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An optimized intelligent boosting model for diabetic retinopathy segmentation severity analysis using fundus images

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Abstract

In today's scenario, many people suffer from Diabetic Retinopathy (DR), due to different lifestyles and cultures. Hence, the exact severity analysis system is the most required application to avoid vision loss. The Neural network with multiple decision functions already existed for this severity analysis case. However, those models do not give the proper outcome in exact segmentation, leading to improper severity analysis outcomes. So, the current study aims to design a novel Squirrel Search-based Extreme Boosting (SSbEB) for accurately segmenting and estimating the severity range. Initially, the DR database was filtered and entered into the classification layer, then the features were extracted, and the abnormal region was segmented. Here, incorporating the squirrel features in the extreme boosting has afforded the finest feature analysis and segmentation outcome, which help predict the DR severity level with the maximum possible rate. The severity score of the segmented region was determined as normal, mild, severe, moderate, and proliferative. Hence, the designed model is implemented in the python platform, and the performance parameters, such as precision, specificity, accuracy, and recall, have been measured and compared with other models. Hence, the recorded exact severity analysis score is 94.4%, which is quite better than the past models. Thus, the implemented model is suitable for the DR severity analysis system and supported for real-time disease analysis applications.

Keywords: Severity classification, Affected region segmentation, Squirrel optimization, Extreme boosting, Feature analysis

1. Introduction

Worldwide, diabetes-mellitus (DM) was viewed as a challenge to global health [1]. In addition, long-term cardiovascular and DM difficulties might cause diabetic retinopathy (DR) [2]. These complications were announced by the epidemiological study [3]. Also, the chief cause of blindness is DR [4]. Even though there are no early warning signs until the disease has severely impaired vision [5]. Hence, progression may result in retina injury, blindness, or visual loss [6]. Moreover, people with diabetes were described as type-I and type-II [7]. The DR patients have diabetes, which may be type I or type II [8]. But, people with type-II diabetes are most affected by DR [9]. Furthermore, DR could be split into dual primary groups, such as non-proliferative and proliferative [10]. Here, the non-proliferative is described in three constraints that are moderate, severe, and mild grades [11].

In traditional fundus pictures, microvascular are not apparent [12]; nevertheless, the microaneurysm appears as isolated red spots unattached to blood vessels [13]. The fundus image is visualized in Figure 1. In addition, Patients with diabetes may have this retinal defect, which is also the first observable indicator of DR [14]. Hence, the abnormal cells in the vision nerve are challenging to predict in the early stage; this has resulted in DR almost for all aged people [15]. In addition, the high Severity of DR has resulted in blindness and other vision problems [16]. Considering these issues, the DR study's cause has played a vital role in the digital imaging industry [17]. So, many researchers and medicalize have reviewed DR affect analysis and treatment procedures [18]. Besides, intelligent models were widely utilized in the digital imaging procedure for getting the exact detection outcome [19]. Models like the neural convolution model, ResNet, V3 inception, random forest, Support Vector Machine, Fuzzy Logic [20] and the K-Means technique [21] have been recorded as the most satisfactory outcome for forecasting the DR types and their Severity [22]. Besides, several review studies were conducted to measure the algorithm effectiveness in DR detection [23], inflammation DR review [24], and biomarkers diagnostic tool [25]. However, less forecasting outcome is recorded in many cases because of the complex noise features data. So, those models failed to find the exact severity score of the predicted DR. Hence; the present study has described the hybrid mechanism based on the boosting and optimized features for predicting the DR and its severity range in a very accurate manner. Finally, the improvement and the need for the designed model were justified by performing the statistical performance validated with other existing models. Few recent efficient methods were introduced for forecasting the abnormal region and finding the severity types. Those studies are explained as follows in the vision of significance and drawbacks. The recently associated literature on DR prediction is described as follows:

DR has been predicted using the convolution neural approach implemented by Tang et al. [26]. In addition, ResNet is utilized to collect the image features in the trained fundus images. The neural convolution scheme has afforded the most satisfactory image features analysis outcome. Also, better segmentation exactness output has been gained. However, oversampling has been reported if the images are too complex and noisy. So, additional resources were required to get error-free data and to achieve the finest outcome.

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Sevgi et al. [27] have introduced the vascular feature analysis for analyzing the DR severity range. The approach adopted for analyzing the vascular features is the random forest model. Finally, the performance of their executed neural model was established by performing the statistical analysis parameters such as variance, mean, Kruskal-Wallis, etc. Hence, the most acceptable vascular feature identification outcome has been reported with less error.

Campbell et al. [28] introduced the Multivariate regression deep network for the DR analysis. A posterior pole is a database that has been adopted to check the efficiency of the designed model and contains multiple disease-affected fundus images with different pixels. Finally, the established model's robustness score was processed using the mean accuracy of DR detection. But, it has recorded high time complexity. Kaur et al. [29] have conducted a broad review of DR forecasting approaches, such as intelligent neural models and optimization approaches to find the most acceptable DR prediction mechanism. The performance analysis was made to justify the effectiveness of the proposed mechanism. That recurrent in the deep networks has recorded an excellent prediction outcome. Finally, recommendation and future work direction has been studied.

