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Diabetic retinopathy detection using convolutional neural network with residual blocks

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ABSTRACT

Diabetic Retinopathy (DR) is a disease that happens in the patient eyes of long-term diabetics. It also affects the retina which causes eye blindness. Therefore, DR has to be detected at its early stage to decrease the risk of blindness. Several researchers suggested approaches to detect the blood abnormalities (hemorrhages, Hard and soft exudates, and micro-aneurysms) in the retina images using deep learning models. The limitation with these approaches is the performance degradation and required high training time. To solve this, we suggest a model for automated detection of DR severity using a convolutional neural network (CNN) and residual blocks (DRCNNRB). Deep learning models work effectively when they have been trained on vast datasets. Data Augmentation helps to increase the training samples as a result avoids the data imbalance problem. In our model, basic data augmentation techniques such as zooming, shearing, rotation, flipping, and rescaling are applied in DRCNNRB to solve the data imbalance problem. Pre-processing techniques are used to enhance the quality of the image. Extensive experimental results on the Diabetic Retinopathy 2015 Data Colored Resized database conclude that DRCNNRB provides better performance compared to other state-of-the-art works. Thus, DRCNNRB achieves better efficiency for real-time diagnosis.

1. Introduction

Diabetic Retinopathy (DR) is the major cause of blindness in diabetic people if it is not predicted or identified in the early stages. As per records, there are 415 million diabetic patients worldwide [1]. It may also affect many organs like the heart, kidneys, eyes, etc. Initial screening is needed to prevent DR. Early detection of DR saves ninety percent of diabetic patients [2]. DR is categorized into (a) Proliferative DR (PDR), and (b) Non-proliferative DR (NPDR). Three different classes of NPDR exits: (1) Moderate NPDR (2) Mild NPDR, and (3) Severe NPDR [3–6]. The numerous types of DR are presented in Fig. 1.

The evaluation and examination of the retina images to detect the DR by ophthalmologists or trained clinicians is a cost-consuming and time taking process. The manual detection of the DR seems to result in an error. So, deep learning (DL) has been used widely in the medical application which will speed up the detection and classification process. It also improves the accuracy of detection. Therefore, several researchers proposed various methods to automate DR detection over the past few years [7–10]. To detect the DR severity, various researchers adopted DL models [11–13]. The limitation of these approaches is the lack of performance. Most researchers experimented with convolutional neural networks (CNN) in their works to detect the DR. However, CNN has several limitations such as performance degradation, vanishing gradient problem, and could not learn basic functions as an identity function due to its deeper network. Residual blocks help to overcome these limitations as it implements skip connections and has a shallow network. In CNN, every layer feeds into the succeeding layer whereas, in residual blocks, each layer connects to the following layer and directly into the layers which are 2–3 hops away [14,15].

Contributions

- We introduce a model (DRCNNRB) to identify the severity of DR automatically using CNN and Residual Blocks.
- Preprocessing & Data Augmentation techniques are used in DRCNNRB to remove noises present in images and to overcome the class imbalance problems.
- Our model has experimented on publicly available dataset [16] and checks the measures like recall, F1-Score, accuracy, and precision to find the efficiency of DRCNNRB.

2. Related works

Deep Neural Networks, especially CNN have shown better efficiency for the classification of images. Existing approaches to detect and classify DR severity using DL methods are categorized into

