



Article Automatic Detection and Classification of Diabetic Retinopathy Using the Improved Pooling Function in the Convolution Neural Network

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Abstract: Diabetic retinopathy (DR) is an eye disease associated with diabetes that can lead to blindness. Early diagnosis is critical to ensure that patients with diabetes are not affected by blindness. Deep learning plays an important role in diagnosing diabetes, reducing the human effort to diagnose and classify diabetic and non-diabetic patients. The main objective of this study was to provide an improved convolution neural network (CNN) model for automatic DR diagnosis from fundus images. The pooling function increases the receptive field of convolution kernels over layers. It reduces computational complexity and memory requirements because it reduces the resolution of feature maps while preserving the essential characteristics required for subsequent layer processing. In this study, an improved pooling function combined with an activation function in the ResNet-50 model was applied to the retina images in autonomous lesion detection with reduced loss and processing time. The improved ResNet-50 model was trained and tested over the two datasets (i.e., APTOS and Kaggle). The proposed model achieved an accuracy of 98.32% for APTOS and 98.71% for Kaggle datasets. It is proven that the proposed model has produced greater accuracy when compared to their state-of-the-art work in diagnosing DR with retinal fundus images.

Keywords: CNN; diabetic retinopathy; fundus image; pooling function

1. Introduction

Glucose in the body is converted into energy, which helps with everyday tasks. Diabetes is caused by obesity, poor nutrition, and limited physical activity. However, elevated blood glucose can build up in the blood vessels of several human organs, including the eye. People who have had diabetes for over a decade have the chance of getting diabetic retinopathy (DR) [1]. Globally, the population suffering from diabetes is expected to reach 552 million by 2030 [2]. Preventing visual loss is possible with early detection and sufficient treatment [3]. DR consists of five classes—no DR, mild, moderate, severe, and proliferative.

DR can affect blood vessels, in severe cases damaging, enlarging, or blocking them, or causing leaks; the abnormal growth of blood vessels can cause total blindness. Microaneurysms, haemorrhages, and exudates are the major signs of retinal DR. The level of the disease can be identified based on the shape, size, and overall appearance of the lesions. The main benefits of DR screening are its high effectiveness, low cost and minimal reliance on clinicians (i.e., ophthalmologists). The global eye screening tool for DR is the fundus photograph [4]. To prevent diabetes-related blindness, automated screening allows for clinically convenient and cost-effective detection [5].

From the field of computer science, deep learning can be a practical approach to automatic DR detection [6]. A deep learning system automatically identifies the DR with



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Copyright: © 2023 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (https:// creativecommons.org/licenses/by/ 4.0/). an accuracy that is equal to or better than that of ophthalmologists. The core deep learning model for medical image diagnosis prediction, and classification is the convolution neural network (CNN). However, there is the possibility to improve the performance of the model by tuning the hyperparameters in these deep learning-based models.

CNN models AlexNet and VGGNet-16 have been implemented for this purpose and the results suggest that VGG-19 performs best; however, the DR stages have not been explicitly ranked [7]. A hybrid technique incorporating image processing and deep learning was proposed for the detection and classification of DR in the publicly available dataset MESSIDOR, and Histogram Equalization (HE) and Contrast Limited Adaptive Histogram Equalization (CLAHE) were implemented to improve the contrast of the image [8]. Other CNN models, like Inception V3, Dense 121, Xception, Dense 169, and ResNet 50, have been explored for the enhanced classification of different DR phases [9].

In another study, the authors proposed a framework with a new loss function by implementing mid-level representations to improve DR detection performance [10]. Another report proved that VGGNet produced higher accuracy compared with other CNN models such as AlexNet, GoogleNet, and ResNet for DR classification [11]. A CNN model implementation with data augmentation for DR image classification was presented in [12].

Other frameworks for the early diagnosis and classification of DR were presented for Grampian [13], MESSIDOR [14], and EYEPACS datasets [15]. In [16], the authors mentioned that 90% of accuracy was achieved in diagnosing microaneurysms and extracting and classifying the candidate lesions. All of these existing studies have implemented built-in hyperparameters. However, model performance can be improved by adjusting hyperparameters within deep learning models. To counter the self-strengthening trend and ensure that as many candidate component models as possible have been properly trained, we have added balance loss to our model. The proposed approach could extract key features from the fundus images that can help make an accurate DR diagnosis.

2. Materials and Methods

The objective of the current study was to accurately categorize DR fundus images into different severities. We discussed an automated system for assessing the seriousness of diabetic retinopathy. The classification accuracy for diabetic retinopathy was improved in the current research using a modified CNN architecture. Figure 1 illustrates the proposed framework.

2.1. Dataset Collection

We collected the dataset from two publicly available fundus image datasets, i.e., AP-TOS [17] and Kaggle [18]. Table 1 tabulates the count for five categories in APTOS and Kaggle datasets. Figure 2 shows the sample fundus images from the two datasets. The first-row fundus images are from APTOS and the second-row fundus images are from the Kaggle dataset.

Dataset	NODR	Mild DR	Moderate DR	Severe DR	PDR	Count
APTOS	1805	370	999	193	295	3662
Kaggle	25,810	2443	5292	873	708	35,126

We employed data augmentation to increase the number of images throughout the training sample. Once provided with more DR to learn from, DL approaches generally improve their performance. Overfitting is avoided and the imbalance in the dataset is corrected by the application of data augmentation. Horizontal shift augmentation was one of the transformations considered for this study; it involves horizontally shifting an image's pixels while maintaining the original image's perspective. The dimension of this transition is specified by a number ranging from 0 to 1 and the viewing angle of the original image is

preserved. The image can also be rotated with an additional type of transformation by a random amount between 0 and 180 degrees. By employing data augmentation methods, we were able to fix the problem of varying sample sizes and convoluted categorizations. After augmentation, the APTOS dataset classes were evenly distributed for the training set—1805 for NODR, 1850 for Mid, 1988 for Moderate, 1737 for Severe, and 1770 for PDR. After augmentation, the Kaggle dataset classes were evenly distributed for the training set—25,810 for NODR, 24,430 for Mid, 26,460 for Moderate, 25,317 for Severe, and 25,488 for PDR. Figure 3 shows some of the augmentation operations followed in this study. Table 2 tabulates the statistics of the data augmentation operations and the final augmented fundus images of each dataset.



Figure 1. Experimental framework.



Figure 2. Multiclass of DR (**a**) NODR, (**b**) Mild DR, (**c**) Moderate DR, (**d**) Severe DR, and (**e**) PDR. (First row—APTOS dataset, second row—Kaggle dataset).



Figure 3. Augmentation (a) Original image, (b) rotation, (c) horizontal flip, (d) brightness, (e) contrast.

Table 2. Dataset augmentation operations.

	APTOS			Kaggle			
Class -	Original	Operations	Augmented	Original	Operations	Augmented	
NoDR	1805	0	1805	25,810	0	25,810	
MildDR	370	5	1850	2443	10	24,430	
Moderate DR	999	2	1998	5292	5	26,460	
Severe DR	193	9	1737	873	29	25,317	
PDR	295	6	1770	708	36	25,488	
Total	3662		9160	35,126		127,505	

2.2. Pre-Processing

In this study, we implemented the enhanced artificial bee colony (ABC) algorithm to improve the lesions' visual contents. Consider $\xi(i, j) \in D$ with dimensions PXQ, where the values of P, Q are taken as 512 for every image in the database D.

The mathematical representation of the transformation function,

$$\Xi_{\rm f} = \frac{1}{\int_0^1 x^{(c-1)} (1-x)^{d-1} dx} X \int_0^v x^{(c-1)} (1-x)^{d-1} dx, \tag{1}$$

where x is an integration variable and c and d are adjustable parameters of a given function where the maximum value of c is compared with d.

We evaluated the fitness function to adjust the values of c and d and also to measure the complete lesion image.

$$\mathbf{F}(\xi_H(\mathbf{i},\mathbf{j})) = \log(\log(\sum_{j=1}(\Psi))) M_{\Psi} E(\xi_H) Y(\xi_H),$$
(2)

where $\sum_{j=1} (\Psi)$ represents the total edge intensities of an image evaluated through a canny edge detector. $Y(\xi_H)$ represents the contrast of the image $\xi_H(i, j)$, M_{Ψ} represents the total edge pixels of the processed image, and $E(\xi_H)$ represents the image entropy $\xi_H(i, j)$, represented as:

$$E(\xi_H) = \sum_{j=0}^{m} q_i log_2(q_i),$$
(3)

where q_i represents the ith pixel intensity probability; the max value is 255.

The contrast of the image is represented as:

$$Y(\xi_H) = \sum_{j=0}^{mI} Y(\xi_H)(I_i),$$
(4)

where I_i represents the image blocks and mI represents the mth image block.

The contrasted local band of each block is represented as:

$$\begin{aligned} \xi_{Hy}(I_i) &= \sum_{\substack{(p,q) \in I}} Y(\xi_H)(p,q) \\ &= \sum_{\substack{(p,q) \in I}} \frac{\xi_H(p,q) \otimes \phi_b}{\xi_H(p,q) \otimes \phi_c}, \end{aligned}$$
(5)

where *p*, *q* represents the pixels of the rows and columns of each block, ϕ_b represents the bandpass filter, and ϕ_c represents the low pass filter.

2.3. Enhanced ResNet-50

The proposed model consists of convolution blocks and includes the improved pooling function, a drop-out layer, dense layers, and a SoftMax classification layer; Figure 4 presents the improved ResNet-50 model.



Figure 4. Improved ResNet-50 model.

Convolution Layer: The convolutional block is the fundamental building component, and each convolution block contains a convolution 2D, an improved activation function, and improved pooling with the average value. The vanishing gradient issue is solved using the improved activation function, simplifying the process so the network can understand and carry out its tasks promptly.

Kernel: The model's initial layer is the convolution layer. This layer initiates the process by applying the filters, also known as the kernel. The kernel size depends on two values—the width and height of the filter. In this study, we set the size of the filter as 3.

This filter enables and identifies the features that help understand low-level visual aspects like edges and curves.

Flattened layer: The flattened layer is located among the convolution and the dense layers. Tensor datatypes are used as inputs for the convolution layers, whereas dense layers demand a one-dimensional layout. The flattened layer was applied to translate the two-dimensional image representation into a one-dimensional input.

Dropout Layer: A dropout value of 0.2 was used in this study, which helps to avoid overfitting. This layer's function was to turn various components on and off to reduce the model's complexity and training time. The model thus acquires all the features that are required.

Dense Layer: A single matrix is accepted as input by the dense layer, which produces output based on the characteristics of the matrix. The identification and class labelling of fundus images occurs in these layers. The model's output is produced by a dense layer with five neurons and an improved activation function, and it assigns the image to one of five categories of diabetes: NoDR, Mild, Moderate, Severe, or Proliferative. After a few layers, the proposed activation is applied; this probability-based activation function measures the number of neurons by the entire number of classes.

