An Efficient DenseNet for Diabetic Retinopathy Screening

Sheena Christabel Pravin[1,*], Sindhu Priya Kanaga Sabapathy[2], Suganthi Selvakumar[2], Saranya Jayaraman[2], Selvakumar Varadharajan Subramani[2]

[1]School of Electronics Engineering, Vellore Institute of Technology, Chennai, India

[2]Department of Electronics and Communication Engineering, Rajalakshmi Engineering College, Chennai, India

Received 05 May 2022; received in revised form 02 December 2022; accepted 03 December 2022

DOI: https://doi.org/10.46604/ijeti.2023.10045

Abstract

This study aims to propose a novel deep learning framework, i.e., efficient DenseNet, for identifying diabetic retinopathy severity levels in retinal images. Diabetic retinopathy is an eye condition that damages blood vessels in the retina. Detecting diabetic retinopathy at the early stage can avoid retinal detachment and effects leading to blindness in diabetic adults. A thin-layered efficient DenseNet model has been proposed with fewer training learnable parameters, leading to higher classification accuracy than the other deep learning models. The proposed deep learning framework for diabetic retinopathy severity level detection has an inbuilt automatic pre-processing module. Afterward, the efficient DenseNet model and classifier will provide data augmentation and higher-level feature extraction. The proposed efficient DenseNet framework is trained and tested using 13000 retinal fundus images within the diabetic retinopathy database and combined with the k-nearest neighbor classifier demonstrating the best classification accuracy of 98.40%.

Keywords: deep learning, diabetic retinopathy, efficient DenseNet, pre-processing, classification accuracy

1. Introduction

Diabetic retinopathy (DR) is one of the main reasons for vision loss among diabetic patients. DR leads to several other vision complications such as cataracts, open-angle glaucoma, diabetic macular edema, neo-vascular glaucoma, and retinal detachment. The initial stage of DR does not cause visible symptoms except trouble reading. Severe DR leads to bleeding in the retinal blood vessels, causing blurred or distorted vision. Thus, screening for DR in the initial stage is important to avoid scarring since the formation of aberrant cells in the retina can cause serious vision problems.

DR has become so prevalent that it is estimated to affect 29 million people before 2050 [1]. The prevalence of diabetes is 11.8% of the population over the age of 50 [2]. Diabetes is more prevalent among people aged 20-80, accounting for 12.8% of the global population. The global statistics on DR are alarming and expected to remain high in Middle East countries, North Africa, and western Pacific nations [3]. Mild non-proliferative diabetic retinopathy (NPDR) is the initial stage of DR, characterized by tiny areas of inflammation in the retinal vessels, and this swelling area is called microaneurysms. There is a 5% risk that mild NPDR will progress to proliferative diabetic retinopathy (PDR) within a year [4]. Vision is not affected at this stage, but blood sugar and cholesterol levels should be continuously monitored.

In moderate NPDR, there is a risk of swollen retinal vessels and accumulation of blood in the macula. This phase is also called pre-proliferative retinopathy which can lead to diabetic macular edema and severely affect vision. Severe NPDR is also known as proliferative retinopathy. When the flow of blood from the retina is blocked, it can lead to creating dark spots. An

* Corresponding author. E-mail address: sheenachristabel.p@vit.ac.in

increase in the risk of vision impairment at this stage is crucial that can result in retinal detachment. Abnormalities in the growth of fragile new blood vessels occur in an advanced stage of PDR. As the retinal veins are fragile, there is a higher chance of fluid leakage, which can result in dangerous blurriness, a narrowed field of vision, and even blindness.

Deep learning, machine learning, and ensemble models have been recently developed to identify the severity level of DR [5]. Deep neural networks (DNN) are artificial neural networks with more than one hidden layer, as shown in Fig. 1. These networks use mathematical modeling to process complex data and require a large number of training datasets to classify millions of data.

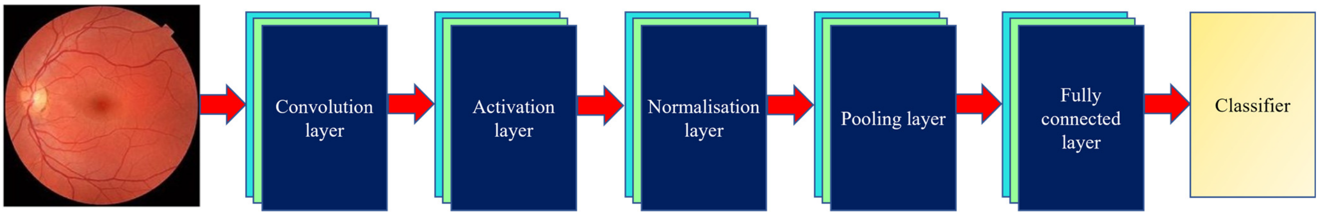


Fig. 1 Basic framework of DNN

Detection of DR using DenseNet-65 based Faster-RCNN was proposed to classify and localize DR lesions from the retinal images [6]. A deep learning ensemble approach with five deep convolutional neural networks (CNN) models such as ResNet50, Inceptionv3, Xception, Dense121, and Dense169 was used to encode features and develop the classification for multiple stages of DR, which yielded a validation accuracy of 70% [7].