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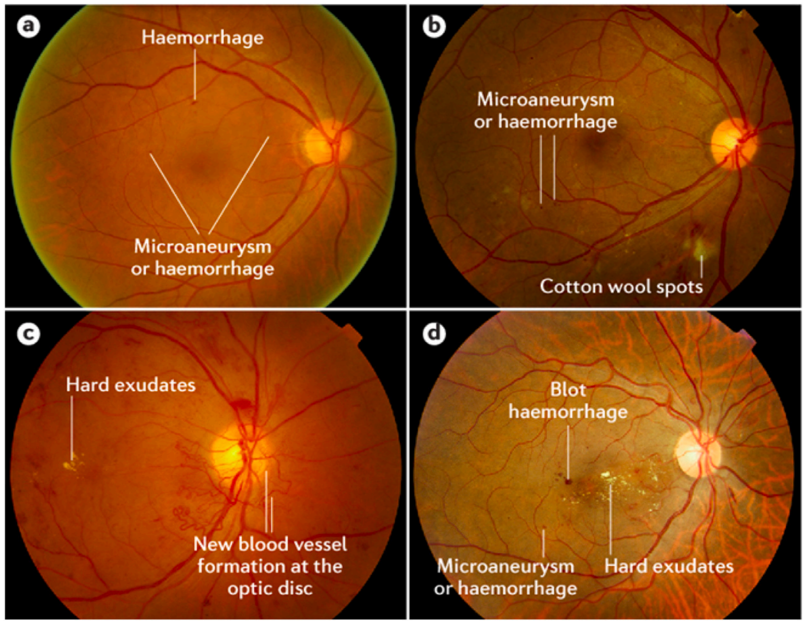

Fig. 1. Severity levels of DR - (a) Mild NPDR (b) Moderate NPDR (c) Severe NPDR (d) Proliferative DR.

vessels-based classification, multi-class classification, binary classification, and lesion-based classification. Some of the existing multi-class classification techniques to detect the DR are discussed in this section.

Pao et al. [17] suggested a technique to compute the entropy images of gray & green levels by using a bichannel CNN model. Gayatri et al. [18] suggested a lightweight CNN model for binary- and multi-class DR grading. The severity of DR is classified by Pratt et al. using the CNN model. Antal et al. [19] utilized the CNN model to classify the several classes of DR. Nagpal et al. [20] explored the use of a pretrained model i.e., InceptionV3 to detect the DR. This approach has an advantage of less training time due to the use of pretrained model. Xiang et al. [21] suggested a multi-level iterative method of CNN and enhanced learning, with an accuracy of 91.79%. Borys Tymchenko et al. [22] used the CNN model and a multistage approach to detect the severity of DR and achieve the quadratic weighted kappa's (QWK) as 0.92. The classification of DR severity and detection of lesions is achieved by Yang et al. [9] using a 2-phase CNN model. S. Dutta et al. [23] explored the use of CNN, deep neural network (DNN), and back-propagation neural network (BNN) to classify & detect the severity of DR. They experimented their approach on 2000 images from the Kaggle dataset [16] and analyzed that DNN achieves fair performance compared to the other two neural networks. Seetah et al. [24] used the CNN model to identify the severity of DR & obtained an accuracy of 84%. wang et al. [25] suggested a zoom-in net architecture to identify the DR severity & experimented on EyePACS and Messidor datasets. All these approaches require more training data and time. To overcome this limitation, some of the researchers used the pretrained models of CNN.

The pretrained architectures such as InceptionNet V3 [26], AlexNet [27], and VGG16 are used to identify the various types of DR severity by X.Wang et al. [28]. Their experiments conclude that InceptionNet V3 achieves fair performance. Similarly, Wan et al. [29] utilized the pretrained CNN architectures such as VggNet, GoogleNet, and AlexNet [27], and ResNet to detect the five stages of DR. From their experiments, VggNet achieves the better performance when compared to other pretrained models. Automated classification is proposed by Nguyen et al. [30] using models such as VGG-16, CNN, and VGG-19. Sandhya et al. [31] proposed a combination of pretrained architecture approaches to identify the DR severity. It can be inferred from their experiments that InceptionV3 + DenseNet169 achieves fair performance. Esfahani MT et al. [32] used the ResNet to identify the stages of DR & obtained an accuracy of 85%.

All the above existing deep learning models achieve improvement over one another. However, these deep learning models suffer from performance degradation. As a result, we propose a method using CNN and residual blocks to find the several stages of DR and also overcome the limitations of existing approaches.

