecision dependency on the model. Multi-task DNN [8] obtains less error and more accuracy. Moreover, due to various confidence levels, it may get inaccurate results. To overcome the mentioned challenges, it is provoked to establish a new approach for diagnosing diabetic retinopathy disease.

III. Architectural View of Multi-Class Severity Classification of Diabetic Retinopathy

A. Proposed DR Classification Model and Description

A new DR severity classification model is developed with a weighted feature fusion model and deep learning approach depicted in Fig. 1. In this model, the DR images data set is considered from the standard data set DIARETDB1 as input. These images are preprocessed by four steps enhancement process such as R, G, and B channel separation, entropy-based spatial filtering, fuzzy-based weight adjustment, and concatenation of R, G, and B channels. Then, the blood vessel segmentation is carried out by utilizing optic disc removal and active control using enhanced images. The abnormality segmentation is done with segmented images by FCM and adaptive thresholding. Then, the feature extraction phase is done by using a couple of models. In model 1, the obtained enhanced images are provided as the input to VGG 16 and ResNet, and the required set of features is extracted as feature set 1. In model 2, the abnormality-segmented images data set is provided as the input to "VGG 16 and ResNet" and the required set of features is extracted as feature set 2. For both feature set1 and 2, the feature fusion is carried out for obtaining "fused features with optimized weight function using the developed MMP-WSA" to obtain optimal weighted fused features. Finally, the DR severity classification is done by using developed ODNFC using the weighted fused features, in which the parameters such as "hidden neurons of DNN, the learning rate of DNN, EXP-bound in fuzzy and weights" are optimized by utilizing the developed MMP-WSA. At last, the DR severity-based outcome is obtained as four categories of DR known as normal, earlier, moderate and severe for the proposed DR severity classification model.

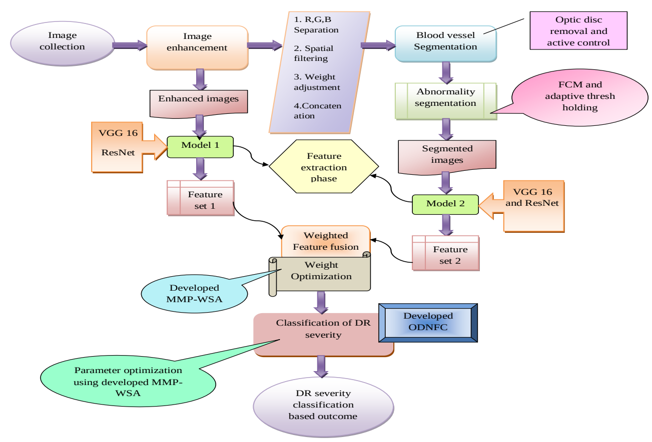

Fig. 1. Developed Multi-Class DR Severity Classification Model with Adaptive Weighted Feature Fusion and Deep Learning Approach.

B. Novel Image Enhancement Process

The images for input are taken from "https://www.it.lut.fi/project/imageret/diaretdb1/". It is a public database for the process of benchmarking the DR severity classification from digital images. the collected database images are denoted as IMG_m^{COL}, where $m = 1,2,\cdots,M$ and the total image count is represented as M . The IMG_m^{COL} is provided as input for the process of image enhancement in the proposed DR severity classification. The image enhancement process is carried out as follows:

- Separation of RGB channels: The input images IMG_m^{COL} are pre-processed for enhancing the quality of the image by removing unwanted elements. The separation of the R, G, and B channels is utilized for the evaluation of elements of primary colors of each region of an image. Hence, the enhanced image obtained after the separation of R, G, and B channels is denoted as ENH_c^{sep}.
- Applying entropy-based spatial filtering: In this step, the RGB-separated images ENH_c^{sep} are given as input. The spatial filtering on the basis of entropy is created for global contrast enhancement of the images. Hence, a single entropy function is applied to the entire image. The algorithm gives contrast enhancement without remarkable deformation on the output image. Thus, the enhanced image obtained from the spatial filtering is represented as ENH_c^{spa}.
- Concatenation of RGB channels: Finally, the separated images are concatenated after removing all kinds of unwanted elements from the image channels. Thus, the quality of the images is enhanced for further processing. Hence, the enhanced image obtained is represented as ENH_c^{img}.

IV. Enhanced Diabetic Retinopathy Segmentation Model through new Abnormality Segmentation

A. *Optic Disc Removal*

The optical disc is removed from enhanced images ENH_c^{img} of the data set for further processing. In the process of optic disc removal for the developed DR severity classification, the enhanced images ENH_c^{img} are provided as the input, and further processing is made. For removing it, the edge-enhanced image on the basis of the curvelet is opened by using a disk-shaped element, which is eliminated from the inverted equalization image. The matching filtering will intensify the visibility of blood vessels present in the enhanced image. The morphological operation is carried out for the processing of optic disc removal. Thus, the segmented image obtained after the process of optic disc removal is represented by SEG_c^{opt}

B. *Active Contour-based Blood Vessels Segmentation*

In the process of blood vessel segmentation, the optic disc removed image SEG_c^{opt} is provided as input to segment the blood vessel using active contour. The active contour is a technique of segmentation that utilizes energy forces and difficulties to split the pixels' interest from images for later evaluation and processing. Active contouring is the methodology of collecting the degradable structures of an image with problems and energy forces for the process of segmentation of blood vessels. The contour model determines the borders of the image elements to create a contour. The curvature of the structure is identified by utilizing various methodologies that comprise internal and external forces. The energy functions are always interrelated to the curve of images. The contour blood vessel segmentation constraints for available images are identified on the basis of requirements. The needed structure is obtained by determining the energy function. A gathering of points that position a contour is utilized to define deformations in contour. Thus, the blood vessel segmented image obtained from active contouring is represented as SEG_c^{act}.