Pooling function: The pooling function in the CNN is primarily used to downsample the feature maps and learn deeper image features that are resilient to subtle local alterations. The features from each spatial region are aggregated in this process. Pooling not only expands the receptive field of convolutional kernels across layers but also reduces memory needs and computational complexity by lowering the resolution of the feature maps while keeping critical features required for processing by the following layers. Pooling can be used in medical image analysis to manage variations in lesion sizes and positions [19,20]. Fundus images frequently have many lesions or parts, which causes their distributions of convolutional activations to be exceedingly complex since unimodal distributions cannot adequately capture statistics of convolutional activations, which limits the CNN performance.

We first pass *Y* throughout a group of prediction layers with parameters θ_p , i.e., $c(\theta_p; Y)$. The weights are outputted throughout by using a fully connected layer with additional noise.

The improved pooling function is presented as:

$$F_k(c(\theta_p;Y)) = T_k^h C(\theta_p;Y) + \sqrt{\delta \log(1 + \exp(T_k^m C(\theta_p;Y)))},$$
(6)

where T_k^h and T_k^m are the fully connected layers, the kth parameter and additional noise, δ is the random variable, $C(\theta_p; Y)$ are the learned weights, and the weight function can be represented as:

$$w_k(Y) = \sqrt{\frac{exp(TOP - Q(F_k(c(\theta_p; Y))))}{\sum_{k=1}^m exp(TOP - Q(F_k(c(\theta_p; Y))))}},$$
(7)

where *TOP-Q* are the *Q* largest weights.

To make learned weights sparse, we maintained the *TOP-Q* weights and set the remaining ones as negative infinity and we used the improved activation function to normalize all the weights.

We added extra loss using the learned weights:

$$L_{s} = 3\sqrt{\beta\left(\frac{S\left(\sum_{s=1}^{N} w_{k}(Y_{s})\right)}{M\left(\sum_{s=1}^{N} w_{k}(Y_{s})\right)}\right)},$$
(8)

where Y_s is the mini-batch training sample, *S* and *M* are the standard deviation and the mean, and β is the parameter.

The improved activation function, which was recommended as a replacement for the activation function ReLU, is represented as:

$$f(x) = \begin{cases} x/2; if -2 \le x < 2 \\ -1; if x < -2 \\ 1; if x > 2 \end{cases}$$
(9)

2.4. Classification

We applied the improved SVM in this study to improve classification accuracy. Initially, the SVM calculates the score for all the extracted features by using linear mapping on feature vectors and uses this to evaluate the loss. The improved SVM uses the linear mapping on extracted features to calculate the feature score for the parts of the region of interest used to differentiate the lesion types, which helps in the evaluation of loss function, which helps to obtain the classification results. Algorithm 1 for the improved SVM is presented below.

Algorithm 1 Improved SVM

- Initialize the values in the training set.
- Repeat for j = 1 to M.

Calculate the loss using the enhanced optimization for all values of j. Compare the extracted regions in the liver images. end

