Detection of Diabetic Retinopathy Using BA- Deep Forest Based Intelligent Model

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ARTICLE INFO

Article history:
Received: 02 February 2023
Revised: 05 June 2023
Accepted: 25 June 2023

Keywords:
Diabetes
Support vector machine
Diagnosis
Diabetic retinopathy
Image

ABSTRACT

Diabetic retinopathy (DR) is an eye condition caused by diabetes, which is a metabolic ailment marked by elevated blood glucose levels in humans. The final stage of DR is total blindness, and it can also cause visual loss in diabetics. Early DR identification may be essential for avoiding visual disruptions. Hence, the objective of this research is to develop a reliable model for the early diagnosis and detection of DR using fundus images. The proposed model consists of fundus images preprocessing, feature extraction, pertinent feature selection, and classification phase for accurate detection of DR. The images preprocessing step corresponds to the elimination of noise and the improvement of image contrast and it is achieved through noise channel and median filter. Further, the k-mean-based segmentation approach is used to determine the lesion region. The multi-level scanning is utilized in the feature extraction phase to extract high dimensional features from improved images. These high-dimensional features are fed to the BA-based algorithm for the selection of prominent features to detect the DR more accurately. In final step, Deep Forest technique is applied on the prominent features for the classification and diagnosis of DR. This technique goal is to provide a binary classification of DR. A total 3,200 fundus images are considered to assess the effectiveness of the proposed diabetic retinopathy model. The simulation outcomes are contrasted against a number of existing models, including Deep Forest, InceptionV3, KNN, ANN, SVM, VGG16, and VGG19. The findings demonstrated that the proposed model outperforms than above mentioned technique utilizing the 10-cross fold method in terms of diagnostic outcomes.

INTRODUCTION

In recent years, one of the most common diseases is now diabetes that can harm the health of the majority of people worldwide. The high levels of blood glucose are the primary cause of the diabetes. Further, the blood vessels can be harmed by prolonged high sugar levels and the abnormalities, and other factors can be developed due to blood sugar. The long-term diabetes sufferers may also experience nerve damage, bleeding gums, blindness, and renal issues. The diabetic also has concurrent heart-related problems. This study focuses on diabetic retinopathy (DR), an injury to the retina of the eye caused by diabetes. Furthermore, Diabetes is ranked as the seventh deadliest illness by the World Health Organization (WHO) [1]. Additionally, a diabetic report showed that more than 61 million individuals worldwide had diabetes., including adults between the ages of 20 and 79, have the disease as of right now and there could be up to 102 million by 2030 [2]. The existing studies shown that high or low glucose levels can harm the retina's blood vessels, which can occasionally lead to blood vessels that leak and cause blindness. One of the key functions of the human body is to heal itself. When a blood vessel leak is discovered, the nearby cell can be activated to handle the situation. As a result, excess blood may flow into blood vessels, weakening them [3] and the diabetes patient's vision may be impacted in a short period of time. Therefore, it is knowing to the diabetic patient's check their eyes and undergo any necessary eye exams as soon as possible. Additionally, it has been observed that fundus photography, a specific kind of eye examination for the early diagnosis of DR, can be used to accurately identify DR. The severity of DR can be determined by the level of abnormalities and its magnitude. Additionally, the testing procedure finds additional indicators like micro-aneurysms, hemorrhage, venous beading etc. The blood clot size and shape in micro aneurysms are roughly 100-120 mm in diameter and circular. The term hemorrhage refers to the bleeding that occurs when a blood vessel is damaged. Neo-vascularization is the term used to describe the atypical

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proliferation of small blood vessels. Fig. 1 shows the several stages of DR, including images of the healthy and unhealthy fundus images. The vision loss can be prevented illness detection; it is also advised that patients have an eye if DR is identified at an early stage for accurate examination [4]. Several techniques for the earlier and more precise detection of DR have been reported in the literature. For the purpose of identifying and detecting the DR, these techniques take into account to find the region of interest i.e. segmentation of fundus images as well as the examination of exudates, lesions, and micro-aneurysms. It has been noted that DR can account for up to 80% of eye-related disorders [5–6] and its symptoms are difficult to identify. As a result, it worsens and is more likely to cause consequences like vision loss. However, early detection and diagnosis of DR can lessen its complications. It is also noticed that Fundus images can also have unnecessary illuminations, blurry areas, and uneven light distribution [7-8].

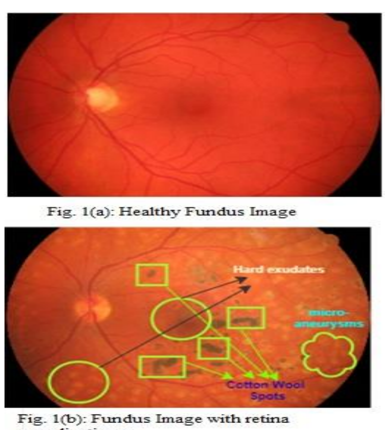

Fig. 1: a) healthy eye image and b) DR image with micro aneurysms, cotton wool spots, exudates etc.

Therefore, a correct diagnosis of DR can be challenging and even result in a misdiagnosis and permanent blindness may result from this incorrect diagnosis. As a result, successful DR identification and detection may require more precision. Another issue with fundus imaging is saturation, which can provide biased results and make the visual analysis of DR challenging [9]. However, luminosity normalization can be used to address the problem of biased solutions [10]. It has also been discovered that there are two ways for addressing the diabetic retinopathy in literature: binary labeling of DR and multiple labeling of DR. For the accurate identification of DR, it has been noted that numerous classification algorithms, including Deep learning, SVM, DT, MLP, DNN, and CNN, have been reported [11–15]. Diabetic patients personal record can be protected using block chain [16] technology The aforementioned strategies produce satisfactory DR outcomes, but there are still a number of challenges that may arise, including the construction of features, selection of prominent features, prediction accuracy and biased solution.

1.1 Objectives of the Work

This work aims to develop an effective DR model for accurate identification of diabetic retinopathy. The proposed model also considers the feature creation, selection and accuracy issues of diabetic retinopathy. The key objectives of this work are mentioned below.

- This study presents an effective model for detecting and diagnosis of DR.
- The feature creation issue of diabetic retinopathy is addressed through a multi-grained scanning method. The features are extracted from retinal funds images to construct the dataset and these features are the combination of visual and statistical techniques.
- Feature selection issue is handled through a meta-heuristic technique based on bat algorithm. This technique aims to choose appropriate features from classification task based on feature creation.
- The Deep Forest based approach predicts the identification of diabetic retinopathy.
- A set of 3200 fundus images is utilized for assessing the effectiveness of the aforementioned diabetic retinopathy model based on several performance measures. These measures are AUC-ROC curve, specificity, F1-Score, sensitivity and accuracy.
- The outcomes of the proposed diabetic retinopathy model are compared utilizing training-testing and cross-fold validation procedures using the well-defined methodologies presented in the literature (InceptionV3, ANN, VGG16, VGG19, SVM and Deep Forest).

The remaining information in the paper is split into four sections. The recently related works on diabetic retinopathy is discussed in section 2. The proposed model for DR detection can be found in Section 3. The suggested model's simulation results are examined in section 4. A summary of the entire work is provided in Section 5.

RELATED WORKS

This section discusses the recent works reported on diabetic retinopathy based on the fundus images.

A diabetic retinopathy model based on CLAHE algorithm presented for earlier and accurate treatment of diabetic retinopathy [17]. The contrasts of the images were improved using average filtering. A binary threshold method was employed for segmentation task and Tri-DWT technique is adopted for decomposition of segmented images. The features were withdraw based on LBP and GLCMs methods. The classification task is performed through NN and CNN classifiers. Further, the classification results were improved using (FR-CSA) search algorithm and this technique incorporated into segmentation and classification tasks. The results confirmed that better detection accuracy obtained by the proposed model.

A CAD diabetic retinopathy model developed for investigating the occurrence of DR [18]. The proposed CAD system combined the several state of art method for the identification of DR. These methods are summarized as deep learning, the archimedes optimization algorithm (AOA) with Kapur's Entropy (AOA-KE), COA-DN, and SNN. Further, the pre-processing phase contained MDL-CADDR method for enhancing the fundus images quality. The AOA-KE algorithm utilized for computing the lesion region and COA-DN method was applied on the segmented region for extracting the pertinent features. This work considered the MESSIDOR dataset to evaluate the efficacy of CAD system. The detection of DR confirmed by SNN classifier. The results confirmed that CAD system obtained 99.73% of accuracy rate.