The DR has tended to cause multiple diseases, so Modjtahedi et al. [30] have described the risk of cerebrovascular for DR patients. Here, the cerebrovascular DR patient data has been considered. This study is mainly about the prediction of future cerebrovascular risk. Moreover, the neural mechanism with imaging models was considered; those models required enormous resources and recorded high design complexity. Sikder et al. [31] have introduced the intelligent Binary Transfer -learning Model (BTM) to improve the database training and testing process. In addition, the binary classification features in the transfer learning were afforded the finest classification outcome. Hence, the binary classification has reduced the risk percentage in specifying the DR types. However, this model is not suitable for all fundus images. To incorporate the additional features in the DR prediction system, Rehman et al. [32] have introduced an optimal self-Organized Vector Approach (SVA) for analyzing the features more exactly. It has recorded a high DR forecasting exactness score. However, it has required more time for the training and testing process. Bhandari et al. [20] have designed the Kernel-Fisher Network (KN) to frame the automatic DR prediction framework by incorporating multi-imaging features. Here, the fisher functioning process in the kernel function has afforded a flexible score in predicting the DR from all types of DR images. However, this model is not suitable for other imaging applications. An automated tumour detection system was introduced by Jena et al. [33] using the Convolutional neural model. Here, the Max pooling features provided the most satisfactory feature analysis outcome for screening the diabetic features. Finally, the Convolutional neural robustness is validated with other recent associated works. In that, the finest feature analysis outcomes were gained. However, it is poor in prediction performance.

Purna Chandra Reddy and Gurrala [34] have implemented deep network features for classifying the DR types by making the proper feature analysis outcome. Hence, these deep network features are good for predicting the DR classification. But, it has recorded poor segmentation outcomes.

Wang et al. [35] implemented a contextual net to analyze the DR lesion segment with a high accuracy rate. In addition, supervision features were incorporated with the contextual net to avoid overfitting occurrences. Here, the performance of this contextual supervision model is analyzed through the fundus database; the exact prediction was reported but poor in severity classification.

Hence, by the discussed literature, finding the DR is the most required task for digital medical processing. Hence, several intelligent models were attracted to analyze the DR features in the retinal fundus images. But in many the raw data contains a high amount of noise features that might affect the prediction system. Considering these models, deep, intelligent models were introduced for forecasting the DR with a high exactness score. That summary is defined by Table 1. Besides, it has required more efficient features for filtering the noise variables and maximizing the resource cost.

Table 1 Summary of related works

Overview of discussed literatures			
Authors	**Methods**	**merits**	**Demerits**
Tang et al. [26]	ResNet	It provided the finest feature analysis outcome	Because of oversampling, the segmentation accuracy is too weak.
Sevgi et al. [27]	vascular feature analysis	Less prediction error rate was recorded	An additional filtering model is required to filter the noisy features.
Campbell et al. [28]	Multivariate regression	Here, the pixel analysis is sufficient for identifying the disease region	It has needed more time to execute the process
Kaur et al. [29]	Optimized deep network	High in prediction outcome	It is poor in the segmentation process. Hence this model required an additional segmentation scheme
Modjtahedi et al. [30]	Imaging neural system	The severity level was predicted at each different stages	High design complexity was recorded
Sikder et al. [31]	BTM	The DR classification is good	It is not apt for all types of fundus images
Rehman et al. [32]	SVA	Disease affected region was forecasted exactly	It has reported a high time complexity score.
Bhandari et al. [20]	KN	A high prediction score was reported	Only trained features are predicted during the testing process.
Jena et al. [33]	The automated tumour detection system	It has extracted the possible meaningful features	The prediction of disease types is not accurate
Purna Chandra Reddy and Gurrala [34]	the deep network features prediction system	It was attained the exact classification outcome	Poor segmentation score was reported
Wang et al. [35]	Contextual net	It has earned a high disease prediction accuracy rate	It has reported poor severity analysis outcome

Furthermore, poor disease tracking and segmentation have recorded poor severity analysis. Hence, the disease tracking and segmentation function has been tuned to earn the finest severity analysis score to gain the proper severity analysis. These issues have motivated designing optimized intelligent boosting models for forecasting the DR. The proposed solution is significant in proper disease region forecasting and segmentation, which will gain an accurate severity analysis outcome. This will help medical researchers to investigate the disease stage more accurately.

The key contribution of this proposed work is described in the way,

- Initially, the disease-affected Fundus images APTOS dataset was trained to the system; it contains typical healthy and DR fundus images.
- Moreover, a novel SSbEB was designed with the required feature analysis variables.
- Then, the filtering process was carried out by performing the preprocessing function with boosting parameters.
- Henceforth, the refined data is imported to the classification phase to analyze the features and the segmentation.
- Subsequently, the DR region was segmented, the severity range was analyzed based on normal, mild, moderate, severe, and proliferative stages**,** and the prediction performance was measured in terms of error rate, recall, precision, accuracy, and F-score.

The present study is arranged in the order of, the first section illustrates the background, recent related studies and problems of the conventional DR severity analysis system. Moreover, the solution to the described problem is defined in the second section. Performance outcome with justification is exposed in the Third section. The comparison discussion is elaborated in section 4, and the 5th section concludes this research chapter.