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    ■ Repeat for every score vector j − 1 to M.
```

Compute the SVM

 $argmax((w \times p j) + b)$ end

• Compute for all weights and finally evaluate the output.

3. Results

All experiments were implemented on Keras. The data split was performed based on an 80:20 ratio, where 80% of the data were used for training and 20% for testing. We implemented the proposed pooling function and activation function in the base models VGG-16, DenseNet, ResNet-50, Xception, and AlexNet for the fundus images. Table 3 tabulates the splitting of training and testing sets of fundus images for two augmented datasets.

Table 3. Augmented dataset image distribution.

Class	АРТ	OS	Kag	Kaggle		
Class	Training	Testing	Training	Testing		
NoDR	1444	361	20,648	5162		
MildDR	1480	370	19,544	4886		
Moderate DR	1598	400	21,166	5292		
Severe DR	1390	347	20,254	5063		
PDR	1416	354	20,390	5098		
Total	7328	1832	102,004	25,501		

3.1. Image Enhancement Evaluation

Image enhancement is a vital concept that changes the intensities of the original image to improve the image's perceptual quality. Figure 5 shows the contrast enhancement results for the APTOS dataset fundus image. Figure 5 compares the proposed model with some other existing enhancement models. Contrast-limited adaptive histogram equalization (CLAHE) models show insufficient image enhancement. The histogram modification framework (HMF) model enhances the image well; however, the hazy look is

not adequately removed. The heuristic adaptive histogram equalization (HAHE) model produces an enhanced image with unwanted artefacts visible in the fundus image. The artificial bee colony algorithm (ABC) yields better results than the other existing models; still, it has some viewable artifacts in the fundus image. The proposed model generates an outstanding result compared to all other existing models and successfully improves every minor detail present in the fundus image.



Figure 5. Comparison of the image enhancement of the proposed model with the existing models.

Evaluation and assessment are important for analysing the proposed model performance quantitatively. The proposed image enhancement model is accessed with performance measures such as entropy, peak signal-to-noise ratio (PSNR), the structural similarity index measure (SSIM), gradient magnitude similarity deviation (GMSD), and the patchbased contrast quality index (PCQI) [21–23].

Entropy defines the amount of information contained in the processed image.

Entropy =
$$\sum_{y=0}^{255} P(n) \log_2(P(n));$$
 (10)

where P(n) represents the probability of the nth level of the image.

PSNR computes the amount of noise content in the processed image.

$$PSNR = 20log_{10} \frac{2}{\frac{1}{AB}, \sum_{x=0}^{A-1} \sum_{y=0}^{B-1} |I_0(x,y) - I_i(x-y)|^2},$$
(11)

where *A*, *B* denotes the image size.

SSIM =
$$\frac{(2\mu_{I_i}\mu_{I_o} + A_1)(2\sigma_{I_i}\sigma_{I_o} + A_2)}{(\mu_{I_i}^2 + \mu_{I_o}^2 + A_1)(\sigma_{I_i}^2 + \sigma_{I_o}^2 + A_2)},$$
(12)

where μ_{I_i} , μ_{I_o} represents the input and the output intensity values, σ_{I_i} , σ_{I_o} represent the input and the output standard deviation values, and A₁, A₂ represent the constant to limit the instability problem.

Table 4 tabulates the average scores for the augmented APTOS dataset. The performance of the proposed model was demonstrated by comparing six state-of-the-art existing models such as Clahe [24], exposure-based sub-image histogram equalization (ESIHE) [25], HAHE [26], BIMEF [27], HMF [28], and ABC. From Table 4, it is clear that the proposed model achieves a higher SSIM value, and its similarity level is up to the mark when compared with the original fundus image. The proposed enhanced model attains a lesser GMSD value for the images and holds more excellent visual quality compared to the other methods. The proposed model gains a higher PSNR value and the noise suppression level is very good compared with that of the other models. The proposed model holds a higher entropy value to the original image and the amount of information preserved is high compared with the state-of-the-art models. The proposed model obtains a more significant PCQI value compared with the other models, and generates a good quality image with minimum structural distortions. The proposed enhanced model offers less running time when compared to the state-of-the-art contrast enhancement models. The running time of the CLAHE and ESIHE models is approximately equal to that of the proposed model. But these models suffer from noise and distortion. From Table 4, we can recognise that the proposed enhanced model is superior in enriching content, maintaining similarity, and suppressing the noise and distortion. The proposed enhanced image enhancement model generated a crisp and clear output.

Model	PSNR	GMSD	Entropy	SSIM	PCQI	Processing Time (s)
Clahe [24]	30.83	0.163	7.263	0.634	1.139	0.155
ESIHE [25]	31.93	0.074	7.316	0.635	1.282	0.153
HAHE [26]	32.82	0.125	7.226	0.693	1.001	0.373
BIMEF [27]	31.68	0.199	7.269	0.736	1.007	0.364
HMF [28]	32.63	0.085	7.283	0.636	1.103	0.218
ABC	34.83	0.048	7.834	0.877	1.378	0.173
Proposed	35.56	0.037	7.935	0.983	1.484	0.151

Table 4. Average scores for the augmented APTOS dataset.

3.2. Segmentation Comparison

The proposed model obtains more accurate and robust segmentation results. From Figure 6 it can be noticed that the proposed model obtains more accurate results.



Figure 6. Segmentation results. (a) original image, (b) ground truth, (c) proposed model, (d) DenseNet, (e) Inception, (f) VGG-19, (g) AlexNet.

Table 5 tabulates the performance of the proposed enhanced ResNet-50 compared to the state-of-the-art models. The proposed system performed very accurately compared with the other lesion segmentation methods in the state-of-the-art models. It saves the obtained accuracy of abnormal fundus images. It achieves accurate, detailed segmentation results with small lesions, so it is the perfect choice for automatic computer-aided diagnosis (CAD) systems that depend on lesion segmentation results as it exceeds the estimations of the alternative models in terms of overall accuracy.

Model	Pool + Act	Accuracy	Precision	Recall
DenseNet [29]	Max + Relu	0.9484	0.8364	0.9584
Inception [12]	Max + Relu	0.9847	0.8578	0.9848
VGG-19 [30]	Max + Relu	0.9795	0.8479	0.9483
AlexNet [31]	Max + Relu	0.9858	0.9378	0.9847
ResNet-50	Proposed	0.9986	1.0000	1.0000
AlexNet	Proposed	0.9986	1.0000	0.9864
DenseNet	Proposed	0.9959	1.0000	0.9916
Inception	Proposed	0.9972	0.9864	0.9864
VGG-19	Proposed	0.9986	0.9866	1.0000

Table 5. Comparison of segmentation results for the APTOS dataset with the state-of-the-art models.

3.3. Evaluation of the APTOS Dataset

Figure 7 illustrates the confusion matrix for the APTOS dataset. We implemented five baseline models—VGG-16, DenseNet, ResNet-50, Xception, and AlexNet—and compared their performances on the APTOS dataset. From these five models, ResNet-50 showed the highest performance.

According to the 5-class confusion matrix mentioned above, the performance of each model was evaluated based on accuracy, recall, precision, and F1-score. Table 6 tabulates the APTOS fundus classification test set results. The improved SVM model achieved the highest accuracy of the remaining classification models. The results show that the augmented APTOS fundus classification for the ResNet-50 model achieves the highest accuracy for the improved SVM model.

CNN Model Classifier Precision Recall F1-Score Class Accuracy 0.99781659 0.99445983 0.99445983 0.99445983 Normal 0.99672489 0.98924731 0.99459459 0.99191375 Mild 0.99617904 0.99126092 **ISVM** 0.99002494 0.99250000 Moderate 0.99137931 0.99280576 0.99727074 0.99423631 Severe PDR 0.99781659 1.0000000 0.98870056 0.99431818 0.99617904 0.98895028 0.99168975 0.99031812 Normal 0.99617904 0.98921833 0.99189189 0.99055331 Mild 0.99508734 0.99000000 0.98876404 SVM 0.98753117 Moderate 0.99617904 0.98850575 0.99135447 0.98992806 Severe 0.99563319 PDR 0.99428571 0.98305085 0.98863636 DenseNet 0.99563319 0.98891967 0.98891967 0.98891967 Normal 0.99290393 0.98113208 0.98378378 0.98245614 Mild RF 0.99344978 0.98258706 0.98750000 0.98503741 Moderate 0.99508734 0.98847262 0.98705036 0.98563218 Severe 0.99344978 0.98295455 PDR 0.98857143 0.97740113 0.99454148 0.98347107 0.98891967 0.98618785 Normal 0.99072052 0.97319035 0.98108108 0.97711978 Mild NB 0.99399563 0.98503741 0.98750000 0.98626717 Moderate 0.99290393 0.98265896 0.97982709 0.98124098 Severe 0.99290393 0.98853868 0.97457627 0.98150782 PDR

Table 6. Performance metrics for APTOS augmented dataset.

Table 6. Cont.

CNN Model	Classifier	Accuracy	Precision	Recall	F1-Score	Class
		0.99781659	0.99173554	0.99722992	0.99447514	Normal
		0.99836245	0.99460916	0.9972973	0.99595142	Mild
	ISVM	0.99836245	0.99749373	0.9950000	0.99624531	Moderate
		0.99945415	1.00000000	0.99711816	0.99855700	Severe
		0.99945415	1.00000000	0.99717514	0.99858557	PDR
		0.99727074	0.99171271	0.99445983	0.99308437	Normal
		0.99727074	0.99191375	0.99459459	0.99325236	Mild
	SVM	0.99563319	0.98756219	0.99250000	0.99002494	Moderate
		0.99727074	0.99421965	0.99135447	0.99278499	Severe
ResNet-50		0.99836245	1.00000000	0.99152542	0.99574468	PDR
		0.99617904	0.98895028	0.99168975	0.99031812	Normal
		0.99563319	0.98655914	0.99189189	0.98921833	Mild
	RF	0.99563319	0.99000000	0.99000000	0.99000000	Moderate
		0.99617904	0.99132948	0.98847262	0.98989899	Severe
		0.99672489	0.99431818	0.98870056	0.99150142	PDR
		0.99508734	0.98351648	0.99168975	0.98758621	Normal
		0.99399563	0.98123324	0.98918919	0.98519515	Mild