3. Diabetic Retinopathy detection using CNN and residual blocks

The flow diagram of DRCNNRB is exhibited in Fig. 2. Pre-processing and Augmentation, CNN & Residual Blocks are the two phases involved in DRCNNRB.

3.1. Preprocessing and data augmentation

The two tasks involved in this phase are (1) Pre-processing: Apply techniques such as circle crop, median subtraction, gamma correction, and adaptive histogram equalization to improve the image quality. (2) Data augmentation: Apply the basic augmentation operations such as rescale, brightness, zoom, shear, rotation, and flipping on the preprocessed images to overcome the data imbalance.

3.1.1. Preprocessing

Usually, all the medical images are extremely difficult to analyze and complicated. So, the pre-processing methods are crucial to embellish the features of the image for classification, and to maintain the uniformity of images. Some of the images of all classes in the considered dataset before preprocessing are exhibited in Fig. 3.

The preprocessing techniques such as (1) Circle-crop (2) Median Subtraction (3) Gamma Correction (4) Adaptive histogram equalization are used in the proposed model. Circle-crop helps to eliminate the unwanted background noise of the image and made all the images into uniform size 256*256. Median Subtraction uses the median filter to eliminate the noise where the median filter prevents the edges and it is faster than other filters. Gamma Correction is generally used for non-linear methods on the pixels of an input image and remodels the saturation of the image. The gamma value builds the relationship between the pixel value & the actual brightness value of an image. Adaptive histogram equalization helps to improve the image contrast concerning several histograms. The images after the pre-processing techniques of different images in the considered dataset are shown in Fig. 4. It can be inferred that the images have no noises and all images are in uniform size after the preprocessing phase.

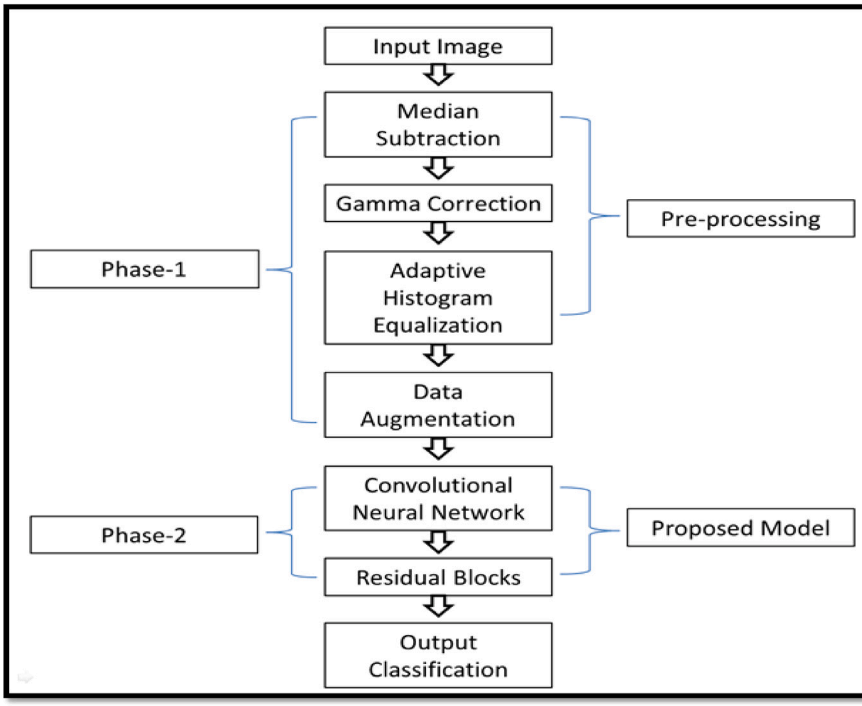

Fig. 2. Phases of DRCNNRB.