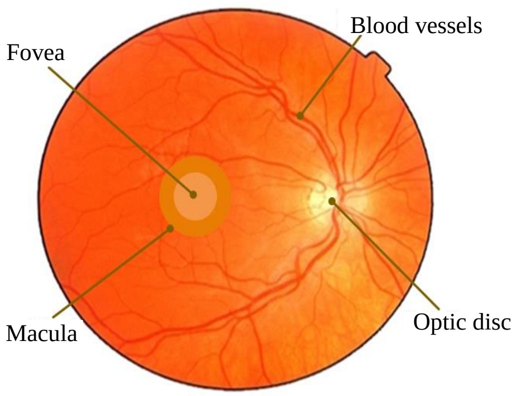


Figure 1 Fundus image

2. Proposed SSbEB for DR segmentation and severity estimation

A novel squirrel search-based Extreme Boosting (SSbEB) has been planned to implement this research study to identify the DR and measure the severity classes, such as normal, mild, moderate, severe, and proliferative stages. Here, the boosting parameters have afforded the finest error-removing outcome that has reduced the algorithm complexity in detecting the DR. Here; the squirrel fitness has enhanced the feature tracking and segmentation outcome. Moreover, the DR has been segmented, and the severity score has been measured. Finally, the DR prediction and severity estimation exactness was analyzed based on the performance metrics, F-score, accuracy, precision, recall, and error rate. The proposed architecture is described in Figure 2. It shows the proper, efficient execution steps to attain the finest severity analysis outcome. Here, the filtering process is executed in the novel SSbEB hidden layer. Hence, the novel SSbEB was accomplished after training DR fundus images, and the filtering function was performed at the primary phase. Henceforth, the filtered data is given to the classification layer as the input then the feature analysis process is performed to extract the required features. Then the disease regions were predicted, and the segmentation function was performed. Finally, the severity levels were predicted, and the robustness was measured.

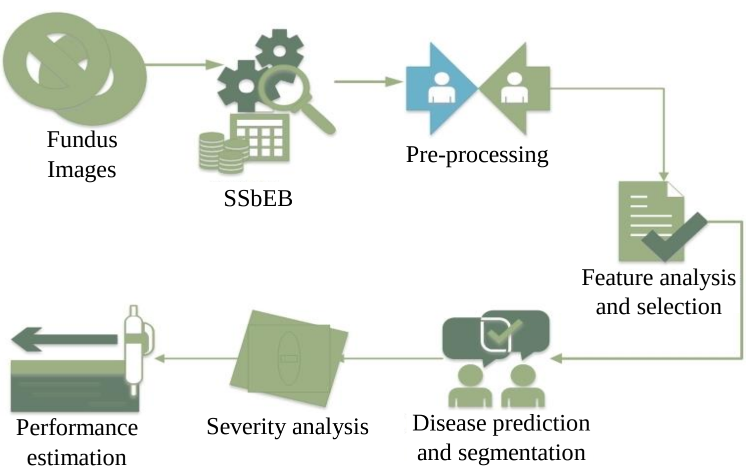


Figure 2 Proposed SSbEB for DR severity estimation

Besides, the need for the designed model in the DR severity analysis has been verified by comparing the outcome of the designed model with recent existing techniques. The key significance of the proposed design is that it helps to find the severity level in the maximum possible accuracy rate, which is beneficial for doctors for treating the disease in its early stages.

2.1 Proposed SSbEB working functions

The presented solution framework has five different layers such as data importing, preprocessing, features analysis, optimal, and an output layer that is figured in Figure 3. Here, the data training process has been executed in the input layer. The noise filtering process was performed in the hidden layers, then features extraction and Severity finding function in the classification phase of the SSbEB.

$$F(D) = D\{1,2,3,4,5\ldots\ldots n\} \tag{1}$$

Here, D represents the dataset, $F(D)$ denotes the training variable, and $1,2,3,4,5\ldots\ldots n$ represents the n number of data.

