Journal of Engineering and Technology for Industrial Applications

ISSN ONLINE: 2447-0228

ITEGAM-JETIA

Manaus, v.12 n.57, p. 1162-1169. January/February, 2026.

DOI: https://doi.org/10.5935/jetia. v12i57.3299

RESEARCH ARTICLE OPEN ACCESS

HIGH-ACCURACY BINARY CLASSIFICATION OF DIABETIC RETINOPATHY FROM FUNDUS IMAGES USING CNN ARCHITECTURE

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ARTICLE INFO

Article History
Received: January 13, 2025
Revised: January 20, 2026
Accepted: January 30, 2026
Published: February 28, 2026

Keywords:
Diabetic retinopathy,
Diabetes mellitus,
Artificial intelligence,
Convolutional neural network.

ABSTRACT

Diabetic Retinopathy (DR), a retinal condition associated with diabetes mellitus, is a leading global cause of blindness. Early detection and treatment is crucial to prevent or mitigate vision loss. Researchers have developed various artificial intelligence-based methods to detect diabetic retinopathy from fundus images, aiming to enhance diagnostic accuracy and efficiency, thereby improving patient outcomes. In this paper, we have introduced a custom convolutional neural network (CNN) architecture for detecting diabetic retinopathy. We have used an open-source "Diabetic Retinopathy 224×224 Gaussian Filtered" dataset from Kaggle, comprising of 3,668 images. The images are then labelled into two classes where one class represents "No Diabetic Retinopathy (No_DR)" and the other class represents "Diabetic Retinopathy (DR)". Then we have applied min-max normalization to scale pixel values to a specified range [0, 1]. Afterwards, the dataset is divided into three parts to train, validate and test the proposed CNN model. Our method has achieved a testing accuracy of 95.27% and F1 score of 95.29%. Then we have performed 5-fold cross validation to observe the performance of the proposed automatic DR detection method. We have also compared our proposed method with some pre-trained models and some existing methods. In observation, it has been shown that the proposed technique outperformed many other existing techniques.

I. INTRODUCTION

Diabetic eye diseases refer to a group of eye problems that can occur as a result of diabetes. Diabetic Retinopathy (DR) is among the most common diabetic eye diseases. It affects a significant portion of individuals living with diabetes, particularly those with poorly controlled blood sugar levels over an extended period of time. DR is caused as a result of Diabetes Mellitus that causes abnormal new blood vessels to grow on the surface of the retina [1]. As a result, the blood vessels of the retina may swell and/or leak fluid or blood. DR may not cause any harm in vision at first but over time it can get worse. It is very important to diagnose DR at the early stages.

But if DR is undiagnosed, it becomes more and more severe over the time through formation of Micro aneurysms, Exudates, Hemorrhages, Cotton Wool Spots, abnormal structure of the Optic Disc, abnormal Foveal Avascular Zone, Neovascularization's, Intra Retinal Microvascular Abnormalities and many more [1]. A person might see spots floating in their vision or may notice a general blurring of vision. Eventually that will result in severe vision loss and even blindness. According to the statistics of International Diabetes Federation [2], there are 537 million people suffering from diabetes globally in 2021 and it is expected to be 643 million and 783 million by 2030, and by 2045 respectively. It is also mentioned there that, by 2030, of all the diabetes patients, around 191 million people will suffer from DR and among them 56.3 million will be facing vision-threatening diabetic retinopathy [3].

According to a report [4] published in 2023, the number of people affected by diabetes in Bangladesh is more than 13 million. Out of them, around 1.85 million is suffering from diabetic retinopathy. This report also states that, a hospital based cross-sectional study was performed among 489 patients having type-2 diabetes, and the researchers have found that 18.8% of those patients were suffering from diabetic retinopathy. So, it can be said from the above discussions that the number of DR patients are increasing day by day. So, early diagnosis of diabetic retinopathy is extremely necessary for the diabetes patient. Artificial intelligence and machine learning techniques are used for the development of computer-aided diagnosis systems for the detection of diabetic retinopathy. These systems can automatically analyze fundus images and provide risk assessments or early detection of DR with high accuracy. Different pre-trained algorithms like VGG-16 [5], Xception [6], EfficientNet [7], ResNet [8] etc. are used for the automatic detection of DR.

