Ensemble Diabetic Retinopathy Severity Classification Framework With Optimized VGG16, Resnet, and Inception Features

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Abstract

Background problem: Diabetic Retinopathy (DR) is characterized by high glucose levels in the blood, which can lead to permanent vision loss and microvascular complications. Various deep learning techniques for DR analysis tend to be more complex and may experience delays in delivering accurate results, thereby limiting their application in clinical settings. Implementing real-time predictionand severity analysisof DR can address this problem by providing real-time diagnostic insights based on DR severity levels.

Aim: So, this paper is intended to offer a new DR detection and severity classification model with the high-ranking-based ensemble learning approach.

Methodology: The preprocessed and segmented images are utilized in the feature extraction processusing ensemble architecture which incorporated VGG16, Resnet, and Inception to get three sets of features. The optimal features are selected using an Adaptive Scavenger-Based Dingo Optimization Algorithm (AS-DOX) to achieve the efficient classification of DR severity. The optimization constraint stake place in the High-Ranking-Based Deep Ensemble Learning (HR-DEL) model helps to enhance the efficacy of classification for the offered approach. The simulation analysis provides enhanced performance with the accurate classification of the designed DR severity classification approach by comparing it with other baseline methods.

Result: From the result analysis, the offered method achieves 96.6 % accuracy and sensitivity rate. Moreover, it achieves a 90.52% precision rate.

Conclusion: Thus, the designed DR severity classification model attains better performance, and also it is utilized for early detection of DR severity.

Keywords

Adaptive Scavenger-Based Dingo Optimization Algorithm, Diabetic Retinopathy Severity Classification, High-Ranking-Based Deep Ensemble Learning, Inception, Resnet, U-net Architecture, VGG16.

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I. Introduction

DR is the main cause of eye vision loss and it will severely affect the eyes. DR is mainly caused due to the occurrence of high sugar content in the blood because of diabetics [1]. A few of the symptoms of early-stage DR are blurry vision and creating more thirstiness than usual. Early diagnosis and simple medications can effectively treat DR in its early stages. In moderate-stage Diabetic Retinopathy, symptoms include blurred vision, fluctuating vision, and vision loss. Injecting medications into the eye and Photocoagulation is the best medicine for moderate-stage DR [2]. Symptoms of severe DR include eye redness, difficulty wearing contact lenses, and watery eyes. Vitrectomy surgery can improve the vision of patients with severe DR if the retina has not been severely damaged. Hence, the presence of an extreme amount of sugar in human blood may lead to cause damage to the retina [3]. The retina, located at the back of the eye, detects light signals and transmits them to the brain through the optic nerve [4]. Diabetic diseases mainly injure the whole blood vessels in the body. High sugar levels can damage the eyes by affecting the small blood vessels connected to the retina, leading to bleeding [5]. These types of issues in the blocked blood cells are unable to be solved through the newly grown blood vessels since they aren't able to work, properly

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and also cause the leakage and bleeding of the blood in the retina [6]. In the early stages of DR, there may be no warning signs, but some individuals may notice changes in their distance vision, which can make reading difficult [7]. In the progression of DR, blood vessels in the retina begin to leak, causing fluid to accumulate. Then, the anomalous blood vessels from DR encourage enlarging the size of scar tissue and making the retina out from the back of the eye [8]. This can result in small spots affecting your vision, significant vision loss, and occasional flashes of light. DR is diagnosed by looking at various types of lesions in the retina image. These abnormalities manifest as soft and hard deposits, hemorrhages, and microaneurysms [9].

Various automatic models for detecting DR are time-saving, cost-effective, and more effective than manual analysis, which requires more effort than other automatic detection models [10]. According to clinical ranking protocols in DR, the gold standard is referred to as the Early Treatment Diabetic Retinopathy Study (ETDRS) grading scheme, and it does not apply to clinical laboratory practices in day-to-day life [11]. Multiple scales have been developed to enhance clinical examination and communication among healthcare providers. Simple DR severity scales have been enhanced in many countries, without progress towards a unified international severity scale [12]. The image analyses are conducted using an automated model that includes advanced algorithms like Restricted Boltzmann Machines (RBM) and Optimum-Path Forest (OPF) [13]. The use of OPF for its cost-effectiveness and practicality reduces the analytical load compared to RBM, which currently requires a large number of input variables for image recognition [14]. Research on using RBM and OPF for DR identification was uncommon. The social and personal burden of blindness due to DR has led to the search for a new screening method that matches the accuracy of the gold standard [15].

Various deep learning applications, including detection, retrieval, classification, registration, and segmentation of images, are utilized in the examination of medical images. Deep learning approaches are commonly used for identifying and classifying DR [16]. Deep learning can learn the characteristics of input data from a wide range of sources, even when incorporating a large amount of data. A lot of deep learning approaches are available such as autoencoder, spare coding, RBM, and Convolutional Neural Networks (CNN) [17] ,[18]. In a short time, Deep Convolutional Neural Network (DCNN) has proved as a very successful technique in image segmentation, and classification [19]. The primary purpose of this is to have a high number of layers that empower the neural network to recognize and capture the intricate parameters within the image [20]. Various deep-learning techniques are employed to automatically detect DR and diabetic muscular edema in all retinal-related fundus images, leading to high specificity and sensitivity in image processing. This technique incorporates transfer learning for expert-labeled laser scars within the dataset. The new structure employs pooling and convolutional layers to reduce the number of trainable parameters and improve the visibility within the network. The limitation is that it cannot diagnose DR in a patient with the same severity stage in both eyes. Furthermore, the classification of a patient with a severity stage as non-referable DR denotes a mild stage of DR, applicable to a significant number of cases when classifying severity stages. DR deteriorates significantly in advanced cases when patients do not receive adequate care. To resolve these types of issues, it is essential to implement a novel DR severity classification method by deep learning architectures.

The significance of this proposed model isdiscussed here.

- To design a DR severity classificationmodel using optimized ensemble approaches for the analysis of severity levels in individuals affected with DR.
- To select optimal features from extracted features from deep learning techniques using developed AS-DOX for improving the classification rate in DR severity identification.
- To develop an ensemble-based classification architecture named HR-DEL for classifying severity level of DR through parameter optimization in VGG16, ResNet, and inception with the help of proposed AS-DOX.
- To introduce the improved algorithm AS-DOX for tuning the constraints such as several epochs in VGG16, activation function in ResNet, and hidden neuron count in inception for obtaining accurate results in DR severity classification.
- To evaluate the offered DR severity classification model with diverse comparative analysis using various baseline algorithms.

The residual of this task is as follows. Part II elaborates on different previousworks related to DR severity classification. Part III explains the detection of DR and severity classification. Part IV discussed the pre-processing and abnormality segmentation performed in the retinal fundus image. Part V explains the developed HR-DEL for DRseverity classification. Part VI represents the outcomes and validations. Finally, Part VII completes the given work.

II. Literature Survey

A. Related Works

In 2020, Qiao *et al.* [21] presented DCNN approaches for detecting a microaneurysm in fundus image that used deep learning as a major parameter along with aGraphics Processing Unit (GPU), and it was used to achieve medical-related image identification and also segmentation through low-latency and high performance. Semantic segmentation was employed to group image pixels based on their shared characteristics, aiding in identifying microaneurysm features. It can enhance the accuracy as well as efficiency of DR prediction. In 2020, Thota and Reddy [22] proposed a VGG16 method, it acted as a pre-trained neural network to perform fine-tuning and also to perform severity classification in DR. This system utilized effective deep learning methods such as dropout layers, learn-rate scheduling, batch normalization, and data augmentation with high-resolution images for achieving higher accuracy rate. An Area Under the Curve (AUC), Average Class Accuracy (ACA), specificity, and sensitivity were achieved. The developed approach achieved better outcomes than other existing pre-trained methods or networks.

In 2020, Wang *et al.* [23] suggested a hierarchical multi-task deep learning framework for the analysis of DR-based features as well as DR severity in the fundus image. A new hierarchical architecture was developed and they were combined with a causal relationship between DR severity levels and DR-based features. Numerous results demonstrate that the developed approach significantly enhances the performance rate. In 2018, Krishnan *et al.* [24] implemented an automatic severity identification of DR with CNN by using transfer learning techniques for the analysis procedure. A comparison was performed between the CNN structures like Inception-ResNet-v2, ResNet, etc, with the help of quadratic weighted kappa metric. The quantitative, as well as qualitative validation was performed in the developed technique by using Kaggle's DR identification dataset.