The earlier DR identification also depends on the detection of lesions bears. Ravala and Rajini [19] addressed this issue of the DR and presented some effective techniques that were capable to segment the different DR abnormalities. These abnormalities described as micro aneurysm, hemorrhages, hard exudates, and soft exudates. The images were improved in terms of contrast through average filtering and histogram equalization. The, top-hat filtering, circular transform and gabor filtering are used to handle the segmentation irregularities. The SIFT, or the entropy-scale-invariant feature transform, GLCM and color morphological techniques were employed for extracting relevant features. Finally, JAYA based RNN algorithm was applied for the classification task. It is revealed that proposed techniques improved the detection accuracy of DR.

A wrapper method based feature subset selection technique was reported for accurate classification of DR in [20]. The image processing technique was employed for removing the dark region in fundus images. The features were extracted by DenseNet and Efficient Net techniques. This work extracted the 512 features from the fundus images. In this work, four algorithms were selected as wrappers: the Grey Wolf Optimizer (GWO), (GSA) and Equilibrium Optimizer (EO) Binary Bat Algorithm (BBA). The classification task was accomplished by RF and SVM classifiers. The results were evaluated using accuracy (96.32%) and kappa (98%).

An effective diagnostic system based on CNN and atom optimization algorithm developed to detect the DR [21]. The working of the diagnostic system described by three components. Initially, morphological gradient method was used to overcome the issue of parasitism in the images. In second component, the data was trained based on transfer learning model and class labels were predicted by last connected layer. In third component, atom optimization algorithm was applied for choosing the dominant activation function. The aforementioned diagnostic model gets higher accuracy compared to other models.

The issues related to DR like higher dimension, hyper parameter tuning, cost extensive etc., were addressed through combination of LSTM and red forex optimization algorithm, called deep LSTM-RFO [22]. The working of deep LSTM-RFO is described using four phases. The noise in fundus images was removed by adaptive histogram equalization technique, while contrast of the images was improved using histogram equalization. Four significant steps make up the suggested framework. Histogram equalization (HE) and Adaptive-HE model are the initial phase in the process, which is known as image preprocessing for removing the noise and enhancing the image contrast. The adaptive watershed method was considered to determine the region of interest. Several intensities, shape and statistical features were extracted from the fundus images for accurate detection of DR. Further, LSTM-RFO algorithm was applied for the classification task. The simulation results were determined in terms of F-score, specificity and sensitivity and proposed algorithm obtained at par DR diagnostic results compared to others.

A cost effective model that can address the time and cost issues of DR presented in [23]. It comprised of several phases like processing of the images, lesion pixel removal, feature set construction and classification. The optic disc and unwanted pixels were eliminated in preprocessing phase and further blood vessels boundary was extracted using morphological operations. The DWT was applied to determine the vertical, diagonal and horizontal coefficients. Moreover, the candidate lesion was computed through adaptive threshold technique. Several local, statistical and geometrical features were extracted from the images for detecting the DR. The classification task was performed using KNN classifier. The results showed that proposed model achieved better results in terms of accuracy (95%), sensitivity (92.6%) and specificity (87.56%).

The manual classification of DR can occasionally produce results that are incorrect in nature. To detect DR automatically, Abirami and Kavitha [24] introduced an automated approach. The proposed approach contains of four phases: preprocessing of the images, enrichment of the images, extraction of feature and classification. The goal of image preprocessing was to reduce noise and enhance image quality. For improving the size and contrast of training image dataset, the augmentation technique was taken. In order to withdraw the features and perform the classification task, a modified Gaussian convolutional deep belief network (M-GCDBN) with a dwarf mongoose optimization technique was used. The ODIR-2019 dataset was used to assess the effectiveness of the proposed approach. The simulation results demonstrated that the suggested framework has an accuracy rate of over 97%.

Karsaz [25] presented image processing model based on support vector domain description (SVDD) and an altered CNN architecture. It is observed that the majority of CNN architecture takes spatial features into account when screening the DR. However, both spatial and spectral features were presented in the proposed architecture. Additionally, this work also considered the pre-trained Alex Net and various SVDD kernel functions can be applied with it. The data was mapped into 2 and 3-dimensional feature spaces by utilizing various kernel functions. The outcomes of the improved CNN were compared with FCM clustering, subtractive and K-Means algorithms. The results showed that the proposed model has a precision rate of more than 98%.

It is analyzed that the training model faces a number of difficulties, including over fitting and inaccurate approximation, because of the high amount of input data i.e. images. Therefore, to solve the aforementioned issues, Murugappan et al. [26] developed the Few-Shot Learning (FSL) paradigm, which takes into account the less amount of training dataset model training. A novel prototype network called the FSL classification network was used to rate and identifies the DR in fundus images. The APTOS2019 dataset was used in this work to detect and grade DR. Additionally, an attention mechanism based on aggregated transformations and gradient activations was developed for capturing the exact image representation. According to the simulation results, the proposed approach obtained 99.73% of accuracy rate, 99.63% of specificity rate, and 99.82% of sensitivity rate

The identification of diabetic retinopathy using an automated approach was introduced in [27]. The automated system has four primary components: (i) pre-processing of image; (ii) blood vessels segmentation; (iii) feature extraction and feature selection; and (iv) detection of DR. In image preprocessing, the Red Green Blue component image was converted into a green channel image then noise was removed using a median filter. The segmentation approach was used to extract the potential lesions, and an iterative segmentation-based technique was used to extract the blood vessel segmentation. Discrete wavelet transforms and a gray-level co-occurrence matrix function was applied to extract the features. Additionally, PCA was used to select the pertinent features, and the DR classification was accomplished by combining neural network with convolutional neural network. Further, the number of hidden neurons was optimized using a modified rider optimization approach. The simulation outcomes showed that the proposed automated framework has a higher level of detection accuracy.

A hybrid model was developed by Gurcan et al. [28] for the earlier diagnosis and detection of DR. The preprocessing, feature subset selection, and classification phases of the proposed model were each separated into their own phases. The preprocessing phase task was to perform noise reduction and quality improvement of the fundus images. Next phase was feature selection in which high dimensional features were obtained using the InceptionV3 technique, and the pertinent features were found using the simulated annealing algorithm. Finally, the XGBoost technique was implemented for DR classification. Messidor-2 dataset was used in this study and simulation results stated that accuracy rate of over 92% was attained by the proposed hybrid model.

A deep learning model for precise detection of DR detection presented in [29]. The features extraction and features optimization were also taken into account by this model. problems of the current DR system and resolved through deep learning technique. The PCA technique also integrated into the model in order to decrease the dimension of the feature vector and extract the pertinent features for the classification task. The deep learning model was also optimized using the Harris Hawk optimization technique. The findings showed that the suggested deep-learning model outperformed compared to previous system using precision, specificity, recall rate and accuracy.

The convolutional neural network (CNN), fire fly optimization (FFO), and improved grey wolf optimization algorithm (iGWO) techniques were combined for detecting and diagnosis of DR [30]. The fundus images were enhanced using a variety of preprocessing techniques as median filtering, CLAHE, and min-max normalization. Furthermore, the region-growing technique was used to identify blood vessels, optic discs, etc. The iGWO algorithm was utilized for calculating the global minima. The pertinent attributes were identified for classification task based on Firefly algorithm. The classification task was accomplished by Convolutional neural network. Further, APTOS DR Dataset was taken into account for evaluating the simulation results and the performance of the iGWO-FFO-CNN model was compared to MACO-CNN PSO-CNN, DCNN-EMFO, CNN and SVM-GSO. According to the findings, the proposed model performance is much better than aforementioned methods in terms of, recall, F1-score rates and accuracy with 93.02%, 92.05%, and 94.11%, respectively.

A deep learning and improved rider optimization based framework was designed to treat the various retinal peculiarities such as micro aneurysms, hemorrhage, hard exudates and soft exudates [31]. The suggested DR detection approach included a number of steps, including the removal of blood vessels and optic discs, segmentation of anomalies, feature extraction, and classification. The CLAHE technique was used at the preprocessing stage to enhance the image quality. The optical disc was removed using the open-close watershed transition method. Grey level thresholding was utilized for segmentation of the blood vessels. Gabor filtering and top hat transformation were also considered to remove segmentation abnormalities.