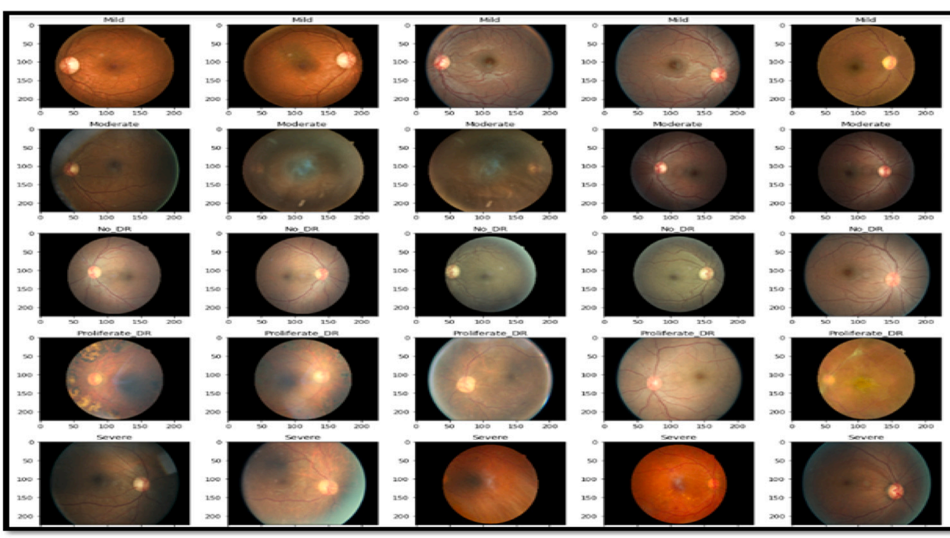

Fig. 3. A few images of each class from the dataset prior to preprocessing.

3.1.2. Data augmentation

Although, if the images are pre-processed and available for the process, there may exist one main challenge which is data imbalance. It can be inferred from Table 1 that all the classes have a different number of images with a large margin before applying the augmentation, this may lead to over-fitting while training. It is a very tedious job to collect the medical images. So, augmentation techniques help to increase the number of images that are very similar to the original images without manual collection of the new data. In DRCNNRB, general data augmentation such as scaling, rotation, & flipping are used to address the data imbalance problem. Since the images of types, No DR & Moderate are more, there is no need to apply the augmentation process for the images of respective types. So, data augmentation is applied only for the images of other types such as mild, severe, and proliferative. A total of 4956, 5238, & 4884 images of types proliferative, severe, and mild are generated by augmenting each image to 7, 6, and 2 respectively. The number of images for each class prior to and subsequent applying data augmentation techniques are shown in Table 1. Only 5292 images of type No DR are considered to maintain uniformity. The process of applying data augmentation is explained below:

Mild DR: 814, 814, and 815 images are generated by applying the scaling, rotation, and flipping techniques on 814, 814, and 815 original images. As a result, a total of 4886 images (2443 original + 2443 augmented) are obtained after the augmentation process.

Severe DR: 1746, 1746, and 873 images are generated by applying the scaling (two scale ratios), rotation (with two different angles), and