C. *Abnormality Segmentation by Fuzzy Logic-based Adaptive Thresholding*

The abnormality segmentation of the developed DR severity classification is carried out on the basis of two models known as FCM and Adaptive Thresholding on the basis of fuzzy logic and it is briefed below.

FCM [31]: Here, the blood vessel segmented images are provided as input and that is segmented into five classes, which are remarked as the blood vessel, the outer area of the eyeball, the healthy area in the background of the retina, cotton wools and hard exudates. In the processing of clustering, the input images are subdivided into 3×3 non-overlapping regions. Then, for each region, the average intensity is computed. There exists p total number of 3×3 regions present in the image.

Suppose we have a collection of N data (xi; i = 1, 2, 3, ... , N) to be segmented into five fuzzy sets. There will be a membership matrix *em* of size 5XN

Then, the value of entries of the matrix *em* is initiated randomly between 0 and 1 while keeping the sum of each column of *em* to 1 and computed on the basis of the following Eq. (6)

$$\sum_{a=1}^{h} em_{ab} = 1 \; \forall b = 1,2,\ldots,p \tag{6}$$

The FCM divides the data into five categories as h and then determines the center of cluster for every group iteratively during the minimization of cost function on the dissimilarity. Thus, the function of dissimilarity is determined on the basis of the following Eq. (7).

$$B = \sum_{a=1}^{h}\sum_{b=1}^{k}\left(em_{ab}\right)^{we} ed_{ab}^{2} \tag{7}$$

Here, the term em_{ab} denotes the entries of *em*, ed_{ab} indicates the Euclidean distance between ath cluster h_a, bth is the data point, and we **represents the weighting exponent.** Then, the cluster center and the entries are upgraded by utilizing the following Eq. (8) and Eq. (9)

$$Ci = \frac{\sum_{b=1}^{em} em_{ab} Y_{ab}}{\sum_{b=1}^{p} (em_{ab})^{we}}, \forall\, b = 1,2,\ldots,C \tag{8}$$

$$em_{ab} = \frac{1}{\sum_{c=1}^{C}\left(\frac{ed_{ab}}{ed_{cb}}\right)^{\frac{2}{we-1}}} \tag{9}$$

The output from the FCM is obtained in the form of non-overlapping regions indicating five clusters. The abnormality segmented image obtained from FCM is denoted as SEG_c^{fcm}.

Adaptive Thresholding [32]: The segmented image SEG_F^{fcm} obtained from FCM is provided as input and further processing is made. This method generates local thresholds for various areas of images. This is also called the dynamic threshold. By utilizing thresholding, the value of pixels of the images can be categorized from the background. The "adaptive thresholding algorithm" is processed by determining the weighted averages available locally in the image by utilizing the recursive filters. Thus, by using adaptive thresholding, the objects can be separated from the background and also the boundaries are separated. This is attained by generating the surface of the threshold so that the threshold value will be available for each pixel. Hence, the adaptive thresholding is computed based on Eq. (10).

$$Th_{gaussian} = \frac{1}{\sqrt{2\pi\sigma_{a,b}}} e^{\frac{pix(a,b)\mu_{a,b}}{2\sigma_{a,b}^2}} \tag{10}$$

Here, the term a denotes the column pixel index, and b indicates the row pixel index σ denotes the standard deviation and μ represents the averages. The abnormality segmented image obtained from adaptive thresholding is indicated as SEG_c^{abn}. The process of abnormality segmentation based on FCM and adaptive thresholding is indicated in Fig. 2

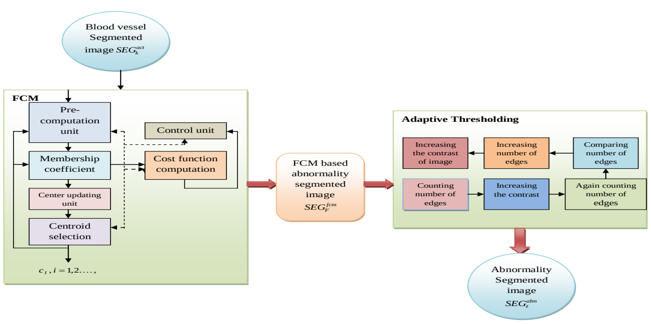

Fig. 2. Abnormality Segmentation based on FCM and Adaptive Thresholding.

V. Deep Feature Extraction and Optimal Feature Selection Process in Two Stage

A. Deep Feature Extraction

The deep feature extraction process for severity classification is determined in "model 1 and model 2". In model 1, the enhanced image obtained from pre-processing is provided as input to VGG16 and ResNet models for extracting the first set of features. In model 2, the abnormality-segmented images are fed as the input for VGG 16 and ResNet models, and the second set of features is extracted as feature set 2. Then both sets of features are optimized by utilizing the proposed MMP-WSA to obtain the optimal deep features, which are elaborated below.

VGG 16 [29]: In this, the enhanced images ENH_c^{img} and segmented images SEG_z^{abn} are provided as input. It is composed of three divisions named "convolutional layer, totally connected layer, and pooling layer". It also consists of a total of 10 layers that are different from the pooling layers. It has a developed network design. For this, the input size of an image is fixed as "224×224 pixels" and the size of the filter in the obtained image is fixed at "3×3 pixels". The output division in the VGG 16 is named "SoftMax". The gathered deep feature element from the VGG-16 is represented as $FESEG_d^{deepVGG16}$ and $FEEN_f^{deepVGG16}$ from ENH_c^{img} and SEG_z^{abn}, respectively.