	NB	0.99508734	0.98997494	0.98750000	0.98873592	Moderate
		0.99344978	0.98550725	0.97982709	0.98265896	Severe
		0.99508734	0.99145299	0.98305085	0.98723404	PDR
		0.99617904	0.98895028	0.99168975	0.99031812	Normal
		0.99454148	0.98648649	0.98648649	0.98648649	Mild
	ISVM	0.99235808	0.98250000	0.98250000	0.98250000	Moderate
		0.99672489	0.99135447	0.99135447	0.99135447	Severe
		0.99727074	0.99433428	0.99152542	0.99292786	PDR
		0.99454148	0.98347107	0.98891967	0.98618785	Normal
		0.99454148	0.98913043	0.98378378	0.98644986	Mild
	SVM	0.99290393	0.98740554	0.98000000	0.98368883	Moderate
		0.99454148	0.98280802	0.98847262	0.98563218	Severe
AlexNet		0.99508734	0.98591549	0.98870056	0.98730606	PDR
These ver		0.99344978	0.98071625	0.98614958	0.98342541	Normal
		0.99126638	0.97580645	0.98108108	0.97843666	Mild
	RF	0.99126638	0.98484848	0.97500000	0.97989950	Moderate
		0.99235808	0.97982709	0.97982709	0.97982709	Severe
		0.99454148	0.98587571	0.98587571	0.98587571	PDR
		0.99290393	0.97802198	0.98614958	0.98206897	Normal
		0.98962882	0.97050938	0.97837838	0.97442799	Mild
	NB	0.99017467	0.98232323	0.97250000	0.97738693	Moderate
		0.99235808	0.9826087	0.97694524	0.97976879	Severe
		0.99235808	0.98022599	0.98022599	0.98022599	PDR
		0.99399563	0.97814208	0.99168975	0.98486933	Normal
		0.99126638	0.97326203	0.98378378	0.97849462	Mild
	ISVM	0.99290393	0.99236641	0.97500000	0.98360656	Moderate
		0.99399303	0.98275862	0.98009078	0.98417266	Severe
		0.99508734	0.99145299	0.98505085	0.98723404	PDK Normal
		0.99544978	0.97808219	0.98891967	0.9834/10/	Normal Mild
	SVM	0.99101223	0.90102901	0.97037030	0.97970230	Madarata
	5 V IVI	0.90902002	0.97904007	0.97250000	0.97010000	Source
T		0.99101223	0.97701149	0.97962709	0.97041727	DDD
Inception		0.99290393	0.90500205	0.96022399	0.90101243	Normal
		0.22101223	0.97327473	0.20227200	0.27231034	Mild
	RE	0.90900297	0.97297297	0.97297297	0.97297297	Moderato
	κι ^ν	0.90744341	0.97243100	0.9700000	0.97121402	Sovoro
		0.99120030	0.979/1014	0.9740034	0.97007001	PDR
		0.99072055	0.96994536	0.98337950	0.97661623	Normal
		0 98967887	0.97820163	0.97027027	0 97421981	Mild
	NB	0.98635371	0.97220103	0.97027027	0.96863237	Moderate
	110	0 98744541	0.96285714	0.97118156	0.96700143	Severe
		0.99126638	0.98011364	0.97457627	0.97733711	PDR
						•

CNN Model	Classifier	Accuracy	Precision	Recall	F1-Score	Class
		0.99290393	0.97540984	0.98891967	0.98211829	Normal
		0.98908297	0.96791444	0.97837838	0.97311828	Mild
	ISVM	0.99017467	0.98477157	0.97000000	0.97732997	Moderate
		0.99454148	0.98840580	0.98270893	0.98554913	Severe
		0.99290393	0.98300283	0.98022599	0.98161245	PDR
		0.99181223	0.97267760	0.98614958	0.97936726	Normal
		0.99072052	0.98092643	0.97297297	0.97693351	Mild
	SVM	0.98744541	0.97721519	0.96500000	0.97106918	Moderate
		0.99126638	0.97421203	0.97982709	0.97701149	Severe
VCC 10		0.98962882	0.97183099	0.97457627	0.97320169	PDR
VGG-19		0.99126638	0.97260274	0.98337950	0.97796143	Normal
		0.98853712	0.97289973	0.97027027	0.97158322	Mild
	RF	0.98689956	0.97474747	0.96500000	0.96984925	Moderate
		0.98962882	0.97126437	0.97406340	0.97266187	Severe
		0.98799127	0.96892655	0.96892655	0.96892655	PDR
		0.98853712	0.96195652	0.98060942	0.97119342	Normal
		0.98635371	0.96495957	0.96756757	0.96626181	Mild
	NB	0.98580786	0.97222222	0.96250000	0.96733668	Moderate
		0.98799127	0.96829971	0.96829971	0.96829971	Severe
		0.98689956	0.97142857	0.96045198	0.96590909	PDR

Table 6. Cont.



Figure 7. Confusion matrix for APTOS augmented dataset on different CNN models.

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3.4. Evaluation of the Kaggle Dataset

Figure 8 illustrates the confusion matrix for the Kaggle dataset. We implemented five baseline models-VGG-16, DenseNet, ResNet-50, Xception, and AlexNet-and compared their performances on the Kaggle dataset. From these five models, ResNet-50 showed the highest performance. In 203 NODR fundus images, the proposed ISVM classifier accurately classified 202 fundus images for the ResNet-50 model. In 54 Mild images, the ISVM classifier accurately classified 54. Out of 69 moderate fundus images, ISVM accurately identified 68. Out of 15 images, ISVM accurately identified 14 for severe, and out of 7 images, ISVM accurately identified 201 NODR images, 53 mild and 67 moderate, 14 severe, and 5 for PDR. For the ResNet-152 model, the RF classifier accurately identified 201 NODR images, 53 mild and 66 moderate, 13 severe, and 5 for PDR. For the ResNet-50 model, the NB classifier accurately identified 201 NODR images, 52 mild and 65 for moderate, 12 for severe, and 5 for PDR. Table 6 tabulated the Kaggle classification test set results.



Figure 8. Confusion matrix for Kaggle augmented dataset on different CNN models.

From Table 7, we can see that the improved SVM model achieved the highest accuracy compared to the remaining classification models. The achieved results revealed that the overall testing accuracy and the performance metrics for the improved ResNet-50 with the improved SVM are the most appropriate for diabetic retinopathy detection, with a testing accuracy of 99.9% for fundus images.

 Table 7. Performance metrics for Kaggle augmented dataset.

BSVM 0.99976472 0.9992141 0.9994823 0.9994862 Mild 0.9998058 0.9995058 0.99901244 0.9994822 Moderate 0.99956664 0.99901244 0.99901244 0.99901244 0.99901245 0.9992143 0.99921422 Moderate 0.99956767 0.9992177 0.9992177 0.9992170 0.9992170 0.99921767 0.99921767 Moderate 0.9995676 0.9988621 0.9988621 0.9988621 0.9988627 0.99886767 0.99876767 0.9987767 Moderate 0.9995684 0.9991184 0.9986217 0.9988621 0.9988621 0.9988621 0.99887667 0.99877161 Moderate 0.9992415 0.9981322 0.99887667 0.99877161 Moderate 0.9992117 0.9981322 0.9981323 Severe 0.9992415 0.99880322 0.9981323 0.9982143 0.9982143 0.9982143 0.9982143 0.9982143 0.9982143 0.9982143 0.9982143 0.9982143 0.9982143 0.9982143 0.9987216 0.9982143 0	CNN Model	Classifier	Accuracy	Precision	Recall	F1-Score	Class
ISVM 0.99980393 0.99995033 0.99943121 0.9994428 Mide" ISVM 0.99966786 0.99901244 0.9991242 0.9995033 Normal 0.99966766 0.9992142 0.99956867 0.99956867 0.99987667 0.9986767 0.9987667			0.99976472	0.99922541	0.99961255	0.99941894	Normal
ISVM 0.999658629 0.99901244 0.99901244 Moderate 0.99956864 0.99901244 0.99901243 0.9992137 0.99922833 NOrmal 0.99966770 0.9992517 0.99986621 0.99985627 0.999857667 Moderate 0.99956864 0.9988621 0.9988621 0.9988621 0.99885234 Normal 0.99956864 0.9988621 0.99987667 0.99877667 0.9987767 0.9987767 0.99959231 0.999903120 0.9988621 0.99885234 Normal 0.9995231 0.99991084 0.9982706 0.9982700 Midd 0.9995231 0.99987667 0.9988700 Midd Moderate 0.99952413 0.9986367 0.9982700 Midd Midd 0.9992415 0.9986322 0.9984701 Midd Midd Midd 0.9992415 0.9986322 0.9984702 0.99877161 Moderate 0.9992157 0.99981028 0.9977141 Midd Midd Midd 0.9992157 0.99980767 <td< td=""><td rowspan="3"></td><td></td><td>0.99980393</td><td>0.99959058</td><td>0.99938600</td><td>0.99948828</td><td>Mild</td></td<>			0.99980393	0.99959058	0.99938600	0.99948828	Mild
NB 0.99961786 0.9992142 0.99962083 Severe 0.99964707 0.99962132 0.99962083 Normal 0.9996676 0.9987667 0.9987667 0.9988767 0.9988767 0.9988767 0.9995768 0.9987667 0.99887667 0.9988767 0.9988767 0.9988767 0.99957843 0.9995184 0.99881517 0.99987667 0.99887767 0.99887767 0.99887767 0.99887767 0.99887767 0.99877161 Moderate 0.9994022 0.99885627 0.9987767 0.99877161 Moderate 0.99911820 0.9986725 0.99877667 0.99877161 Moderate 0.99911752 0.99972187 0.99847217 0.9982583 0.99811071 Mida 0.99911752 0.99872322 0.9982322 0.9982167 0.99741487 Mida 0.9992157 0.99972867 0.99741847 Moderate 0.99971867 0.99741847 Mida 0.9992157 0.99992187 0.9995067 0.99971867 0.99971867 0.999751104 Moderate		ISVM	0.99968629	0.99905553	0 99943311	0.99924428	Moderate
PenseNet 0.99956864 0.9992182 0.9992283 PDR 0.99960736 0.99980767 0.9992751 0.9992511 0.9992581 0.9988621 0.9988621 0.9988621 0.9988621 0.9988621 0.9988621 0.9988621 0.9988621 0.9988621 0.9988621 0.9995251 0.9995251 0.99952664 0.99952664 0.99952664 0.99952664 0.99957667 0.9987767 0.99867008 Mild 0.99924022 0.99886621 0.99857667 0.99827161 Moderate 0.99924151 0.9986322 0.99827261 Mild Mild 0.99924151 0.9986322 0.9984323 0.998767 Mild Moderate 0.99922415 0.9986352 0.9984323 0.998724867 Mild		10 / 111	0.99960786	0 99901244	0 99901244	0 99901244	Severe
0.99964707 0.9998766 0.9998767 0.9998767 0.9998767 0.9998767 0.9998767 0.9998767 0.9998767 0.9998767 0.9998767 0.9998767 0.9998767 0.9998767 0.9998767 0.9998767 0.9998767 0.99982244 0.99981312 0.99981312 0.99982244 0.99982242 Normal 0.9995641 0.99983620 0.9998767 0.9998708 Mild Mild 0.99924125 0.99883621 0.9988767 0.9998708 Mild 0.9992415 0.9980322 0.9983224 0.9982345 PDR 0.9992415 0.9980322 0.99843021 0.9982467 Mild 0.9992415 0.9990322 0.9994102 0.9997467 0.9974867 Mild 0.99924157 0.9997467 0.9997467 0.99974867 0.9974867 Mild Mild 0.9992157 0.9997467 0.99974867 0.99980628 0.99980628 Normal 0.9992157 0.9997467 0.99974867 0.99980767 Mild Moderate 0.9997550 0.99980767			0.99956864	0.99921492	0.99862691	0.99892083	PDR
SVM 0.9986767 0.9987667 0.9987667 0.9987667 DenseNet 0.99952943 0.99886621 0.99886621 0.99881766 0.99981379 Severe 0.99952943 0.99901844 0.99986767 0.99983766 0.99982442 PDR 0.99940022 0.99883627 0.99887667 0.99987161 Moderate 0.99940022 0.99886123 0.9985123 0.99821453 0.9985123 0.9985123 Severe 0.99929415 0.99860532 0.99867667 0.99973667 Mild Moderate 0.99921572 0.99774867 0.99774867 0.99774867 Normal 0.99921572 0.99821628 0.999802499 Severe 0.99913729 0.99774867 0.99774867 Mild 0.99921572 0.99980628 0.999802499 Severe 0.99981144 PDR 0.99921572 0.999810628 0.999802489 0.999802489 Severe 0.9995067 Mild Moderate 0.99951250 0.9992157 0.99981104 0.99980628 Normal 0.999711			0.99964707	0.99903157	0.99922511	0.99912833	Normal