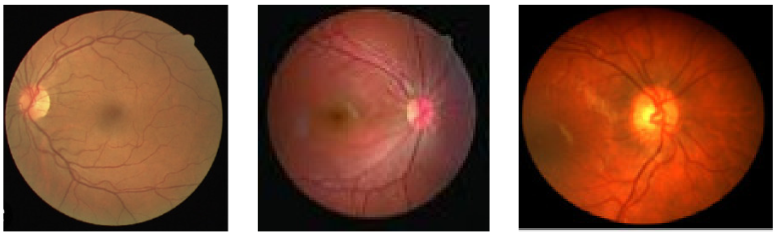
Birajdar et al. [8] presented the detection and classification of DR using an AlexNet architecture of the CNN, which was trained on a fundus image database containing various examples of retinal hemorrhage and micro-aneurism. This makes the process of classification and localization of DR precise. Gao et al. [9] proposed a DR classification using efficient CNN [9]. The retinal images were pre-processed using auto cropping techniques and then the efficient CNN model was implemented to categorize the retinal images in the database that yielded an accuracy of about 83%.

Zhang et al. [10] proposed an automated identification and severity grading of DR using DNNs. The severity level was deciphered by applying classification techniques that rendered high recall and specificity values. Deshpande and Pardhi [11] proposed an automatic detection of DR using visual geometry group (VGG16) architecture, where the blindness detection dataset was used as the training dataset with 3668 retinal images. Fundus photography was used to acquire retinal images and the CNN-VGG16 model was utilized to identify stages of DR in retinal images. The framework was tested using 1728 images that were not included in the training dataset and could achieve a precision rate of about 74.58%. Barros et al. [12] attempted a machine learning-based DR severity detection for glaucoma detection. The model is comprised of a data augmentation unit along with image processing, feature engineering, and classification modules. This study aims to introduce a novel deep-learning network that can screen DR, indicating the severity level as well. To classify the intensity levels of DR, an efficient DenseNet model has been proposed for feature extraction from retinal images

2. Database Description

The Kaggle dataset for DR used in this research is the Asia-Pacific Tele-Ophthalmology Society (APTOS) image dataset, which contains 5590 retinal images collected from Asia. By data augmentation, the number of retinal images is increased to 13000, 80% of the data is used for training and the remaining 20% of the data is used for testing the proposed model. Thus, 10400 retinal images constituted the training set, while 2600 images constituted the test set. The images under different classes are as follows: Class 0: 4560 images, Class 1: 1250 images, Class 2: 2510 images, Class 3: 2100 images, and Class 4: 2580 images. Among the 13000 retinal images. 7410 retinal images were augmented under different classes, viz. Class 0: 2490 images, Class 1: 825 images, Class 2: 1355 images, Class 3: 1250 images, Class 4: 1490 images.

Data augmentation is implemented by using the horizontal flip, vertical flip, and zooming techniques as shown in Figs. 2(a)-(c). The DR classification methodology includes retinal image data collection from the Kaggle database. This is followed by the pre-processing stage. The proposed deep learning model is built and trained on the retinal images. Following the training phase, the deep learning model is in the pilot mode to test its efficacy in the classification of DR severity levels over unknown test data.



(a) Horizontal flip (b) Vertical flip (c) Zooming

Fig. 2 Image augmentation techniques

Table 1 shows the classes and observations of the DR severity level. The images have been rated from 0 to 4, based on the five severity levels: Class 0: corresponds to the healthy retina, Class 1: corresponds to mild cases of DR, Class 2: moderate, Class 3: severe, and Class 4: PDR. For variability in the APTOS dataset, retinal images had been collected from several clinics using a variety of cameras over a long period. These images had been reviewed by trained doctors before the publication of the APTOS dataset [13].

Table 1 Description of the diabetic retinopathy dataset

DR stages	Observations	Severity level
Class 0	No microaneurysm	No DR
Class 1	Presence of a Single microaneurysm	Mild DR
Class 2	Hemorrhage, microaneurysms, and white spots	Moderate DR
Class 3	Serious hemorrhage and microaneurysms	Severe DR
Class 4	Neovascularization	PDR

3. Proposed Efficient DenseNet Mechanism

The efficient DenseNet framework, a novel deep learning model is proposed for effective feature extraction and accurate grouping of DR severity levels. The process flow of DR severity level detection using the efficient DenseNet is illustrated in Fig. 3. The retinal images from the dataset were pre-processed using the auto-cropping approach of Ben Graham's pre-processing algorithm [14]. The flipping techniques include the interchange of rows and columns while the zooming technique introduced pixel interpolation. The distinguishing features in the images were improved after pre-processing, which helps to train the efficient DenseNet model. The efficient DenseNet framework adopts an automatic feature learning technique to assess if the pre-processed image has been impacted by DR or not.

The efficient DenseNet framework for multi-class classification is presented in Fig. 4, with the following hyper-parameters: the baseline filter size was set to 32, and the filter size was increased by a factor of two at each block. In a multi-class framework, batch normalization was adopted with dropout at the hierarchical layers at every block. Furthermore, instead of using the standard rectified linear unit (ReLU) activation function, the leaky_ReLU activation function was employed, which reduced the diminishing gradient effect.

By lowering the number of pixels in the output from the preceding layer, the max-pooling layer is commonly added to the efficient DenseNet model to minimize the dimensionality of the retinal image. After each max-pooling layer, a dropout layer was introduced to improve the performance of the proposed efficient DenseNet model by removing data overfitting. In the fully connected layers FC1, FC2, and FC3, the number of neurons was set to 2048, 512, and 128 sequentially. The sigmoid layer was introduced at the output layer with 5 class probabilities instead of the software layer. As a result, the proposed efficient DenseNet model minimizes the overall computational complexity and maintains a higher classification accuracy.