ResNet-150 [29]: For this, the selected features of enhanced images ENH_c^{img} and segmented images SEG_z^{abn} are provided as input for the ResNet model. It is a developed form of the CNN model. The ResNet gives the shortest route between the divisions to resolve the problems. It also eliminates the level of dispersion, which occurs at the time of complex generation of the network. Moreover, the "bottleneck blocks" are used to fasten the learning process in the ResNet mode. The extracted features from the ResNet model are denoted as $FESEG_e^{deepRN}$ and $FEEN_g^{deepRN}$ from ENH_c^{img} and SEG_z^{abn}, respectively.

B. Optimal Feature Selection: Model 1

In model 1, the enhanced images ENH_c^{img} are provided as input for the feature extraction with VGG 16 and ResNet. Then, by utilizing developed MMP-WSA, the extracted features such as $FEEN_g^{deepRN}$ and $FEEN_f^{deepVGG16}$ are optimized for obtaining optimal deep features denoted as F_1. Total counts of 10 features are extracted from model 1.

C. Optimal Feature Selection: Model 2

In model 2, the abnormality-segmented form of images is fed as input and the feature element extraction is done by utilizing two models known as VGG 16 and ResNet. Then, by utilizing the developed MMP-WSA, the selected segmented features such as $FESEG_e^{deepRN}$ and $FESEG_d^{deepVGG16}$ are optimized for obtaining optimal deep features denoted as F_2. Total counts of 10 features are extracted in model 2.

D. Proposed Feature Fusion

The obtained optimal features F_1 and F_2 from model 1 and model 2 are then fused for obtaining optimal fused features. The weight function is considered during the process of feature fusion, which is optimized using the developed MMP-WSA, and the fusion process takes place as shown in the following Eq. (11).

$$F_{fu} = [F_1 * W + (1 - W) * F_2] \tag{11}$$

Here, the terms F_1 and F_2 indicate the optimal features sets from model 1 and model 2, represent the optimized weight function and denote the feature fusion.

VI. Diabetic Retinopathy Severity Classification by Optimized Deep Neuro Fussy Classifier

A. Proposed MMP-WSA

The developed MMP-WSA algorithm is utilized and implemented in the DR severity classification approach for optimization of parameters such as “hidden neurons of DNN, the learning rate of DNN, EXP-bound in fuzzy and weights” in the feature fusion phase for enhancing the DR classification performance. WSA [26] is selected in this model since it attains efficient performance in optimization issues. In the stage of mating, the probability of attraction is transferred to adaptive or dynamic instead of static, which gives effective convergence performance, but there exist certain limitations in WSA such as the evaluation count is not an acceptance function of the internal elements and so there exists potential complexity in programming languages, which cannot help the global variable to control the total function and evaluation count. Due to the presence of such difficulties in conventional WSA, it is essential to propose an enhanced WSA named MMP-WSA for improving the DR severity classification. In this MMP-WSA, the probability of mating is updated with an adaptive concept, whereas in the traditional algorithm, it is updated with a random parameter.

WSA is an algorithm designed on the basis of feeding mechanism, mating style, territorial behavior, and succession of water strider bugs. The step involved in the algorithm is briefed below.

Initial Birth: The creation of candidate solutions randomly in the searching platform as indicated in Eq. (12) below.

$$Ws_j^0 = l_b + rand.(u_b - l_b): \quad j = 1,2,\dots,NWs \tag{12}$$

Here, the initial positions Ws are analyzed by utilizing an objective function to compute the fitness. The term u_b and l_b indicates the lower and upper bound of variables, Ws_j^0 denotes the initial positions of the j^{th} Ws in the searching space, NWs indicates the population size and $rand$ represents the random number that lies between $[0,1]$.

Territory Establishment: For introducing ni count of territories, the i^{th} member of every group is allocated to the i^{th} territory $(i = 1,2,\dots,ni)$. Hence, the number of Ws_r nesting in every territory is equal to $\frac{NWs}{ni}$ and $\frac{NWs}{ni}$ count of groups is generated orderly and Ws_r are sorted on the basis of fitness. The territory locations with good and bad fitness are obtained as female and male, respectively.

Mating: The male Ws gives a “ripple to the female” Ws for the process of mating. Since the female side response is not clear, the mating probability $\Pr$ is considered for attracting the female. In the conventional algorithm, Pr is fixed in the constant range of 0.5, which degrades the performance of an algorithm. Hence, in the developed MMP-WSA, the mating probability P_r is updated on the basis of upper-bound and lower bound based concepts as shown in Eq. (13) below.

$$\Pr = \left[\left(me(R) - me(l_b)\right) / \left(me(u_b) - me(l_b)\right)\right] * (1-0) + 0 \tag{13}$$

Here, the term $me(l_b)$ denotes the mean of the lower bound and $me(u_b)$ indicates the mean of the upper bound. Then, the value of R is computed by the following Eq. (14).

$$R = Ws_j^s - Ws_j^{s+1} \tag{14}$$

Then, the male location is upgraded in Eq. (15).

$$Ws_j^{s+1} = \begin{cases} Ws_j^s + T.rand & \begin{array}{c} if\ mating\ happens \\ (with\ probablity\ of\ \Pr) \end{array} \\ Ws_j^s + T.(1+rand) & otherwise \end{cases} \tag{15}$$

The length T is computed by Eq. (16).

$$T = Ws_f^{s-1} - Ws_j^{s-1} \tag{16}$$

Here, the term Ws_j^{s-1} and Ws_f^{s-1} indicates the male and female Ws in (s-1) th cycle.