SVM 0.9955643 0.99881621 0.99881621 0.9988121 DenseNet 0.9955943 0.999011844 0.9982244 PDR 0.99952943 0.99901320 0.99882244 PDR 0.9994022 0.9983667 0.9987676 0.9987708 Mild 0.9994022 0.9988660 0.9987751 Moderate 0.9992915 0.9981322 0.9982244 0.99877867 0.99878767 0.99878767 0.99929155 0.9981322 0.9981372 0.99823457 0.99878767 0.99784676 0.99784674 0.99980767 Mild 0.99980767 Mild 0.99978757 0.999811071 Moderate 0.9977257 0.999810761 0.99978676 0.9998797897 Mild 0.99979257 </td <td></td> <td></td> <td>0.99960786</td> <td>0.99897667</td> <td>0.99897667</td> <td>0.99897667</td> <td>Mild</td>			0.99960786	0.99897667	0.99897667	0.99897667	Mild
DenseNet 0.99956864 0.99981317 0.99911244 0.99981329 Severe 0.99952943 0.99901884 0.99983366 0.99983424 PDR 0.9994002 0.99883766 0.9983767 0.9988767 Normal 0.9994002 0.99883626 0.99867755 0.99987161 Moderate 0.99924155 0.99881423 0.99881243 0.99823495 PDR 0.99924155 0.99863522 0.99843245 D.99823495 PDR 0.99921572 0.99774867 0.99774867 Mild Moderate 0.99921572 0.9972186 0.99980289 0.999802489 0.9		SVM	0.99952943	0.99886621	0.99886621	0.99886621	Moderate
DenseNet 0.99962643 0.99901184 0.99862641 0.99882244 PDR 0.99994022 0.9986366 0.99897667 0.9988708 Mild 0.9994022 0.9988367 0.9988708 Mild 0.9994022 0.9988500 0.9988775 0.9987161 Moderate 0.9992415 0.9981270 0.9982583 Normal 0.99921572 0.9987467 0.997467 0.99724867 Normal 0.99921572 0.9997228 0.9982583 Normal Noderate 0.99921572 0.9997289 0.9980628 0.9998067 Normal 0.9992157 0.9997067 0.9997144 PDR Normal 0.99991372 0.9999067 0.9999067 0.9999067 Mild Normal 0.99991372 0.9999067 0.9999067 0.9999067 Normal Normal 0.99991372 0.9999067 0.9990676 0.9990676 Normal Normal 0.99972550 0.99901333 0.9992157 0.99901333 0.9992133 0.99921133 0.9			0.99956864	0.99881517	0.99901244	0.99891379	Severe
Denserver 0.9994022 0.9983366 0.99837667 0.99887700 Mild RF 0.99940022 0.9988670 0.99887725 0.998871823 Severee 0.99924115 0.99813922 0.99834076 0.99823495 PDR 0.99924115 0.9981372 0.99823495 PDR Normal 0.99921572 0.9981720 0.9981720 0.9981726 0.9981726 0.9981726 0.9981726 0.9981726 0.9981726 0.9981727 0.9981727 0.9981727 0.9981727 0.9998172	DeneNist		0.99952943	0.99901884	0.99862691	0.99882284	PDR
0.9994002 0.99856367 0.9985767 0.9985700 Mild RF 0.9994002 0.99858123 0.9985123 0.99851823 Severe 0.9992415 0.9985162 0.9985162 0.99852683 Normal 0.9992157 0.9987218 0.9987467 0.9987467 Mild 0.99921572 0.997467 0.9977467 0.9977467 Mild 0.99921572 0.99972189 0.9982082 0.99980428 0.9980678 0.99971457 Mild 0.99992157 0.9997067 0.99974498 0.9999067 Mild Mild 0.99992157 0.9999067 0.9997667 0.9996067 0.9996067 Mild 0.99992157 0.99960198 0.99960679 0.99960679 Normal 0.99972550 0.9990678 0.99960796 0.9996079 0.9990172 Normal 0.99972550 0.9990678 0.9990678 0.9990172 Normal 0.99972550 0.99906767 0.9990175 0.9990172 Normal 0.99972550 0.9990178 <t< td=""><td>DenselNet</td><td></td><td>0.99956864</td><td>0.99903120</td><td>0.99883766</td><td>0.99893442</td><td>Normal</td></t<>	DenselNet		0.99956864	0.99903120	0.99883766	0.99893442	Normal
RF 0.99941170 0.99924115 0.9988000 0.9986725 0.99877161 0.99823455 Moderate Severe 0.9992415 NB 0.99924115 0.99803922 0.99843076 0.99825633 Normal 0.99921572 0.99974867 0.99774867 0.99774867 Moderate 0.99913729 0.99774867 0.99774867 0.99774867 Moderate 0.99921572 0.9980628 0.99980628 0.99980628 0.99980628 0.99980628 0.99980628 Normal 0.999913729 0.99980628 0.99980628 0.99980628 0.99980628 Normal 0.99991372 0.99980628 0.99980677 0.99997067 0.99970677 Midd 0.99992157 0.99981104 0.99981104 0.99981104 Moderate 0.99972550 0.99901255 0.99961786 Normal 0.99972550 0.99902075 0.99931325 PDR 0.9997250 0.99902075 0.99931325 PDR 0.9997250 0.99940735 0.99931325 PDR 0.9997250 0.99940735 0.99931325 <			0.99949022	0.99836367	0.99897667	0.99867008	Mild
0.99941179 0.99881423 0.99851823 Severe 0.99929415 0.9980652 0.99843076 0.99823495 PDR 0.99913729 0.99974867 0.99774867 0.99774867 Mild 0.99913729 0.9982932 0.99811071 Moderate 0.99913729 0.99802489 0.99802489 0.99802489 0.99802489 0.99802489 0.99802489 0.9980149 0.99974144 PDR 0.99913729 0.9980322 0.9980628 0.99980124 0.99980124 0.9998104 Moderate 0.99967550 0.99980134 0.99961255 0.99931325 PDR Normal 0.99967676 0.99967676 0.99981314 0.99991124 0.99911311 Sev		RF	0.99949022	0.99886600	0.99867725	0.99877161	Moderate
0.99924115 0.99803922 0.99823455 0.99825683 Normal 0.99913729 0.99774867 0.99774867 0.99774867 Mild 0.99921572 0.99802489 0.99714867 0.99774867 Mild 0.99921572 0.99802489 0.99781444 PDR 0.999913729 0.99980628 0.99980628 0.99980628 Normal 0.999913727 0.99980628 0.99980676 Mild Mild 0.99992157 0.99980678 0.99980676 Mild Moderate 0.99992157 0.9998104 0.9998104 0.9998104 0.9998104 0.99980767 Mild 0.99992157 0.99991079 0.99960769 0.99960769 0.99960769 PDR 0.99972550 0.9990755 0.9993133 0.9992333 Moderate 0.99960786 0.9996175 0.99931325 PDR 0.9996775 0.9994183 0.99931325 PDR 0.9996766 0.9994114 0.99924184 Moderate 0.9996766 0.99941184 0.99924184			0.99941179	0.99881423	0.9982224	0.99851823	Severe
0.9992415 0.99806322 0.99824567 0.99724867 0.99724867 0.99724867 0.99724867 0.99774867 0.99774867 0.99774867 0.99774867 0.99774867 0.99774867 0.998102489 0.998002489 0.998002489 0.998002489 0.999800248 0.99980027 Nila 0.999913729 0.99980028 0.99980067 0.99980028 Normal 0.99992157 0.99980028 0.99980076 0.9998007 Mild 0.99992157 0.99981014 0.9998007 Mild Moderate 0.99992157 0.99981104 0.99981104 Moderate 0.99960769 0.99960769 0.99960769 PDR 0.99972550 0.99901235 0.99960769 0.99960769 D.99960769 Normal 0.99972550 0.99902177 0.99962077 Normal Normal Normal 0.99972550 0.99960764 0.99901224 0.99931325 PDR 0.99972550 0.99960767 0.99920864 Severe PDR 0.9995644 0.99987725 0.99987677 Moderate			0.99929415	0.99803922	0.99843076	0.99823495	PDR
NB 0.9991372 0.9974867 0.9974867 Mild NB 0.9992157 0.99822932 0.99820932 0.9981107 Moderate 0.9991372 0.9982032 0.9974198 0.99971498 0.99971498 0.99971498 0.999714194 PDR 0.99991372 0.9998006 0.99980767 0.99980628 Normal 0.99992157 0.99981104 0.99995067 0.99991014 Moderate 0.99981314 0.99960769 0.99960789 0.99960789 0.99960789 0.99960789 0.99972550 0.9992035 0.9992095 0.99920351 Moderate 0.99972550 0.99920735 0.9992095 0.9993084 Severe 0.99967676 0.99961783 0.9992095 0.9993084 Severe 0.99972550 0.9992095 0.9993084 Severe Severe 0.9996767 0.9992095 0.9993084 Severe Severe 0.9996750 0.9992095 0.9993084 Severe Severe 0.99966760 0.99984110 0.9996756 <td></td> <td></td> <td>0.99929415</td> <td>0.99806352</td> <td>0.99845021</td> <td>0.99825683</td> <td>Normal</td>			0.99929415	0.99806352	0.99845021	0.99825683	Normal
NB 0.99921572 0.9982218 0.9982149 0.99802489 0.99802489 0.99802489 0.99802489 0.99802489 0.99802489 0.99802489 0.99802489 0.99980258 Normal 0.99992157 0.99980628 0.99980628 0.99980676 Mid Mid 0.999941314 0.99996175 0.999800769 0.999961769 0.999960769 PDR 0.99994314 0.99960769 0.999961755 0.99992157 0.99961255 0.99932217 Normal 0.99972550 0.99906769 0.99962207 0.99924433 0.99962207 Normal 0.99972550 0.99907646 0.99901922 0.99938354 Severe 0.99972550 0.9996767 0.99931376 Normal 0.99968629 0.99901922 0.9993176 Normal 0.99968629 0.9992414 0.9991110 Severe 0.99968629 0.99941707 0.9986247 0.99887465 Midd RF 0.99964707 0.9984146 0.9991111 Severe 0.99956666 0.99941107 0.998626			0.99913729	0.99774867	0.99774867	0.99774867	Mild
0.99921572 0.99802489 0.99802489 0.99802489 Severe 0.9991372 0.9983232 0.9974498 0.99784144 PDR 0.99984314 0.99959067 0.99985062 Normal 0.99981104 0.99981104 0.99981104 Moderate 0.99981114 0.99960769 0.99960769 PDR 0.9992550 0.99938388 0.99960769 0.99932217 Normal 0.99972550 0.99938888 0.99960769 0.99923217 Normal 0.99972550 0.99940735 0.99943321 Moderate 0.99972550 0.99940735 0.99943321 Moderate 0.99972550 0.99940735 0.99943833 0.9996183 0.9991111 0.99972550 0.99940735 0.9994183 0.9991111 Severe 0.99960786 0.99967725 0.99981104 0.99921111 Severe 0.99960786 0.99941107 0.99962414 0.99921111 Severe 0.99960786 0.99941107 0.9986725 0.9988745 Mild N		NB	0.99921572	0.99792218	0.99829932	0.99811071	Moderate
AlexNet 0.99913729 0.99823322 0.99784144 PDR 0.99992157 0.99980628 0.99980629 0.99980629 0.99980629 0.99980629 0.99980629 0.99990629 0.999922359 0.999922350 0.99960766 0.99992550 0.99960766 0.9992175 0.99990176 Normal 0.99972550 0.99960766 0.99921725 0.99980767 0.99930176 Normal 0.99960786 0.99967725 0.99980767 0.9992414 0.9992414 Moderate 0.99960786 0.99921725 0.9986267 0.9986267 Nild Moderate 0.99960786 0.99921107 0.99924144 0.9992414 0.99921111 Sveree 0.99960786 0.99961101 0.99862627 <td></td> <td></td> <td>0.99921572</td> <td>0.99802489</td> <td>0.99802489</td> <td>0.99802489</td> <td>Severe</td>			0.99921572	0.99802489	0.99802489	0.99802489	Severe
0.9992157 0.99980628 0.99980628 0.99980628 0.99980628 Normal ISVM 0.99984114 0.9995067 0.9995067 0.9995067 Mild 0.99984314 0.99960780 0.99960769 0.99960769 0.99960769 PDR 0.99972550 0.99960769 0.9992055 0.9992055 0.9992055 Normal 0.99972550 0.99920755 0.99920955 0.99930443 0.99920767 Normal 0.99972550 0.99920755 0.99920955 0.99930445 Severe 0.9995664 0.99960766 0.9988745 Mild 0.9995664 0.9992095 0.99921111 Severe 0.99960786 0.99887414 0.99921111 Severe 0.99960786 0.9984144 0.99921111 Severe 0.99952943 0.9986446 0.99980725 0.99805627 Mild NB 0.99961715 Severe 0.99961715 Severe 0.99952943 0.99861725 0.99861715 Severe 0.999941830 0.99861725			0.99913729	0.99823322	0.99744998	0.99784144	PDR