The first triumph was taken in 1990s to classify retinal images in order to detect whether an eye has DR or not [9]. In this research, Gardner and his fellow researchers have proposed an artificial neural network (ANN) based tool that detects retinal images with DR. Their proposed tool provides 88.4% sensitivity and 83.5% specificity. In [10], the researchers have applied different algorithms i.e. random forest classifier, support vector machine, K-nearest neighbor, logistic regression, regression tree classifier, and the Naïve Bayes theorem to detect DR. They have found that, in terms of performance in evaluation and accuracy, the Naïve Bayes performs better among the six. According to [5] have used VGG-16 architecture for the automatic detection of diabetic retinopathy. They have used a dataset containing 3668 retinal images, captured through fundus photography. The model was then trained for 30 epochs. They have used ADAM optimizer to adjust the characteristics of the neural network. Categorical cross entropy loss function was used in their proposed method. The authors of [11] have proposed Inception-v3 based diabetic retinopathy detection process.

The datasets used in their work are from Kaggle, named the “Diabetic Retinopathy Detection 2015” dataset and “Aptos 2019 Blindness Detection” dataset. They have resized the images to 256×256. Then they have applied Gaussian blur technique to remove the Gaussian noise in the image. The model is then trained and tested to achieve an accuracy of 88.1% while detecting Diabetic Retinopathy by [7] have presented a method for classifying Diabetic Retinopathy (DR) severity using an ensemble of EfficientNet models (B1, B2, B3, and B5). They have trained the models with different datasets and have achieved a high quadratic kappa score of 0.924377 on the APTOS test dataset. The study highlights the importance of selective training data and appropriate loss functions in enhancing performance. Despite its high accuracy, the method is simpler than other models, ranking around 64th out of 2913 in the APTOS submission ranking for the private test set. The researchers of [8] have proposed ResNet-34 based CNN architecture for the diagnosis of diabetic retinopathy.

They have used fundus image datasets from Kaggle. Several image processing techniques like filtering, normalization, data augmentation have been applied to remove the noises and to increase the dataset size. Their method has achieved a high F1 score of 93.2% for stage-based DR classification, indicating strong performance in accurately identifying different stages of the disease. In turn. [12] have introduced a CNN based Diabetic Retinopathy (DR) detection using the lightweight SI2DRNet-v1. They have applied Otsu’s threshold method and image enhancing methods for finding the region of interest (ROI) in the image and improve the image quality respectively. Then their model has been trained, validated and tested. The accuracy of the proposed method is 91%. For [6] have proposed a novel feature extraction method for Diabetic Retinopathy (DR) diagnosis using a modified Xception architecture with deep layer aggregation. To improve the overall classification performance, they have used transfer learning technique and hyper-parameter tuning. Their proposed method achieves classification accuracy of 83.09%, sensitivity of 88.24%, and specificity of 87.00% on the Kaggle APTOS 2019 dataset.

In [13], the authors have proposed an automatic DR detection method using an ensemble of five deep CNN models: Inception ResNet V2, VGG19, Xception, ResNet50, and DenseNet112. They have used the Kaggle retina image dataset. After training and testing the proposed ensemble model, they have achieved specificity of 92.02% while detecting DR.In this paper, a custom deep learning CNN model has been proposed to automatically detect diabetic retinopathy. For our research, we have used an open source dataset from Kaggle containing 3668 fundus images. Our proposed model consists of two classes named as ‘DR’ and ‘No_DR’. The proposed model has been trained, validated and tested using the image dataset. To evaluate the performance of the proposed model, 5-fold cross validation technique is also applied. We have also used four pre-trained models (VGG-16, ResNet-50, Inception-V3, and EfficientNet-B0) to compare the results with our proposed CNN model to classify the diabetic retinopathy disease.