Feeding: The process of mating requires a huge amount of energy for male water sliders Ws searches the food later than the process of mating. The access of objective function for the presence of food is carried out. If the value of fitness is better than the prior condition, the male Ws has identified food in a new location, or else it was not. In the further circumstance, the male Ws transport to the superlative Ws of the pond $\lfloor Ws_{bp} \rfloor$ for founding the food, which is computed in Eq. (17).

$$Ws_j^{s+1} = Ws_j^s + 2rand * \left(Ws_{bp}^s - Ws_j^s\right) \tag{17}$$

Fatality and Progression: If the chap Ws could not identify food in a new location, then it will die and another male Ws will replace the position of the old one. This process is expressed in Eq. (18)

$$Ws_j^{s+1} = l_{bi}^s + rand * \left(u_{bi}^s - l_{bi}^s\right) \tag{18}$$

Here, the term u_{bi}^s and l_{bi}^s indicates Ws location for the maximum and minimum values inside the i^{th} territory.

WSA Execution: If the circumstance of the termination is not satisfied, the baseline approach will send back to the step of mating again for creating a new disk. Here, the “Maximum Number of Function Evaluation (MaxNfes)” is represented as the execution condition. The pseudo-code of the developed MMP-WSA is indicated in Algorithm 1.

Algorithm 1: Pseudo Code of Developed MMP-WSA

```
Initialize random population
Compute the value of fitness Ws
While (execution circumstance is not satisfied) do
    Introduce ni region count and allow the Ws
    For (every region) do
    Update the mating probability Pr
        The male gives "mating ripples" and the chosen female predicts
        the reply to attract the female by Eq. (13)
        Update the location on the basis of the female response with Eq.
```

(15)
Analysis of the new location to search for foodstuff for compensate the obsessive power during the process of mate
If (the male could not identify the foodstuff) then
Searching for foodstuff sources and reaching the territory of the food-rich region by Eq. (16)
If (male could not identify the foodstuff again)
The starving male will be died due to malnourishment
Another male is replaced in the place of died one by Eq. (18)
End
End
End
Return Ws_{opt}

The flowchart of the projected MMP-WSA is represented in Fig. 3

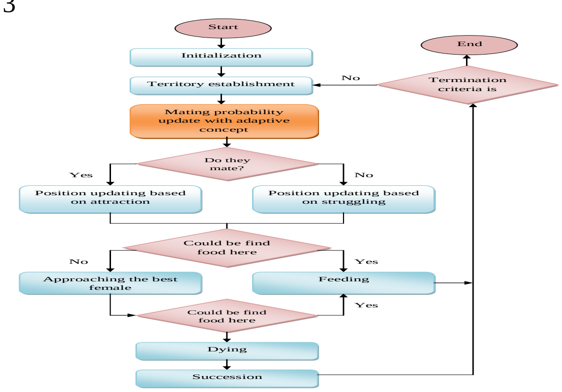

Fig. 3. Flowchart of Proposed MMP-WSA.

B. Optimized Deep Neuro-Fuzzy Classifier

The obtained optimal fused features are given as input for the process of "DR severity classification" by utilizing the developed ODNFC. For the process of image analysis, a rule-based system is modeled by fuzzy network operation. Fuzzy logic is a type of many-valued logic whose variables' truth values can be any real number between 0 and 1. To enhance this operation, the computation of "Single-Input-Multi-Output (SIMO)" is carried out based on Eq. (19).

$$if\ \ y\, is\, A_n\, then \begin{pmatrix} f_{1n}(y) \\ f_{2n}(y) \\ f_{3n}(y) \end{pmatrix}, n = 1,2,\ldots,N \tag{19}$$

Here, the term y represents the input variable from the discourse universe (Y), N is denoted as count of rules, n indicates the output count, A_n denotes the fuzzy set for n^{th} rule determined over (Y) and f_{in} implies the output of n^{th} rule, the outputs are considered as non-linear functions of the inputs. For the process of analysis of images, the universe of discourse is considered as the sub-region set of the considered image. Also, the set of fuzzy is considered as the remarkable pattern. Lastly, the membership grade is considered as the similarity in-between the provided pattern and the sub-regions. Every fuzzy rule present in the rule set is entrapped in various patterns present in the image. Hence, the rewrite equation is obtained as shown in Eq. (20).

$$\begin{pmatrix} f_{1n}(y) \\ f_{2n}(y) \\ f_{3n}(y) \end{pmatrix}, n = 1,2,\ldots,N \tag{20}$$

Thus, the proposed model considers SIMO-based system, where the provided image is given as the individual input, the n^{th} rule attracts the pattern in the images of sub-regions, every output represents a non-linear function against the sub-regions for n^{th} pattern, and the output of de-fuzzification is affected by joining of the specific patterns by fuzzy set in every image rules. The operation of fuzzy interference involves the following steps:

1) Computing of the membership: For every rule, the membership grade (M_n) of the matrix is computed, where every element present in the matrix indicates identity in between the sub-regions present in the image and fuzzy set (A_n). The membership values are allotted at the range of $[0,1]$.

$$M_n = [m_{in}] = [a_i, A_n] \tag{21}$$

Here, the term a_i is the i^{th} image sub-region and m_{in} is the item in M_n.