In 2020, Shankar *et al.* [25] initiated an automated Hyper Parameter Tuning Inception-v4 (HPTI-v4) system for the detection and classification of DR with color fundus images. In the beginning, the contrast range of the fundus image was improved using the CLAHE method. Later, segmentation was performed in the preprocessed images by using histogram-related segmentation. Then, the HPTI-v4 model was applied to acquire the characteristics from classification

TABLE I. Superiorities and Downsides of Baseline Diabetic Retinopathy Detection With Deep Learning

Author [citation]	Frameworks	Superiorities	Downsides
Sambyal,*et al.*[21]	DCNN	• It achieves a high segmentation rate as well as image detection by utilizing low-latency-based inference.	• It didn't have the capacity for encoding objects as well as the position of the data.
Thota and Reddy[22]	Inception-V3 and VGG-16	• It utilizes the VGG16 method as a pre-trained neural network to perform fine-tuning.	• It requires high computational power and also it is time-consuming.
Wang *et al.* [23]	Hierarchical multi-task neural network	• It attained a very good performance rate when compared with ophthalmologists.	• It didn't enhance the performance rate of DR-based characteristic observation and DR severity analysis.
Krishnan *et al.* [24]	DCNN	• It can identify significant features without the supervision help of humans.	• It needs large data for training.
Shankar *et al.* [25]	MLP	• It provides quick prediction after training. • It provides high efficiency on severity classification with a minimal number of iterations	• It requires high computational time
Bhardwaj *et al.* [26], [31]	DNN and CNN	• It will improve the network performance. • It has very high accuracy in image recognition problems.	• It didn't provide any expressive assistance to the analyzer by giving a second option to DR classifying issues.
Devi *et al.* [27]	Xception and VGG16	• It contains a gated attention block which can allow the method to speed up the system with a huge number of rental images.	• It didn't allow multiple channels for testing.
Sambyal*et al.* [28]	Modified ResNet18, ResNet34 and ResNet50	• It can train a large number of layers easily without enlarging the training error percentage.	• It will Increase the complexity of architecture.

and the segmented image was performed by utilizing Multilayer Perceptron (MLP). Various validation over-developed models clearly showed that the developed modelhad better performance than existing models. In 2021, Bhardwaj *et al.* [26] developed deep-structured architecture techniques for the recognition and classification of DR over other existing models that mainly depended on handcrafted feature extraction. The challenges in proficient DR discrimination were addressed using a developed automated DR grading technique that combined Inception, Resnet-V2, and DNN structures.

In 2021, Devi *et al.* [27] recommended a multiple pre-trained DCNN, which was utilized for the representation of color fundus retinal images. Spatial pooling models were created to condense these representations without losing significant data. The developed modelhad learned independently from all the minimized representations from multiple channels and it has enhanced the generalization of the system. Furthermore, this method included gated attention blocks to emphasize lesion areas in the retinal image while reducing non-lesion areas. The developed models have produced more generalized predictions compared to the uni-modal presentation. In 2022, Sambyal *et al.* [28] implemented a system for the classification of DR. The binary classification was performed with the help of modified ResNet34, ResNet50, and ResNet18 and these models have showcased a better accuracy rate in DR classification. In multistage classification, the enhanced accuracy was attained by utilizing modified ResNet50, modified ResNet18, and modified ResNet34. The developed model demonstrated an overall enhanced accuracy rate for multi-stage and binary classification through comparisons with various methods.

1. Applications Related to Medicine Such as Skin Cancer, and Brain Tumors Through Deep Learning

In 2022, Zahid et al. [29] presenteda fully automated design for categorizing brain tumors. Thedevelopedstrategy performed accurate deep structured features for the categorization of T2, T1, T1CE, and FLAIR tumors. Initially, the data was inputted into the ResNet101 model for normalization. As a result, the ResNet101 model has fine-tuned the brain tumor classification. Here, the Principal component analysis (PCA) was applied to achieve the finaltuned feature vector. Finally, the tuned feature vector was analyzed by different types of classifiers to categorize tumors.

In 2022, Attique *et al.* [30] developed a deep learningand explainable Artificial Intelligence (AI) approach for the diagnosis and categorization of COVID-19 by chest X-ray images. At first, a hybridized contrast enhancement approach was implemented and used in thecollected images. Then, the features were extracted using the deep transfer learning concept. A Whale-Elephant Herding algorithm was utilized to optimize the features.By this algorithm, the accurate features were selected and categorized by an Extreme Learning Machine (ELM), a type of machine learning algorithm. Throughout the result analysis, the designed method has attained a 96.7% accuracy rate.

B. Problem Statement

DR is a serious eye condition that is primarily caused by diabetes. DR is never considered a resolvable procedure taking correct action only brings the vision back. Early detection is crucial for reducing the risk factors associated with DR. Different strategies are used for designing the DR detection and severity classifications are depicted in Table I. DCNN [21] achieves a high segmentation rate as well as image detection by utilizing low-latency-based inference. At the same time, it didn't encode the position and orientation of the object. Inception-V3 and VGG-16 [22] utilize the VGG16 method as a pre-trained neural network for fine-tuning purposes. However, it is time-consuming and requires high computational power. The Hierarchical Multi-Task Neural Network [23] achieved a high-performance rate in comparison to ophthalmologists' assessments. However, it did not improve the accuracy of observing DR characteristics or analyzing DR severity. DCNN [24] can detect important features without human supervision. However, it requires a large amount of data for training. Multilayer Perceptron [25] provides quick prediction after training and high efficiency on severity classification with a minimal number of iterations. But it requires high computational time. Dense Neural Network and CNN [26] improve the network performance at the same time it has very high accuracy in image recognition problems. However, it didn't provide any expressive assistance to the analyzer by giving a second option to DR classifying issues. Xception and VGG16

[27] contain a gated attention block that can allow the method to speed up the system with a huge number of rental images. But, it can't able allow multiple channels for testing. Modified ResNet18, ResNet34, and ResNet50 [28] can train a large number of layers easily without increasing the training error percentage. But, it will Increase the complexity of architecture. So, it is necessary for an alternative and advanced model for the detection of the severity level of DR detection.

C. Motivation

It is necessary for an alternative and advanced model for detectingthe severity level of DR. A new DR severity classification system is implemented for severity level identificationto detect the individuals affected by DR. Additionally, the AS-DOX algorithm is introduced for optimizing the parameters of the deep learning strategies and also the HR-DEL approach is used for categorizing severity stage of DR. This efficacy of the designed model is suitable for the real world applianceslike clinical and medical appliances. The experimental results of the proposed approach attained highereffectiveness than the other existing models. It is proved that the results are statistically significant. The convergence rate is minimized than the other approaches.

III. Detection of Diabetic Retinopathy and Severity Classification by Optimized Deep Learning

A. Proposed Methodology

Recently, DR has caused sightlessness issues for working people worldwide. Patients with DR often show no symptoms from the early to advanced stages, leading to delays in effective treatment. Multiple studies have demonstrated the effectiveness of examining DR for early identification and treatment. Owing to inadequate resources and ophthalmologists in the detection of DR; it becomes a complex task to examine the entire parts of the patient, who are affected by diabetes mellitus. Improving computer-based models for automated DR examinations is essential. Various traditional techniques are employed for analyzing DR and identifying specific DR-related characteristics in fundus images, such as HM, hard exudates, cotton wool spots, and MA. The main challenge in fundus images is that all retinal parts appear abnormal due to DR [32]. However, fewer regions of the input image have a huge impact on the DR-based final image label. CNN techniques are primarily used for DR classification, processing input data without patient-specific information [33]. Nowadays, deep learning models have very efficient applications in medical image examination and other applications that have huge support in designing a computer-based technique to perform automated DR severity analysis in fundus images. Among deep learning networks, CNN-related techniques demonstrate a higher success rate in classifying DR grades. These techniques generally provide fundus image as input for the prediction of referable DR or vision-threatening referable DR, having DR, absence, and presence of pre-defined DR severity, etc. In various DR severity classification models, DR severity ranges are determined based on their appearance in fundus images with multiple signs. If it contains DR-based features, then it will enhance the diagnosis outcome quality by adding more detailed classification results of the DR severity range. To solve these complexities in baseline approaches, it is required to build up a new Diabetic Retinopathy severity classification framework with optimized deep learning techniques, which is represented in Fig.1.

A new DR severity classification method is developed usingadvanced deep learning techniques to observe the DR severity level for the patient affected by DR. Various DR images aretaken from online sources. Initially, the gatheredimages aregiven to the pre-processing stage utilizing the CLAHE technique.The preprocessed images are thenprovided to the image segmentation phase, where the images are segmented by utilizing U-net architecture, and it generates

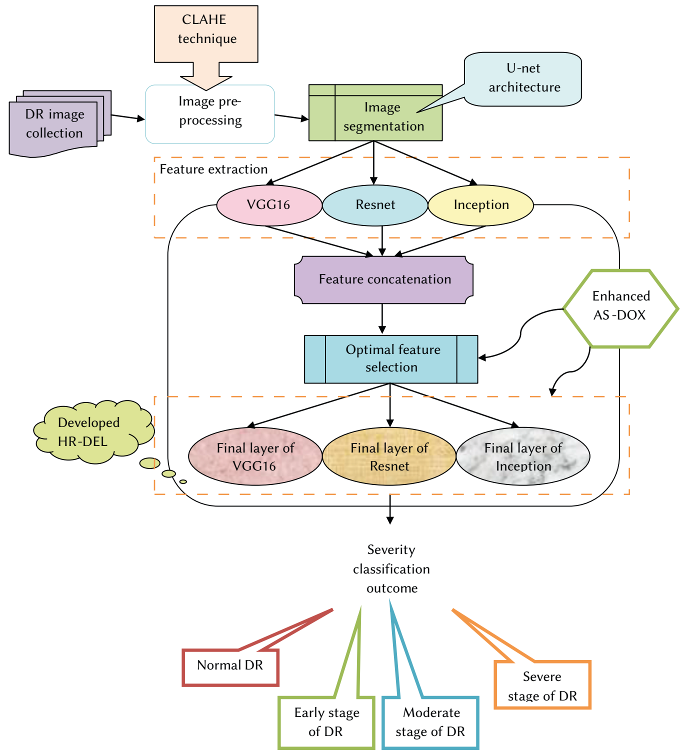

Fig1. A new DR severity classification modelwith optimized deep learning features.

the segmented output. Later, the segmented images are subjected to the feature extraction process.three sets of features. Feature extraction is performed by using ResNet, Inception, and VGG16 to attain three different sets of features. After attaining three multiplesets of extracted features, concatenation is achieved between them. Then, these combined features are fed into the optimal feature selection phase. Here, the developed AS-DOX has optimized the parameters such asthe number of epochs in VGG16, activation function in ResNet,and hidden neuron counts in inception to enhance the accuracy in DR severity classification. The optimal features are chosenthrough developed AS-DOX.By using the final layers of VGG16, inception, and ResNet, a new HR-DEL method is implemented for classifying the DR severity level through the optimal features. Finally, the classified output regarding the DR severity is obtained.