Dayana and Emmanuel [32] proposed cascaded deep learning technique to select the features for calculating DR severity. Fast Non-Local Means (FNLM) de-noising algorithm and CLAHE were integrated into pre-processing stage to reduce noise in images as well as enhance the image contrast and quality. The blood vessels segmentation was performed using the combination of regularized level set evolution and coherence enhancing energy approach. The optic disc was segmented using the canny method. Further, the candidate lesion region was identified based on attention-based fusion network. The prominent features from the feature set were retrieved based on the Harris Hawk optimization algorithm. The severity of DR was computed based on deep CNN classifier. The results indicated that deep learning enabled model obtained superior results in terms of F1-score, precision, recall and accuracy.

The issues associated with DR, such as time consumption, real-time convenience, and the possibility of human mistake, were handled by Mohan et al. [33] and proposed an ensemble DNN framework for resolved these issues. The proposed DNN framework described by four phases. In the first step, entropy was utilized for increasing the image quality for retinal characteristics. In the second stage, ensemble DL algorithms such as Vgg19, InceptionV3 and ResNet101 were adopted for features extraction from the fundus images. Furthermore, Chi-Square, Relief, Ftest, minimum redundancy, and maximum relevance were used to shorter the feature vector and the classification was accomplished using the support vector machine (SVM). The proposed framework efficacy was assessed using IDRiD and MESSIDOR-2 dataset. The results demonstrated that the proposed framework produced superior results compared with existing techniques and models.

A DRNet i.e. end-to-end encoder-decoder network was presented for the segmenting the optic disc localization and fovea centers [34]. In proposed DRNet, a residual skip connection was integrated to make up for any spatial information which is possible to lose during encoder pooling. For evaluating the efficacy of DRNet, open datasets like IDRiD, DRISHTI-GS, DRIVE and RIMONE are considered. The simulation findings suggested that DRNet produced at par DR results for the DRIVE and IDRiD datasets.

In [35], the attention layer mechanism and mask RCNN based model was reported for DR detection. Based on the gradient-based edge detection approach for locating the unusable portion of DR pictures, the non-usable section of the images was retrieved. Further, mask RCNN was utilized for identification of the lesion areas than faster RCNN. The classification was accomplished through DenseNet, Mobile Net, and ResNet. The experimental results revealed that the VGG19 model outperforms compared to other methodologies and models.

A study on selection of supervised and unsupervised methods for detecting micro-aneurysms (MAs) was presented in [36]. To achieve the higher accuracy, the background color was removed initially. The radon transforms (RT) and overlapping windows concept were used to identify the optic nerve head and retinal arteries. The support vector machine and radon transform were combined to detect MSs effectively. The findings claimed that above combination achieve higher sensitivity (95.7%) and specificity (93%).

An automated technique for the identification of diabetic retinopathy based on texture and grey level intensity parameters was developed by Sikdar et al. [37]. This study considered the APTOS 2019 BD dataset. The GLCM and histogram techniques adopted in order to get the features from the images. The prominent features were identified based on the DT enabled GA and the XGBoost algorithm was implemented for detecting the DR using reduced set of features. Further, the accuracy and f-measure metrics were used to assess the simulation results. The simulation results reported that the proposed automated system obtained better f-measure (93.51%) and accuracy (94.20%).

An automated model was developed by Boix and Fernandez [38] for the earlier diagnosis of DR. The fundus-colored images were considered. Additionally, the CNN was utilized for the classification task and further, the synaptic meta-plasticity was implemented in the back propagation phase with an inference between learning and memory. The F1-score, accuracy, recall, and precision parameters were used to analyze the effectiveness of the model. It can be seen that CNN combined with synaptic meta-plasticity provided the superior results than other approaches in terms of recall, F1-score, precision and accuracy.

The VGG-NiN model was presented to identify the various stages of DR [39]. The proposed model was computational effective and further considered the nonlinear features for detecting the DR. The VGG16 network-in-network (NiN), and the spatial pyramid pooling layer (SPP) were the components of the VGG-NiN model, which were stacked on top of one another to design the deep learning model. The accuracy, recall, precision, and F1-score parameters were adopted to assess the simulation results of VGG-NiN. The results demonstrated that the proposed VGG-NiN model performed excellent in terms of F1-score, precision and recall compared to existing techniques.

The majority of research on diabetic retinopathy that published in literature based on high quality images. Wang et al. [40] considered the Low resolution retinal fundus images for the diagnosis of DR. The CNN technique was utilized for learning of the multi-level task of DR grading, known as Deep MT-DR. The Deep MT-DR was created to take on low-level ISR tasks, mid-level lesion segmentation tasks, and high-level disease severity assessment activities. Three image datasets were used to test the effectiveness of Deep MT-DR, and the accuracy parameter was used to assess the experimental outcomes. It is discovered that Deep MT-DR achieved an accuracy rate of 83.6%.

An automated approach for detecting diabetic retinopathy was presented in [41]. A modified CNN UNet architecture was utilized for identifying retinal haemorrhages in fundus images. The IDRiD dataset was considered in this study to assess the efficacy of automated approach. Further, the UNet was used for training task and identifying potential DR symptoms. The sensitivity, specificity, and accuracy parameters were adopted to evaluate the experimental results. The proposed automated approach attained better sensitivity (80.49%), specificity (99.68%), and accuracy (98.68%).

The performance of the classifiers, particularly with image datasets, was significantly impacted by the selection of prominent features. This issue of the image dataset was taken into account by Vijayan et al. [42], who created a color histogram filter as a method for choosing features for retinal fundus pictures. The J48 and KNN approaches were adapted to diagnosis of DR in fundus images. The findings stated that the accuracy rate for KNN using the feature selection approach was 81.99%.

Jangir et al. [43] presented the functional link based CNN for the classification of diabetes mellitus. The efficacy of the FLCNN classifier was evaluated on real world diabetes datasets. The simulation results were compared with several state of art methods like MLP, SVM, DT, CNN, and Xgboost based on accuracy parameter. The findings claimed that FLCNN obtained at par results for diabetes mellitus.

Choubey et al. [44] investigated the performance of the several ML classifiers for accurate prediction of diabetes. Further, this work considered the PCA and PSO algorithm to compute the relevant features for classification task. The results demonstrated that C4.5 classifier achieved more optimal results for diabetes. In continuation of their work, a diabetes detection model for timely detecting the diabetes presented in [45]. The RBFNN and MLPNN were implemented in the proposed detection model for accurate and timely diagnosis of diabetes. Furthermore, the relevant features were extracted based on the genetic algorithm. The efficacy of the model was determined using AUC-ROC curve and accuracy parameters. The results show that proposed detection model provided superior results. A detailed review on classification of diabetes mellitus was reported in [46].

PROPOSED MODEL FOR DETECTING THE DIABTEIC RETINOPATHY

This section presents the multi-level scanning, BA algorithm and deep forest cascading based diabetic retinopathy model for diagnosing of DR effectively. The main components of the proposed model are preprocessing of images, feature extraction based on multi grained scanning, pertinent features using bat based algorithm, deep forest for DR detection, and interpretation of results and validation. The description of each component is summarized as below.

3.1 Fundus Images Pre-Processing

This phase corresponds to the fundus images that will be used to evaluate how well the suggested model performs have been preprocessed. The goal of this phase is to improve the images quality and resizing. The fundus images are taken from https://ieee-dataport.org. These images are in color format and saved on local system. The first step corresponds to enhance the color of images and further, extracts the color component (RGB) from the images. Threshold and luminosity functions are utilized for improving the images initially. Further, images are resized into 64×64 based on resize () function and rgd2gray () function is utilized for converting the color images into corresponding greyscale images. Moreover, the median filter is considered for removing the noise from the images and CLAHE algorithm is considered for enhancing the contrast of the Canny function is used for determining the edge of the images and k-mean algorithm is adopted for segmentation task whose aim is to compute the lesion region from the images. Furthermore, this work considers the spatial and statistical features for diabetic retinopathy detection. The process of preprocessing phase is demonstrated using Fig. 2 (a-b)

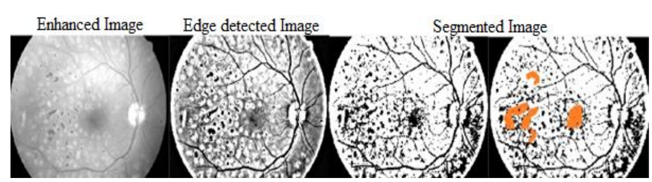

Fig. 2(a): Demonstrates original fundus image, grayscale image, noise removal and enhanced image using preprocessing phase.