2) Computing firing strength: The firing strength of every rule is determined by membership grade normalization matrix grade as represented in Eq. (22).

$$\overline{M}_n = \frac{M_n}{\sum_{x=1}^{N} M_x} \tag{22}$$

3) Computing final output: The final outputs of the system rules are provided as shown in Eq. (23) below.

$$w_i = \sum_{n=1}^{N} w_{in} = \sum_{n=1}^{N} \overline{M}_n f_{in}(y) \tag{23}$$

Here, the term w_i denotes the output while w_{in} indicating the output of n^{th} rule. From the categorization by developed ODNFC, the output is obtained in the form of severe, moderate, normal, and abnormal DR.

The proposed approach focuses on the main objective function for parameter optimization in developed DR severity classification. The parameters considered for the optimization are "hidden neurons of DNN, learning rate of DNN, EXP-bound in fuzzy and weights of fused features". The objective function is computed in Eq. (24).

$$OBFN = \underset{\{HN_{DVV}, LR_{DNN}, EX_{FUZZ}, WE\}}{\arg\max} (ACCU) \tag{24}$$

Here, the term HN_{DVV} indicates the hidden neurons of DNN, LR_{DNN} denotes the learning rate of DNN, EX_{FUZZ} indicates the Exp-bound in fuzzy, and WE represents the weight. The hidden neurons count for DNN is fixed in the "range of $[5,255]$ and the learning rate count for DNN is fixed in the range of $[0.01,0.99]$ and the weight range is fixed in-between $[0.01, 0.99]$", respectively. The term $ACCU$ represents the accuracy "closeness of measuring the distance to a specific value", which is computed in the following Eq. (25).

$$ACCU = \frac{(tru_p + tru_n)}{(tru_p + tru_n + fal_p + fal_n)} \tag{25}$$

Here, the term tru_p and tru_n denotes" the true positive and true negative values" and the terms tru_p and fal_n indicates the "false negative and false positive values". The developed ODNFC-based DR severity classification is diagrammatically depicted in Fig. 4.

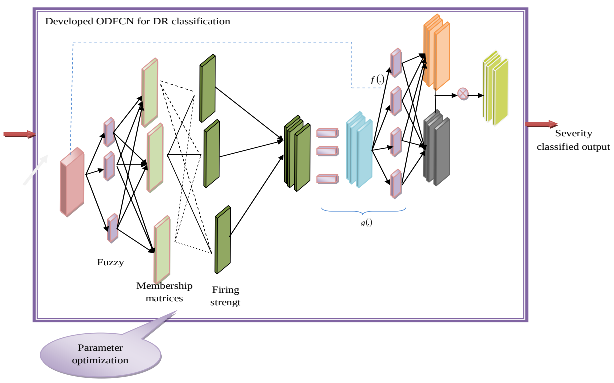

Fig. 4. Flowchart of Proposed MMP-WSA.

VII. Results and Discussions

A. Experimental Setup

The developed DR severity categorization sculpt was established in python and the experimentation analysis is carried out. The concert evaluation of the projected approach was done by the relative examination with traditional models using several quantitative procedures. These quantitative procedures were further divided into two divisions named "positive measures and negative measures". "Positive measures or Type I includes Negative Predictive Value (NPV), Specificity, Accuracy, MCC, Precision, Sensitivity, and F1Score. Negative measures were taken as Type II measures such as False Discovery Rate (FDR), False Negative Rate (FNR), and False Positive Rate (FPR)". The experimentation was carried out on "10 counts of population and the total count of iterations was considered as 25". The proposed MMP-WSA was compared with various algorithms like "Particle Swarm Optimization Algorithm (PSO) [4], Grey Wolf Optimization (GWO) Algorithm [28], Butterfly Optimization Algorithm (BOA) [27], Water Strider Algorithm (WSA) [26] and machine learning algorithms like Deep Neural Network (DNN) [8], Resnet-VGG16 [29], Fuzzy [7], and ODNFC [30]".

B. Performance Metrics

The concert of the established DR severity classification model was tested for quality evaluation of the enhanced approach with several quantitative measures that are briefed as follows.

a) MCC Mcc is "a measure of the quality of binary classifications of testing" as Eq. (26)

$$Mcc = \frac{tru_p \times tru_n - fal_p \times fal_n}{\sqrt{(tru_p + fal_p)(tru_p + fal_n)(tru_n + fal_p)(tru_n + fal_n)}} \tag{26}$$

b) Specificity Spe is "the proportion of negatives that are correctly identified" as Eq. (27)

$$Spe = \frac{tru_n}{tru_n + fal_p} \tag{27}$$

c) NPV Npv is "the sum of all persons without disease in testing" as denoted in Eq. (28)

$$Npv = \frac{tru_n}{tru_n + fal_n} \tag{28}$$

d) F1-score $Fsco$ is "the measurement of the accuracy in the conducted test" as Eq. (29)

$$Fsco = 2 \times \frac{2tru_p}{2tru_p + fal_p + fal_n} \tag{29}$$

e) FNR Fnr is "the proportion of positives which yield negative test outcomes with the test" as Eq. (30)

$$Fnr = \frac{fal_n}{fal_n + tru_p} \tag{30}$$

f) Sensitivity Sen is "the proportion of positives that are correctly identified" as Eq. (31)

$$Sen = \frac{tru_p}{tru_p + fal_n} \tag{31}$$

g) FPR Fpr is "the ratio between the numbers of negative events wrongly categorized as positive (false positives) and the total number of actual negative events" as Eq. (32).

$$Fpr = \frac{fal_p}{fal_p + tru_n} \tag{32}$$

h) FDR is "a method of conceptualizing the rate of errors in testing when conducting multiple comparisons" as denoted in Eq. (33)

$$Fdr = \frac{fal_p}{fal_p + tru_p} \tag{33}$$

C. Performance Evaluation on Several Baseline Approaches

The concert evaluation of the developed DR severity classification is carried out by comparison with several algorithms as shown in Fig. 5 at different learning percentages. By taking into consideration, the precision of the proposed MMP-WSA, the performance is 0.3%, 0.42%, 0.38%, and 0.49% enhanced than the PSO-ODNFC, GWO-ODNFC, BOA-ODNFC, and WSA-ODNFC, respectively at the learning percentage of 75. Likewise, for every performance measure, the proposed MM-WSA outperformed in terms of the developed DR severity classification model than the traditional approaches.