B. Explanation of Diabetic Retinopathy Dataset

The designed DR severity classification model collects the image samples from standard benchmark sources named High-Resolution Fundus (HRF). The input data are obtained from the link [34]. The sample images for the normal stage, earlier stage, moderate stage, and severe stage are analyzed from the given dataset. This dataset provides 3 different sets of image data in all categories. In the first set, it holds 15 multiple images of physically healthy patients and in the second set, it holds 15 different images of patients, who are affected by DR, and the final set of images attained from the individuals affected by glaucomatous. This dataset mainly provides binary gold standard vessel segmented images and masksthat determine the Field of View (FOV) for particular datasets. The gold standards are established by a group of professionals in the retinal image examination and also by clinicians from different ophthalmology centers. In addition, the dataset has included different gold standard data to the previous images to localize the optic disk, macula, or difference between veins and arteries. The entire dataset is divided into two stageswith one asthe training stage and also the other one as thetesting stage. 75% of sample images are utilized for the training stage and 25% of images are used for the testing stage. Sample images of DR severity classification for the normal stage, earlier stage, moderate stage, and severe stage in the dataset are presented in Fig. 2.

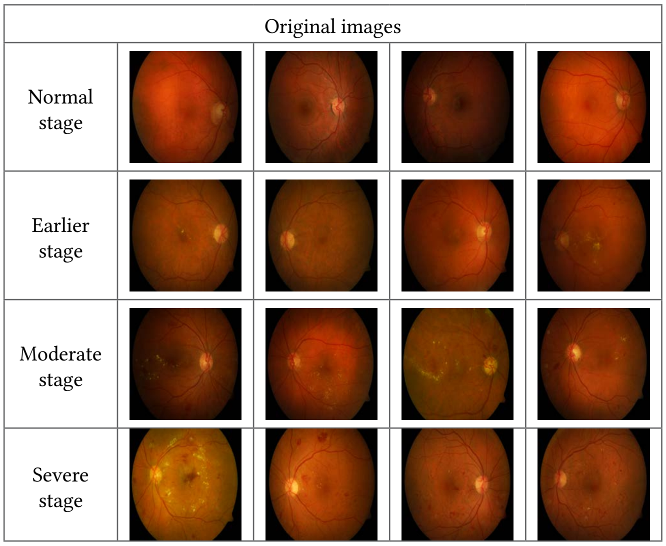

Fig 2. Sample images DR severity classes in the dataset.

The collected DR severity-related images are indicated by Im_a^{inp} and it is provided to the image pre-processing stage. Here, $a = 1, 2, \ldots, A$ and A denotes the total image collected for DR severity classification.

IV. Pre-Processing and Abnormality Segmentation of Retinal Fundus Images

A. Image Pre-Processing

The collected DR severity-based images Im_a^{inp} are provided in the image preprocessing phase. To perform image pre-processing, the CLAHE technique is utilized. In CLAHE [35], pixel values of the entire tiny region in the input image are converted into Rayleigh distribution. Then, Rayleigh distribution is performed by fusing neighboring reasoned bilinear interpolation to neglect the presence of artificially induced boundaries. Equation (1) refers to a new image, which is generated by applying the CLAHE approach to the actual image.

$$IG_{ce} = \alpha IG(b,c) + \beta Z(b,c;\sigma) * IG(b,c) + \mu \quad (1)$$

Here, the terms $Z(b,c;\sigma)$ indicate the Gaussian filter in σ scale, $*$ denotes the convolution operator, $\alpha, \beta, \sigma, \mu$ represents the parameters, and its value is selected as 4,128, -4, and 300/30, respectively. The local average color along with the coefficient β is subtracted from the original image and its local average is mapped into 50% of a grayscale level μ. Finally, the pre-processed images are acquired and termed as Im_a^{ppi}.

B. Segmentation of Retinal Abnormalities by U-Net

The pre-processed images Im_a^{ppi} are fed as the input in the segmentation phase. The segmentation process for retinal abnormalities is performed using U-Net architecture. U-Net [36] architecture is based on CNN and it consists of both decoding and encoding parts. The encoding part hasa padded 3×3 convolutional layer with stride 1 and they are accompanied by Rectified Linear Unit (ReLU), and 2×2 max-pooling operation is performed by stride 2 on the 4th level. In all down-sampling steps, the image dimension of the input image is minimized partially and the channel feature is increased. Ata low level, it has added two 3×3 convolutional regionsthat do not consider the pooling layer. The decoder part is otherwise said to be the expansive path and it is presented on the right side, its main goal is to recover the actual dimension of the input image by performing up-sampling in the feature image. Integration is performed using respective channel features and two different 3×3 convolutional regions, where the first path follows the dropout layer and ReLU layer,and also the second layer only follows ReLU. The modifications occurred when applying the U-Net structure, where the count of channels obtained in the entire layer was invariably deduced into half. Additionally, the U-Net structure is said to be partial U-Net, and the network is provided with 2D image patches and givena 2D segmented probability map for all the provided patches. Finally, the segmented images occur and are indicatedby Im_a^{seg} and further, the segmented images are subjected tothe feature extractionstage. The architectural view of U-Net is represented in Fig. 3.

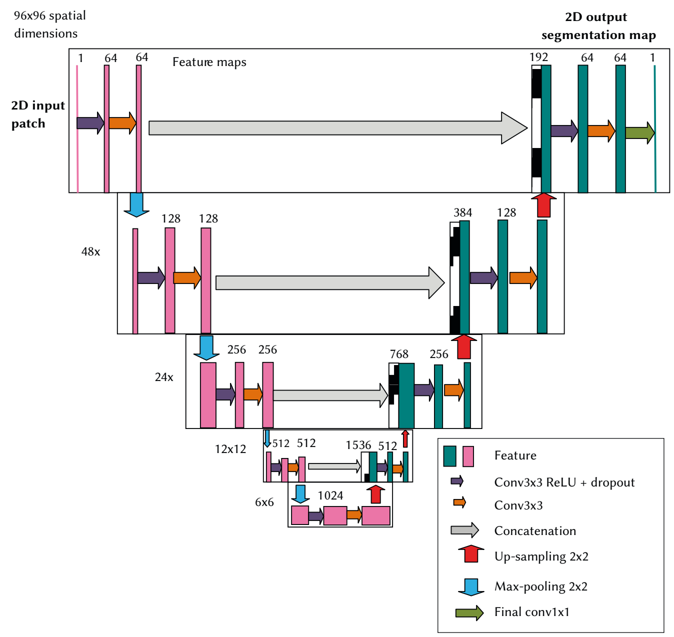

Fig 3. Architectural view of U-Net-based Retinal Abnormalities segmentation.

V. Optimal Feature Selection Induced on Ensemble Deep Structured Architectures for Severity Classification of Diabetic Retinopathy

A. Ensemble Deep Feature Extraction

The segmented images Im_a^{seg} are given as input in the deep feature extraction stage. The single or automated feature extraction process creates overfitting problemsand also it cannot provide superior results. It reduces the computation time for some situations which can affect the system's performance. Here, ensemble approaches like VGG16, ResNet, and Inception are used for the feature extraction process. It is utilized to acquire significant features.The ensemblemodel-based feature extraction helps to avoid overfitting, class imbalance, and exploding gradient issues. The deep features are acquired by using three different techniques such as VGG16, ResNet, and Inception are explained as follows.

VGG16 [37] network is trained with the help of the ImageNet database. These VGG16 networks have experienced large-scale training. This VGG16 network mainly holds 16 convolutional layers and also it has a small receptive field the size of 3×3. This VGG16 network has 5 max pooling layers. These layers are accompanied by three fully connected layers and utilize a softmax classifier as its final layer. The extracted features from VGG16 are denoted Sf_t^{vgg} and then, it is given to the integration stage.