ISVM 0.99984314 0.99959067 0.99995104 Moderate 0.99984314 0.99960198 0.99960198 0.99960198 0.99960769 PDR 0.99984314 0.99960769 0.99960759 0.99960759 0.99932550 0.99960759 0.99932217 Normal 0.99972550 0.9993104 0.99922339 Mild Moderate 0.99972550 0.99940735 0.9992095 0.99930864 Severe 0.99972550 0.99960746 0.9996125 0.99930864 Severe 0.99972550 0.99960746 0.99901922 0.99931325 PDR 0.99960786 0.99940735 0.9992095 0.99931325 PDR 0.99956864 0.99921414 0.99921414 0.99921414 Moderate 0.99964707 0.99920980 0.99911111 Severe Severe 0.99964707 0.9992080 0.9991138 0.9998144 0.9992144 0.9992144 0.9992144 0.9992144 0.9992144 0.9992144 0.9992144 0.9992144 0.99921414 0.99921414 0.9			0.99992157	0.99980628	0.99980628	0.99980628	Normal
ISVM 0.99981104 0.99981104 0.99981104 0.99981104 0.99981104 0.99981104 0.99981104 0.99981104 0.99981104 0.99981104 0.99981104 0.99981104 0.99981104 0.99981104 0.99981104 0.99981104 0.99961255 0.99906769 0.99960769 0.99960769 0.99960769 0.99961255 0.99902177 Normal 0.99972550 0.99940735 0.999402207 0.99931325 PDR 0.99972550 0.99940736 0.99967677 0.99931325 PDR 0.99967666 0.99864490 0.9992414 0.9992338 0.99837250 0.9985250 0.9985250 0.9986725 0.9986725 0.9986725 0.9986725 0.9986725 0.99867			0.99984314	0.99959067	0.99959067	0.99959067	Mild
AlexNet 0.99984314 0.99960769 0.99960769 PDR 0.99994314 0.99960769 0.99960769 PDR 0.99972550 0.99903195 0.9993217 Normal 0.99972550 0.99938588 0.99918133 0.9992359 Mild 0.99972550 0.99940735 0.9992095 0.99931325 PDR 0.99972550 0.99960766 0.99991183 0.9990176 Normal 0.9996786 0.99967767 0.99987725 0.99987725 0.99987767 Normal 0.9996786 0.99987255 0.99987257 0.99887485 Mild Moderate 0.9996786 0.99987257 0.9988785 0.99987257 0.9988788 Normal 0.9996786 0.99941107 0.99882144 0.99901884 NDPDR 0.9995243 0.99975005 0.99885267 0.9988520 Moderate 0.9992527 0.9988146 0.99941125 0.99843014 PDR 0.9992527 0.9988214 0.9996207 0.9987200 Moderate 0.99994022		ISVM	0.99992157	0.99981104	0.99981104	0.99981104	Moderate
AlexNet 0.99964314 0.99960769 0.99960769 0.99961769 PDK 0.99972550 0.99903195 0.99992550 0.999918133 0.99928359 Mild 0.99972550 0.99924433 0.9999207 0.99943221 Moderate 0.99972550 0.99940735 0.999901922 0.99930864 Severe 0.99970756 0.99960766 0.99991833 0.9990375 Normal 0.99956864 0.99972550 0.99960766 0.99987445 Mild 0.99956864 0.99924114 0.99921414 0.99921414 Moderate 0.99960786 0.999862691 0.999911111 Severe 0.99961786 0.99981446 0.999911111 Severe 0.99960786 0.99984310 0.99986267 0.99883788 Normal 0.99992493 0.9997505 0.99886267 0.99883788 Normal 0.99992493 0.999848857 0.99880788 Normal 0.9998146 0.99994170 0.99984805 0.9988146 0.9988146 0.99881715 Severe 0.999			0.99984314	0.99960498	0.99960498	0.99960498	Severe
NB 0.999/2530 0.9993135 0.99961255 0.99928359 Mild SVM 0.99977550 0.99938588 0.99918133 0.99928359 Mild 0.99972550 0.99940735 0.9992095 0.99930864 Severe 0.99972550 0.99960746 0.99901922 0.99931325 PDR 0.99972550 0.99972550 0.99941883 0.99903176 Normal 0.9995644 0.99977505 0.99987474 0.99987474 Moderate 0.9996786 0.99924414 0.99924414 Moderate 0.9996786 0.99901244 0.9991184 PDR 0.9996786 0.9991170 0.99836267 0.99805627 Mild 0.9992543 0.9975055 0.9983526 0.9984314 PDR 0.99945100 0.9988146 0.99961755 0.9984314 PDR 0.99985243 0.99964207 0.99960627 0.9996175 Severe 0.99984314 0.9997525 0.99984020 0.9997039 Normal 0.99984526 0.99964207 <t< td=""><td></td><td>0.99984314</td><td>0.99960769</td><td>0.99960769</td><td>0.99960769</td><td>PDR</td></t<>			0.99984314	0.99960769	0.99960769	0.99960769	PDR
SVM 0.999/2530 0.9992433 0.99924133 0.99924331 Mild ResNet-50 0.99972550 0.99940735 0.9992195 0.99931325 PDR 0.99960786 0.99960746 0.99921433 0.99931325 PDR 0.99956864 0.99887667 0.99987445 Mild RF 0.9996786 0.9992414 0.9992414 Moderate 0.9996786 0.99940707 0.99987667 0.999883788 Normal 0.99958649 0.9992414 0.9992114 Moderate 0.99921111 Severe 0.9996786 0.9994107 0.9986767 0.99883788 Normal 0.99952943 0.99775005 0.99836267 0.9985292 Mild 0.99952943 0.997525 0.9986267 0.9985267 Mild NB 0.99945100 0.99848375 0.9986267 0.9985262 Moderate 0.99945100 0.99848146 0.99961715 Severe 0.9995058 Mild 0.9994520 0.9990161 0.9994777 0.99950517 Se			0.99972550	0.99903195	0.99961255	0.99932217	Normal M:14
SVM 0.99970472 0.99942443 0.9994321 Moderate 0.99972550 0.99940735 0.99920995 0.99931325 PDR 0.99972550 0.99960746 0.99901922 0.99931325 PDR 0.99956664 0.99864499 0.99941883 0.99903176 Normal 0.99956664 0.9987667 0.9988745 Mild RF 0.99966786 0.9992414 0.99924414 Moderate 0.99952943 0.99924117 0.998826691 0.9991111 Severe 0.99952943 0.9995505 0.99836267 0.99888788 Normal 0.99952943 0.99981446 0.99981725 0.99858290 Moderate 0.99937257 0.99881446 0.99841991 0.99858290 Moderate 0.99945100 0.99881424 0.99981331 PDR 0.9998624 0.99981255 0.999830314 PDR 0.99986824 0.99981333 0.99961255 0.9997039 Normal 0.99986829 0.99941173 0.99995058 Moderate 0.9998662		SVM	0.99972550	0.99938588	0.99918133	0.99928359	Mild
ResNet-50 0.9997/250 0.99940/35 0.99920920 0.99930849 0.99931325 PDR ResNet-50 0.9996786 0.9986449 0.99941883 0.99903176 Normal 0.99956864 0.99877225 0.99897667 0.99887455 Mild RF 0.99968629 0.9992414 0.99924414 0.99924414 Moderate 0.99960786 0.9994107 0.9982667 0.9991111 Severe 0.99952943 0.99975005 0.99836267 0.99805627 Mild 0.99925493 0.9975005 0.9986725 0.9988527 Mild NB 0.99941107 0.9986725 0.9988527 Mild 0.99937257 0.9988214 0.9984314 0.9984314 PDR 0.9998833 0.9996402 0.99941025 0.9997039 Normal 0.99984314 0.9997200 0.9997200 0.9997217 Severe 0.9998629 0.99901161 0.99940727 0.999753 PDR 0.99996629 0.9990161 0.99941153 0.99921553		5 1 1 1	0.99970472	0.99924443	0.99962207	0.99945521	Source
ResNet-50 0.99960786 0.99960740 0.99941822 0.9995132.2 1.0K 0.99956864 0.99877225 0.99887667 0.99887445 Mild RF 0.99966829 0.9992414 0.9992414 0.9992414 0.99924114 0.99966786 0.99924114 0.99924114 0.99924113 0.99911111 Severe 0.99960786 0.9992080 0.99901244 0.99911111 Severe 0.99952943 0.999826661 0.99983788 Normal 0.99925493 0.99975005 0.9986725 0.99858290 Moderate 0.9992543 0.99981466 0.99981191 0.9988521 0.9986725 0.99881715 Severe 0.99937257 0.9988214 0.99981255 0.99990588 Mild 0.99984314 0.9997555 0.999937257 0.9988236 0.99995058 Mild 0.99986236 0.999917651 0.99991755 0.99991753 PDR 0.99961021 0.99964202 0.9994172 0.99940747 0.9995058 Mild 0.99941163			0.99972550	0.99940733	0.99920993	0.99930004	DDD
AlexNet 0.9995864 0.9987667 0.9987667 0.9987445 Mild RF 0.99968629 0.99924414 0.99924414 0.99924414 Moderate 0.99960786 0.99920980 0.99901244 0.99921111 Severe 0.99952943 0.99960786 0.99901384 PDR 0.99952943 0.99975055 0.99836267 0.9986725 0.99887788 Normal 0.99925977 0.9988257 0.9986725 0.9986725 0.9986725 0.9986725 0.9986725 0.9986725 0.9986725 0.9986725 0.9986725 0.9986725 0.9986725 0.9986725 0.99986725 0.99986725 0.99986725 0.99986725 0.99986725 0.99986725 0.99986725 0.99984301 0.99979039 Normal 0.999988236 0.99980624 0.99991255 0.99970939 Normal 0.999898236 0.99980624 0.999910747 0.99950517 Severe 0.99998033 0.99960400 0.99992077 0.9997525 0.99987200 0.9987210 0.9987210 0.9987210 0.99877200	ResNet-50		0.99972330	0.99900740	0.99901922	0.99931323	Normal
RF 0.99968629 0.99924414 0.99924414 0.99924414 Moderate 0.99964707 0.99920980 0.99901111 Severe 0.9996786 0.99941107 0.99862691 0.99901184 PDR 0.9995243 0.99964446 0.99903138 0.99883788 Normal 0.99925493 0.9975005 0.99832667 0.9985290 Moderate 0.99925493 0.9998191 0.99861715 Severe 0.99937257 0.99881246 0.9998191 0.99861715 Severe 0.99937257 0.99882214 0.9998191 0.99861715 Severe 0.9998236 0.99997255 0.999800 0.99997039 Normal 0.99980393 0.9996207 0.9994321 Moderate 0.99980393 0.99964400 0.9994747 0.9995058 Mild ISVM 0.99976472 0.99941153 0.9997533 PDR 0.9994022 0.99845111 0.9994747 0.99950517 Severe 0.99949022 0.99845111 0.99977200 0.99877200 <td></td> <td></td> <td>0.99956864</td> <td>0.99804499</td> <td>0.99941005</td> <td>0.999003170</td> <td>Mild</td>			0.99956864	0.99804499	0.99941005	0.999003170	Mild
Al 0.99964707 0.99901711 0.99911111 Severe 0.99960786 0.99901171 0.99901111 Severe 0.99952943 0.999504107 0.99862691 0.99901184 PDR 0.9992543 0.9975005 0.99836725 0.99805627 Mild 0.99925493 0.99775005 0.99867725 0.99805627 Mild NB 0.99941179 0.99848857 0.99843014 PDR 0.9993257 0.99882214 0.99843014 PDR 0.9993257 0.99882214 0.99980385 0.99980314 PDR 0.99984314 0.99924433 0.9992077 0.99993321 Moderate 0.9998629 0.9990161 0.9992077 0.99950617 Severe 0.99998033 0.99964900 0.99921533 PDR Normal 0.99994022 0.99845111 0.99991386 0.99871200 Moderate 0.999949022 0.9980186 0.9987200 0.99877200 Mild SVM 0.99943022 0.99867663 0.9987200 0.998		RF	0.99968629	0.99924414	0.99924414	0.99924414	Moderate
AlexNet 0.99940786 0.99941107 0.99862691 0.99901884 PDR 0.99952943 0.99864466 0.99903138 0.99883788 Normal 0.99925493 0.99775005 0.99836267 0.99885272 Mild NB 0.99941107 0.99848857 0.99867725 0.9985290 Moderate 0.99945100 0.99881446 0.99981305 0.999813014 PDR 0.9998236 0.99980624 0.99980345 0.999830345 0.9998030 Normal 0.99986360 0.999960220 0.99941105 0.9995255 0.99930321 Moderate 0.9998636 0.999901961 0.99941153 0.9992153 PDR 0.9994022 0.99845111 0.9992153 PDR 0.9992153 0.99949022 0.99847200 0.99877200 0.99877200 Mild SVM 0.9992433 0.9982964 0.99943025 0.9983336 0.99877200 0.99877200 Mild AlexNet 0.9994022 0.99867725 0.99843076 0.99872461 Normal		i ci	0.99964707	0.99920980	0.99901244	0.99911111	Severe
AlexNet 0.99952943 0.99864446 0.99903138 0.99883788 Normal NB 0.99925493 0.9975005 0.99836267 0.99805627 Mild NB 0.99941179 0.99848857 0.9986725 0.99858290 Moderate 0.99945100 0.9988146 0.999811991 0.9988536 0.999861715 Severe 0.99937257 0.9988226 0.99981325 0.999938600 0.99995058 Mild 0.99988236 0.9997525 0.99938600 0.99995058 Mild 0.99984314 0.9997525 0.99938600 0.99995058 Mild ISVM 0.99976472 0.99924443 0.99962207 0.99943321 Moderate 0.99980393 0.9996140 0.99940747 0.9995058 Mild ISVM 0.99952943 0.99877200 0.99877200 0.99877200 0.9994022 0.99901166 0.99841991 0.99871580 Severe 0.9994022 0.99856763 0.99877200 0.99872869 PDR 0.99941179 0.99866264<			0.99960786	0.99941107	0.99862691	0.99901884	PDR