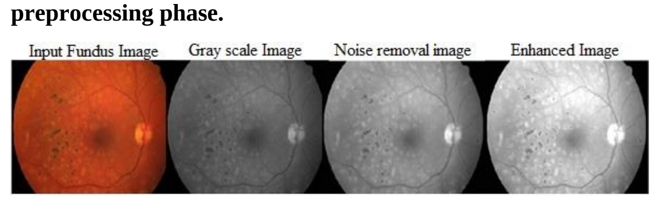

Fig. 2(b): Demonstrates enhanced image, edge detected image and segmented image using preprocessing phase.

3.2 Multi level scanning method for Extraction Feature

The multi-level scanning technique is taken into consideration in this study to extract the high-dimensional feature from the fundus pictures. A bi-cubic interpolation method is employed in multi-level scanning method to extract features from the grayscale images [47]. Further, smoothing property is utilized for extracting the edge features and it is implemented through canny-edge()

function. The scanning method is also discovered the sequential and spatial relationship among pixels. The scanning process is illustrated in Fig. 3. The relationship between sequential and spatial features is also evaluated through scanning process. The main benefits of this process are to enhance the diversity as well as repeated samplings of the images are not required. For scanning task, this work considers the image size (64×64) and sliding window size(10×10). The scanning process is initiated by moving the sliding window across images and initially ten features are obtained. Moreover, the random forest classifier is trained through these ten features and further; twenty-one features are obtained for every forest. Finally, twenty-one features are determined through scanning process as two forests are considered in this work.

3.3 Bat Algorithm (BA) Based Feature Selection

The pertinent features for diabetic retinopathy are extracted using bat algorithm. The proposed model extracts the significant number of features from fundus images using multi-level scanning process, but extracted features are not equally important to detect the DR. In turn, performance of the classifier can be affected and cost of the model can be increased. These aforementioned issues can be handled through selection of relevant features. Hence, this work considers the bat algorithm for selecting the appropriate features for the classification task and this algorithm is incorporated into proposed diabetic retinopathy model.

Furthermore, high dimensional features are fed as input to the bat algorithm and the task of the bat algorithm is to select the features subset that are more relevant in nature as well as for classification task. The bat algorithm is based on the behaviour micro bats and it is widely utilized for solving large number of optimization problems [48-50]. The population of the bat algorithm is defined in random order. The main task of the bat algorithm is to sense the prey and avoid the hurdle that can occur during the searching of the prey. The echo feature is utilized for determining size and shape of objects. Moreover, these bats are also emitted the short pulses. Furthermore, the velocity (v_i) and frequency (f_i) of bats are initialized using the equations 1-2.

$$v_i = v_{i,old} + (x_i - x^*)f_i \tag{1}$$

$$f_i = f_{min} + \beta(f_{max} - f_{min}) \tag{2}$$

The loudness (L) and pulse emission rate (r) parameter of bat algorithm is computed using equations 3-4.

$$L_i = \rho L_{i-1} \tag{3}$$

$$r_i = r_{i-1}(1 - e^{\tau}) \tag{4}$$

In equations 3-4, ρ and τ are defined as constraints. In this work, sum of squared error is described as objective function and it is computed for each position of bats. Further, the data objects are allocated based on minimum sum of squared error. The new position and frequency of bats are determined using equations 5. Further, the food source in the neighborhood is determined using the equation 6.

$$x_{i,new} = x_{i,old} + v_i. \tag{5}$$

$$x_{new} = x_{old} + \varepsilon\bar{L} \tag{6}$$

ε in the range of -1 to1.

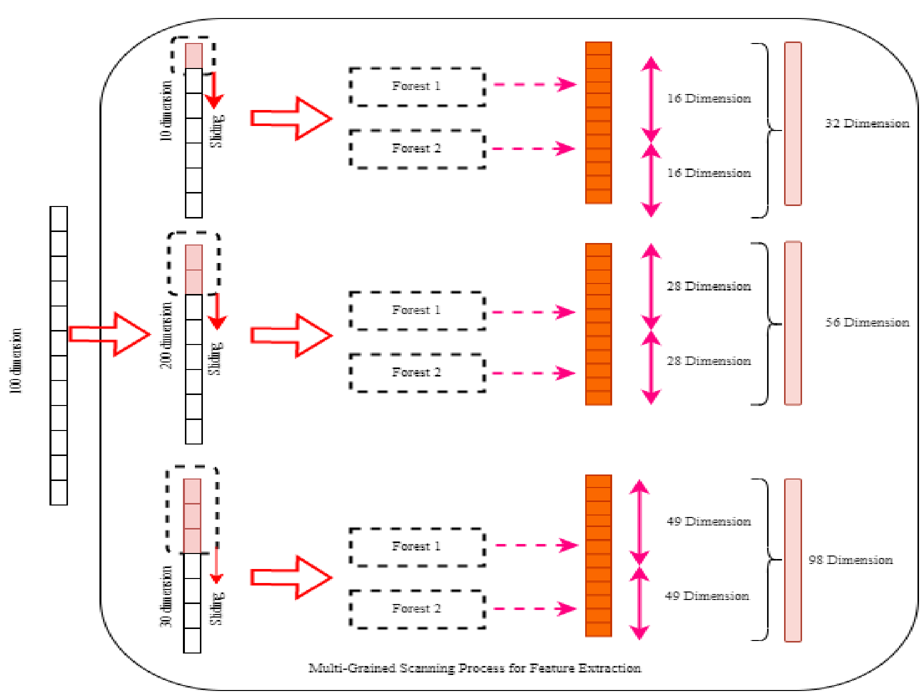

Fig. 3: Depicts multi-level scanning procedure.

After obtaining the optimal partitioning of the data objects, the weight of the features (f_i) are computed using the equation 7.

$$f_i = \left(\sum_{i=1}^{d} \sum_{j=1}^{h} \sum_{k=1}^{k} \frac{X_{ih}}{C_{ik}}\right) \times \frac{1}{d} \quad (7)$$

The flowchart of the BA based feature selection algorithm is mentioned in the Fig. 4.

3.4 Deep Forest Technique

This section presents the deep forest technique to detect the diabetic retinopathy through fundus images. This technique is an ensemble classifier based on the cascade structure and provided state of art results and features compared to existing techniques [51-52]. The behavior of this technique is formulated through cascade forest and scanning. The scanning task is utilized for computing the features for classification and detection tasks. While behavior of cascade structure is defined through forest and trees. Further, multiple forest and trees are presented into cascade structure. Moreover, the cascade structure contains several trees in the forest and these tresses are rooted tree represented through the features. But, the feature presented on the root node is selected through Gini Based measure and it is computed for all features. Further, the features are ranked in order of increasing Gini index. The minimum Gini index feature is chosen as root node and it is also utilized to partition task. The final tree is based on the Gini index. The aforementioned process of deep forest is described using Fig. 5. It is also described the computation behind the labeling of class to data objects. It is assume that the data object (O_i) is estimated using the mean of all distributions. In this work, both scanning and cascade structure are taken into consideration. The scanning process extracts the features from fundus images, while, classification task is accomplished through cascade structure. Furthermore, each cascade structure contains two forest and thirty trees in forest for DR detection. The deep forest method's parameters are used in the same way as those described in [36–37] and the cascade structure is illustrated using Fig. 6. As input to the cascade structure, the feature vector is provided and it can be parsed into 1st level to nth level. It is noted that at each level, input is combined with parsed input to generate optimal solution and this process is continued until the nth level reached. Finally, the diabetic retinopathy is detected through nth level. The procedural steps of cascade structure are mentioned in Algorithm 1.