ResNet [38] is a common deep learning architecture and it contains the modification number in all the layers as 50, 150, 101, etc. Various studies related to ResNet are performed using residual representation in the network. This network works by using the prior layer outcome as the input for the current layer without performing any alteration. This ResNet model has significant features such as localization and recognition. It can separate the images into tiny regions to observe the DR severity level. This ResNet network is fused with two different blocks a convolutional block and an identity block. Hence, the residual system can improve building blocks for the organization of the residual layer and ResNet network, the design is classified as a convolution layer. Equation (2) and Equation (3) refers the units represents in the ResNet network model.

$$C_t = x(H_t) + y(H_t, N_t) \tag{2}$$

$$H_{v+1} = y(C_t) \tag{3}$$

Here, the input is indicated by H_t, the residual function of v^{th} the unit is termed as y, and the output of v^{th} the unit is given as H_{t+1}. Equation (4) shows the identity mapping.

$$x(H_t) = H_t \tag{4}$$

Here, the ReLU function of identity mapping is indicated by $x(H_t)$, respectively. To build a ResNet, the total number of parameterized layers is utilized with recurrent connection and they act as a remaining block with transfer learning features. The attained extracted features from ResNet are termed as Sf_n^{insp} and further they are provided into the concatenation phase.

Inception [39] is a deep CNN structure developed in 2014. Inception architecture is selected by ILSVCRasthe top 5th position with a high accuracy rate.This inception structure has a high complexity rate and also it has 22 layers in the structure. It has a new building block and it is said to be an inception model. The inception design didn't follow any typical sequential process but it utilized the network which is presented in the pooling layer, small and large conventional layers, and network layers are calculated in parallel. This 1*1 convolutional operation is performed to acquire the dimensional reduction. The introduction of dimensional reductionand parallelism was used to perform effectiveoperations, provide low computational cost, and save memory. The obtained extracted features are indicated Sf_n^{insp} and they are provided in the concatenation phase.

In this phase, three different sets of features $\{Sf_t^{vgg}, Sf_g^{resnet}, Sf_n^{insp}\}$ are extracted from VGG16, ResNet, and Inception are provided for concatenation. The occurred concatenated features are indicated $Sf_a^{Cf} = \{Sf_t^{vgg}, Sf_g^{resnet}, Sf_n^{insp}\}$ and they are further provided in the features selection phase.

B. Feature Selection

The concatenated features Sf_a^{Cf} are given as the input in feature selection, for selecting the features by utilizing developed AS-DOX to attain significant features for DR severity classification. Feature selection has better capability to enhance the accuracy rate and at the same time, it minimizes overfitting and training time-based problems. Using developed AS-DOX, 10 features are selected as the optimal features, and the selected optimal are indicated by Sf_i^{slf}, which can be further utilized in the DR severity classification phase.

C. Proposed AS-DOX for Parameter Optimization

The newly developed AS-DOX algorithm is utilized in the DR severity classification model to optimizethe number of epochs in VGG16, the activation function of ResNet, and hidden neuron count in inception to enhance the classification performance. This algorithm is developed leveraging the features of DOX. The DOX optimization needless mathematical effort and it is very effective inproviding the best optimal value. But, finding search space in the real instance becomes a challenging task as it has a huge number of local optimal search spaces. Therefore, the AS-DOX is developed to tackle the problems in the existing DOXto attain better performance. Equation (5) depicts the probability of determining the hunting or scavenger phase is computed through the fitness-based perception based on developed AS-DOX algorithm.

$$E = \frac{BSTft}{mean(ft)} \tag{5}$$

Here, the term *BSTft* denotes the best fitness and *mean(ft)* denotes the mean of fitness.The proposed AS-DOX utilizes the probability of hunting or scavenger activity through the fitness-based concept, whereas in the baseline algorithm, it is fixed to a constant value of 0.5. This probability factor is utilized in the condition ($ran < E$) for deciding the position update with hunting strategy or scavenger strategy.

DOA [40] is a biological model that is used for global optimization, and it replicates the hunting techniques of the dingo. These dingoes perform different hunting approaches such as scavenging behavior, persecution, and grouping tactics.

Approach 1 (Group attack): At the time of hunting, dingoes always prefer group activity and execute it. The most important feature of the dingoes is that will easily detect the prey and then, all the other dingoes start to cover the prey. Equation (6) specifies the characteristics of dingoes.

$$\vec{M}_d(v+1) = \beta_1 \sum_{q=1}^{ef} \frac{[\overrightarrow{\phi q(v)} - m\vec{d}(v)]}{ef} - \vec{m} * (v) \tag{6}$$

Here, the location of the new candidate is indicated by $\vec{m}(v+1)$, the search agent subset is denoted by $\phi q(v)$, the present candidate is noted as $\vec{m}_d(v)$, the random number of an integer is given by *ef* and the best search agent achieved from the prior iteration is referred as $\vec{m} * (v)$, respectively. The uniformly distributed random numbers are denoted by β_1 present in the interval of $[-2, 2]$.

Approach 2 (Persecution): Dingoes' main scope is to grab the tiny prey and follow the prey until it gets along. Equation (7) refers to character of dingo.

$$\vec{m}_d(v+1) = \vec{m} * (v) + \beta_1 * e^{\beta_2} * (\vec{m}_{b_1}(v) - \vec{m}_d(v)) \tag{7}$$

Here, the movement of the dingo is indicated as $\vec{m}(v+1)$, the current search agent is denoted by $\vec{m}_d(v)$, the random variable is termed as β_2 at the interval of $[-1, 1]$, the random variable is given as b_1 and $\vec{m}_{b_1}(v)$ be the search agent of $v_1{}^{th}$, respectively.

Approach 3 (Scavenger): The behaviors of the solution are mentioned as the attack when the dingo detects the food. Equation (8) specifies to dingoes' behavior.

$$\vec{m}_d(v+1) = \frac{1}{2}\left[e^{\beta_2} * \vec{m}_{d_1}(v) - (-1)^{\sigma} * \vec{m}_d(v)\right] \tag{8}$$

Here, the binary number is indicated σ and they are constructed arbitrarily.

Approach 4 (Survival rate): Equation (9) refers to the survival rate of dingoes.

$$sur(d) = \frac{ft_{px} - ft(d)}{ft_{px} - ft_{mw}} \tag{9}$$

Here, the variable ft_{px} and ft_{mx} indicates the worst and best fitness value of the current generation and $ft(d)$ denotes the d^{th} search agent fitness function. Equation (10) indicates the survival rate.

$$\vec{m}_d(v+1) = \vec{m} * (v) + \frac{1}{2}\left[\vec{m}_{b_1}(u) - (-1)^{\sigma} * \vec{z}_{b_2}(v)\right] \tag{10}$$

Here, a low survival rate is indicated by $\vec{m}_d(v)$, random numbers given as v_1 and v_2. The term $\vec{z}_{v_1}(u)$ is the search agent of v_1 and $\vec{z}_{v_2}(u)$ be the selected candidate of v_2. The pseudo-code for the offered AS-DOX is presented in Algorithm 1.

Algorithm 1: Proposed AS-DOX

Input: Weight of VGG VGGWt_j^{VGG}, weight of Resnet Wt_k^{res} and weight of Inception Wt_m^{incp}, respectively.

1. Initialize the parameters
2. **The probability of hunting or scavenger techniques updated with Eq. (5)**
3. The probability of a group attack or persecution attack is considered as ($F = 0.7$)
4. Determine the initial population
5. **While** (iteration < Max number of iteration) **Do**
6. If ($ran < E$) then
7. If ($ran < F$) then
8. The solution updated by Eq. (6)
9. Else
10. The solution updated by Eq. (7)
11. End If
12. Else
13. Update the solution by Eq. (5)
14. End if
15. Upgrade the search agent which holds a low survival rate
16. Compute $\vec{m}(v+1)$,the new search agent fitness value
17. End If
18. (Iteration=iteration+1)
19. End while
20. Return the best optimal solution
21. End procedure

The flow diagram for the designed AS-DOX is given in Fig. 4.

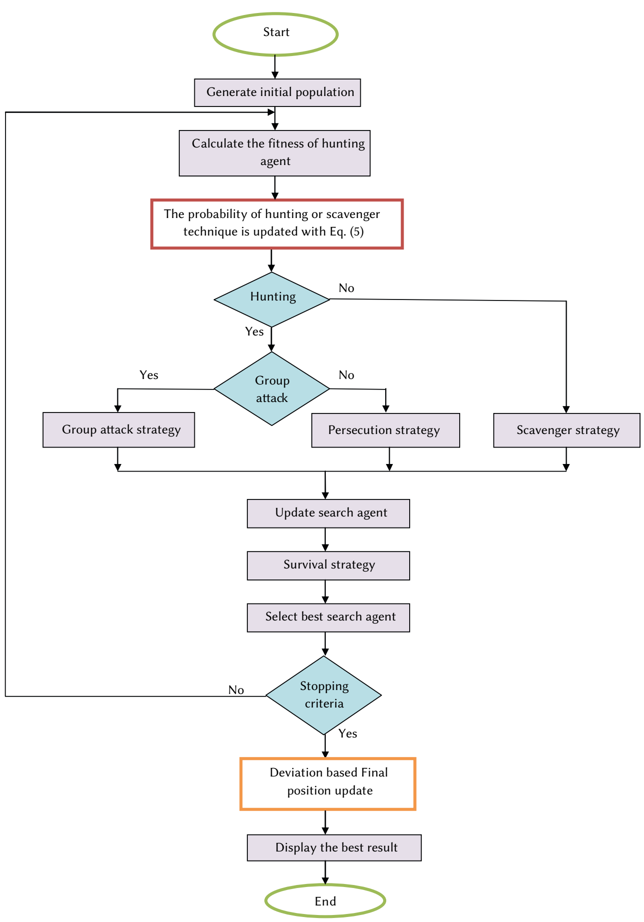

Fig4. Flow diagram of the offered AS-DOX.