II. PROPOSED METHODOLOGY

In this section, we will briefly discuss about the methodology of the proposed method. The method has several key steps: dataset collection, analysis & labelling, image normalization, splitting the dataset into training, validation & testing sets, creation of the proposed model, training, validating & testing the model, and lastly applying K-fold cross validation. Figure 1 represents the flow diagram of the proposed DR detection method.

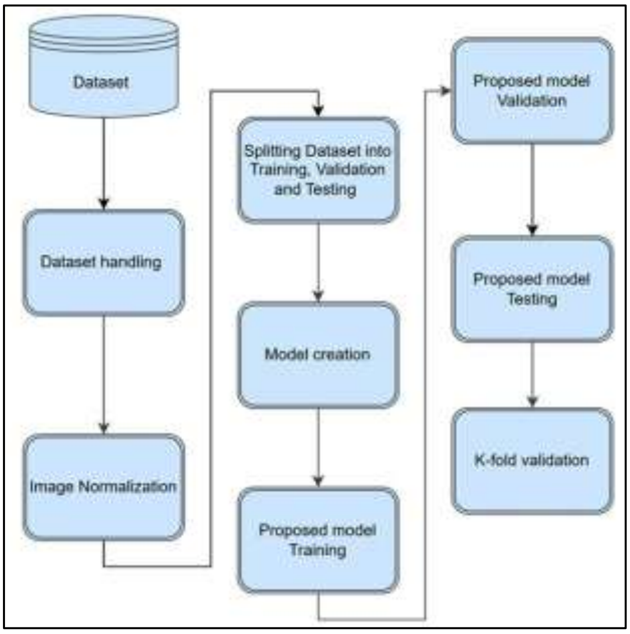

Figure 1: Flow diagram of the proposed model.
Source: Authors, (2026)

II.1 DATASET

For our research we have used an open-source dataset from Kaggle titled "Diabetic Retinopathy 224×224 Gaussian Filtered" by [14]. This dataset includes Gaussian filtered retina scan images used for detecting diabetic retinopathy. It contains 3,668 fundus images with a resolution of 224×224 pixels. A sample image is shown in Figure 2. There are five classes of diabetic retinopathy images named as No DR (1805 images), Mild (370 images), Moderate (999 images), Severe (199 images), and Proliferate_DR (295 images), along with a corresponding CSV file for the images. Then we have to delete six images from "Moderate" due to very bad condition.

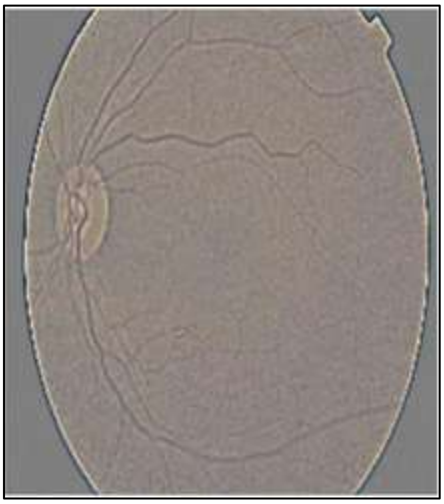

Figure 2: Original image of the dataset.
Source: [14].

II.2 DATASET HANDLING

In order to enhance model accuracy and error analysis, dataset labeling is used in the image dataset. For dataset labeling, initially, the four classes-mild, moderate, severe and proliferate_DR are combined into a single class named as "DR" which means Diabetic Retinopathy. We have used "Pandas library" for this task. It is especially effective for managing structured data such as CSV files. After compressing the four classes into one, the DR class contains 1857 images, while the No_DR class contains 1805 images. This results in a balanced image ratio between the classes.

II.3 IMAGE NORMALIZATION

To improve model performance and convergence, particularly in machine learning and deep learning applications, image normalization is crucial in image processing. It ensures consistency by standardizing pixel values, typically within the range of 0 to 1 or -1 to 1. This standardization is essential for reliable image comparison, processing, and analysis. A common technique, min-max normalization is used in the proposed method to scale pixel values to a specified range [0, 1].