AlexNet 0.99925493 0.99775005 0.99836267 0.99805627 Mild NB 0.99941179 0.99848857 0.99867725 0.99858290 Moderate 0.99935257 0.9988214 0.99803845 0.99843014 PDR 0.99988236 0.99980624 0.99980625 0.99979399 Normal 0.99984314 0.9997525 0.9993600 0.9995058 Mild ISVM 0.99976472 0.9996120 0.99943321 Moderate 0.99986829 0.99901961 0.9995058 Mild 0.99986629 0.99901961 0.999401747 0.9995017 Severe 0.99952943 0.99877200 0.9987106 Moderate 0.99940022 0.99981111 0.99877200 0.99877200 Mild SVM 0.99952943 0.99877200 0.99871580 Severe 0.9994022 0.99901186 0.99843076 0.99871580 Severe 0.9994022 0.99867673 0.9987200 0.9986643 Moderate 0.99994022 0.99867673			0.99952943	0.99864446	0.99903138	0.99883788	Normal
NB 0.99941179 0.99848857 0.99867725 0.99858290 Moderate 0.99945100 0.99881446 0.99841991 0.99861715 Severe 0.99937257 0.99882214 0.99903845 0.99943014 PDR 0.99988236 0.999961255 0.9997039 Normal 0.99984314 0.999525 0.9994300 0.99943321 Moderate 0.99980393 0.99960490 0.9994177 0.99921553 PDR 0.9994022 0.99901961 0.99941153 0.99921553 PDR 0.9994022 0.99845111 0.99921553 PDR Normal 0.99952943 0.99877200 0.99877200 0.99877200 Moderate 0.9994022 0.998111 0.99852669 PDR O O O Moderate 0.99949022 0.99901186 0.99843076 0.99852669 PDR O O Severe O O Severe O O Severe O O Severe O Severe O D <td></td> <td></td> <td>0.99925493</td> <td>0.99775005</td> <td>0.99836267</td> <td>0.99805627</td> <td>Mild</td>			0.99925493	0.99775005	0.99836267	0.99805627	Mild
AlexNet 0.99945100 0.99881446 0.99841991 0.99861715 Severe 0.99937257 0.99882214 0.99803845 0.99843014 PDR 0.99988236 0.9998624 0.99961255 0.99970939 Normal 0.99984314 0.9997525 0.9993600 0.999943321 Moderate 0.99984314 0.99976472 0.9992443 0.99940747 0.99950617 Severe 0.9998629 0.99901961 0.99940747 0.99950617 Severe 0.9994022 0.99845111 0.99940747 0.99950617 Severe 0.99940022 0.99845111 0.99940747 0.99950617 Severe 0.99940022 0.99845111 0.9992153 PDR Normal 0.99940022 0.99847200 0.9987200 Mild Mild SVM 0.9994022 0.9990186 0.99843076 0.99871580 Severe 0.9994022 0.9985664 0.99843076 0.99852869 PDR AlexNet 0.9994022 0.99856763 0.99877200 0.998668643		NB	0.99941179	0.99848857	0.99867725	0.99858290	Moderate
AlexNet 0.99937257 0.99882214 0.99803845 0.99843014 PDR 0.99988236 0.99980624 0.99961255 0.99970939 Normal 0.99984314 0.9997525 0.99938600 0.9995058 Mild 0.99976472 0.99924433 0.99962207 0.99943321 Moderate 0.99980393 0.99960490 0.99940747 0.99950617 Severe 0.99968629 0.99901961 0.99941153 0.99921553 PDR 0.99952943 0.999877200 0.99877200 0.99877200 Mild SVM 0.9993336 0.99829964 0.9984828 0.99839395 Moderate 0.9994022 0.99901186 0.9984828 0.99839395 Moderate 0.9994022 0.99901186 0.99841991 0.99857630 Severe 0.9994022 0.99903157 0.99925151 0.999878580 Severe 0.99949022 0.99856763 0.99877200 0.99866980 Mild RF 0.99949022 0.99856763 0.99977200 0.99866980 <			0.99945100	0.99881446	0.99841991	0.99861715	Severe
AlexNet 0.99988236 0.99980624 0.99961255 0.99970939 Normal ISVM 0.99976472 0.9997525 0.99938600 0.9995058 Mild 0.99980393 0.99960490 0.99940747 0.9995057 BW 0.99980393 0.99960490 0.99940747 0.99950517 Severe 0.9994022 0.99940747 0.99921553 PDR 0.99949022 0.99845111 0.99921553 PDR 0.99952943 0.99877200 0.99877200 0.99877200 0.99949022 0.99901186 0.99841991 0.99871580 Severe 0.99949022 0.99901186 0.99843076 0.99852669 PDR 0.99949022 0.99985763 0.99987200 0.99852869 PDR 0.99949022 0.99856763 0.99877200 0.99862684 Moderate 0.99949022 0.99856763 0.99877200 0.99866980 Mild RF 0.999952943 0.99867775 0.99905518 0.9986643 Moderate 0.99949022 0.99881470 <td></td> <td></td> <td>0.99937257</td> <td>0.99882214</td> <td>0.99803845</td> <td>0.99843014</td> <td>PDR</td>			0.99937257	0.99882214	0.99803845	0.99843014	PDR
AlexNet 0.99984314 0.99979525 0.99938600 0.99959058 Mild ISVM 0.99976472 0.99924443 0.99962207 0.99943321 Moderate 0.99980393 0.99960490 0.99940747 0.99950617 Severe 0.99986629 0.99901961 0.99991153 0.99921553 PDR 0.99952943 0.99877200 0.99877200 0.99877200 Mild SVM 0.9993336 0.99829964 0.9984828 0.99839395 Moderate 0.9994022 0.99901186 0.99843076 0.99857580 Severe 0.9994022 0.99903157 0.99925511 0.99912833 Normal 0.99940707 0.99867750 0.999866980 Mild RF 0.99952943 0.9986775 0.99925511 0.99886643 Moderate 0.9994022 0.9986775 0.999857200 0.99886643 Moderate 0.99949022 0.99881470 0.99881742 0.99871605 Severe 0.99949022 0.99986775 0.99985766 0.99877266 <			0.99988236	0.99980624	0.99961255	0.99970939	Normal
ISVM 0.99976472 0.99924443 0.99962207 0.99943321 Moderate 0.99980393 0.99960490 0.99940747 0.99950617 Severe 0.99968629 0.99901961 0.99941153 0.99921553 PDR 0.9994022 0.99845111 0.99903138 0.99877100 Moderate 0.99952943 0.99877200 0.99877200 0.99877200 Moderate SVM 0.9994022 0.9980186 0.99881828 0.9983935 Moderate 0.9994022 0.99901186 0.99843076 0.99871800 Severe 0.99941179 0.99862664 0.99843076 0.99852869 PDR AlexNet 0.9994022 0.99903157 0.99922511 0.99912833 Normal AlexNet 0.99949022 0.99856763 0.99877200 0.9986643 Moderate 0.99949022 0.99856763 0.99877200 0.9986643 Moderate 0.99949022 0.99867775 0.999871605 Severe 0.99949022 0.99881470 0.99886643 Moderate			0.99984314	0.99979525	0.99938600	0.99959058	Mild
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AlexNet 0.99949022 0.99845111 0.99903138 0.99874116 Normal AlexNet 0.99952943 0.99877200 0.99877200 0.99877200 Mild AlexNet 0.99933336 0.99829964 0.99848828 0.99839395 Moderate AlexNet 0.99940022 0.99901186 0.99843076 0.99852869 PDR AlexNet 0.99964707 0.99903157 0.99922511 0.99912833 Normal 0.9994022 0.99856763 0.99877200 0.99866980 Mild 0.99949022 0.99856763 0.9997200 0.99866980 Mild 0.99949022 0.99856763 0.9997200 0.99866980 Mild 0.99949022 0.99856763 0.9997200 0.99866433 Moderate 0.9994022 0.9986775 0.99905518 0.9987605 Severe 0.9994022 0.99981470 0.99861742 0.99871605 Severe 0.99994022 0.99901865 0.99843076 0.99872461 PDR 0.99990807 0.99748306			0.99968629	0.99901961	0.99941153	0.99921553	PDR
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SVM 0.99933336 0.99829964 0.99848828 0.99839395 Moderate 0.99940022 0.99901186 0.99841991 0.99871580 Severe AlexNet 0.99941179 0.99862664 0.99843076 0.99852869 PDR 0.99940022 0.99903157 0.99922511 0.99912833 Normal 0.99940022 0.99856763 0.99877200 0.99866980 Mild 0.99940022 0.99856763 0.99905518 0.99886643 Moderate 0.99949022 0.99881470 0.99861742 0.99871605 Severe 0.99940022 0.99901865 0.99843076 0.99872461 PDR 0.99990807 0.99748306 0.99806277 0.9977283 Normal 0.99917650 0.99836099 0.99733934 0.99773285 Moderate 0.99905886 0.99752439 0.9972139 0.99773285 Moderate 0.99909807 0.99782695 0.99762986 0.99772840 Severe			0.99952943	0.99877200	0.99877200	0.99877200	Mild
AlexNet 0.99949022 0.99901186 0.99841991 0.99871580 Severe AlexNet 0.99941179 0.99862664 0.99843076 0.99852869 PDR 0.99964707 0.99903157 0.99922511 0.99912833 Normal 0.99949022 0.99856763 0.99877200 0.99866980 Mild 0.99949022 0.99856763 0.99905518 0.99886643 Moderate 0.99949022 0.99881470 0.99861742 0.99871605 Severe 0.99949022 0.99901865 0.99843076 0.99872461 PDR 0.99990807 0.99748306 0.99806277 0.99777283 Normal 0.99917650 0.99836099 0.99733934 0.99773285 Moderate 0.99905886 0.99752439 0.9972139 0.99773285 Moderate 0.9990807 0.99782695 0.99762986 0.99772840 Severe		SVM	0.99933336	0.99829964	0.99848828	0.99839395	Moderate
AlexNet 0.999411/9 0.99862664 0.99843076 0.99852869 PDR 0.99964707 0.99903157 0.99922511 0.99912833 Normal 0.9994022 0.99856763 0.9987200 0.99866980 Mild RF 0.99952943 0.99867775 0.99905518 0.99886643 Moderate 0.9994022 0.99881470 0.99861742 0.99871605 Severe 0.9994022 0.99901865 0.99843076 0.99872461 PDR 0.99990807 0.99748306 0.99806277 0.9977283 Normal 0.99917650 0.99836099 0.99733934 0.99773285 Moderate 0.99905886 0.99754439 0.99762986 0.99773285 Moderate 0.9990807 0.99782695 0.99762986 0.99772840 Severe			0.99949022	0.99901186	0.99841991	0.99871580	Severe
0.99964/07 0.99903157 0.99922511 0.99912833 Normal 0.99949022 0.99856763 0.99877200 0.99866980 Mild RF 0.99952943 0.99867775 0.99905518 0.99886643 Moderate 0.99949022 0.99881470 0.99861742 0.99871605 Severe 0.99949022 0.99901865 0.99843076 0.99872461 PDR 0.99909807 0.99748306 0.99806277 0.9977283 Normal 0.99917650 0.99836099 0.99733934 0.99773285 Moderate 0.99905886 0.99754439 0.99792139 0.99773285 Moderate 0.9990807 0.99782695 0.99762986 0.99772840 Severe	AlexNet		0.99941179	0.99862664	0.99843076	0.99852869	PDR
0.99949022 0.99856763 0.99877200 0.99866980 Mild RF 0.99952943 0.99867775 0.99905518 0.99886643 Moderate 0.99949022 0.99881470 0.99861742 0.99871605 Severe 0.99949022 0.99901865 0.99843076 0.99872461 PDR 0.99909807 0.99748306 0.99806277 0.9977283 Normal 0.99917650 0.99836099 0.99733934 0.99773285 Moderate 0.99905886 0.99754439 0.99792139 0.99773285 Moderate 0.9990807 0.99782695 0.99762986 0.99772840 Severe			0.99964707	0.99903157	0.99922511	0.99912833	Normal
Kr 0.9992243 0.9960775 0.99905318 0.99886643 Moderate 0.9994022 0.99881470 0.99861742 0.99871605 Severe 0.9994022 0.99901865 0.99843076 0.99872461 PDR 0.99909807 0.99748306 0.99806277 0.9977283 Normal 0.99917650 0.99836099 0.99733934 0.99784990 Mild NB 0.99905886 0.99754439 0.99722139 0.99773285 Moderate 0.9990807 0.99782695 0.99762986 0.99772840 Severe		DE	0.99949022	0.99856763	0.998/7200 0.00005519	0.99866980	Madarata