D. Developed HR-DEL for Severity Classification

The HR-DEL is developed for classifying the DR severity classification. Here, several parameterssuch asthe number of epochs in VGG16, activation function in ResNet, and hidden neuron count in inception are tuned using developed AS-DOX for enhancing the accuracy rate at the time classification. The optimal features obtained using the developed AS-DOX are utilized in the final layers of VGG16, ResNet, and Inception for performing DR severity classification to get accurate results. Equation (11) shows the fitness function of the developed DR severity classification method is to enlarge the accuracy rate.

$$ft = \underset{\left\{Wt_j^{VGG}, Wt_k^{res}, Wt_m^{incp}\right\}}{argmin} \left(\frac{1}{Acry}\right) \tag{11}$$

Here, the optimized weight of VGG is given by Wt_j^{VGG},Resnet is indicated by Wt_k^{res} and inception is denoted by Wt_m^{incp}, respectively. Different parameters are tuned and their ranges are listed, where several epochs in VGG16are tuned in the range of [50,100], the activation function of Resnet is tuned at the range of [1,5], and the hidden neuron count in inception istuned at the range of [5,225], respectively. Equation (12) refers to Accuracy Ary, which is defined as the exact calculations of a particular value. Equation (12).

$$Ary = \frac{(i+j)}{(i+j+r+s)} \tag{12}$$

Here, the true negative and true positive rates are given as i and j and false negative and false positive rates are given as r and s. The diagrammatic structure of the offered HR-DEL approach for DR severity classification is presented in Fig. 5.

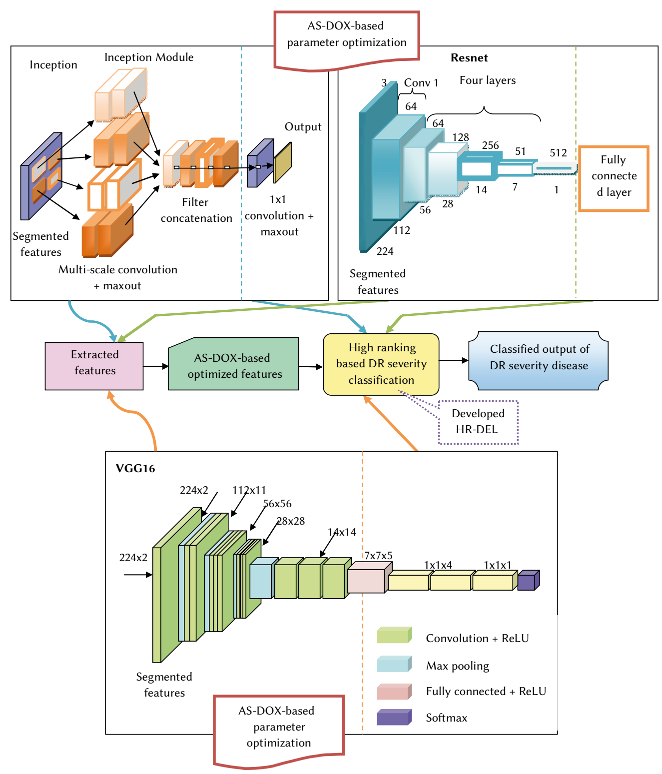

Fig. 5. Developed HR-DEL approach-based DR severity classification model.

VI. Computation of Results

A. Evaluation Setup

The simulation analysis on the DR severity classification was developed in Python and the efficiency was computed by utilizing

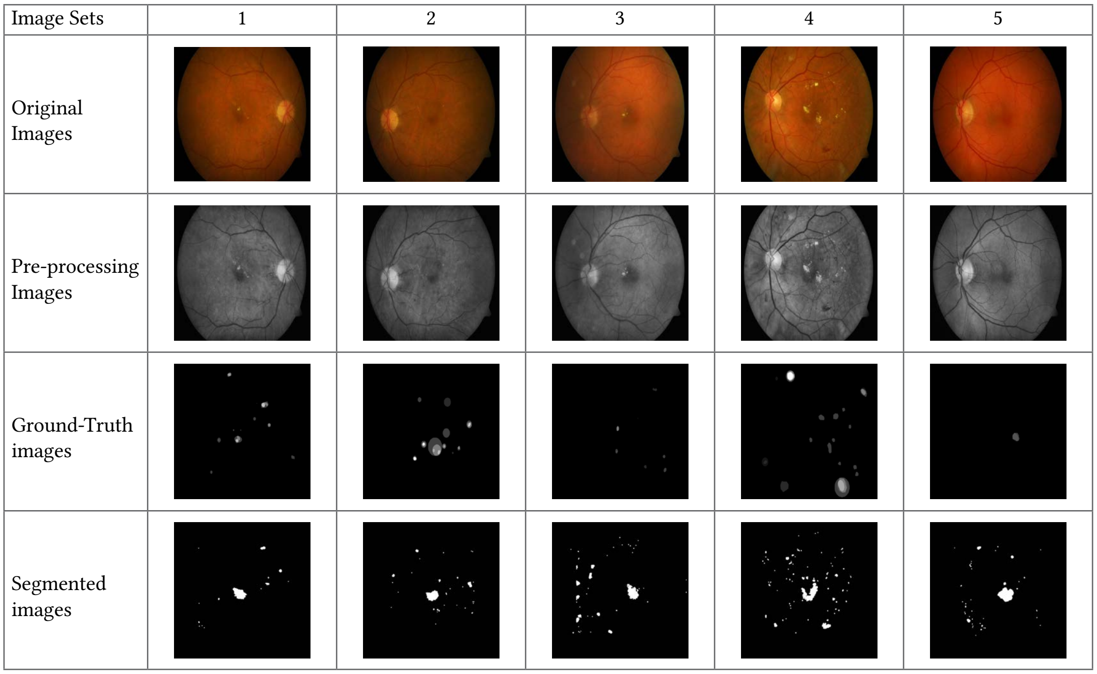

Fig. 6. CLAHE-based pre-processed and U-Net-based segmented DR severity images.

various conventional models in the comparative analysis. The overall population utilized for experimentswas 10 and the maximum iteration count was 25. Different baseline algorithms utilized for the investigation are Particle swarm optimization (PSO) [41], Fruit Fly Optimization (FFO) [42], Butterfly Optimization Algorithm (BOA) [43], DOA [40], and multiple classifiers such as CNN [44], DCNN [21], VGG16-InceptionV3 [22] and Ensemble [28].

B. Performance Metrics

The developed DR severity classification model is computed andgiven as follows with different quantitative measures.

(a) Equation (13) refers to F1-score. *F*1 is a computation of the accuracy rate in the present experiment.

$$F1 = 2 \times \frac{2i}{2i+r+s} \tag{13}$$

(b) Equation (14) denotes the specificity measure. Specificity *Sfcy* is defined as the ratio of negative observations.

$$Sfcy = \frac{j}{j+r} \tag{14}$$

(c) Equation (15) refers to FNr. *FNr* is a ratio of positive observations that achieves negative results from the experimentation.

$$FNr = \frac{j}{j+r} \tag{15}$$

(d) Equation (16) refers to Sensitivity. *Svty* is a ratio of positive observations.

$$Svty = \frac{i}{i+s} \tag{16}$$

(e) in Equation (17) specifies to MCC. *MCC* is a calculation of binary categorization from the experimentation.

$$MC = \frac{i \times j - r \times s}{\sqrt{(i+r)(i+s)(j+r)(j+s)}} \tag{17}$$

(f) Equation (18) refers to NPV. *NPv* is the average of all humans without disease for experimentation.

$$NPv = \frac{j}{j+s} \tag{18}$$

(g) Equation (19) refers to FPr. *FPr* is an average of real negative activities.

$$F\,Pr = \frac{i}{i+s} \tag{19}$$

(h) K-Fold is also known asthe resampling procedurewhich is utilized to validate anexpert system on an inadequate data sample.

C. Pre-Processed and Segmented Results

The U-Net-based segmentation is performed and its outcomes are given in Fig. 6.

D. Calculation of the Proposed Method With Various Existing Algorithms

The validation is made on the developed DR severity classification modelwith different baseline algorithms are represented in Fig. 7. The proposed model achieved the validation accuracy is 8.3% higher than PSO-HR-DEL, 10.2% better than FFO-HR-DEL, 5.1% greater than BOA-HR-DEL and 3.2% above than DOA-HR-DEL. Thus, the suggested AS-DOX-HR-DEL model providesa better detection rate in DR severity classification.

E. Validation of Developed Method With Diverse Classifiers

Various analysis is made on the developed AS-DOX-HR-DEL-based DR severity classification model with multiple classifiers to represent its efficiency asgiven in Fig. 8. The F1-score on the enhanced model provides 27.7%, 17.9%, 10.8%, and 8.2% higher than CNN, DCNN, VGG16-InceptionV3, and Ensemble over the learning percentage of 65. The offered AS-DOX-HR-DEL has good capability in classifying the DR severity level in affected individuals.