II.4 DATASET SPLITTING

Our dataset has been meticulously divided into three distinct subsets to facilitate robust model development and evaluation [15]. The training set comprising 70% of the dataset was dedicated to the initial training phase. The remaining 30% of the dataset was evenly split between the validation set and the testing set. We have used the "train_test_split' function and array slicing technique to split the dataset. The details of the number of images are shown in Table 1.

Table 1: Number of images at each set.

Name of Set	Number of images
Training Set	2562
Validation Set	550
Testing Set	550

Source: Authors, (2026).

II.5 DEVELOPMENT OF CNN MODEL

We have used several convolutional layers, max-pooling layers, batch normalization layers, and dropout layers to design and develop the proposed model in "Keras". It uses "Tensor-flow" as a backend with Python. The proposed model proceeds with three successive sets, each comprising of sequentially stacked 2D convolutional layers, 2D max-pooling layers, and batch normalization layers. We have used two sets of fully connected layers in our proposed model. Different steps of the proposed model are given below:

1. The process begins with an input layer designed to accept images at a resolution of 224×224 pixels.
2. The proposed model starts with a convolutional layer consists of 8 filters, each of size 3×3. The "ReLU" activation function is used in this layer.
3. To down-sample the image by (2, 2), we have used a max-pooling layer with a filter size of 2×2.
4. One batch normalization layer is inserted after the max-pooling layer to enhance training stability and accelerate convergence in neural networks.
5. After the first set of the convolution, max-pooling, and batch normalization layers, the proposed model has the same set of layers sequentially placed for two times. The difference is that the convolutional layer in the second and third set consists of 16 filters (filter size: 3×3) and 32 filters (filter size: 4×4) respectively. All the other parameters are same.
6. After that, to flatten the input shape, we have used a flatten layer. This layer prepares the data for input into the fully connected layers.
7. Now, to classify the images, two fully connected layers are used. The first layer is a dense layer having 32 hidden neurons. The "ReLU" activation function is used in this layer. After that, a dropout layer with a dropout rate of 0.15 is used to reduce over fitting [16].
8. The second fully connected layer is the decision making layer having 2 hidden neurons with the Softmax activation function.
9. The loss function and optimizer used in the proposed model is the categorical cross-entropy loss function and the adam optimizer with a learning rate of 0.00001.

The summary of the proposed CNN model is presented in Table 2.

Table 2: Configuration of different parameters for the proposed diabetic retinopathy detection model.

Parameters	Diabetic Retinopathy Detection Model
Convolutional Layer	1 (8 filters with size 3×3)
	1 (16 filters with size 3×3)
	1 (32 filters with size 4×4)
Max Pooling	3 (each with 2×2 filters)
Dropout layer	1 (0.15)
Learning rate	0.00001
Activation Function	ReLU
Optimizer	Adam
Batch Size	16
Epochs	50

Source: Authors, (2026).

III. RESULTS AND DISCUSSIONS

In this section, we are going to discuss about the training, validation and testing results of the proposed DR detection method. We will also compare the achieved results with some of the pre-trained models and also with some other proposed methods. The computing environment of our research is a laptop having an operating system of 64 bit Windows 10 Pro, Intel Core i3 CPU, 500 GB hard disk, SSD of 128 GB, and 4 GB RAM.

III.1 TRAINING AND VALIDATION RESULTS

The proposed CNN model for the DR detection is trained, and validated for 50 epochs with 2562 images and 550 images respectively. The system has achieved outstanding training and validation results as depicted in Table 3. Figure 3 and Figure 4 represent the accuracy curve and loss curve respectively of the training and validation stages with respect to the epochs. The proposed system has achieved a training accuracy of 99.92% and a validation accuracy of 95.45%, at the 50^{th} epoch. It has also achieved a training loss of 0.0123 and a validation loss of 0.1671, at the 50^{th} epoch.

Table 3: Training and validation accuracy table for the proposed DR detection model.

Phases	Sample Size	Average Accuracy
Training	2562	99.90%
Validation	550	94.27%

Source: Authors, (2026).