0.99949022 0.9981470 0.99861742 0.99871605 Severe 0.99949022 0.99901865 0.99843076 0.99872461 PDR 0.99990807 0.99748306 0.99806277 0.99777283 Normal 0.99917650 0.99836099 0.99733934 0.99773285 Moderate 0.99905886 0.99754439 0.99792139 0.99773285 Moderate 0.99909807 0.99782695 0.99762986 0.99772840 Severe		KF	0.99952945	0.99867775	0.999000018	0.99880043	Moderate
0.99949022 0.99901805 0.99845076 0.99972461 PDK 0.99909807 0.99748306 0.99806277 0.99777283 Normal 0.99917650 0.99836099 0.99733934 0.99784990 Mild NB 0.99905886 0.99754439 0.99792139 0.99773285 Moderate 0.99909807 0.99782695 0.99762986 0.99772840 Severe			0.99949022	0.9900194	0.99001/42	0.99871603	Severe
0.99909007 0.99740006 0.99800277 0.99777285 Normal 0.99917650 0.99836099 0.99733934 0.99784990 Mild NB 0.99905886 0.99754439 0.99792139 0.99773285 Moderate 0.99909807 0.99782695 0.99762986 0.99772840 Severe			0.77747022	0.99901000	0.77043070	0.990/2401	FDK Normal
NB 0.99905886 0.99754439 0.99762986 0.99773285 Moderate 0.99909807 0.99782695 0.99762986 0.99772840 Severe			0.99909807	0.77740300	0.77000277	0.77111203	Mild
0.99909807 0.99782695 0.99762986 0.99772840 Severe		NB	0.99917000	0.99030099	0.99703934	0.99704990	Moderate
			0.99909807	0.99782695	0.99762986	0 99772840	Severe
0.99894122 0.99725436 0.99744998 0.99735216 PDR			0.99894122	0.99725436	0.99744998	0.99735216	PDR

CNN Model	Classifier	Accuracy	Precision	Recall	F1-Score	Class
		0.99980393	0.99961248	0.99941883	0.99951564	Normal
		0.99972550	0.99938588	0.99918133	0.99928359	Mild
	ISVM	0.99984314	0.99962207	0.99962207	0.99962207	Moderate
		0.99960786	0.99861851	0.99940747	0.99901283	Severe
		0.99976472	0.99960754	0.99921538	0.99941142	PDR
		0.99941179	0.99825750	0.99883766	0.99854750	Normal
		0.99937257	0.99795501	0.99877200	0.99836334	Mild
	SVM	0.99937257	0.99867675	0.99829932	0.99848800	Moderate
		0.99933336	0.99861660	0.99802489	0.99832066	Severe
Incention		0.99937257	0.99862637	0.99823460	0.99843045	PDR
niception		0.99945100	0.99864394	0.99864394	0.99864394	Normal
		0.99937257	0.99795501	0.99877200	0.99836334	Mild
	RF	0.99925493	0.99848743	0.99792139	0.99820433	Moderate
		0.99929415	0.99822240	0.9982224	0.99822240	Severe
		0.99933336	0.99843045	0.9982346	0.99833252	PDR
		0.99898043	0.99728892	0.99767532	0.99748208	Normal
	NB ISVM	0.99890200	0.99733825	0.99693000	0.99713408	Mild
		0.99890200	0.99716660	0.99754346	0.99735500	Moderate
		0.99898043	0.99743235	0.99743235	0.99743235	Severe
		0.99905886	0.99784144	0.99744998	0.99764567	PDR
		0.99980393	0.99980616	0.99922511	0.99951555	Normal
		0.99964707	0.99897688	0.99918133	0.99907910	Mild
		0.99984314	0.99981096	0.99943311	0.99962200	Moderate
		0.99945100	0.99802722	0.99920995	0.99861824	Severe
		0.99968629	0.99941130	0.99901922	0.99921522	PDR
		0.99937257	0.99825716	0.99864394	0.99845051	Normal
		0.99933336	0.99795459	0.99856734	0.99826087	Mild
	SVM	0.99933336	0.99867650	0.99811036	0.99839335	Moderate
		0.99921572	0.99822170	0.99782738	0.99802450	Severe
VGG-19		0.99921572	0.99803845	0.99803845	0.99803845	PDR
VUU 17		0.99925493	0.99787028	0.99845021	0.99816016	Normal
		0.99929415	0.99795417	0.99836267	0.99815838	Mild
	RF	0.99917650	0.99829836	0.99773243	0.99801531	Moderate
		0.99909807	0.99782695	0.99762986	0.99772840	Severe
		0.99925493	0.99823426	0.99803845	0.99813634	PDR
		0.99890200	0.99709527	0.99748160	0.99728840	Normal
		0.99878436	0.99692938	0.99672534	0.99682735	Mild
	NB	0.99886279	0.99716607	0.99735450	0.99726027	Moderate
		0.99886279	0.99703791	0.99723484	0.99713637	Severe
		0.99909807	0.99803729	0.99744998	0.99774355	PDR

Table 7. Cont.

Figure 9 presents the evaluation of the performance metrics for the different models. According to the achieved results, overall testing accuracy, and performance metrics, the proposed model is appropriate for detecting and classifying DR with a testing accuracy of 98.32% on the APTOS dataset.

Table 8 tabulates the varying sizes of the training and testing sets and the corresponding mean and standard deviation.

Table 8. Varying training and test size.

Dataset	Training	Testing	Accuracy	Mean	Standard Deviation
	70	30	0.981225		
APTOS	75	25	0.983202	0.982543	0.0011409
	80	20	0.983202	_	
	70	30	0.971344		
Kaggle	75	25	0.982213	0.980237	0.0080882
	80	20	0.987154	_	



Figure 9. DR classification comparison of various classifiers of different datasets. It displays the performance results of the two datasets. Pink color represents the messidor and the green represents the APTOS.

4. Discussion

This study aimed to identify and classify DR based on fundus images from two different datasets. Initially, all the images in the dataset were of different sizes; the images were resized to 225×225 using the RGB colour. The hyperparameters were tuned to optimize the proposed model. Model training can be accelerated, and the possibility of performance improved using the pooling function. There is no ideal batch size, and we implemented the experiments with various batch sizes. If we find the suitable batch size in addition to the suitable kernel and hidden layers, the model will yield a high performance. Batch size 64 produces better results than batch sizes 16 or 32. The batch size was 64 for the fundus images because this study's dataset was large. From previous studies, we observed that the batch sizes, in conjunction with a suitable kernel and hidden layer, will yield a high performance. The parameters (i.e., a batch size of 64, epochs of 1000, and a learning rate of 0.001) were adjusted to achieve a high performance.

After extracting the features, the improved SVM classifies the lesions. In [15], the authors implemented AdaBoost to extract the features and the Gaussian mixture model, KNN, and SVM to classify the lesions and analyse the retina fundus images with different illuminations and views. A new unsupervised approach based on PCA for detecting microaneurysms was presented in [16]. The manual identification and differentiation of diabetic retinopathy from fundus images is time-consuming. Table 9 presents the processing time analysis of the existing techniques for the Kaggle and APTOS datasets to calculate the computation overhead. The achieved results revealed that the overall processing time for the improved SVM classifier is the most appropriate for diabetic retinopathy classification, with a minimum of 14 ms for Kaggle and 15 ms for APTOS datasets.

Classifier	Kaggle (s)	APTOS (s)
Logistic regression [32]	21	29
DT [33]	15	21
KNN [34]	23	30
NB [35]	20	25
RF [36]	20	23
SVM [37]	22	31
Improved SVM	14	15

Table 9. DR classification comparison of the processing time for the proposed model with different optimizations.

A study based on feature extraction using the RF model produced 74% accuracy in DR image classification [38]. Another two proposed hybrid models are based on combining the Gaussian mixture model and SVM to diagnose microaneurysms [18] and using KNN for the detection and classification of DR [39]. All the above-discussed studies used the existing classifiers to classify the DR lesions.

Some studies implemented CNN models to perform the binary classification of DR datasets [40,41]. Dropout regularization, augmentation, and pre-processing were performed manually by using the image editing tools in [42]. A deep CNN was proposed by [43] to classify normal and NPDR with two neural networks (i.e., the global and the local) and model performance was evaluated by the kappa score. The main disadvantage of this work is that it classifies only normal and NPPR, but it only works to detect the PDR.

To overcome those issues, the diagnostic results of the proposed model proved that it can achieve a satisfactory diagnostic performance, which can significantly assist the medical professional in the decision-making process in the early stages of detecting the infection, and timely treatment can decrease risk. Automatic screening and differentiation of diabetic retinopathy from fundus images will significantly reduce the effort of the medical professional and accelerate the diagnosis process.

Five class classifications are realized in the model, providing feasibility for the diagnosis of DR and its severity levels. The proposed model for the feature extraction and classification of DR performs better than the state-of-the-art models with high accuracy and less complexity. We will further optimize the model to model the accuracy of DR diagnosis and try to develop a more powerful DR detection model to assist doctors in clinical examinations.

The limitation of this model is that it is trained with only fundus image-level supervision, making it very challenging to accurately locate some minute lesion regions. Next, we need to specify the coarse location of the lesion along with the DR grading, which will help from the perspective of clinical application.

5. Conclusions

High blood pressure leads to DR, which causes retinal damage. Retinal vascularization is damaged by DR and can lead to blindness and potentially death. Fundoscopy examinations, which are time-consuming and expensive, allow ophthalmologists to see retinal vascular swelling. There is a need to automatically identify diabetic retinopathy by examining retinal fundus images. This study proposed an enhanced pooling function technique to minimize the loss to detect retina lesions, and an improved SVM classifier to classify the lesions using linear mapping. Five pre-trained deep learning models were recognized during the selection of the implementation, namely VGG-16, DenseNet, ResNet-50, Inception, and AlexNet. The proposed pooling and activation function results outperformed all the existing models. This study's proposed model provided efficient accuracy results compared to the existing models.

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