Feature maps of the previous layers are utilized as inputs to each new layer, along with the feature maps. Convolutional networks with dense connectivity have several clear advantages such as eliminating the vanishing-gradient issue, improvement of feature transfer from one layer to another, feature reuse, a significant reduction in the tuning parameters, and less computational complexity [15].

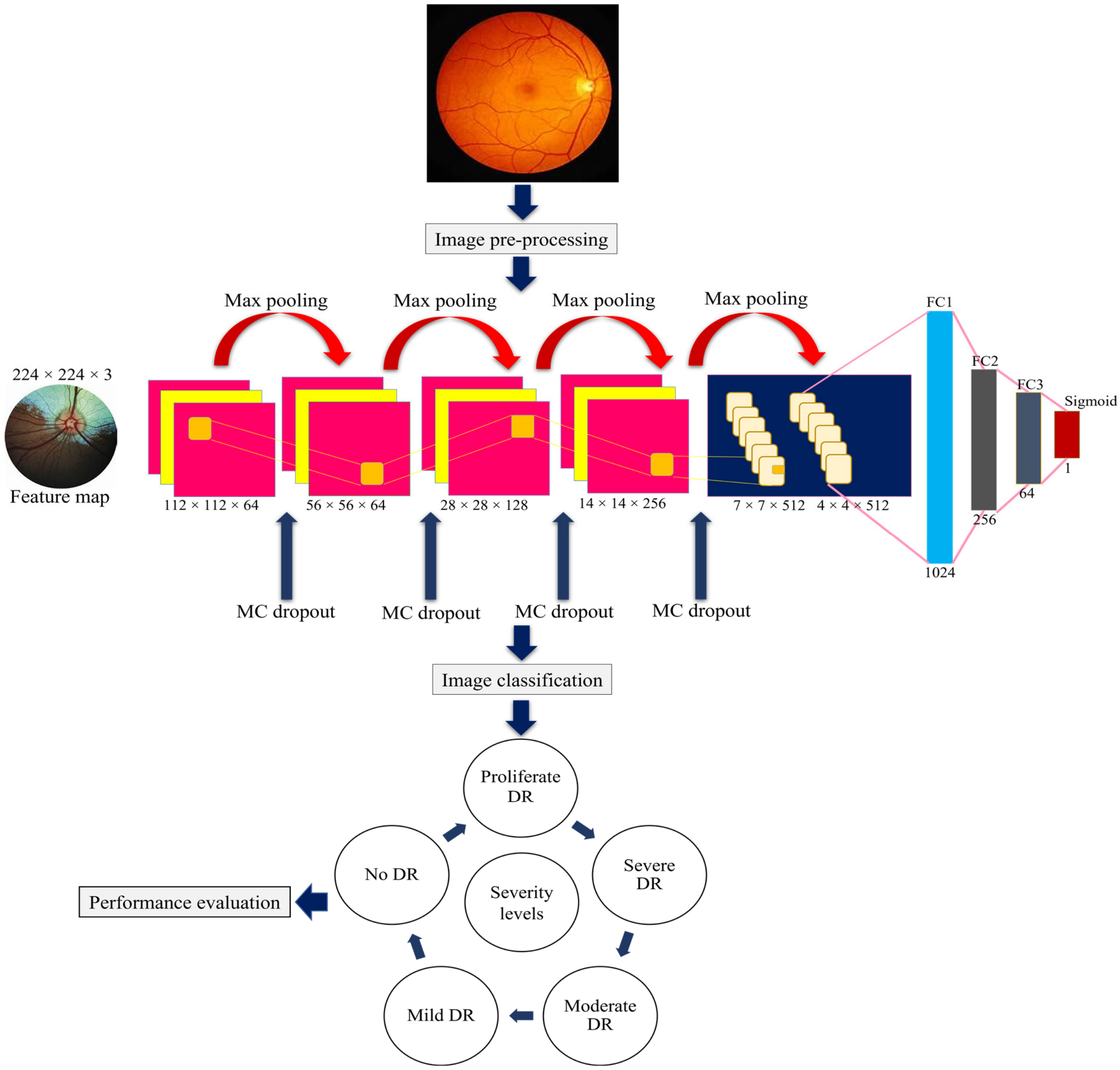


Fig. 3 The pipeline of the proposed method using efficient DenseNet

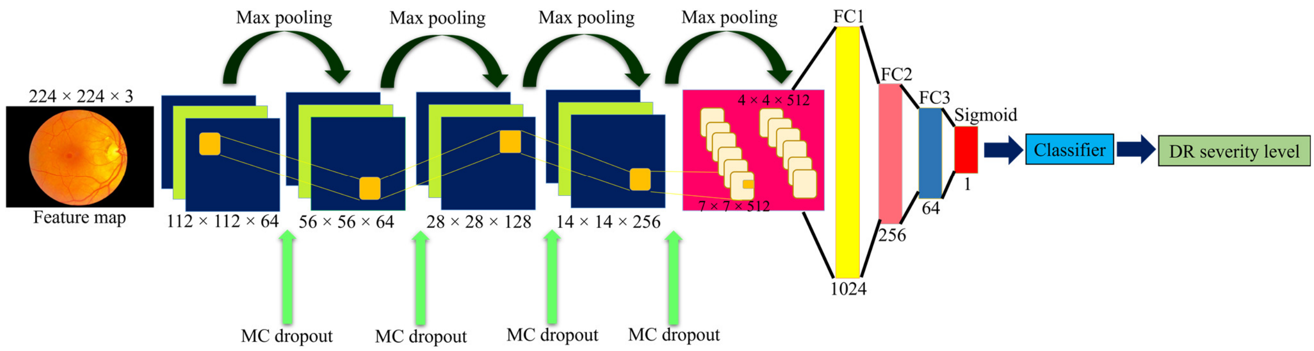


Fig. 4 System overview of DR recognition based on the Efficient DenseNet

4. Experimental Baseline Deep Learning Model

Various deep learning networks have been experimented as baseline models for feature extraction and classification of the severity levels of DR. The deep learning networks include ResNet50, VGG16, VGG19, ResNet101, MobileNet, MobileNetV2, InceptionV3, InceptionResNetV2, DenseNet-169, DenseNet-121, and XceptionNet. The features extracted from these deep neural nets are used to train and test three classifiers: k-nearest neighbors (k-NN), support vector machine (SVM), and the random forest model.

4.1. ResNet50

CNNs with 50 layers are commonly used ResNet50 model. A residual network (ResNet) is an artificial neural network (ANN) that builds a network by stacking residual blocks one on top of the other [7]. ResNet is constructed in layers, but the fundamental architecture is retained. And Resnet50 is a 50-layered deep neural network. The test accuracies over the features extracted by the ResNet50 are presented in Table 2.

Table 2 Evaluation of ResNet50

Model	Accuracy (%)	F1 score	Kappa coefficient	Recall	Precision
k-NN	85.17	0.8	0.81	0.75	0.85
SVM	87.27	0.8	0.81	0.77	0.87
Random forest	86.67	0.8	0.81	0.77	0.87

4.2. VGG16

VGG16 model has 16 convolutional layers and a fairly homogeneous architecture, making it appealing. It features only 3x3 convolutions [16] with many filters, similar to AlexNet. Although it has a higher time complexity, it is one of the most popular models for extracting unique features from images. The performance of the VGG16 model with the classifiers is displayed in Table 3.

Table 3 Evaluation of VGG16

Model	Accuracy (%)	F1 score	Kappa coefficient	Recall	Precision
k-NN	87.27	0.83	0.81	0.87	0.81
SVM	87.27	0.8	0.81	0.87	0.82
Random forest	86.67	0.8	0.81	0.87	0.86

4.3. VGG19