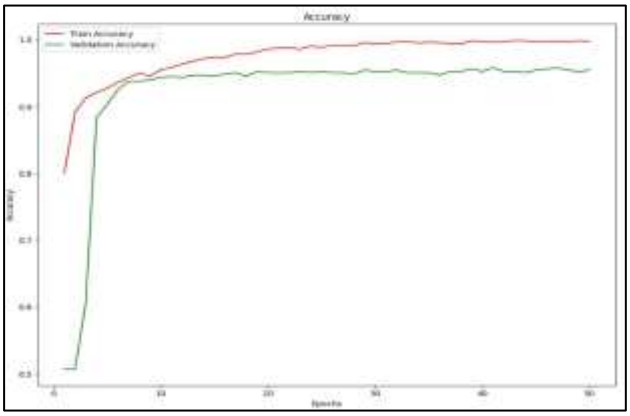

Figure 3: Accuracy curve of the proposed model.
Source: Authors, (2026).

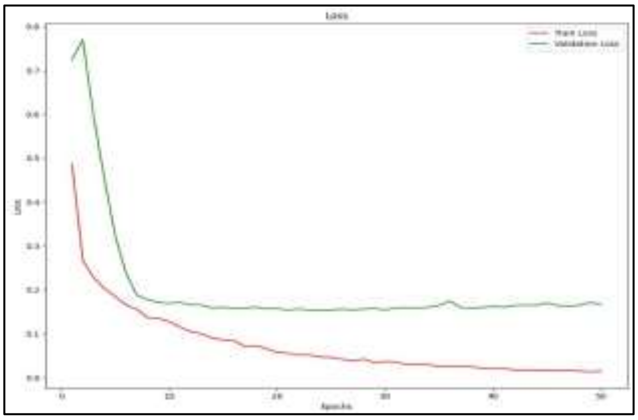

Figure 4: Loss curve of the proposed model.
Source: Authors, (2026).

III.2 TESTING RESULTS

The proposed model is tested with 550 fundus images. The confusion matrix of the DR detection model is presented in Figure 5. It represents the overall performance of the proposed model. The exact number of True Positive (TP), False Positive (FP), True Negative (TN), and False Negative (FN) values can also be understood from the confusion matrix. It is seen that; the model has successfully detected 524 fundus images out of 550 images. So, the accuracy of the proposed model is 95.27% as calculated using Equation 1.

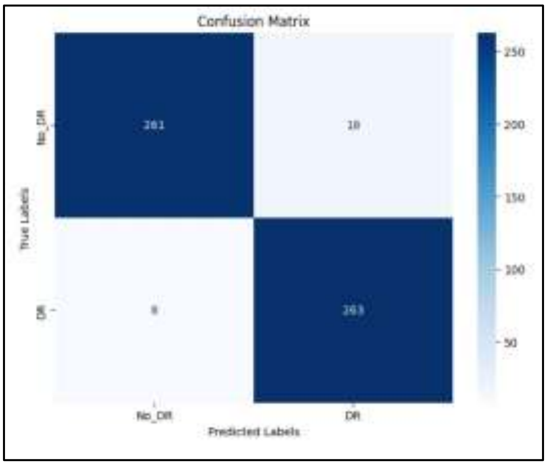

Figure 5: Confusion matrix.
Source: Authors, (2026).

$$Accuracy\ of\ a\ model = \frac{TP+TN}{TP+TN+FP+FN} \times 100\% \tag{1}$$

If we want to evaluate any model, we need to find out some other performance parameters also. Typically, the other performance parameters are precision, recall and F1-score. Equation (2-4) represents the equations of these parameters.

$$Precision = \frac{TP}{TP+FP} \times 100\% \tag{2}$$

$$Recall = \frac{TP}{TP+FN} \times 100\% \tag{3}$$

$$F1-score = \frac{2\times Precision\times Recall}{Precision+Recall} \times 100\% \tag{4}$$

The model has provided an impressive result of F1-score of 95.29% along with precision of 93.59% and recall of 97.04% as shown in Table 4.

Table 4: Performance parameter values for DR detection model.

Parameters	**Value** (%)
Precision	93.59
Recall	97.04
F1-score	95.29

Source: Authors, (2026).