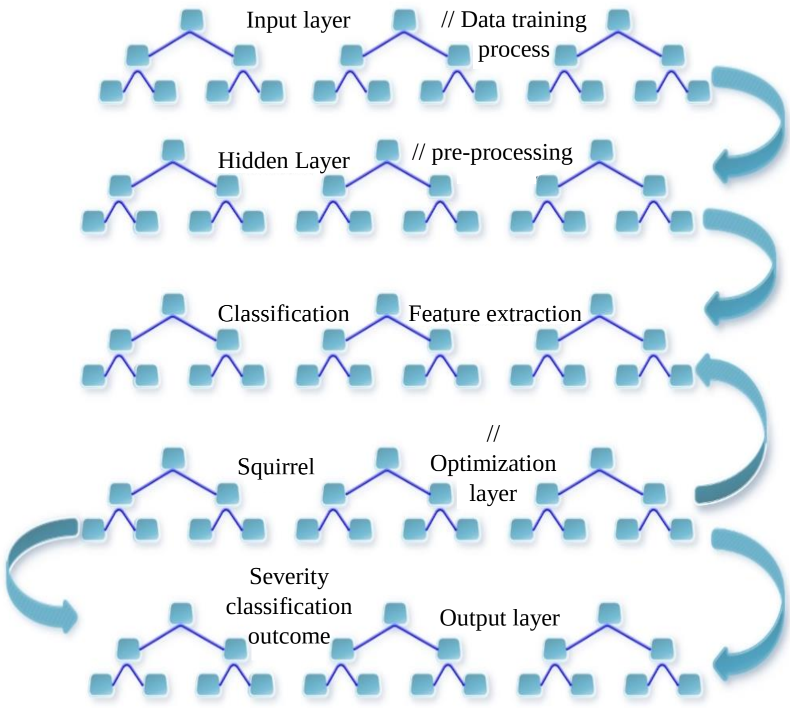


Figure 3 Layers of a novel SSbEB

Besides, the proposed DR prediction and severity estimation system is processed based on the Extreme boost intelligent model [36] and squirrel algorithm [37]. To gain the finest severity specification outcome, the fitness function of the squirrel is given in the classification phase of the boosting model to tune the classification features that have gained the correct severity estimation outcome. Several intelligent models like deep networks and machine learning models are available for the mathematical complex problem for performing detection and analysis. However, those models are limited by the boosting parameters, so the filtering process was inadequate for filtering the highly noisy images. Considering these limitations, the extreme boosting models were considered for this work. In addition, several bio-inspired optimizations are executed for imaging applications to analyze the imaging features at more possible rates. But, only the squirrel optimization is considered for this work because of their best solution. The seed fruit tree is the best solution for this squirrel optimization. Here, that function is utilized to find the DR-affected area in the fundus images. In addition, updating the squirrel fitness in the boosting intelligent model is the key novelty of this work. Before, no work was conducted for combining the Extreme boost intelligent model and the squirrel algorithm for the DR segmentation and severity analysis applications.

2.1.1 Preprocessing

The filtering process is the major function of the neural networks and imaging application to reduce the overfitting issues and to maximize the DR forecasting exactness score. Moreover, it has optimized the computational time and resource usage; hence, the preprocessing function was processed by eqn. (2).

$$H(D) = \frac{1}{2}D(y - e) \tag{2}$$

The preprocessing variable is determined as H, all raw databases contain normal and noise features. Hence, the noise features were represented as e, and the normal features are determined as y. By performing the eqn. (2) the noise features were eliminated from the trained database. In addition, RGB gray preprocessing packages were used to execute this noise-filtering process. In addition, the kernel function is processed with the Open CV package for de-noising the imported images. Hence, the image features are presented in the matrix form based on the present features like normal features, noisy features, and high pixel range features. After analysis, the noisy features were eliminated based on the kernel module. Hence, the total number of images considered for this work is 3662. The noise features in all imported images were analyzed and removed during preprocessing. Then finally, the RGB images were changed to the gray form.

2.1.2 Feature analysis

To find the severity score of the predicted DR, the maximum level of present features was extracted using eqn. (3). Here v is the meaningless feature removed in this feature extraction function.

$$L = D(g_{max} - v) \tag{3}$$

The maximum related features in the fundus image are represented as g_{max}, and the feature extraction function is defined as L. Here, the features analysis function has been performed with the help of the squirrel fitness.

2.1.3 Disease prediction and segmentation

The trained database contains both normal and disease-affected images. Hence, the disease forecasting function has been performed to predict the abnormal DR and normal retina. The segmentation process has been performed to find the affected region and segment them. This disease prediction formulation is attained from the squirrel searching fitness equated in eqn. (4).

$$J = \begin{cases} if(L = 0) & normal \\ else & DR \end{cases} \tag{4}$$

Here, the disease prediction variable is represented as j. If the extracted features are equal to 1, it is recognized as DR. if the extracted feature count is 0, then it is normal.

2.1.4 Segmentation and severity calculation

The segmentation process has functioned based on squirrel searching fitness. Here, that function is utilized to track and segment the affected region. Hence, incorporating the segmentation function in the severity validation objective has reduced resource usage and algorithm design complexity.

$$Z = T[J \neq (0) - j(0)] \tag{5}$$

From the disease prediction function, 0 is the normal feature. Hence, finding the exact disease-affected region T is utilized as the tracking variable and Z represents the segmentation parameter. If the $J \neq (0)$, then that region is segmented, the mathematical segmentation description is exposed in eqn. (5).

$$S_c = \begin{cases} if(Z = 1) & mild \\ if(Z = 2) & moderate \\ if(Z = 3) & severe \\ if(Z = 4) & \text{Proliferative DR} \end{cases} \tag{6}$$

After segmenting the affected region, the Severity of the DR was classified under four categories such as mild, moderate, severe, and Proliferative DR. Hence, the Classification condition is defined in eqn. (6).

Algorithm 1: SSbEB

```
Start
{
int F(D)=1,2,3,…n;
// dataset initialization
    Preprocessing ()
    {
        int H, y, e
        //preprocessing variables were initialized
        enable → B
        // here, B is the boosting parameters
        B(H) → filter(D)
        // noise filtering has been performed by eqn. (2)
    }
    Feature Analysis ()
    {
        int L, gmax, v;
        // initiating feature extraction variables
        Extract = gmax(D)
        // extracting the required meaningful features
    }
    DR prediction ()
    {
        int J;
        if(L = 0)
```

```
        {
        Normal
        }else (DR)
    }
    Segmentation ()
    {
        int Z, T;
        // segmentation parameters were initialized
        affected region = J ≠ 0(segment)
        // Affected region was segmented
    }
    Severity estimation ()
    {
        if(Z=1)
        {
        Mild
        }
        if(Z=2)
        {
        Moderate
        }
        if(Z=3)
        {
        Severe
        }
        if(Z=4)
        {
        Proliferative DR
        } else (normal)
        // Severity classification condition checking using eqn. (9)
      }
}
Stop
```

The working flow of the built model is defined in Figure 4 and algorithm 1. Hence, the key novelty of this work is to improve the disease severity classification outcome. Here, the finest outcome has been gained by tuning the boosting parameters by the squirrel searching function.