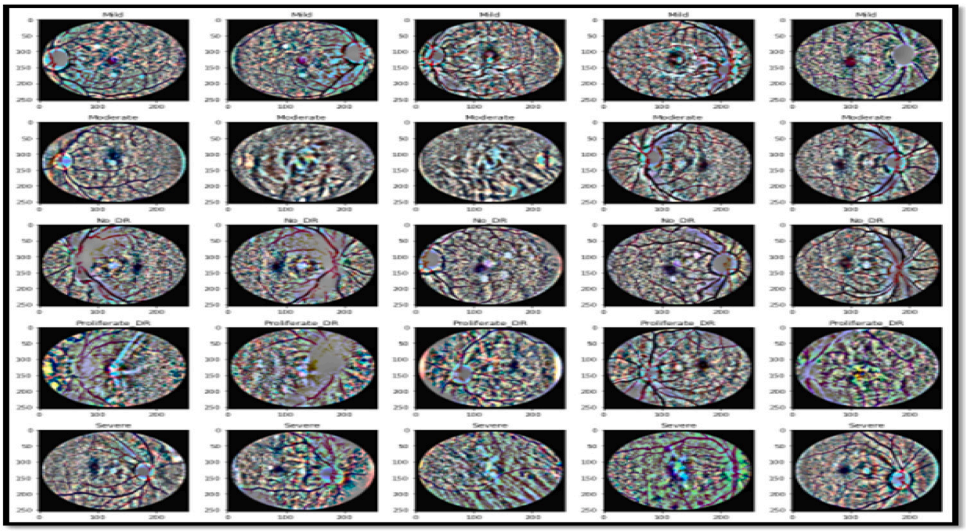

Fig. 4. Some images of each class from the dataset after preprocessing.

Table 1
Number of images in each class prior to and subsequent to augmentation process.

Class	Before augmentation	After augmentation
No DR	25,810	25,810
Mild	2,443	4,886
Moderate	5,292	5,292
Severe	873	5,238
Proliferative	708	4,956

flipping (horizontal) techniques on 873 original images. As a result, a total of 5238 images (873 original + 4365 augmented) are used in the proposed approach.

Proliferative DR: 1416, 2124, and 708 images are generated by applying the scaling (two scale ratios), rotation (with three different angles), and flipping (horizontal) techniques on 708 original images. As a result, a total of 4956 images (708 original + 4248 augmented) are used in the proposed approach.

3.2. Convolutional neural network and residual block

Convolutional Neural Network (CNN) has several limitations such as performance degradation, vanishing gradient problems, and could not to learn basic functions as an identity function due to its deeper network. Residual blocks help to overcome these limitations as it implements skip connections and has a shallow network. In CNN, every layer feeds into the succeeding layer whereas, in residual blocks, each layer connects to the following layer and directly into the layers which are 2–3 hops away [14,15]. As a result, DRCNNRB uses the Residual Blocks. A CNN with multiple residual blocks is used to classify the type of a DR image. Fig. 5(a) depicts the proposed model and the layers involved in the respective blocks. The proposed model consists of 8 main layers. (1) Zero-Padding is used to add zeros symmetrically to the input matrix so that all the pixels can be used equally. (2) Convolutional Layer uses filters and parameters which are useful to learn through training and it also decreases the size of the input matrix. (3) Batch Normalization speed up the training and uses higher learning rates. ReLU is used to prevent the exponential growth to operate the neural network. (4) Max pooling considers the maximum value over the input window for every channel of the input as a result it down-samples the input along its spatial dimensions. (5) Residual block (Res-Block) is useful to prevent vanishing gradient problem with the help of a skip connection or short path. The different layers present in Res-Block are shown in Fig. 5(b). As shown in Fig. 5(b), Res-Block consists of a convolution block and two identity blocks. (6) Average pooling considers the mean value over the input window for every channel of the input as a result it down-samples the input along its spatial dimensions. (7) Flatten Layer is used to convert all the 2D-Dimensional arrays from the pooling layer into a single linear vector and the flattened vector is fed as input to a fully connected layer. (8) Dense layer receives all the neurons of the previous layer and classifies the images using the softmax activation function. The different layers of convolutional block and identity block are shown in Fig. 5(c). The convolutional block consists of 2 paths, in the main path has 7 layers and the short path (skip connection) contains only 3 layers as presented in Fig. 5(d). The identity block consists of 2 paths, the main path has 6 layers and the short path (skip connections) does not have any layer it directly sends the input to the output.

4. Implementation details and results

The dataset details, experimental setup, and metrics that are used to access the performance of DRCNNRB are mentioned in this section. A comparison analysis is also provided.

4.1. Implementation details

Description of the Dataset: DRCNNRB is experimented on the 'Diabetic Retinopathy 2015 Data Colored Resized' dataset [16] to check the performance. This dataset contains 25810 no DR images, 2443 mild DR images, 5292 moderate DR images, 873 severe DR images, and 708 of proliferative DR images. A total of 35,126 retina fundus images are there in the dataset. The distribution of images in all classes is imbalanced. So, we are increasing the images in all the classes as interpreted in Section 3.1.2.