III.3 5-FOLD CROSS VALIDATION RESULT

To further evaluate the proposed DR detection model performance and reliability, a 5-fold cross-validation approach is employed. This method ensures that the model is rigorously tested and validated across different subsets of data. Figure 6 illustrates the accuracy achieved through this 5-fold cross-validation process. In the 5-folds, the highest accuracy achieved is 96% in the 3rd fold, while the lowest was 92% in the 5th fold. The average accuracy of the 5-fold cross validation is 93.86%. The differences in accuracy across each folds are minimal, indicating that the model is consistent and stable.

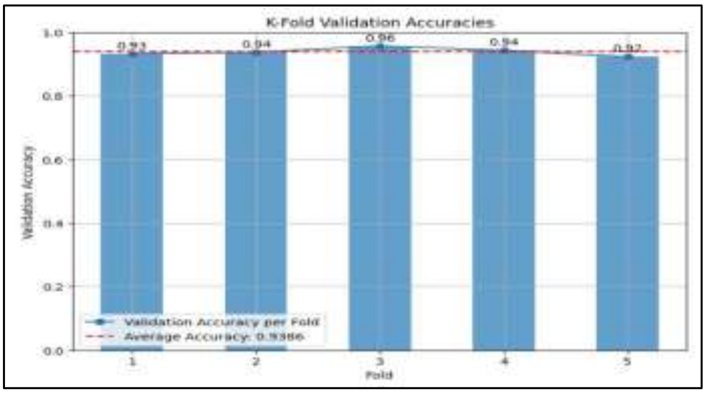

Figure 6: Accuracies of 5-fold cross validation.
Source: Authors, (2026).

III.4 MODEL COMPARISON RESULT

We have used four existing pre-trained models: VGG-16, ResNet-50, Inception-V3, and EfficientNet-B0 to compare the results with our proposed model. We have also compared our method with other proposed methods for DR detection. In all of the pre-trained models, we have used "ReLU" activation function, and "softmax" function in the layers and in the final layer respectively. We have used categorical cross-entropy loss function and adam optimizer in the pre-trained models. The batch size and epochs are same as the proposed model. Table 5 presents a comparison of accuracies between four pre-trained models and our proposed model. It can be observed from Table 5 that our proposed model has higher accuracy than the other pre-trained models. Figure 7 presents a graphical comparison of accuracies between several pre-trained models and our proposed model.

Table 5: Comparison of accuracies between several pre-trained models and our proposed model.

Model Name	**Accuracy**
VGG-16	95%
ResNet-50	92%
Inception-V3	95.23%
EfficientNet-B0	50%
Proposed model	95.27%

Source: Authors, (2026).

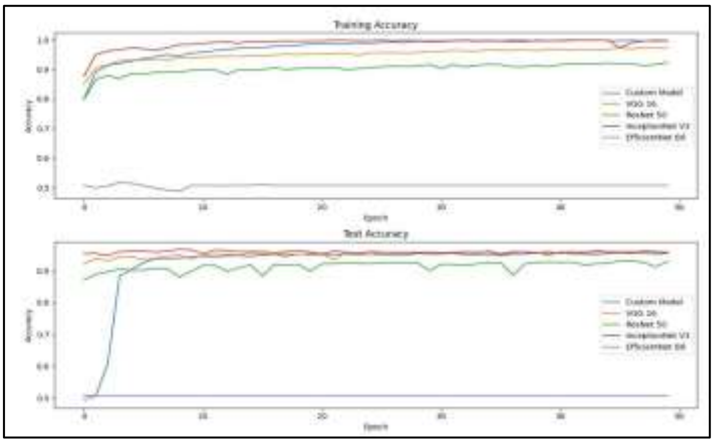

Figure 7: Graphical representation of accuracies between several pre-trained models and our proposed model.
Source: Authors, (2026).

A comparison between the proposed method and several other existing methods in automatic DR detection system is provided in Table 6. Over the years, the researchers have tried to make their system more robust, user friendly and having higher accuracies in DR detection system. The dataset size of [17] is 2500 fundus images. The authors first preprocessed the input image by removing the black surrounding pixels from the image and then resizing it to 300×300 pixels. Then they have trained and tested their Inception-V3 based model. Stochastic Gradient Descent (SGD) is used as the optimizer and Cosine loss function is used as the loss function. Their proposed method provides an accuracy of 90.9%. Both [18] and [5] have used the same dataset that we have used in our research. In [18], the authors have resized the image to 416×416 pixels and converted it to grayscale image.