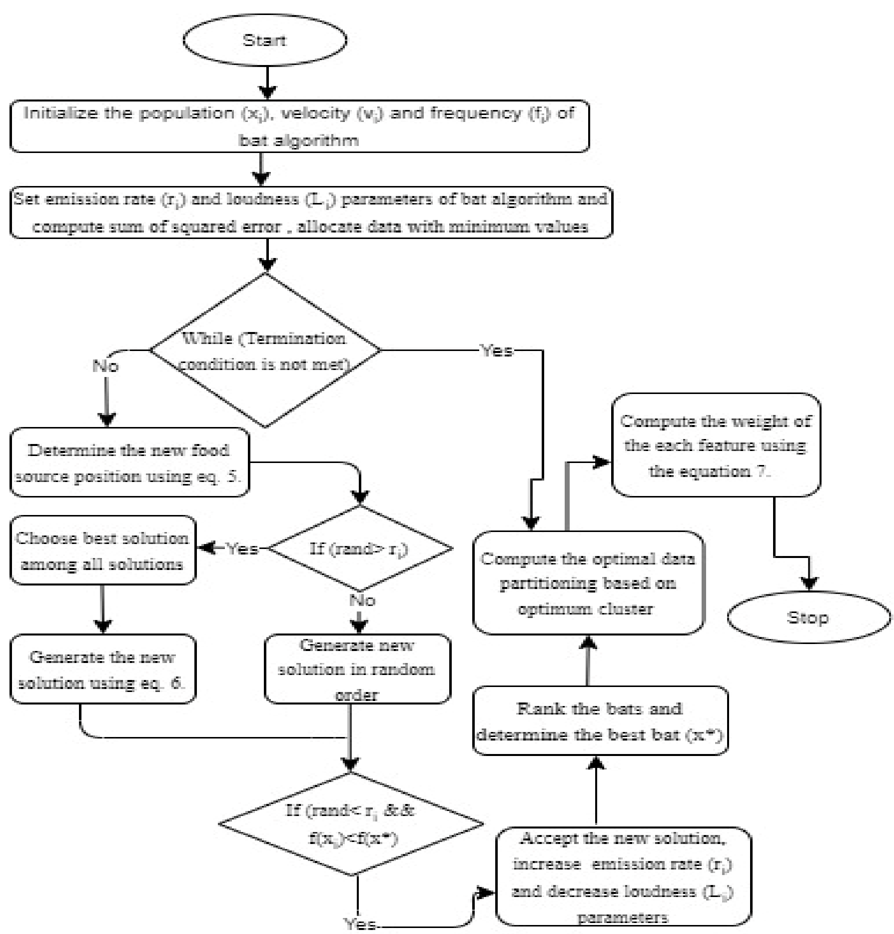

Fig. 4: Flowchart of the bat based feature selection algorithm.

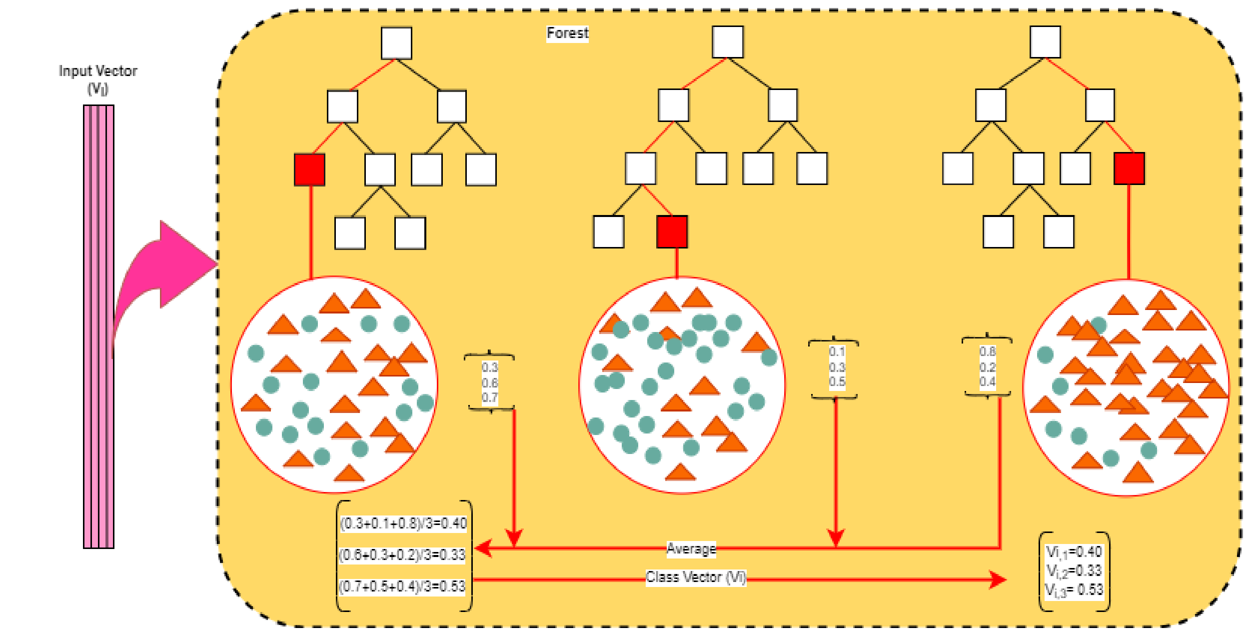

Fig. 5: Computing the average tree probability

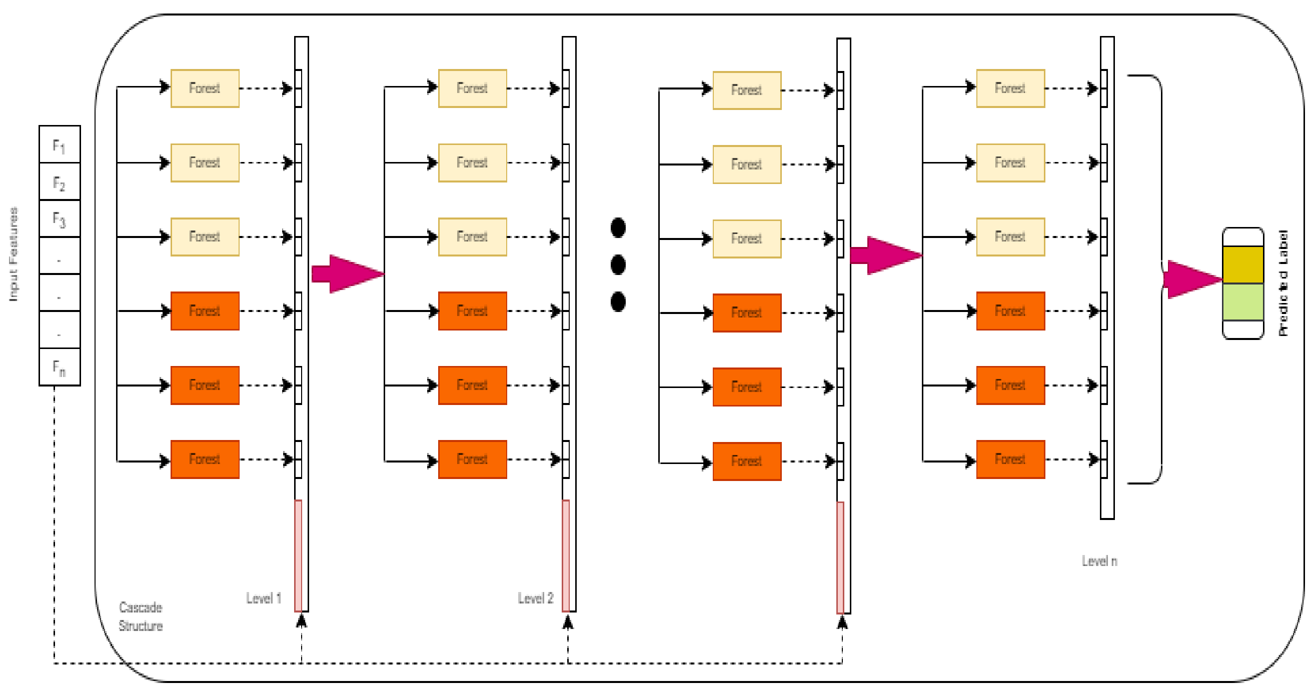

Fig. 6: Depicts the cascaded deep forest structure.

3.5 Proposed model based On BA-Deep Forest for Diabetic Retinopathy based

This subsection discusses about how the proposed model for diabetic retinopathy works. The proposed model comprises of following phases- preprocessing of images, feature extraction based on multi grained scanning, pertinent features selection using BA based algorithm, deep forest for DR detection, and interpretation of results and validation.

Fig.7 illustrates the proposed model of DR detection and using the dataset of fundus eye image, the effectiveness of the proposed model is assessed. Initially, the eye images are fed to the preprocessing phase to enhance the image quality. Threshold () and luminosity () function are utilized to enhance the initial fundus images. Further, Grayscale () function is used for converting the color images into grayscale images Next phase corresponds to features extraction from enhanced fundus images and it is accomplished through multi grained scanning.