Experimental Setup: The results or outcomes of DRCNNRB have experimented on a core i5/2.4 GHz processor with 8 GB RAM and an NVIDIA GeForce GTX 1070 Laptop (graphic processing unit) with deep learning libraries, tensor flow, and Keras.

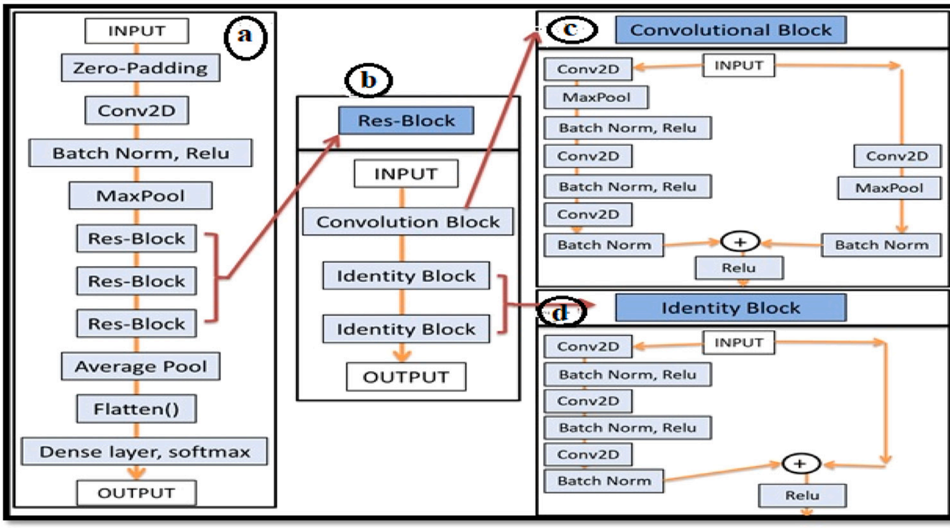

Fig. 5. Layers involved in (a) CNN with residual blocks (b) Residual blocks (c) Convolutional block (d) Identity block.

Table 2
Observations of various parameters.

Class	Precision	Recall	F1 score	Support
No DR	0.98	1	0.99	1101
Mild NPDR	0.96	0.97	0.97	1110
Moderate NPDR	0.95	0.94	0.94	998
Severe NPDR	0.95	0.97	0.96	1150
Proliferative DR	0.97	0.95	0.96	1100

4.2. Performance evaluation and comparison analysis

4.2.1. Metrics considered for performance evaluation

The performance measurements such as recall, accuracy, F1-score, & precision respectively [33] are used to measure the performance of DRCNNRB. Given the false negatives (x), false positives (y), true negatives (z), and true positives (w), the mathematical representation of the above measures are given below:

$$Accuracy = \frac{z+w}{x+y+z+w} \tag{1}$$

$$Precision\ (P) = \frac{w}{y+w} \tag{2}$$

$$Recall\ (R) = \frac{w}{x+w} \tag{3}$$

$$F1-score = \frac{2*(R*P)}{R+P} \tag{4}$$

4.2.2. Performance evaluation

The F1-score, recall, and precision of DRCNNRB are shown in Table 2. DRCNNRB considers the results by taking the average of 10 runs. Fig. 6 depicts the confusion matrix of DRCNNRB. It can be inferred from Fig. 6 that the accuracies for Proliferative DR, various types of NPDR, and No DR are 95%, 96%, 95%, 97%, and 100% respectively. The accuracy obtained for DRCNNRB is 96.23%.

4.2.3. Comparison analysis

The comparison of DRCNNRB with the existing approaches in terms of the accuracy on the considered database [16] is mentioned in Table 3. It can be observed from Table 3 that DRCNNRB accomplishes fair performance when compared to the existing approaches. The approaches [8,24,32] utilized the CNN model to identify the severity of DR. The fair performance is due to the inclusion of residual blocks in CNN.