F. K-Fold Study on Designed Model With Diverse Algorithms

K-fold analysis on suggested AS-DOX-HR-DEL-based DR severity classification models with different baseline algorithms are given in Fig. 9. The accuracy rate of offered method over various algorithms like PSO-HR-DEL, FFO-HR-DEL, BOA-HR-DEL, and DOA-HR-DEL has secured 4.4%, 3.6%, 2.3%, and 1.5%, respectively. Thus, the offered DR severity classification model clearly shows whether the individual is affected by DR or not.

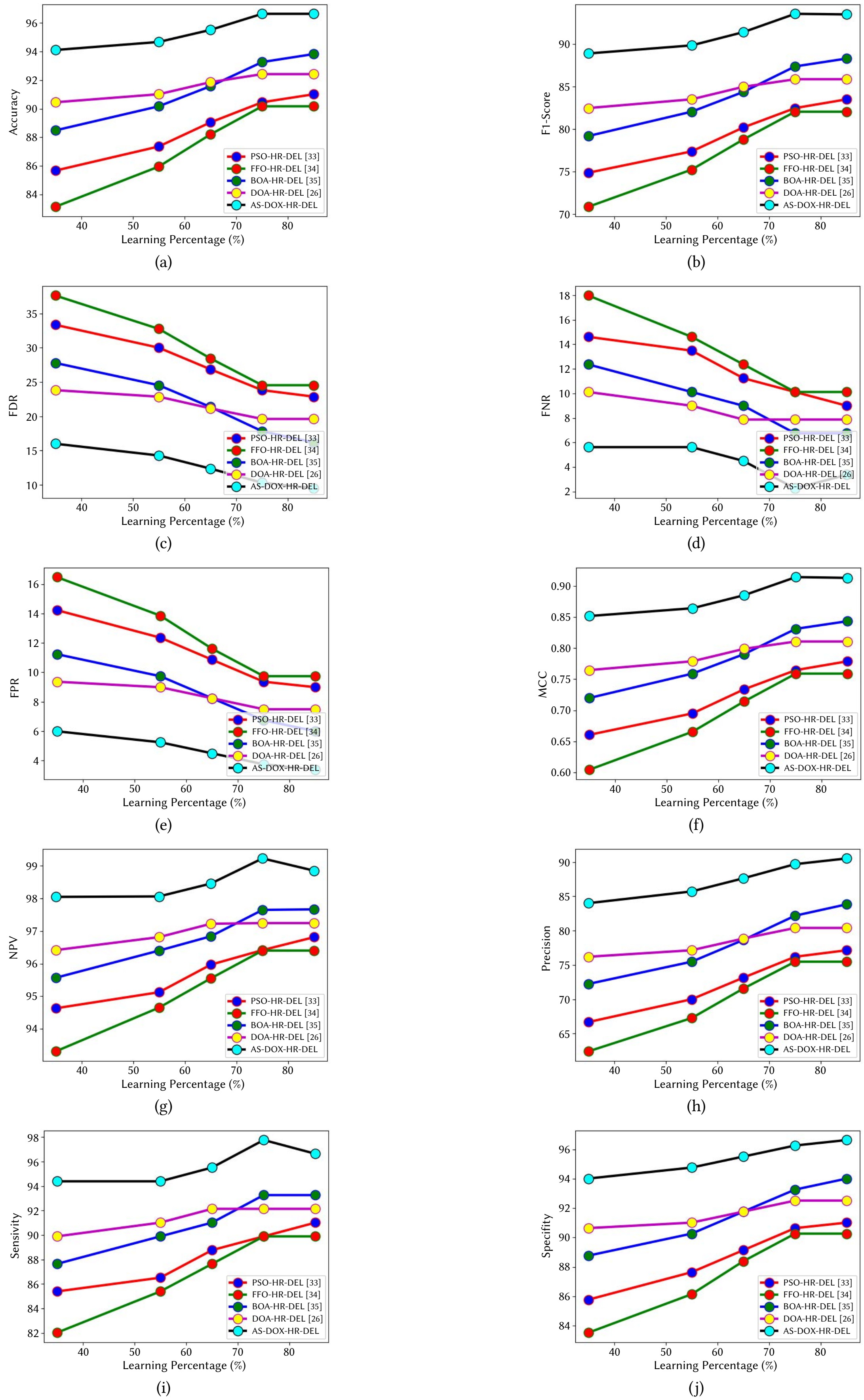

Fig. 7. Validation of developed DR severity classification model with diverse algorithms over (a)accuracy, (b) F1-score, (c) FDR, (d) FNR, (e) FPR, (f) MCC, (g) NVP, (h) precision, (i)sensitivity and (j) specificity.

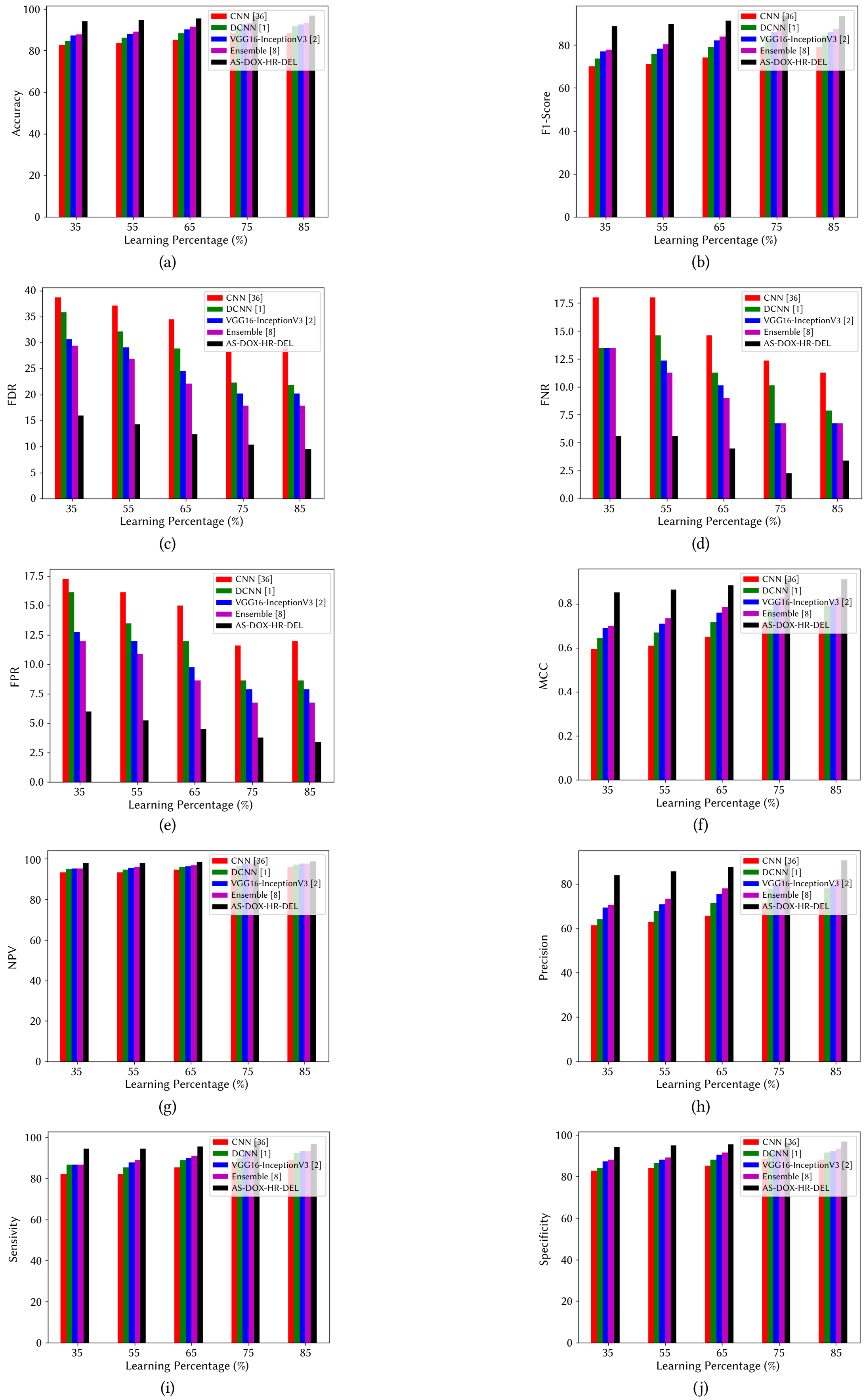

Fig. 8. Validation of developed DR severity classification model with diverse classifiers over (a)accuracy, (b) F1-score, (c) FDR, (d) FNR, (e) FPR, (f) MCC, (g) NVP, (h) precision, (i)sensitivity and (j) specificity.