Then they have trained and tested the EfficientNet-B3 based CNN model with the fundus images and achieved an accuracy of 85%. The authors of [5] have used VGG-16 based CNN model to automatically detect DR. They have trained their model for 30 epochs. Adam optimizer is used in their proposed method. Their model provides an accuracy of 74.5%. In our proposed method, we have created a custom CNN model to detect DR automatically. The testing accuracy of our method is 95.27%. We have also performed 5-fold cross validation to evaluate the performance of our model. The average cross validation accuracy that our model provides is 93.86%. So, it can be said from above discussion that our proposed method outperforms different existing methods.

Table 6: Comparison of accuracies between existing methods and our proposed method.

Research work	Model Used	Dataset Size	Testing Accuracy
[17]	Inception-V3	2500	90.9%
[18]	EfficientNet-B3	3668	85%
[5]	VGG-16	3668	74.5%
Proposed method	Custom CNN architecture	3662	95.27%

Source: Authors, (2026).

IV. CONCLUSION

As we know that, manual diagnosis of retinal images poses significant challenges, demanding highly trained specialists and needed substantial time, so it is required to diagnose DR using automatic computer vision techniques. That is why in this paper, a CNN based automatic system has been proposed to detect diabetic retinopathy from fundus images. As CNN requires large number of data to train, we have used a dataset containing 3662 Gaussian filtered fundus images. The images are labelled into two classes and then normalized to scale pixel values to [0, 1]. The proposed model has been trained, validated and tested with 2562, 550, and 550 fundus images respectively. The training, validation and testing accuracy of the proposed system are 99.92%, 95.45%, and 95.27% respectively. The system also provides precision score of 93.59%, recall score of 97.04% and F1 score of 95.29%. The average accuracy of the 5-fold cross validation is 93.86% that depicts how well the proposed model is performed to detect DR. The results of our proposed method demonstrate that it outperformed different pre-trained models and existing methods.

V. AUTHOR'S CONTRIBUTION

Conceptualization: Forhad Javed, Ashraful Islam, Mohammed Hasibul Hasan Chowdhury, Sayma Sultana, Nazmul Islam Frahim, Atikur Rahman.
Methodology: Mohammed Hasibul Hasan Chowdhury, Sayma Sultana, Nazmul Islam Frahim, Atikur Rahman.
Investigation: Forhad Javed, Ashraful Islam, Mohammed Hasibul Hasan Chowdhury, Sayma Sultana, Nazmul Islam Frahim, Atikur Rahman.
Discussion of results: Forhad Javed, Md. Ashraful Islam, Mohammed Hasibul Hasan Chowdhury, Sayma Sultana, Nazmul Islam Frahim, Atikur Rahman.
Writing – Original Draft: Mohammed Hasibul Hasan Chowdhury, Sayma Sultana, Nazmul Islam Frahim, Atikur Rahman.
Writing – Review and Editing: Mohammed Hasibul Hasan Chowdhury, Sayma Sultana, Nazmul Islam Frahim, Atikur Rahman.
Resources: Forhad Javed, Ashraful Islam, Mohammed Hasibul Hasan Chowdhury, Sayma Sultana, Nazmul Islam Frahim, Atikur Rahman.
Supervision: Forhad Javed, Ashraful Islam, Mohammed Hasibul Hasan Chowdhury, Sayma Sultana, Nazmul Islam Frahim, Atikur Rahman.
Approval of the final text: Forhad Javed, Ashraful Islam, Mohammed Hasibul Hasan Chowdhury, Sayma Sultana, Nazmul Islam Frahim, Atikur Rahman.

VI. DATA AVAILABILITY STATEMENT

The original contributions presented in the study are included in the article; further inquiries can be directed to the first author. The datasets used during the study are public datasets.

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