The varieties of features like statistical, shape etc. are extracted in this phase. The next phase corresponds to selection of pertinent features from the set of extracted features. The pertinent features are extracted through bat based algorithm. These extracted features are passed to the detection phase and this phase utilizes the deep forest method for accurate identification of the diabetic retinopathy. The diabetic retinopathy divided into two classes either healthy or diabetic retinopathy. The deep forest model consists of two forests and every forest contains thirty tree. Finally, the results and validation phase evaluates the efficiency of the deep forest method. In order to measure the effectiveness of the proposed diabetic retinopathy model several performance parameters are incorporated.

```
Algorithm 1: Steps of the Deep Forest Method
Input: Fundus Images D), Level (L), Results (Init Res)Forests (F)
and Trees (P)
Output: Healthy or No-Healthy (DR)

 1. Initialize no. of forests (F), trees (P), features, training
    data (N) and Init_Res=0;
 2. While( i = 1 to I), //Training Phase
 3. While (j = 1 to J),
 4. While (k = 1 to K),
 5. Construct decision tree based on training data by considering
    relevant features (L) and store the results in  Init_Res.
 6. Compute the Gini Index for best spilt node.
 7. Compute depth level (d) to construct tree.
 8. For each forest construct "P" number of tree.
 9. End While
10. End While
11. End While
12. While (i = 1 to I), //Testing Phase
13. While (j = 1 to J),
14. While (k = 1 to K),
15. Construct decision tree based on training data by considering
    relevant features (L) and store the results in  Init_Res.
16. Compute the Gini Index for best spilt node.
17. Compute depth level (d) to construct tree.
18. For each forest construct "P" number of tree.
19. End While
20. End While
21. End While
22. Compute class labels based on ensemble decision trees.
23. Evaluate simulation results based on performance measures.
```

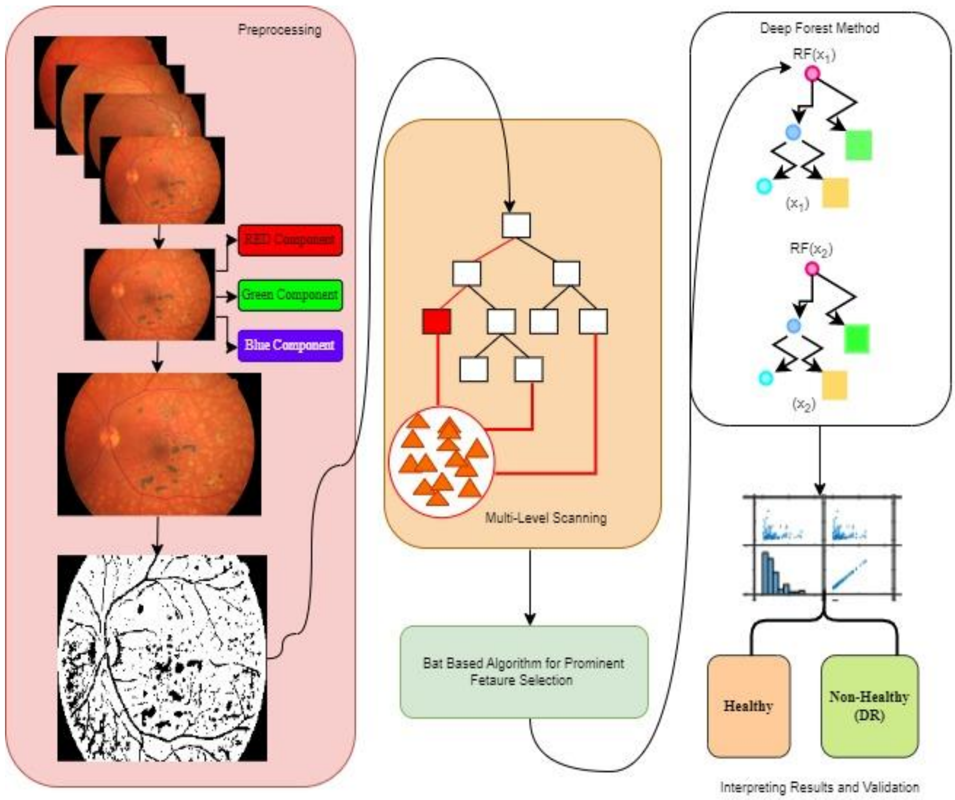

Fig. 7: Proposed Multi Scanning-BA-Deep Cascade model for detection of diabetes retinopathy

4. SIMULATION RESULTS

The experimental results of diabetic retinopathy are presented in this section. The results are taken over a set of thirty-two thousand fundus images and having binary classes- diabetic and non-diabetic. The efficiency of the model is assessed through variety of performance measure like accuracy, F1-score, sensitivity, AUC and specificity. The efficacy of the model is also investigated based on training-testing and fold cross validation methods. This work considers training-testing (70%-30%) (train-test (70%-30%)), training-testing (80%-20%) (train-test (80%-20%)), and 10-cross fold methods for assessing the model performance. In Train-Test (70%-30%) method, 70% of data is considered to train the model, while 30% data is utilized as test data for evaluating the effectiveness of the model. In case Train-Test (80%-20%) method, 80% data is used for training purpose, while 20% data is utilized for testing purpose. In 5-cross fold method, entire dataset divided into five subsets, four subsets are utilized as training set, while fifth subset is considered as test set to evaluate the proposed model performance. The aforementioned process is performed five times and every time test is different. In 10-cross fold method, entire dataset divided into ten subsets, nine subsets are utilized as training set, while tenth subset is considered as test set to evaluate the proposed model performance. The aforementioned process is repeated five times and every time test is different. Further, the results are also demonstrated in terms of confusion matrix and it is useful to derive the measures of accuracy (Acc), F1-Score (Fs), sensitivity (Sen), AUC and specificity (Spc) parameters.

4.1 Results and Discussion

The proposed model simulation results for diabetic retinopathy are discusses in this section. Confusion matrix is used to compute the simulation results for the suggested model and other methodologies. The results of the accuracy, sensitivity, F-Score, AUC, and specificity parameters are obtained using this matrix. Additionally, the training-testing method and the cross fold methodology, which are explained in subsections 4.1.1 and 4.1.2, are used to observe the results of the proposed model.

4.1.1 Using Training-Testing method

The results of the proposed methodology and other aforementioned methods based on the Train-Test (70%-30%) and (80%-20%) employing accuracy, F1-score, sensitivity, and specificity parameters are discussed in this subsection. Table 1 demonstrates the results of the proposed methodology based on the F1-Score and accuracy parameters using aforementioned evaluation methods. It is observed that proposed model and other techniques obtain significantly better results with train-test (80%-20%) as compared to train-test (70%-30%). It is depicted that the accuracy measure of the proposed model is 88.14% using training-testing (80%-20%), while accuracy with train-test (70%-30%) is 87.21% %. By analyzing the F1-Score parameter, it is reported that with train-test (80%-20%), the F1-Score is 88.94%, while with train-test (70%-30%), the F1-Score rate is 88.03%. Hence, it is determined that the suggested model offers improved accuracy and F1-Score rates with train-test (80%-20%) as opposed to train-test (70%-30%). The proposed model's simulation results are showing in Table 2 based on the sensitivity and specificity parameters and the aforementioned assessment techniques. It is showing that proposed model and other techniques obtain significantly improved results with train-test (80%-20%) than train-test (70%-30%). It is analyzing that the sensitivity computation of the proposed model is 90.01% with train-test (80%-20%), while sensitivity measure with train-test (70%-30%) is 88.46%. Analysis of the specificity parameter reveals that the specificity rate with train-test (80%-20%) is 90.62% and that with train-test (70%-30%) is 89.29%. As a result, it is noted that the suggested model has higher sensitivity and specificity rates with train-test (80%-20%) than train-test (70%-30%). Fig.8-9 demonstrates the graphical representation of the proposed methodology outcomes and other aforementioned techniques based on train-test procedures. Fig. 8 demonstrated the F1-Score and accuracy results of the proposed methodology and other aforementioned techniques. It is showing that train-test (80%-20%) method achieves better results of the proposed methodology and other aforementioned techniques in significant manner compared to train-test (70%-30%). It is also noted that proposed methodology obtains superior F1-Score and accuracy rates than other technique based on train-test (80%-20%).