VGG19 is a variant of the VGG network with deep learning CNN architecture for image classification. It has been built with 19 layers in all [17]. It has 16 convolution layers and 3 fully connected layers. Additionally, the framework has five max-pooling layers and one softmax layer. Other VGG variations include VGG11, VGG16, and VGG19. Table 4 shows the classification accuracies.

Table 4 Evaluation of VGG19

Model	Accuracy (%)	F1 score	Kappa coefficient	Recall	Precision
k-NN	88.77	0.84	0.82	0.89	0.82
SVM	85.45	0.89	0.88	0.85	0.86
Random forest	83.94	0.88	0.85	0.84	0.86

4.4. ResNet101

ResNet101 is a 101-layered CNN framework, which is a pre-trained network [18-21] trained with over a million images from the ImageNet database. Here, the ResNet101 is trained over healthy retinal images and the images depicting DR. After training, it, yields rich feature representations for the retinal images. The performance of the feature classification from the ResNet101 model is presented in Table 5.

Table 5 Evaluation of ResNet101

Model	Accuracy (%)	F1 score	Kappa coefficient	Recall	Precision
k-NN	84.24	0.89	0.85	0.84	0.88
SVM	87.27	0.82	0.81	0.87	0.85
Random forest	80.3	0.81	0.81	0.85	0.88

4.5. MobileNetV2

The MobileNetV2 design is based on an inverted residual structure, with narrow bottleneck layers serving as the input and output of the residual block [18]. Standard residual models employ symbolic representations on the input side, whereas the MobileNetV2 does not. Table 6 presents the efficacy of MobileNetV2.

Table 6 Evaluation of MobileNetV2

Model	Accuracy (%)	F1 score	Kappa coefficient	Recall	Precision
k-NN	80.0	0.85	0.86	0.85	0.85
SVM	80.61	0.88	0.88	0.81	0.84
Random forest	82.42	0.86	0.87	0.82	0.88

4.6. MobileNet

MobileNet is a variant of CNN, open-sourced by Google, and is a pre-trained model which is ideal to be trained over a given image database [16]. It is an incredibly condensed and agile classifier. MobileNet is a depth-wise separable convolution network. It dramatically reduces the number of parameters compared to other networks with regular convolutions of the same depth. The test accuracy, F1 score, Kappa coefficient, recall, and precision of the models are presented in Table 7.

Table 7 Evaluation of MobileNet

Model	Accuracy (%)	F1 score	Kappa coefficient	Recall	Precision
k-NN	86.36	0.83	0.88	0.86	0.81
SVM	81.82	0.86	0.85	0.82	0.81
Random forest	81.51	0.87	0.85	0.82	0.85

4.7. InceptionV3

InceptionV3 is a variant of the CNN used as a deep learning network for image classification [7]. The model has been successfully trained on 8, 128, and 512 parameters and yielded good feature representation at 170 epochs. Table 8 shows the performance of the classifiers, recorded with the features of InceptionV3.