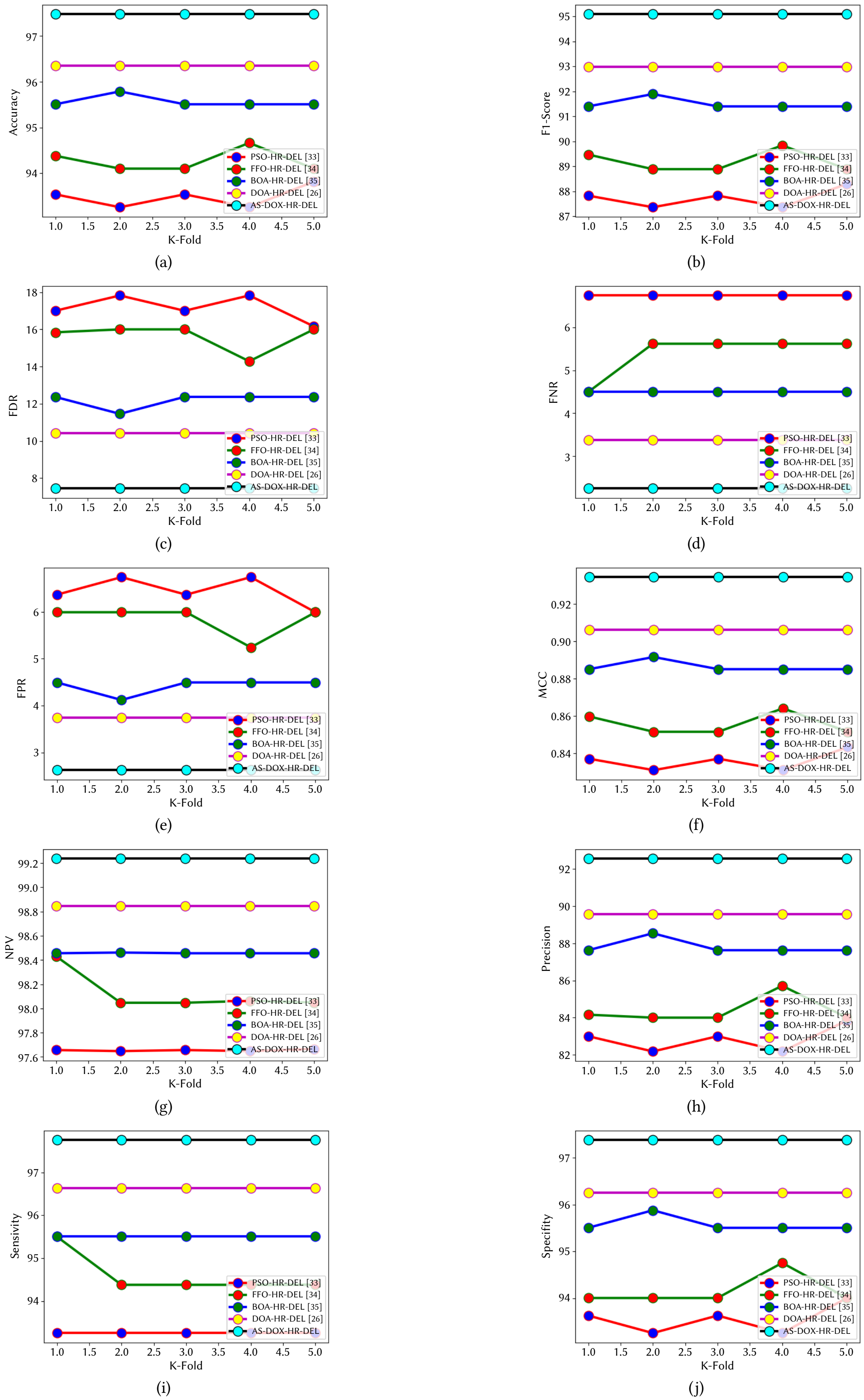

Fig. 9. K-fold validation of developed DR severity classification approach with diverse algorithms over (a)accuracy, (b) F1-score, (c) FDR, (d) FNR, (e) FPR, (f) MCC, (g) NVP, (h) precision, (i)sensitivity and (j) specificity.

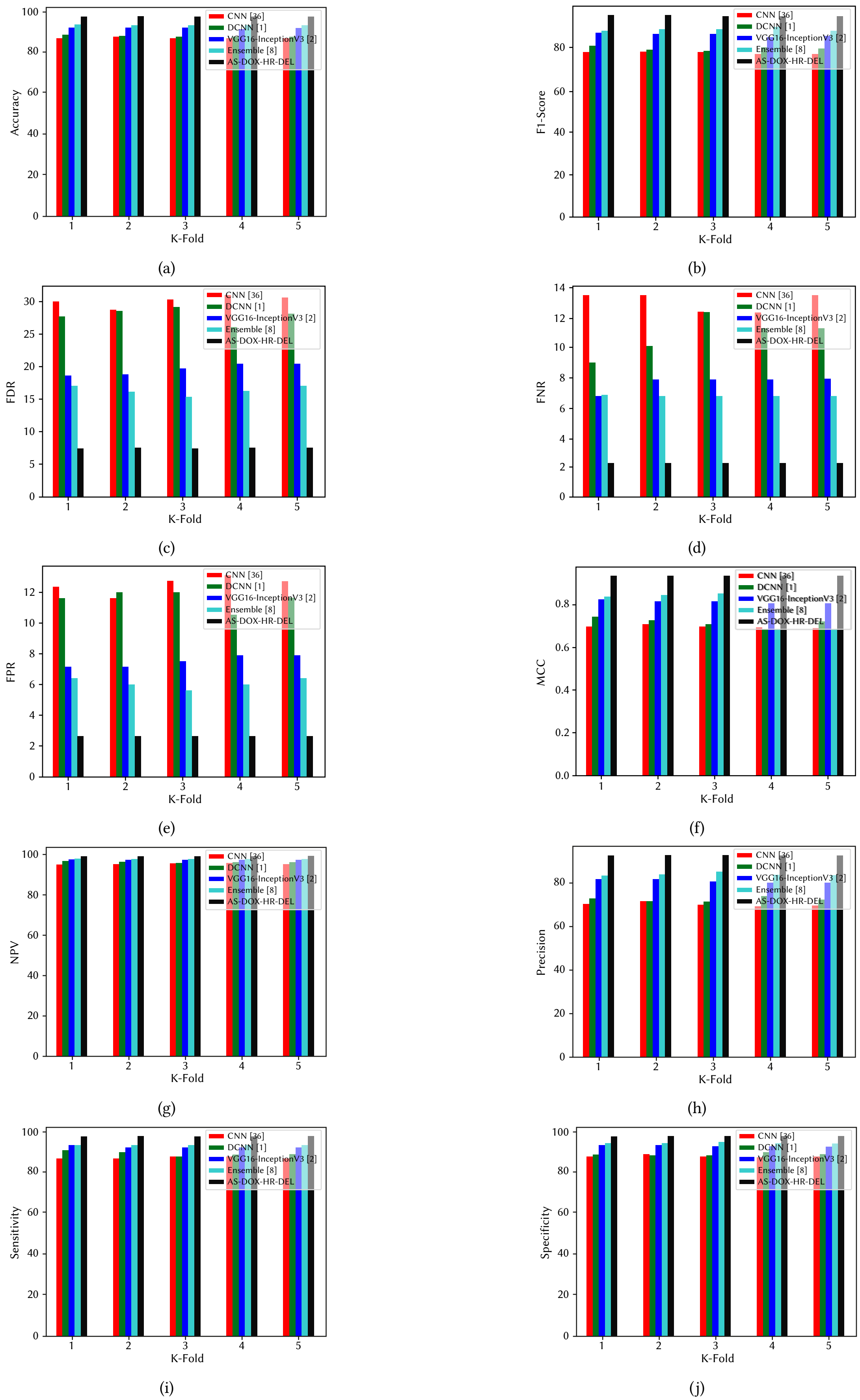

Fig. 10. K-fold validation of offered DR severity classification model with diverse classifiers over (a)accuracy, (b) F1-score, (c) FDR, (d) FNR, (e) FPR, (f) MCC, (g) NVP, (h) precision, (i)sensitivity and (j) specificity.

TABLE II. Validation of Offered DR Severity Classification Model With Diverse Existing Algorithms

Metrics	PSO-HR-DEL [41]	FF-HR-DEL [42]	BOA-HR-DEL [43]	DOA-HR-DEL [40]	AS-DOX-HR-DEL
Accuracy	91.0112	90.1685	93.8202	92.4157	96.6292
Sensitivity	91.0112	89.8876	93.2584	92.1348	96.6292
Specificity	91.0112	90.2622	94.0075	92.5094	96.6292
Precision	77.1429	75.4717	83.8384	80.3922	90.5263
FPR	8.9888	9.7378	5.9925	7.4906	3.3708
FNR	8.9888	10.1124	6.7416	7.8652	3.3708
NPV	96.8127	96.4000	97.6654	97.2441	98.8506
FDR	22.8571	24.5283	16.1616	19.6078	9.4737
F1-score	83.5052	82.0513	88.2979	85.8639	93.4783
MCC	0.7788	0.7590	0.8434	0.8106	0.9130

TABLE III. Validation of the Offered DR Severity Classification Model With Different Classifiers

Metrics	CNN [44]	DCNN [21]	VGG16-InceptionV3 [22]	Ensemble [22]	AS-DOX-HR-DEL
Accuracy	88.202247	91.573034	92.41573	93.258427	96.629213
Sensitivity	88.764045	92.134831	93.258427	93.258427	96.629213
Specificity	88.014981	91.385768	92.134831	93.258427	96.629213
Precision	71.171171	78.095238	79.807692	82.178218	90.526316
FPR	11.985019	8.6142322	7.8651685	6.741573	3.3707865
FNR	11.235955	7.8651685	6.741573	6.741573	3.3707865
NPV	95.918367	97.211155	97.619048	97.647059	98.850575
FDR	28.828829	21.904762	20.192308	17.821782	9.4736842
F1-score	79	84.536082	86.010363	87.368421	93.478261
MCC	0.7177095	0.7930722	0.8131249	0.8310374	0.9129703

G. K-Fold Validation of the Proposed Model With Different Classifiers

K-fold analysis of the proposed AS-DOX-HR-DEL-based DR severity classification model when comparing withdiverse architectures are given in Fig.10. Various validations over accuracy attains 12.3% higher than CNN, 11.6% greater than DCNN, 7.8% better than VGG16-InceptionV3 and 5.4 % above than Ensemble. Thus, the developed AS-DOX-HR-DEL-based DR severity classification model has a better classification rate than other existing models.