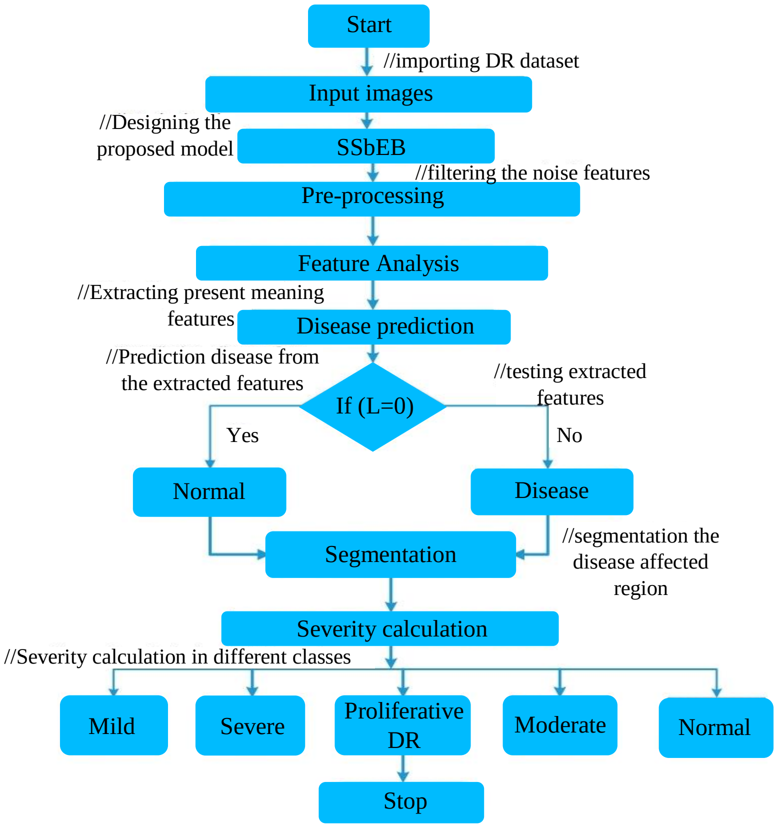


Figure 4 Overall Work process of SSbEB

3. Results

The introduced model is texted in the python framework and processed in the windows 10 platform. Initially, the fundus images were trained to the system that contains healthy fundus and abnormal fundus. Initially, the noise features were eliminated in the preprocessing phase, then the retinal features were identified, and segmentation was performed. Henceforth, the DR types have been classified, and the severity level has been noted. The execution parameter specification is defined in Table 2.

Table 2 Execution parameter specification

Programming specification	
Programming tool	Python 3.10
Operating system	Windows 10
Dataset	Fundus images (Diabetic retinopathy)
Training model	XGboost
Optimization	Squirrel algorithm

Table 3 Dataset Description: training and testing

Database description	
Specification	**Images count**
Total images	3662
Training images	2929
Testing images	733
Normal	1805
Mild	370
Moderate	999
Severe	193
Proliferate	295

The dataset considered in this present research work is diabetic retinopathy from the kaggle site; it contains 3662 images. Here, the images taken for testing are 733, and the images used for training are 2929. Hence, this study's training and testing ratio are 80:20, i.e., 80% training and 20% testing. The Dataset Description is defined in Table 3.

3.1 Case study

This case study has been conducted to check the working process of the designed mechanism; a few testing outcomes were discussed. In this study, the severity analysis exactness has been described based on the exact segmentation score. Moreover, the training testing ratio of the present study is 80% training and 20% testing.

The testing function has been validated for the five classes described in Table 4. Moreover, the five severity classes are normal, severe, mild, moderate, and Proliferative DR.

The normal retina images were trained to prove that the presented model was working properly, and the testing process was performed, defined in Table 3 normal rows. It indicates the tracking outcome, but no tracking outcomes were obtained because there are no disease features.

Table 4 Testing validation

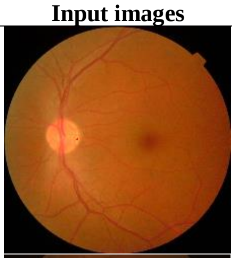
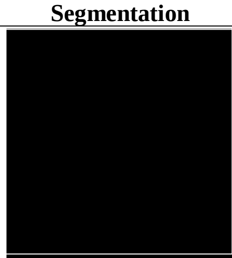
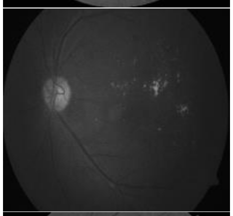
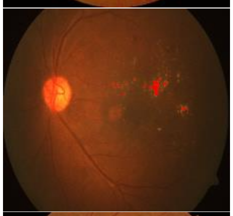
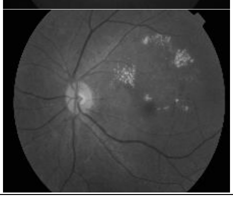
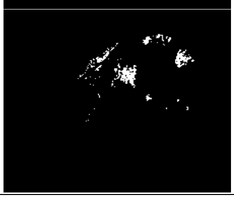
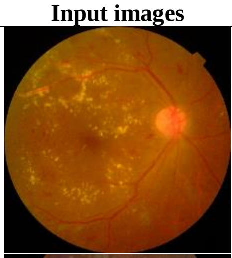
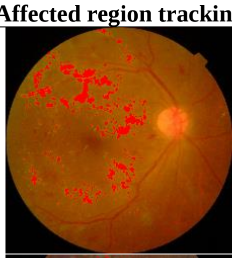
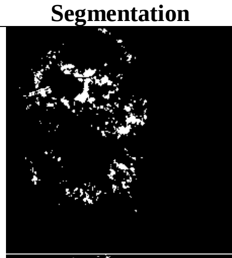
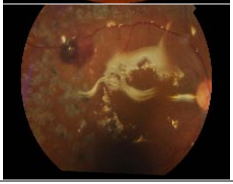
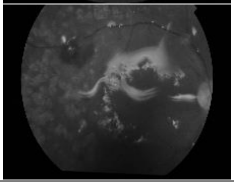
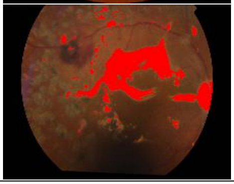
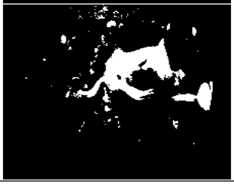
Disease types	**Input images**	**Preprocessed image**	**Affected region tracking**	**Segmentation**
Normal				
Mild				
Moderate				