Table 8 Evaluation of InceptionV3

Model	Accuracy (%)	F1 score	Kappa coefficient	Recall	Precision
k-NN	84.55	0.89	0.83	0.85	0.88
SVM	83.64	0.87	0.89	0.84	0.83
Random forest	80.0	0.85	0.82	0.76	0.79

4.8. InceptionResNetV2

The InceptionResNetV2 CNN model has been pre-trained with over a million images from the ImageNet database [17]. It is a 164-layered network that categorizes images into 1000 separate groups. The InceptionResNetV2 is trained on retinal images in this study, and useful features are retrieved for classification. As shown in table 9, the classifiers performed better when they are trained with the InceptionResNetV2 features.

Table 9 Evaluation of InceptionResNetV2

Model	Accuracy (%)	F1 score	Kappa coefficient	Recall	Precision
k-NN	89.09	0.82	0.81	0.89	0.8
SVM	82.42	0.85	0.84	0.82	0.83
Random forest	82.42	0.85	0.84	0.82	0.83

4.9. DenseNet-169

The DenseNet-169 is a deep learning network with 169 layers. Although it has many hidden layers, it retains a lower parameter count compared to other deep neural networks. Thus, the architecture is well-suited for medical image classification. It also deals with the vanishing gradient problem [7] and facilitates better feature extraction for classification, as shown in Table 10.

Table 10 Evaluation of DenseNet-169

Model	Accuracy (%)	F1 score	Kappa coefficient	Recall	Precision
k-NN	87.58	0.83	0.82	0.88	0.82
SVM	87.27	0.81	0.80	0.87	0.89
Random forest	87.27	0.81	0.80	0.87	0.86

4.10. DenseNet-121

For visual object recognition, DenseNet-121 is a new neural network framework [7]. It is similar to ResNet but mitigates the representation capacity issue in ResNet by introducing multi-layered feature concatenation DenseNet. It helps solve the vanishing gradient impact on weight updation in deep-layered neural networks. As shown in Table 11, it produces better classification features and is shown to give optimal classification performance.

Table 11 Evaluation of DenseNet-121

Model	Accuracy (%)	F1 score	Kappa coefficient	Recall	Precision
k-NN	86.67	0.8	0.81	0.87	0.82
SVM	87.27	0.8	0.80	0.87	0.82
Random forest	87.27	0.8	0.80	0.87	0.82

4.11. XceptionNet

The XceptionNet retains the deep CNN architecture. Its weights are adapted by depth-wise separable convolution, introduced by Qummar et l. [7]. XceptionNet is one of the most used image classification models and is capable of delivering cutting-edge features for classification. As shown in Table 12, it aids in improving the classification accuracy of the SVM and random forest models.

Table 12 Evaluation of XceptionNet

Model	Accuracy (%)	F1 score	Kappa coefficient	Recall	Precision
k-NN	83.94	0.87	0.80	0.84	0.82
SVM	87.27	0.81	0.80	0.87	0.82
Random forest	87.27	0.83	0.80	0.87	0.82

5. Results and Discussion

A summary of the proposed efficient DenseNet model's evaluation compared to all the baseline models is presented in Table 13. The test accuracy of each model is compared. The proposed efficient DenseNet framework acts as a competitive generative model, yielding the best features for classification than the experimented baseline models. All three classifiers, viz. the k-NN, SVM, and random forest produced higher classification accuracies with the features extracted from the proposed efficient DenseNet model.

Table 13 Accuracy Comparison of the efficient DenseNet and the baseline models

Deep learning models	k-NN	SVM	Random forest
Proposed efficient DenseNet	**98.40**	**90.30**	**92.62**
ResNet50	85.15	87.27	86.67
VGG16	87.27	87.27	86.67
VGG19	88.77	85.45	83.94
ResNet101	84.24	87.27	80.30
MobileNetV2	80.00	80.61	82.42
MobileNet	86.36	81.82	81.52
InceptionV3	84.55	83.64	80.00
InceptionResNetV2	89.09	82.42	82.42
DenseNet-169	87.58	87.27	87.27
DenseNet-121	86.67	87.27	87.27
XceptionNet	83.94	87.27	87.27

It can be inferred from Table 13 that the efficient DenseNet-based feature extraction has improved the accuracy scores of the k-NN, SVM, and random forest classifiers. Furthermore, when the efficient DenseNet combined with the k-NN classifier, it yielded the highest classification accuracy of 98.40% with a better confusion matrix as displayed in Fig. 5. The performance metrics such as confusion matrix, model loss, precision, recall, and F1-score are also measured to evaluate the proposed efficient DenseNet model against the baseline models. The proposed efficient DenseNet model could automatically extract higher-level features from the input retinal images, making the analysis and classification easy. Thus, the proposed framework is chosen for automatic feature engineering and superior performance concerning classification accuracy.