Table 1: Demonstrates the results based on accuracy (Acc) and F1-Score (Fs) parameters

Technique	Training/Testing (70%-30%)		Training/Testing (80%-20%)	
	Accuracy	F1-Score	Accuracy	F1-Score
KNN	69.21	71.23	73.21	76.06
ANN	70.93	72.06	75.64	79.26
SVM	73.24	76.76	77.52	80.03
VGG16	74.67	77.18	78.97	81.12
VGG19	77.03	78.73	81.53	83.05
InceptionV3	79.89	81.78	84.93	86.53
Deep Forest	86.37	86.91	87.02	88.24
Proposed System	87.21	88.03	88.14	88.94

Table 2: Demonstrates the results based on sensitivity (Sen) and specificity (Spc) parameters

Technique	Training/Testing (70%-30%)		Training/Testing (80%-20%)	
	Sensitivity	Specificity	Sensitivity	Specificity
KNN	71.42	71.04	74.28	77.92
ANN	71.04	73.12	78.34	80.21
SVM	75.34	78.23	78.73	81.37
VGG16	76.81	77.56	80.03	82.23
VGG19	77.43	80.07	82.64	83.46
InceptionV3	80.21	83.41	86.02	87.04
Deep Forest	87.11	89.04	88.46	90.65
Proposed System	88.46	89.29	90.01	90.62

Additionally, the train-test (80%-20%) approach shows that the proposed methodology has the highest accuracy and F1-Score rates of all strategies. Fig. 9 demonstrated the specificity and sensitivity rates of the proposed model as compared to other techniques. It is showing that train-test (80%-20%) method achieves better results of the proposed methodology and other aforementioned techniques in significant manner compared to train-test (70%-30%). It is also revealed that proposed methodology gains better specificity and sensitivity rates than other technique based on train-test (80%-20%). It is also observed that proposed model gets higher F1-Score and accuracy rates among all techniques using train-test (80%-20%) method. Finally, it is concluded that train-test (80%-20%) method have advantage as compared with train-test (70%-30%) for detecting of the diabetes retinopathy.

4.1.2 Using Cross fold method

The experimental results of the proposed methodology and other aforementioned methods based on 5 and 10-crossfold method employing accuracy, F1-score, specificity and sensitivity parameters are discussed in this subsection. Table 3 demonstrates the simulation results of the proposed methodology based on the F1-Score and accuracy parameters using afore mentioned evaluation methods. It is determined through analysis that the proposed methodology and other methods greatly outperform the 5-cross fold method when using the 10-cross fold approach. It is depicted that the accuracy computation of the proposed methodology is 91.38% with 10-cross fold method, while accuracy rate with 5-cross fold method is 90.28%.

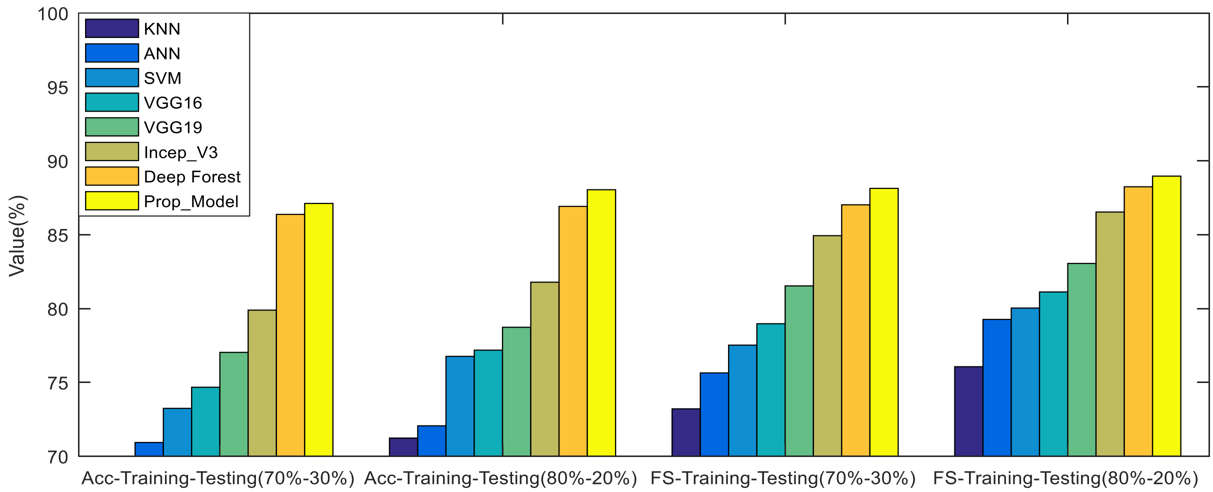

Fig. 8: Accuracy (Acc) and F1-Score (FS) results of the proposed model compared other techniques based on training-testing methods.

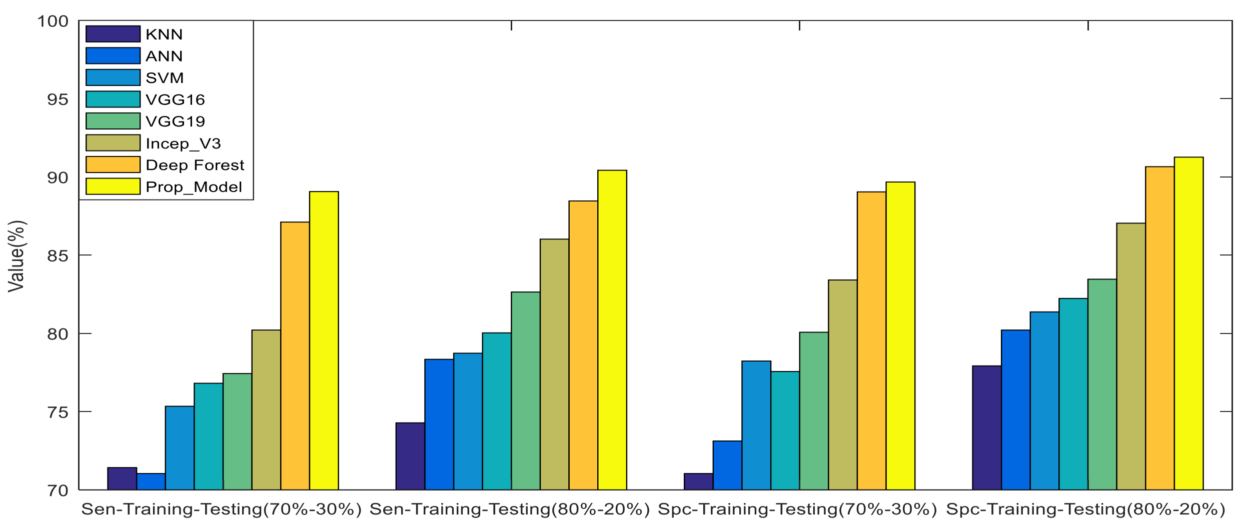

Fig. 9: Sensitivity (Sen) and Specificity (Spc) results of the proposed model compared other techniques based on training-testing method.

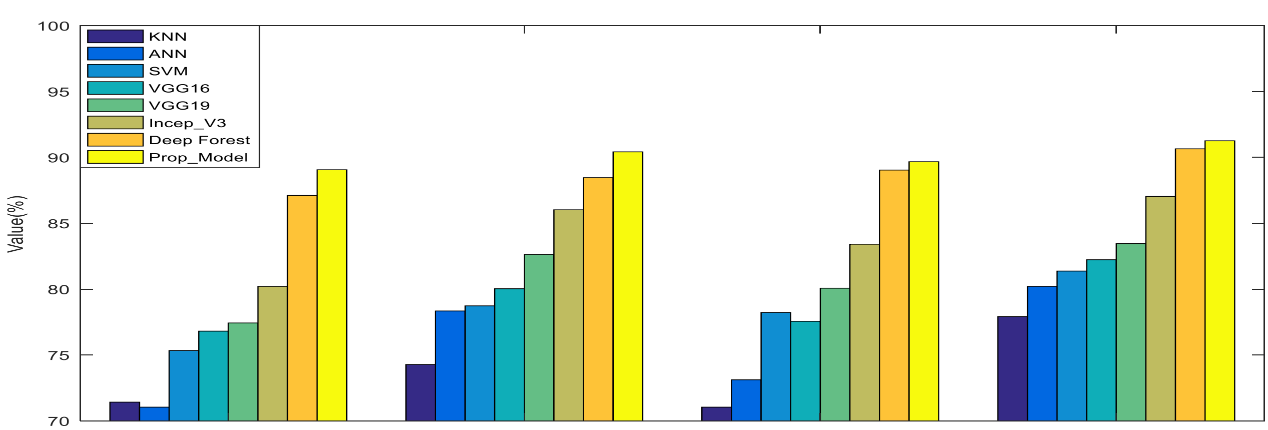

Fig. 10: F1-Score (FS) and Accuracy (Acc) results of the proposed model compared other techniques based on cross fold method.