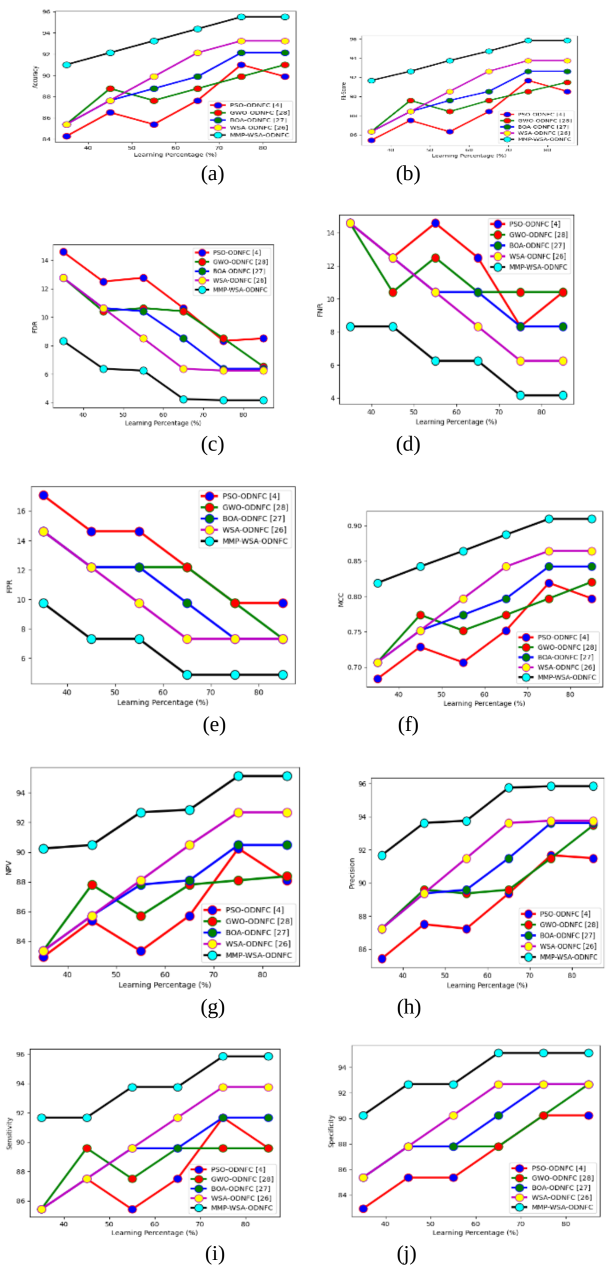

Fig. 5. Performance Analysis of Developed DR Severity Classification Model with Various Algorithms in Terms of "(a) Accuracy, (b) F1-Score, (c) FDR, (d) FNR, (e) FPR, (f) MCC, (g) NPV, (h) Precision, (i) Sensitivity, (j) Specificity".

D. Evaluation of the Proposed DR Diagnosis Model for Different Optimized Algorithms

The performance of the proposed DR severity classification model is carried out on the basis of developed ODNFC on comparison with different conventional classifiers as shown in Fig. 5 at varying "learning percentages". The DR severity classification model is compared with several meta-heuristic baseline approaches as indicated in Table I for analysing the performance. The comparative analysis of the proposed algorithm with other models denotes the improved performance of the proposed MMP-WSA by minimizing the errors. The performance of the proposed MMP-WSA is 0.0.9%, 0.1%, 0.08% and 0.045% enhanced than the PSO-ODNFC, GWO-ODNFC, BOA-ODNFC, and WSA-ODNFC, respectively. Hence, the proposed DR severity classification model improves its performance among several available models.

TABLE I. COMPARATIVE NALYSIS ON DR SEVERITY CLASSIFICATION MODEL BASED ON EXISTING META-HEURISTIC ALGORITHMS

TERMS	PSO-ODNFC [4]	GWO-ODNFC [28]	BOA-ODNFC [27]	WSA-ODNFC [26]	MMP-WSA-ODNFC
"ACCURACY"	91.0112	89.8876	92.1348	93.2584	95.5056
"SENSITIVITY"	91.6667	89.5833	91.6667	93.75	95.8333
"SPECIFICITY"	90.2439	90.2439	92.6829	92.6829	095.122
"PRECISION"	91.6667	91.4894	93.617	93.75	95.8333
"FPR"	09.7561	09.7561	07.3171	07.3171	04.878
"FNR"	08.3333	10.4167	08.3333	06.25	04.1667
"NPV"	90.2439	88.0952	90.4762	92.6829	95.122
"FDR"	08.3333	08.5106	06.383	06.25	04.1667
"F1-SCORE"	91.6667	90.5263	92.6316	93.75	95.8333
"MCC"	81.9106	79.7058	84.2213	86.4329	90.9553

E. Evaluation of the Proposed DR Diagnosis Model for Various Classifiers

The complete evaluation is made on the proposed DR severity classification model for performance estimation among several classifiers as portrayed in Table II. By considering the precision of the developed ODNFC, the performance improves O.047%, 0.035%, 0.037% and 0.045% than the DNN, RESNET-VGG16, FUZZY, and DNFC, respectively. Therefore, the proposed DR severity classification model improves its performance than other available models.