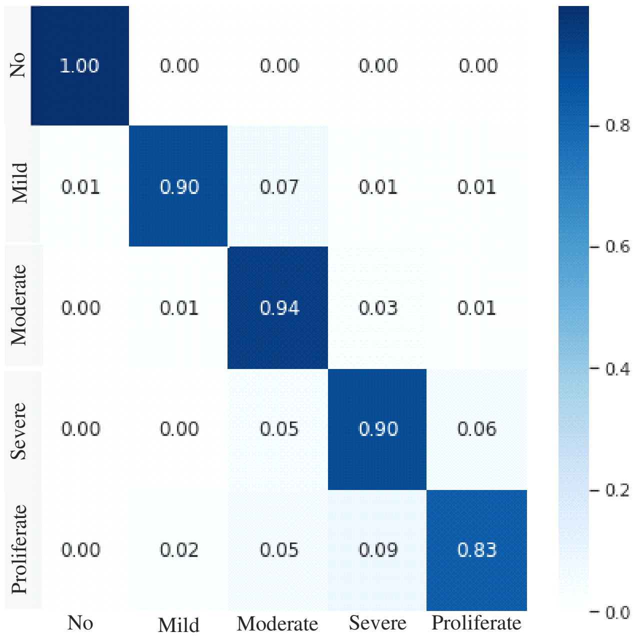


Fig. 5 Confusion matrix of the final classification

The loss of the efficient DenseNet model in terms of the number of epochs is plotted in Figs.6 and 7, and the evaluation metric values are displayed in Table 14. Figs. 6-7 represent the accuracy and loss over the training and testing sets of the proposed efficient DenseNet model. The overall test accuracy of the proposed model reaches 98.40% at the 50th epoch.

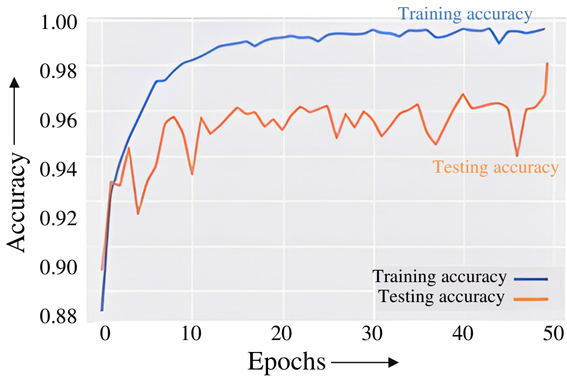


Fig. 6 Accuracy of the training set and testing set

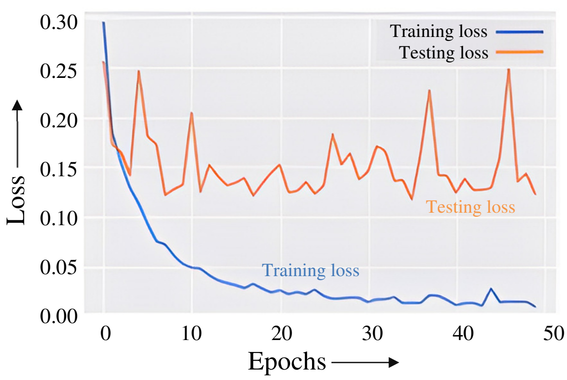


Fig. 7 Loss of training and testing set

The model loss, test accuracies, precision, recall, F1-score, and Kappa coefficient at each progressive epoch of the proposed efficient DenseNet framework with a fixed batch size of 512, are presented in Table 14. The proposed model achieves the best outcome at 50 epochs.

Table 14 Performance metrics of efficient DenseNet model

Epoch	Loss	Accuracy	Precision	Recall	F1 score	Kappa coefficient
0	0.29	0.71	0.81	0.82	0.83	0.80
1	0.18	0.82	0.83	0.85	0.86	0.82
2	0.18	0.85	0.85	0.86	0.88	0.84
3	0.18	0.88	0.88	0.89	0.91	0.87
4	0.17	0.89	0.91	0.92	0.93	0.87
5	0.17	0.91	0.94	0.95	0.95	0.88
6	0.16	0.93	0.94	0.94	0.93	0.89
7	0.16	0.94	0.95	0.95	0.95	0.90
8	0.15	0.95	0.95	0.96	0.96	0.90
9	0.15	0.95	0.96	0.96	0.96	0.91
⋮	⋮	⋮	⋮	⋮	⋮	⋮
47	0.13	0.97	0.97	0.97	0.97	0.93
48	0.12	0.98	0.98	0.98	0.97	0.93
49	0.12	0.97	0.97	0.97	0.97	0.93
50	0.11	0.98	0.98	0.97	0.98	0.93

Table 15 Performance evaluation of baseline frameworks

Study	Year	Model	Test accuracy (%)
Proposed model	**2022**	**Efficient DenseNet**	**98.40**
Ayala et al. [19]	2021	DenseNet121	97.78
Yi et al. [20]	2021	Residual attention EfficientNet	98.36
Chen et al. [21]	2019	Two-stage training method	92.5
Maswood et al. [22]	2020	EfficientNet B5	94.02
Revathy et al. [23]	2020	SVM	68
		k-NN	76
		Random forest	90

As depicted in Table 15, the proposed efficient DenseNet model performs well in unique feature extraction for accurate classification of the severity levels of DR, and it has enhanced the efficacy of DR screening. Moreover, the computational complexity [24-29] has been reduced compared with the baseline models. The metrics such as precision, recall, and F1 score are used to monitor the grading of DR by the efficient DenseNet model as depicted in Table 16, along with the trainable parameters in Table 17.