Table 4 (continued) Testing validation

Disease types	Input images	Preprocessed image	Affected region tracking	Segmentation
Severe				
Proliferative				

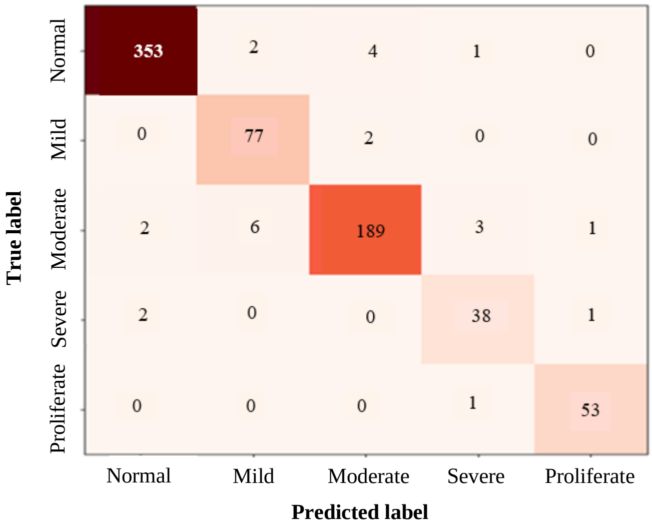


Figure 5 Confusion matrix

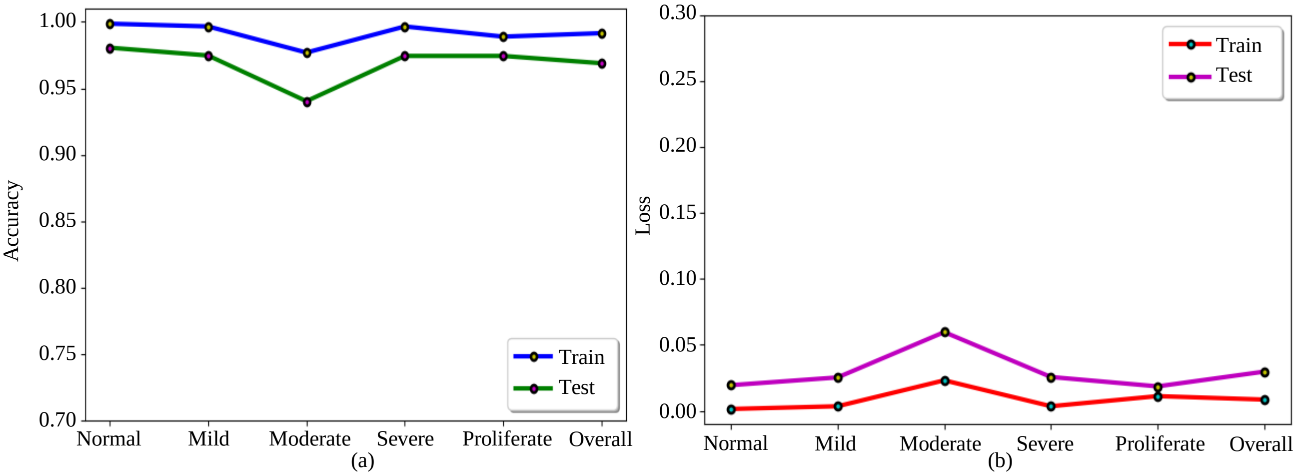


Figure 6 Training performance: a) training accuracy, b) training loss

The performance parameters have to be measured to measure the segmentation and Severity calculation efficiency. Hence, for measuring the performance parameters, the confusion matrices were drawn in Figure 5.

Here, the training accuracy graph almost reaches the full exactness score, which is 100%. It has exposed that the implemented model is capable of the disease classification and severity analysis framework. Also, the less error score has described the exact DR prediction in all stages. The details are graphically described in Figure 6. Moreover, the performance analysis based on different disease types is defined in Table 5.

Moreover, the training and testing performance was measured in accuracy and loss. Normal 360 testing cases, Mild 79 testing cases, 101 testing cases, severe 41 cases for testing, and proliferate 54 testing cases. Those testing results statistics are defined in Table 6.