TABLE II. COMPARATIVE ANALYSIS OF DR SEVERITY CLASSIFICATION MODEL BASED ON EXISTING CLASSIFIERS

CLASSIFIERS	DNN [8]	RESNET-VGG16 [29]	FUZZY [7]	DNFC [30]	MMP-WSA-ODNFC
"Accuracy"	87.6404	87.6404	88.764	93.2584	95.5056
"Sensitivity"	85.4167	87.5	89.5833	93.75	95.8333
"Specificity"	90.2439	87.8049	87.8049	92.6829	95.122
"Precision"	91.1111	89.3617	89.5833	93.75	95.8333
"FPR"	09.7561	12.1951	12.1951	073.171	04.878
"FNR"	14.5833	12.5	10.4167	06.25	04.1667
"NPV"	84.0909	85.7143	87.8049	92.6829	95.122
"FDR"	08.8889	10.6383	10.4167	06.25	04.1667
"F1-Score"	88.172	88.4211	89.5833	93.75	95.8333

VIII. CONCLUSION

This paper has developed a novel DR severity classification model with enhanced meta-heuristic-based feature fusion and fuzzy categorization approaches. It includes a number of procedures, together with image enhancement, optic disc removal, image segmentation, and two sets of "model 1 and model 2" characteristics. The acquired fused features were then obtained after performing feature fusion between two feature sets. Where the weighted utility was optimized by utilizing the developed MMP-WSA in fused features and the optimal weighted fused features were obtained, then the classification of DR severity was carried out by utilizing developed ODNFC, in which its hyperparameters such as hidden neurons and learning percentage of DNN, EXP-bound in fuzzy were optimized by utilizing the developed MMP-WSA. The developed MMP-WSA-ODNFC model has provided higher accuracy as 0.047% than DNN, 0.035% than ResNet-VGG 16, 0.037% than fuzzy, and 0.045% than ODNFC. Hence, the developed DR severity classification model with ODNFC-based categorization using MMP-WSA has provided improved performance than other available DR severity classification models. It also acts as a potential path for clinicians for evaluating huge data and for fastening up DR severity classification.

REFERENCES

[1] J. Vaishnavi, S. Ravi, and A. Anbarasi, "An efficient adaptive histogram-based segmentation and extraction model for the classification of severities on diabetic retinopathy", Multimedia Tools and Applications, Vol. 79, pp. 30439–30452, 2020.

[2] Charu Bhardwaj, Shruti Jain and Meenakshi Sood, "Hierarchical severity grade classification of non-proliferative diabetic retinopathy", Journal of Ambient Intelligence and Humanized Computing, Vol. 12, pp. 2649–2670, 2021.

[3] Hemanth Kumar Vasireddi, Suganya Devi K and Raja Reddy G N V, "Deep feed-forward neural network–based screening system for diabetic retinopathy severity classification using the lion optimization algorithm", Graefe's Archive for Clinical and Experimental Ophthalmology, Volume 260, pp. 1245–1263, 2022.

[4] Nasr Y.Gharaibeh, "Detection of diabetic retinopathy using partial swarm optimization (PSO) and Gaussian interval type-2 fuzzy membership functions (GIT2FMFS)", Materials Today: Proceedings, 2020.

[5] Kuna, Sri Laxmi, and Prasad, Dr. A. V. Krishna, Deep Learning Models for Classification of Diabetic Retinopathy Color Fundus Images (September 14, 2022).http://dx.doi.org/10.2139/ssrn.4218649.

[6] Sayan Das and Sanjoy Kumar Saha, "Diabetic retinopathy detection and classification using CNN tuned by genetic algorithm", Multimedia Tools and Applications, Vol. 81, pp. 8007–8020, 2022.

[7] Yueguo Luo, Jing Pan, Shaoshuai Fan, Zeyu Du and Guanghua Zhang, "Retinal Image Classification by Self-Supervised Fuzzy Clustering Network", IEEE Access, Vol. 8, pp. 92352 - 92362, 2020.

[8] Juan Wang, Yujing Bai and Bin Xia, "Simultaneous Diagnosis of Severity and Features of Diabetic Retinopathy in Fundus Photography Using Deep Learning", IEEE Journal of Biomedical and Health Informatics, Vol. 24, Issue. 12, pp. 3397 - 3407, 2020.

[9] Nitigya Sambyal, Poonam Saini, Rupali Syal and Varun Gupta, "Modified U-Net architecture for semantic segmentation of diabetic retinopathy images", Biocybernetics and Biomedical Engineering, Vol. 40, Issue. 3, pp. 1094-1109, 2020.

[10] Qianjin Li, Shanshan Fan and Changsheng Chen, "An Intelligent Segmentation and Diagnosis Method for Diabetic Retinopathy Based on Improved U-NET Network", Journal of Medical Systems, Vol. 43, No. 304, 2019.

[11] A. Shanthini, Gunasekaran Manogaran, G. Vadivu, K. Kottilingam, P. Nithyakani and C. Fancy, "Threshold segmentation based multi-layer analysis for detecting diabetic retinopathy using convolution neural network", Journal of Ambient Intelligence and Humanized Computing, 2021.