Table 16 Performance metrics for DR severity level

Stages of DR	Precision	Recall	F1 score
No DR	0.95	0.97	0.96
Mild DR	0.97	0.96	0.97
Moderate DR	0.98	0.97	0.96
Severe DR	0.97	0.96	0.97
PDR	0.9	0.97	0.97

Table 17 Parameters and computational time of the models

Deep learning models	Trainables	Non-trainables	Total parameters	Computational time (sec)
Proposed efficient DenseNet	**91,107**	**89,603**	**1,80,710**	**16.52**
ResNet50	420,685	235,879	3,26,986	31.03
VGG16	270,866	187,165	2,78,272	39.96
VGG19	120,863	191,165	2,82,272	42.15
ResNet101	420,651	235,877	3,26,984	89.65
MobileNetV2	556,872	435,678	5,26,785	24.00
MobileNet	623,544	354,679	4,45,786	22.68
InceptionV3	164,957	126,780	2,17,887	46.53
InceptionResNetV2	124,928	158,400	2,49,507	96.72
DenseNet-169	411,106	199,573	2,90,680	652.03
DenseNet-121	591,108	369,455	4,60,562	878.41
XceptionNet	696,005	573,648	6,64,755	41.85

6. Conclusions

Since early detection of DR is crucial to avoid blindness, this study proposed a novel deep learning framework, namely the efficient DenseNet, for categorizing the severity levels of DR. The significant contributions of this research are as follows:

(1) To classify the intensity levels of DR, an efficient DenseNet model has been proposed for feature extraction from retinal images. It is a thin-layered architecture that takes fewer training learnable parameters to train the model and renders higher classification accuracy than the other deep learning models. The model was trained to classify retinal images into 5 classes, viz. healthy, mild, moderate, severe, and PDR. When associated with the k-NN classifier, the efficient DenseNet, displayed a high test accuracy of 98.40% and exhibited a high kappa coefficient, precision, recall, and F1 score.

(2) A modification in the existing dataset is done by data augmentation technique which increased the number of retinal images from 5590 to 13000 samples. Among the 13000 samples, 10400 samples (80% of the data) were used for training and testing the proposed model. 7410 samples were segregated by using the augmented technique and divided into separate classes, viz. Class 0: 2490 images, Class 1: 825 images, Class 2: 1355 images, Class 3: 1250 images, and Class 4: 1490 images.

(3) Also, eleven state-of-the-art deep learning models have been implemented to validate the efficacy of the proposed model. They were trained on the same retinal images to compare the proposed deep learning framework with the models in the literature. The proposed efficient DenseNet could outperform them in total learnable parameters, computational time, test

accuracy, and other evaluation metrics. Thus, the proposed model may be used as a medical aid by ophthalmologists in diagnosing DR precisely. It can facilitate the screening of DR accurately and early.

In the future, **e**xperiments will be considered on multiple retinal datasets to estimate the outcomes and also intend to improve the technique in other eye-related disorders. Furthermore, the training and test dataset size would be varied to observe its impact on the model's performance and generalization ability by using ensemble models and k-fold cross-validation.

Data Availability Statement

The data used in this research is taken from Kaggle [12]. It will be made available on request.

Conflicts of Interest

The authors declare no conflicts of interest.

Statement of Ethical Approval

For this type of study, the statement of human rights is not required.

Statement of informed consent

For this type of study, informed consent is not required.

References

[1] J. F. Arévalo, A. F. Lasave, D. G. Zeballos, and S. Bonafonte-Royo, "Diabetic Retinopathy," Retinal and Choroidal Manifestations of Selected Systemic Diseases, New York: Springer, 2013.

[2] "Government Survey Found 11.8% Prevalence of Diabetes in India," https://www.livemint.com/science/health/government-survey-found-11-8-prevalence-of-diabetes-in-india-11570702665713.html, April 12, 2022.

[3] "IDF Atlas 9th Edition 2019," https://www.scribd.com/document/435995283/IDF-Atlas-9th-Edition-2019, April 12, 2022.

[4] Koetting, "The Four Stages of Diabetic Retinopathy," https://modernod.com/articles/2019-june/the-four-stages-of-diabeticretinopathy?c4src=article:infinite-scroll, April 12, 2022.

[5] R. E. Putra, H. Tjandrasa, and N. Suciati, "Severity Classification of Non-Proliferative Diabetic Retinopathy Using Convolutional Support Vector Machine," International Journal of Intelligent Engineering and Systems, vol. 13, no. 4, pp. 156-170, 2020.

[6] S. Albahli, T. Nazir, A. Irtaza, and A. Javed, "Recognition and Detection of Diabetic Retinopathy Using Densenet-65 Based Faster-RCNN," Computers, Materials & Continua, vol. 67, no. 2, pp. 1333-1351, February 2021.

[7] S. Qummar, F. G. Khan, S. Khan, S. Shah, A Khan, S. Shamshirband, Z. U. Rehman, et al, "A Deep Learning Ensemble Approach for Diabetic Retinopathy Detection," IEEE Access, vol. 7, pp. 150530-150539, 2019.

[8] U. Birajdar, S. Gadhave, S. Chikodikar, S. Dadhich, and S. Chiwhane, "Detection and Classification of Diabetic Retinopathy Using AlexNet Architecture of Convolutional Neural Networks," Proceeding of International Conference on Computational Science and Applications, pp. 245-253, January 2020.