Table 5 Disease type-based performance analysis

Disease parameters	Accuracy	Precision	Recall	F-measure	Specificity
No DR	94.3%	97%	94%	95%	99.1%
Mild	97.1%	92%	97%	94%	98%
Moderate	89.9%	94%	88%	91%	98.3%
Severe	100%	97%	99%	98%	99.3%
Proliferate DR	98.8%	97%	99%	98%	99.3%

Table 6 Training and testing specification of specific disease cases

Disease parameters	Training accuracy	Training loss	Testing accuracy	Testing loss (error rate)
No DR	99.8%	0. 13%	94.3%	5.6%
Mild	99.5%	0. 48%	97.1%	2.8%
Moderate	97.9%	2%	89.9%	10%
Severe	100%	0%	100%	0%
Proliferate DR	98.8%	1.1%	98.8%	1.13%

4. Discussion

To find the improvement score of the proposed design compared to another existing mechanism, some recent approaches were considered that are Support Vector approach (SVA), Kernel Neighbours (KN) [38], Convolutional Neural Model (CNM), Recurrent Neural Approach (RNA) [39] and Binary Tree Model (BTM). For the severity analysis framework, proper segmentation is the much needed task. Hence, metrics like sensitivity, specificity, accuracy, error rate, precision and F-measure were considered to measure the segmentation exactness scores.

4.1 Accuracy and Recall

To measure exact severity estimation, the performance parameter accuracy was validated. Hence, this metric accuracy is based on the summation of all true and false values. If the model has recorded the best severity classification exactness score, then that model is good in the segmentation process. The right segmentation was afforded the finest severity specification outcome.

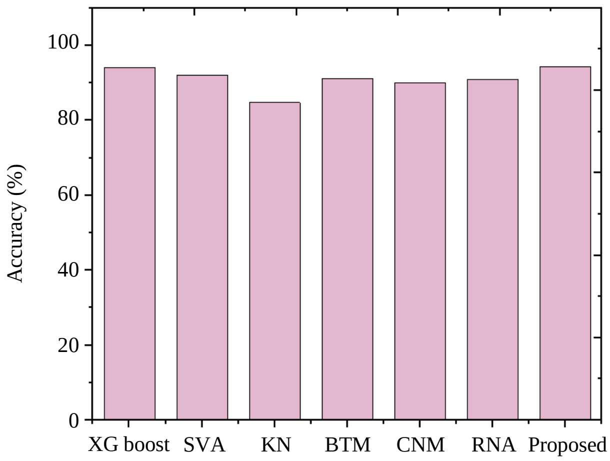


Figure 7 Assessment of Accuracy

$$Accuracy = \frac{TN+TP}{TN+TP+FN+FP} \quad (7)$$

Here, the accuracy was determined based on the correct severity estimation from the total images. Moreover, the class metrics like True Negative (TN), false Negative (FN), True positive (TP), and False Positive (FP) scores were utilized to find the exactness value. Hence, the parameter accuracy is defined using eqn. (7). These statistics are graphically represented in Figure 7.

4.2 Recall assessment

The recall metric was measured to find the introduced model's scalability. Here, the recall is measured in the vision of positive and negative scores. For imaging applications, recall is the chief parameter. Also, it is called a sensitive score.

$$\mathrm{Re}call = \frac{TP}{FN+TP} \quad (8)$$

Here, the recall is measured on the basis of the positive scores with the mean of negative values, which is exposed in eqn. (8).

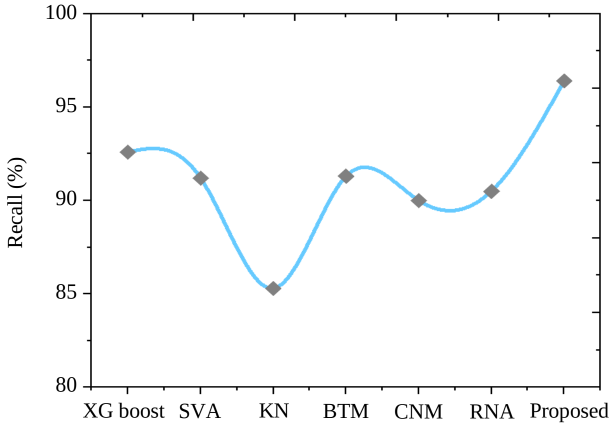


Figure 8 Recall validation

The gained maximum sensitivity score by the designed scheme is 96.4%, which is exposed in Figure 8. Moreover, the presented novel SSbEB recorded the maximum recall than the other models.

4.3 Precision and sensitivity

The precision parameters were applied to find the recorded positive scores for the DR classification. Gaining a high precision score has verified the exact DR tracking and classification. Hence, the precision score is formulated in eqn. (9). Besides, the specificity was measured to find all the negative scores with the mean of FP, which is described in eqn. (10). The recorded precision and specificity of the designed model is 98%.

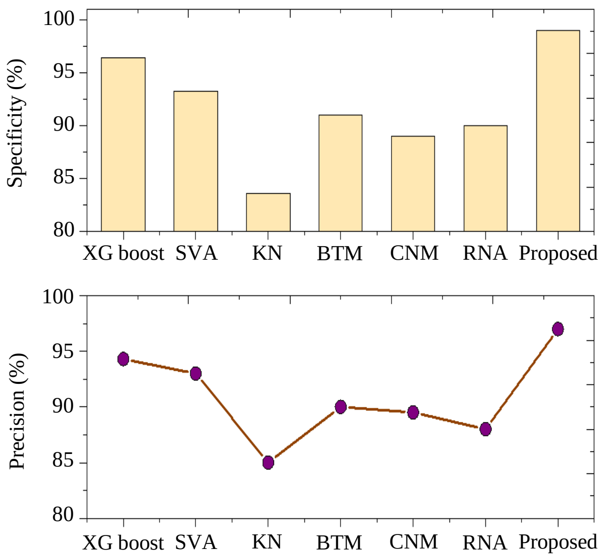


Figure 9 Specificity and Precision

Hence, the precision and specificity metrics were calculated to find the attained difference score between the positive and negative scores.

$$Precision = \frac{TP}{FP+TP} \quad (9)$$

$$Specificity = \frac{TN}{FP+TN} \quad (10)$$

The precision and specificity comparison validation between SVA, KN, CNM, RNA and BTM with a proposed model is defined in Figure 9. For the proposed model, the specificity and precision have recorded a similar score of 98%, indicating the proposed framework's proper working function.