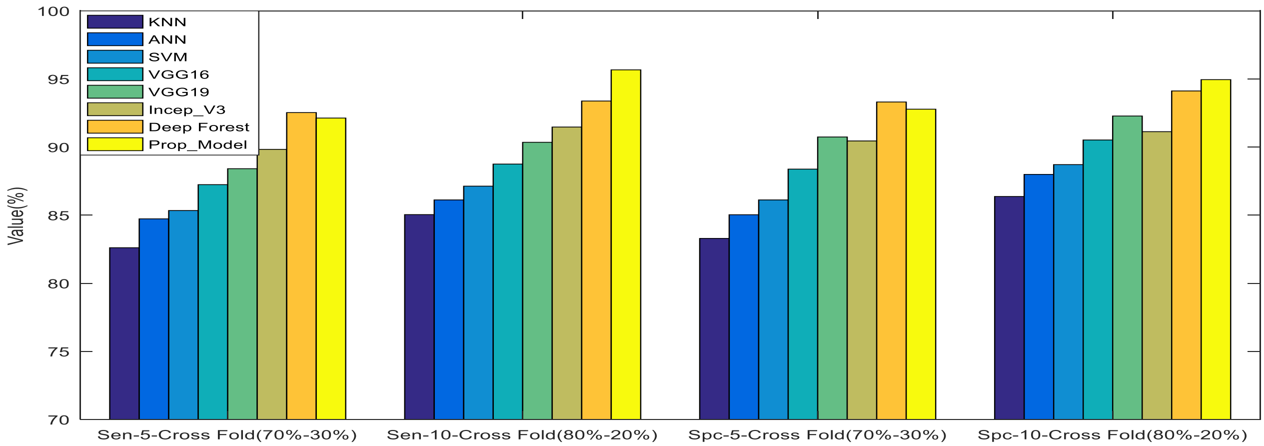

Fig. 11: Sensitivity (Sen) and Specificity (Spc) results of the proposed model compared other techniques based on cross fold method.

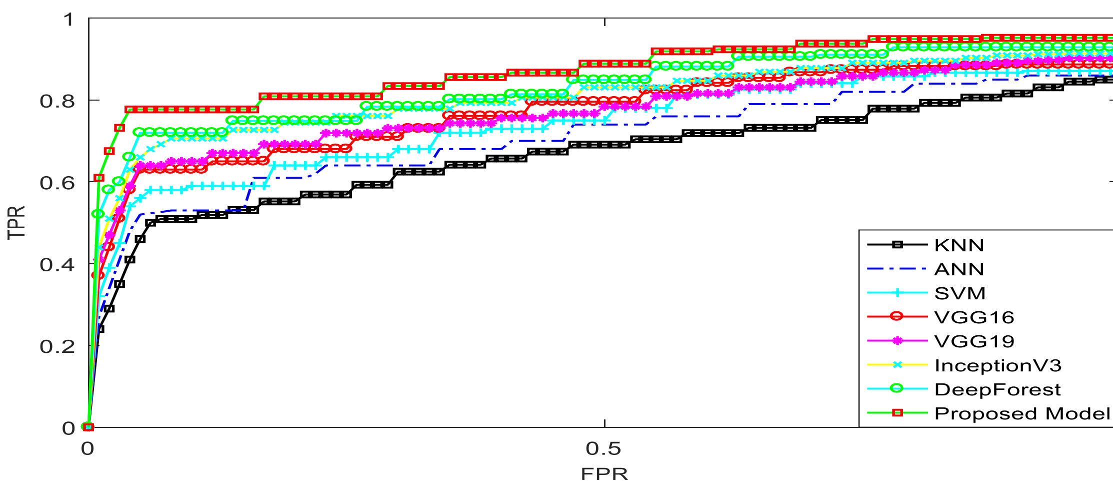

Fig.12: Demonstrates the results of receiver operating characteristics -area under curve (ROC-AUC).

By analyzing the F1-Score parameter, it is noted that with 10-cross fold method, the F1-Score is 94.12%, while with 5-cross fold method; the F1-Score rate is 91.73%. Hence, it is determined that the proposed model offers better F1-Score and accuracy rates with 10-cross fold technique as compared with 5-cross fold method. The results of the proposed model based on specificity and sensitivity parameters are shown in Table 4 and compared with other aforementioned techniques. It is determined through analysis that the 10-cross fold approach yields results that are noticeably better than those of the 5-cross fold method for the proposed model and other methodologies. According to the 10-cross fold approach, the proposed model sensitivity rate is 93.41%, while with5-cross fold method is 91.67%. After examining the specificity parameter, it is reported that with 10-cross fold method the specificity rate is 93.73%, while with 5-cross fold validation method, the specificity rate is 91.84%. Hence, it is observed that proposed methodology provides better specificity and sensitivity rates with 10-cross fold method than 5-cross fold method.

Table 3: Illustrated the results based on accuracy (Acc) and F1-Score (Fs) parameters

Technique	5-Cross Fold		10-Cross Fold	
	Accuracy	F1-Score	Accuracy	F1-Score
KNN	76.46	82.95	78.22	85.72
ANN	77.09	84.88	80.78	87.04
SVM	80.41	85.73	82.03	87.91
VGG16	82.94	87.81	84.59	89.63
VGG19	85.91	89.56	86.94	91.31
InceptionV3	87.09	90.14	88.72	91.38
Deep Forest	88.61	90.38	90.66	93.75
Proposed System	90.28	91.73	91.38	94.12

Fig.10-11 demonstrates the graphical representation of the proposed methodology outcomes and other aforementioned techniques using cross fold validation method. Fig. 10 demonstrated the F1-Score and accuracy results of the proposed methodology and other aforementioned techniques. It is showing that 10-cross fold validation method achieves better results of the proposed model and other techniques in significant manner compared to 5-cross fold method. It is also observed that proposed methodology obtains excellent F1-Score and accuracy rates than other technique based on 10-cross fold method. The specificity rate and sensitivity rate of the proposed methodology and other aforementioned techniques is illustrated in Fig. 11.

Table 4: Illustrated the results based on sensitivity (Sen) and specificity (Spc) parameters

Technique	5-Cross Fold		10-Cross Fold	
	Sensitivity	Specificity	Sensitivity	Specificity
KNN	82.61	83.29	85.04	86.37
ANN	84.73	85.03	86.12	87.99
SVM	85.34	86.12	87.13	88.71
VGG16	87.24	88.38	88.75	90.52
VGG19	88.41	90.74	90.35	92.28
Inception V3	89.83	90.45	91.47	91.13
Deep Forest	92.53	93.31	93.38	94.12
Proposed System	92.13	92.78	95.67	94.95

In comparison to the 5-cross fold approach, it is determined that the 10-cross fold method significantly improves the outcomes of the proposed methodology and other techniques. It is also observed that proposed methodology obtains excellent specificity and sensitivity rates than other technique based on 10-cross fold method. It is also showing that proposed methodology also gets excellent F1-Score and accuracy rates among all techniques using 5-cross fold method. Finally, it is concluded that 10-cross fold method have significantly improvement over 5-cross fold method for detecting of the diabetes retinopathy. AUC-ROC curve of the proposed methodology and other aforementioned techniques are graphically presented in the Fig. 12. This parameter is defined based on TPR and FPR. In comparison to existing methods, it is claimed that the suggested model yields better ROC-AUC results. It can also be demonstrated that the proposed model converges faster than existing methods. Hence, it is said that proposed model is capable for detecting diabetic retinopathy more efficiently than other techniques.

5. CONCLUSION

In this study, a deep forest model and the bat algorithm are used to create a model of diabetic retinopathy. The deep forest model is used to diagnose DR, while the bat algorithm is used to extract the relevant features. Further, a multi scanning method is also considered to compute the initial feature from fundus images. The bat algorithm is provided with these extracted features and the task of this algorithm is to determine pertinent features for DR identification. The performance of the aforementioned diabetic retinopathy model is evaluated using popular performance parameter and number of current models for diabetic retinopathy is compared to simulation results. The results are evaluated using cross fold validation and training-testing methods. It is analyzed that proposed model achieves higher accuracy (92.94%), sensitivity (95.67%), specificity (94.95%) and F1-score (95.31%) based on the 10-cross fold validation method. It is also observed that proposed model provides state of art diabetic retinopathy results with 5 and 10-CrossFold, training-testing (70%-30%), and (80%-20%) method compared with other techniques. It is also noticing that 10-cross fold, and training-testing (80%-20%) methods significantly enhance results of proposed model as well as other aforementioned techniques in comparison to training-testing (70%-30%) and 5-cross fold validation. As a result, it is also said that the 10-cross fold method is superior to other ways like the 5-Cross Fold, train-test (70%-30%), and train-test (80%-20%). In comparison to existing methods like KNN, SVM, deep learning, and VGG variations, finally it is stated that the suggested diabetic retinopathy model is effective for diagnosing diabetic retinopathy based on fundus pictures and produces state-of-the-art results.

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