[9] J. Gao, C. Leung, and C. Miao, "Diabetic Retinopathy Classification Using an Efficient Convolutional Neural Network," IEEE International Conference on Agents, pp. 80-85, October 2019.

[10] W. Zhang, J. Zhong, S.Yang, Z. Gao, J. Hu, Y. Chen, et al., "Automated Identification and Grading System of Diabetic Retinopathy Using Deep Neural Networks," Knowledge-Based Systems, vol. 175, pp. 12-25, July 2019.

[11] A. Deshpande and J. Pardhi, "Automated Detection of Diabetic Retinopathy Using VGG-16 Architecture," International Research Journal of Engineering and Technology, vol. 8, no. 3, pp. 2936-2940, March 2021.

[12] D. M. S. Barros, J. C. C. Moura, C. R. Freire, A. C. Taleb, R. A. M. Valentim, and P. S. G. Morais, "Machine Learning Applied to Retinal Image Processing for Glaucoma Detection: Review and Perspective," Biomedical Engineering Online, vol. 19, article no. 20, April 2020.

[13] S. Anwaar, "Diabetic-Retinopathy_Sample_Dataset_Binary," https://www.kaggle.com/datasets/sohaibanwaar1203/prepossessed-arrays-of-binary-data, April 15, 2022.

[14] A. A. Kumari and S. K. Henge, "A Hybrid Model on Deep Learning for the Diagnosis of Diabetic Retinopathy Using Image Cropping," Intelligent Sustainable Systems, vol. 333, pp. 515-525, January 2022.

[15] G. Huang, Z. Liu, G. Pleiss, L. Van Der Maaten, and K. Q. Weinberger, "Convolutional Networks with Dense Connectivity," IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 44, no. 12, pp. 8704-8716, December 2022.

[16] S. Patel, "Diabetic Retinopathy Detection and Classification Using Pre-Trained Convolutional Neural Networks," International Journal on Emerging Technologies, vol. 11, no. 3, pp. 1082-1087, 2020.

[17] J. Kim, "Finding the Best Performing Pre-Trained CNN Model for Image Classification: Using a Class Activation Map to Spot Abnormal Parts in Diabetic Retinopathy Image," American Journal of Biomedical and Life Sciences, vol. 9, no. 4, pp. 176-181, August 2021.

[18] C. Lahmar and A. Idri, "On the Value of Deep Learning for Diagnosing Diabetic Retinopathy," Health and Technology, vol. 12, no. 1, pp. 89-105, January 2022.

[19] A. Ayala, T. O. Figueroa, B. Fernandes, and F. Cruz, "Diabetic Retinopathy Improved Detection Using Deep Learning," Applied Sciences, vol. 11, no. 24, article no. 11970, December 2021.

[20] S. L. Yi, X. L. Yang, T. W. Wang, F. R. She, X. Xiong, and J. F. He, "Diabetic Retinopathy Diagnosis Based on RA-EfficientNet" Applied Sciences, vol. 11, no. 22, article no. 11035, November 2021.

[21] P. N. Chen, C. C. Lee, C. M. Liang, S. I. Pao, K. H. Huang, and K. F. Lin, "General Deep Learning Model for Detecting Diabetic Retinopathy," BMC Bioinformatics, vol. 22, no. 5, article no. 84, November 2021.

[22] M. M. S. Maswood, T. Hussain, M. B. Khan, M. T. Islam, and A. G. Alharbi, "CNN Based Detection of the Severity of Diabetic Retinopathy from the fundus Photography Using EfficientNet-B5," 11th IEEE annual information technology, electronics and mobile communication conference, pp. 0147-0150, November 2020.

[23] R. Revathy, B. S. Nithya, J. J. Reshma, S. S. Ragendhu, and M. D. Sumithra, "Diabetic Retinopathy Detection Using Machine Learning," International Journal of Engineering Research & Technology, vol. 9, no. 6, pp. 122-126, June 2020.

[24] S. C. Pravin and M. Palanivelan, "A Hybrid Deep Ensemble for Speech Disfluency Classification," Circuits, Systems, and Signal Processing, vol. 40, no. 8, pp. 3968-3995, August 2021.

[25] S. C. Pravin and M. Palanivelan, "Regularized Deep LSTM Autoencoder for Phonological Deviation Assessment," International Journal of Pattern Recognition and Artificial Intelligence, vol. 35, no. 4, article no. 2152002, March 2021.

[26] S. C. Pravin and M. Palanivelan, "Acousto-Prosodic Delineation and Classification of Speech Disfluencies in Bilingual Children," Proceedings of the 12th International Conference on Soft Computing and Pattern Recognition (SoCPaR 2020), Advances in Intelligent Systems and Computing, vol. 1383, pp. 618-628, December 2020.

[27] Padmanayana and B. K. Anoop, "Binary Classification of DR-Diabetic Retinopathy Using CNN with Fundus Colour Images," International Conference on Artificial Intelligence & Energy Systems, vol. 58, no. 1, pp. 212-216, 2022.

[28] S. C. Pravin and M. Palanivelan, "WDSAE-DNDT Based Speech Fluency Disorder Classification," Malaysian Journal of Computer Science, vol. 35, no. 3, pp. 222-242, July 2022.

[29] B. Latha, S. C. Pravin, J. Saranya, and E. Manikandan, "Ensemble Super Learner Based Genotoxicity Prediction of Multi-Walled Carbon Nanotubes," Computational Toxicology, vol. 24, article no. 100244, November 2022.