4.4 F-measure validation

The F-score parameters have been considered to find the average performance of the executed model. It gives the outcome of recall and precision mean value, which means the intersection of positive and negative scores for the DR classification. Hence, the F-score is equated in eqn. (11).

$$F\_Value = 2 \times \frac{Recall \times precision}{Recall+precision} \quad (11)$$

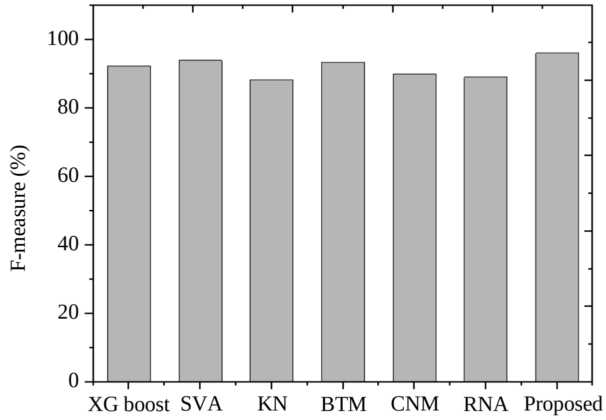


Figure 10 Assessment of F-score

The proposed framework has scored the maximum F-score of 96%. Compared to the existing models, the proposed model has recorded the finest F-value of the other models, exposed in Figure 10.

The error score was measured and compared with past studies to justify the efficient working of the proposed model. In that, the novel SSbEB recorded a misclassification score is 4.5%. It shows that the misclassification score has been reduced considerably, which is exposed in Figure 11. Also, in many cases, all the DR images were the same, which tended to gain a 4.5% of error score; this error validation is shown in Table 6.

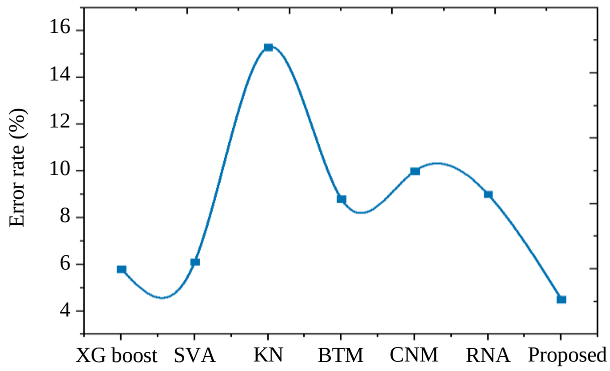


Figure 11 Error rate validation

The performance evaluation has proved the effectiveness and need of the introduced model for digital imaging applications, especially in the medical field. Moreover, the performance exactness of the designed novel SSbEB is validated by calculating the error score. Here, the error score is defined as the wrong DR classification or miss classification. Hence, the designed mechanism has achieved less prediction miss classification score. The overall performance is described in Table 7. To check the accurate performance improvement score of the proposed model, the XG boost, (SVA), Kernel Neighbours (KN), Binary Tree Model (BTM) [38], CNM and RNA [39] models were considered and compared with each other. This result has verified the need for the optimization features in XG boost.

Table 7 Overall Performance assessments

			Robustness validation				
Performance metrics	**Proposed**	**XG boost**	**SVA**	**KN**	**BTM**	**CNM**	**RNA**
Accuracy	94.4	93.2	92	84.7	91.2	90	91
Precision	97	94.3	93	85	90	89.5	88
Specificity	99	96.4	93.28	83.6	91	89	90
Sensitivity	96.4	92.6	91.2	85.3	91.3	90	90.5
F-score	96	92.3	93.9	88.3	93.4	90	89
Error rate	4.5	5.8	6.1	15.3	8.8	10	9
Time (ms)	10	28	41	55	34	30	20

In addition, the time complexity is also measured and validated with other models. The novel SSbEB scored less time as 10ms, which is quite less than the compared models. Also, the presented model is more sufficient for DR prediction and severity classification. Hence, the improved severity classification is reported more than the compared models.

It has been verified that the designed model has sufficient features for predicting diabetic retinopathy in the trained fundus images. Hence, the proposed framework is the required digital medical imaging application mechanism.

5. Conclusion

A novel SSbEB has been implemented for this present research work to enrich the severity classification. Moreover, to obtain the exact severity analysis outcome, the squirrel fitness tracked the disease-affected part, which is considered the key novelty module of this present research study. Hence, the disease tracking iteration has repeated continuously till it attains the finest tracking outcome. Moreover, the presented model has maximized the severity estimation exactness score by 3%. Also, the specificity, F-score and recall score is improved by 3%. Moreover, the time requirement of the proposed model is validated to measure the time complexity range; the recorded time complexity is 10ms, and the recorded miss classification rate is 4.5%. Hence, these outstanding results within less computation time and error rate have verified the requirement of the designed model for the DR detection application. However, some DR image databases needed more features for detecting the present DR types and Severity. In the future, implementing the deep network and an optimized boosting model will offer additional features for analyzing all DR fundus images.

6. References

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