H. Convergence Validation on the Offered Method

The convergence analysis performed over the proposedAS-DOX-HR-DEL DR severity classification model is provided in Fig.11. The proposed model achieved a better cost function rate atthe 5th iteration is 1.6% higher than PSO-HR-DEL, 1.4% better than FFO-HR-DEL, 1.3 % above than BOA-HR-DEL and 3.1% greater than DOA-HR-DEL. Thus, the result proved that the cost function of the designed method was low when compared with different baseline algorithms, so it proved high accuracy and performed well in DR severity classification.

I. Evaluation of Developed Model With Various Baseline Algorithms

The performance evaluation of the developed DR severity classification model overvarious baseline algorithms is presented in Table II. The sensitivity analysis of the developed AS-DOX-HR-DEL-based DR classification model is 6.17% higher than PSO-HR-DEL, 7.5% better than FF-HR-DEL, 3.6% above than BOA-HR-DEL and 4.8% greater than DOA-HR-DEL, respectively. Thus, the developed DR severity classification model has a better performance rate than other conventional models.

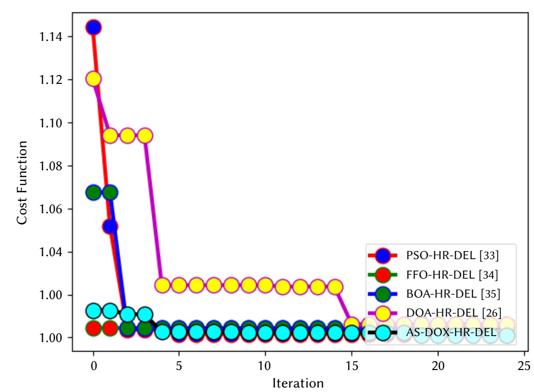

Fig. 11. Convergence analysis of offered DR severity classification model with different baseline algorithms.

J. Evaluation of Developed Model With Various Classifiers

A comparison evaluation of the designed AS-DOX-HR-DEL model with diverse classifiers is represented in Table III. The accuracy of the proposed AS-DOX-HR-DEL model is 9.5 %, 5.5%, 4.5%, and 3.6% better than other classifiers like CNN, DCNN, VGG16-InceptionV3, and Ensemble, respectively. Thus, the developed DR model attained a better classification rate than other existing classifier models.

K. Statistical Evaluationof the Offered Approach

The statistical analysis of the developed AS-DOX-HR-DEL model with different baseline algorithms is represented in Table IV. The best score of the developed model is 0.6%, 3.4%, 0.2%, and 5.3% higher than other algorithms such as PSO-HR-DEL, FF-HR-DEL, BOA-HR-DEL,

TABLE IV. Statistical Evaluation of the Proposed Dr Severity Classification Model With Various Algorithms

Algorithm	PSO-HR-DEL [41]	FF-HR-DEL [42]	BOA-HR-DEL [43]	DOA-HR-DEL [40]	AS-DOX-HR-DEL
Best	1.0014965	1.0043068	1.001091	1.0062458	1.0008573
Worst	1.1441512	1.0043068	1.0675451	1.1202426	1.0127338
Mean	1.0094627	1.0043068	1.0085904	1.0291793	1.0035755
Median	1.0014965	1.0043068	1.0042352	1.0236774	1.0024253
STD	0.0291884	0	0.0174294	0.0325246	0.0036575

and DOA-HR-DEL, respectively. Thus, the suggested DR severity classification model acquired a better classification rate than other baseline algorithms.

L. Confusion Matrix for the Designed Method

The confusion matrix for the designed DR severity classification model regarding accuracy is shown in Fig. 12. From the given graph analysis, it is revealed that the predicted value of the designed method slightly reaches the actual value regarding accuracy.The accuracy of the developed modelbased on confusion matrix evaluation is 96.63%.

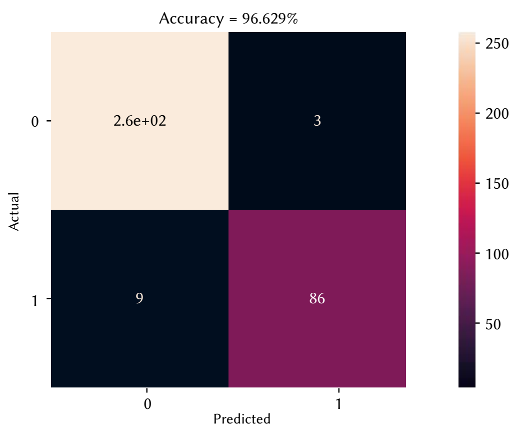

Fig 12. Confusion matrix for the developed DR severity classification model regarding the accuracy.

M. Validation for the Designed Method Using Diverse Parameters

The performance evaluation of the designed DR severity classification model using diverse parameters like hidden neurons and number of epochs is shown in Fig. 13 and Fig. 14. From Fig. 13, the accuracy of the proposed AS-DOX-HR-DEL model is 15.85%, 18.01%, 11.11%, and 10.46% more than CNN, DCNN, VGG16-InceptionV3, and Ensemble for the number of hidden neurons at 100. Consequently, from Fig. 14, the precision of the proposedAS-DOX-HR-DEL model is 21.42%, 28.78%, 8.9%, and 8.28% superior to CNN, DCNN, VGG16-InceptionV3, and Ensemble for the number of epochs at 40.Thus, the developed DR classification model attained a better classification rate than other existing classifier models.

N. Ablation Study of the Designed Approach

The ablation experiment of the designed DR severity level classification model is shown in Table V. Thus, the simulation yields elevated outcomes than the other baseline approaches.

VII. Conclusion

The DR mainly affects the healthcare systems and the economic status of society. Effective treatment planning for the DR-affected peoplecould avoid 90% of vision loss. Thus it is significant to classify the phases and severity level of DR to offer an accurate better treatment plan. Therefore, a new DR severity level classification model was developed to provide accurate classification results for all the DR-affected individuals. By utilizing the gathered images, image pre-processing was done, and the pre-processed images were given into the

(a) (b)

Fig. 13. Validation for the developed DR severity classification model using the number of hidden neurons (a) accuracy and (b) precision.

(a) (b)

Fig.14. Validation for the developed DR severity classification model using the number of epochs (a) accuracy and (b) precision.

TABLE V. Statistical Analysis of the Proposed Dr Severity Classification Model With Various Algorithms

Terms	Xception [27]	MobileNet [45]	EfficientNet [46]	AS-DOX-HR-DEL
Accuracy	92.13	91.29	93.12	96.63
Sensitivity	92.13	91.57	93.26	96.63
Specificity	92.13	91.20	93.07	96.63
Precision	79.66	77.64	81.82	90.53
FPR	7.87	8.80	6.93	3.37
FNR	7.87	8.43	6.74	3.37
NPV	97.23	97.01	97.64	98.85
FDR	20.34	22.36	18.18	9.47
F1-Score	85.44	84.03	87.15	93.48
MCC	80.49%	78.61%	82.82%	91.30%

segmentation stage. Then, the resultant segmented images were used for extracting the efficient features through the utilization of VGG16, ResNet, and Inception, and further, the three sets of obtained features were combined. The combined features were utilized in the optimal feature selectionphase using the developed AS-DOX. Finally, the DR severity classification was performed using developed HR-DEL using the optimal features and it provided accurate severity classification for the individuals through the parameter optimization using the developed AS-DOX.The accuracy of the developed DR severity classification model was 3% superior to PSO-HR-DEL, 10.2% better than FFO-HR-DEL, 5.1% more than BOA-HR-DEL, and 3.2% more than DOA-HR-DEL respectively when comparing with algorithms.The accuracy of the developed AS-DOX-HR-DEL model is 9.5 %, 5.5%, 4.5%, and 3.6% better than other classifiers like CNN, DCNN, VGG16-InceptionV3, and Ensemble, respectively. Thus, the developed DR severity classification model provided a better classification performance rate than other existing models. However, the background of the image is in the presence of poor illumination, which affects the outcomes of the designed approach. Accordingly, the acquisition of retinal images is essential in this work. Time optimization in implementation needs more attention. The recommended approach will be extended and evaluated with a compressed sensing framework which helps to enhance the efficacy of the model. The recommended approach will be enhanced with the application of classification techniques.

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