[12] J. Pradeep Kandhasamy, S. Balamurali, Seifedine Kadry and Lakshmana Kumar Ramasamy, "Diagnosis of diabetic retinopathy using multi level set segmentation algorithm with feature extraction using SVM with selective features", Multimedia Tools and Applications, Vol 79, pp. 10581–10596, 2020.

[13] Lifeng Qiao, Ying Zhu and Hui Zhou, "Diabetic Retinopathy Detection Using Prognosis of Microaneurysm and Early Diagnosis System for Non-Proliferative Diabetic Retinopathy Based on Deep Learning Algorithms", IEEE Access, Vol. 8, pp. 104292-104302, 2020.

[14] Sehrish Qummar, Fiaz Gul Khan, Sajid Shah, Ahmad Khan, Shahaboddin Shamshirband and Zia Ur Rehman, "A Deep Learning Ensemble Approach for Diabetic Retinopathy Detection", IEEE Access, Vol. 7, pp. 150530 - 150539, 2019.

[15] P. Saranya, S. Prabakaran, Rahul Kumar and Eshani Das, "Blood vessel segmentation in retinal fundus images for proliferative diabetic retinopathy screening using deep learning", The Visual Computer, Vol. 38, pp. 977–992, 2022.

[16] V. Desika Vinayaki and R. Kalaiselvi, "Multithreshold Image Segmentation Technique Using Remora Optimization Algorithm for Diabetic Retinopathy Detection from Fundus Images", Neural Processing Letters, 2022.

[17] Gule Saman, Neelam Gohar, Salma Noor, Ambreen Shahnaz, Shakira Idress, Neelam Jehan, Reena Rashid and Sheema Shuja Khattak, "Automatic detection and severity classification of diabetic retinopathy", Multimedia Tools and Applications, Vol 79, pp. 31803–31817, 2020.

[18] Charu Bhardwaj, Shruti Jain and Meenakshi Sood, "Deep Learning–Based Diabetic Retinopathy Severity Grading System Employing Quadrant Ensemble Model", Journal of Digital Imaging, Vol. 34, pp. 440–457, 2021.

[19] Jyostna Devi Bodapati, Nagur Shareef Shaik and Veeranjaneyulu Naralasetti, "Composite deep neural network with gated-attention mechanism for diabetic retinopathy severity classification", Journal of Ambient Intelligence and Humanized Computing, Vol. 12, pp. 9825–9839, 2021.

[20] Shailesh Kumar, Abhinav Adarsh, Basant Kumar and Amit Kumar Singh, "An automated early diabetic retinopathy detection through the improved blood vessel and optic disc segmentation", Optics & Laser Technology, Vol. 121, 2020.

[21] G. Bhuvaneswari and G. Manikandan, "A novel machine learning framework for diagnosing the type 2 diabetics using temporal fuzzy ant miner decision tree classifier with temporal weighted genetic algorithm", Computing, Vol. 100, pp. 759–772, 2018.

[22] Sulaimon Ibrahim, Pradeep Chowriappa, Sumeet Dua, U. Rajendra Acharya, Kevin Noronha, Sulatha Bhandary and Hatwib Mugasa, "Classification of diabetes maculopathy images using data-adaptive neuro-fuzzy inference classifier", Medical & Biological Engineering & Computing, Vol. 53, pp. 1345–1360, 2015.

[23] Nogol Memari, Abd Rahman Ramli, M. Iqbal Bin Saripan, Syamsiah Mashohor and Mehrdad Moghbel, "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, Vol. 39, pp. 713–731, 2019.

[24] Sarni Suhaila Rahim, Vasile Palade, James Shuttleworth and Chrisina Jayne, "Automatic screening and classification of diabetic retinopathy and maculopathy using fuzzy image processing", Brain Informatics, Vol. 3, pp. 249–267, 2016.

[25] T. Senthil Kumar and D. Kumutha, "Comparative Analysis of the Fuzzy C-Means and Neuro-Fuzzy Systems for Detecting Retinal Disease", Circuits, Systems, and Signal Processing, Vol. 39, pp. 698–720, 2020.

[26] A.Kaveh and A.Dadras Eslamlou, "Water strider algorithm: A new metaheuristic and applications", Structures, Vol. 25, pp. 520-541, 2020.

[27] Y. Zhu and J. Teng, "Beetle swarm optimization for solving investment portfolio problems," in The Journal of Engineering, vol. 2018, no. 16, pp. 1600-1605, 11 2018.

[28] Seyedali Mirjalili, Seyed Mohammad Mirjalili and Andrew Lewis, " Grey Wolf Optimizer", Advances in Engineering Software, vol.69, pp.46–61, 2014.

[29] M.Toğaçar, B.Ergen, Z.Cömert and F.Özyurt, "A Deep Feature Learning Model for Pneumonia Detection Applying a Combination of mRMR

Feature Selection and Machine Learning Models", IRBM, Vol.41, Issue.4, pp.212-222, August 2020.

[30] M. Hanmandlu and D. Jha, "An Optimal Fuzzy System for Color Image Enhancement," IEEE Transactions on Image Processing, vol. 15, no. 10, pp. 2956-2966, Oct. 2006.

[31] Haniza Yazid, Hamzah Arof and Hazlita Mohd Isa, "Exudates segmentation using inverse surface adaptive thresholding", Measurement, vol. 45, pp.1599–1608, 2012.

[32] L. Atikah, N. A. Hasanah, R. Sarno, A. Fajar and D. Rahmawati, "Brain Segmentation using Adaptive Thresholding, K-Means Clustering and Mathematical Morphology in MRI Data," 2020 International Seminar on Application for Technology of Information and Communication (iSemantic), 2020