5. Conclusion

In this paper, we introduce a model (DRCNNRB) to identify the severity of DR automatically using a convolutional neural network and residual block. DRCNNRB helps to solve the issues of existing approaches like performance degradation and vanishing gradient problem. DRCNNRB is tested on Diabetic Retinopathy 2015 Data Colored Resized dataset to find its effectiveness. Preprocessing techniques are applied in DRCNNRB to make the images more clear and to eliminate unwanted background information. Basic Data Augmentation is applied to maintain the uniformity of images in all classes. Extensive experimental results conclude that DRCNNRB provides fair accuracy compared to the existing works.

The work can be extended in the future by using either the generative adversarial network or variational autoencoder as a data augmentation technique.

Statements and declarations

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CRediT authorship contribution statement

Rajasekhar Kommaraju: Conceptualization, Methodology, Writing – review & editing, Investigation, Validation. **M.S. Anbarasi:** Conceptualization, Methodology, Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability statements

The dataset used in DRCNNRB to analyze its performance is available in the Kaggle repository, Diabetic Retinopathy 2015 Data Colored Resized https://www.kaggle.com/datasets/sovitrath/diabetic-retinopathy-2015-data-colored-resized?select=colored_images

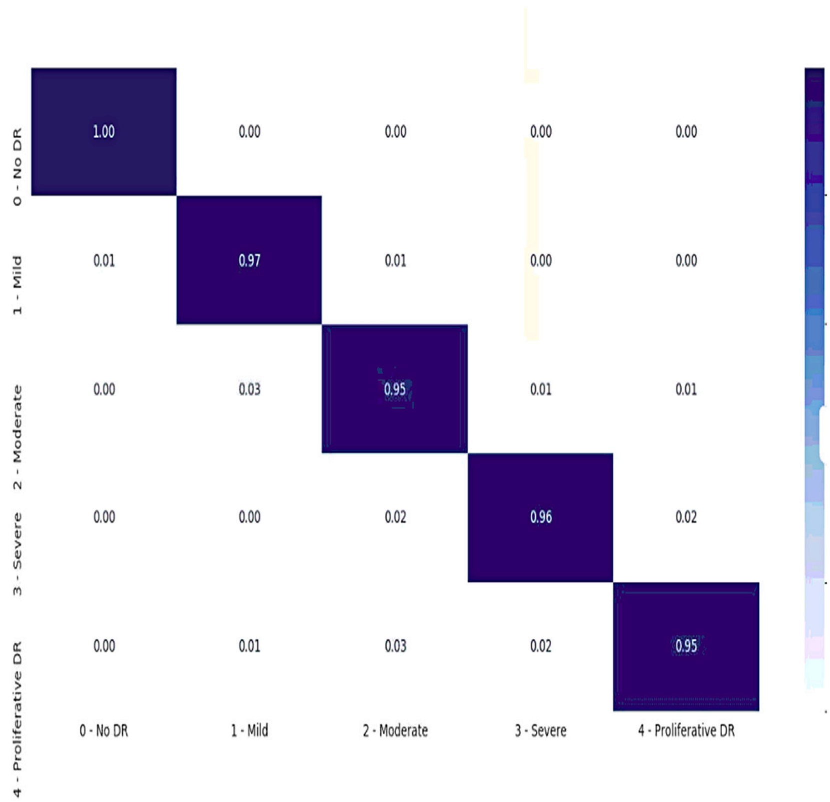

Fig. 6. Confusion Matrix.

Table 3
Comparison of DRCNNRB with other approaches.

	Number of images Considered	Testing accuracy (in %)
Pratt et al. [8]	80,000	75
Esfahani MT et al. [32]	35,000	85
S. Dutta et al. [23]	2,000	CNN = 78.3, BNN = 42, DNN = 86.3
Wan et al. [29]	35,126	CNN (VggNet) = 95.68
Seetah et al. [24]	1,000 images for training and 200 images for validation	84
Proposed method	25,664	96.23

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