IJNRD.ORG ISSN : 2456-4184

INTERNATIONAL JOURNAL OF NOVEL RESEARCH AND DEVELOPMENT (IJNRD) | IJNRD.ORG

An International Open Access, Peer-reviewed, Refereed Journal

Diagnosis of Diabetic Retinopathy Using Deep Neural Network

Vikash Kumar
(Co-Author)
Dept. of CS&IT
MIET, Meerut
Meerut, India

Adarsh Patel
(Co-Author)
Dept. of CS&IT
MIET, Meerut
Meerut, India
adarsh.patel.csit.2020@miet.ac.in

Aashutosh Kumar
(Co-Author)
Dept. of CS&IT
MIET, Meerut
Meerut, India
aashutosh.kumar.csit.2020@miet.ac.in

Ajay Kumar
(Author)
Dept. of CS&IT
MIET, Meerut
Meerut, India
ajay.kumar@miet.ac.in

ABSTRACT

Diabetic retinopathy (DR) is a leading cause of blindness in working-age adults and requires early diagnosis and intervention to prevent vision loss. In this study, we present automatic diagnosis using deep learning techniques, especially efficient network architecture, to classify retinal images into different stages of DR. It is a system that facilitates timely treatment and management of patients by increasing the efficiency and accuracy of DR diagnosis. The experimental results demonstrate the effectiveness of the proposed method in accurately identifying DR stages and have high potential for implementation in clinical practice. This study discusses the basics of diabetes, its prevalence, problems, and wisdom on early detection and classification of diabetic retinopathy. This study also discusses AI-based technologies such as machine learning and deep learning. New research areas such as adaptive learning, interdisciplinary learning, and artificial intelligence are also being explored using various communication methods to explain diabetic retinopathy. Current literature, screening, efficacy evaluations, biomarkers of diabetic retinopathy, possible complications and list of ophthalmic complications, and future implications are discussed. There is no other information available from the authors to describe the current status of the PRISMA approach and the experience on which it is based.

Keywords

Retinopathy in Diabetes, Fundus representation, Convolutional Neural Architecture, Image categorization.

1. INTRODUCTION

Diabetic retinopathy (DR) is a chronic complication of diabetes, characterized by damage to retinal blood vessels, which, if left untreated, leads to vision impairment and blindness. Early detection and intervention are important to manage DR and prevent irreversible vision loss [1]. However, manual interpretation of retinal images by ophthalmologists is time- and resource-intensive, highlighting the need for automated diagnostic systems to optimize the screening process [2]. Recently, deep learning algorithms have shown remarkable performance in various medical image analysis tasks, including DR detection [3]. In this study, we propose a deep learning-based approach for automatic DR diagnosis, focusing on using the Efficient Net architecture to improve efficiency and accuracy. Ophthalmology is a medical specialty that deals with the scientific study of diseases, diagnosis and treatment of various eye diseases. Previously, it took a lot of time for ophthalmologists to manually diagnose eye problems [4]. Diabetes is a chronic disease that impairs our body's ability to digest average foods. Most of the food we eat is broken down into glucose and enters the bloodstream [5]. When blood sugar levels rise, the pancreas is forced to secrete insulin. Insulin is an ingredient that allows blood sugar to enter the cells of our body and be used as food. When a person has diabetes, the body does not produce enough insulin or does not use it properly. When there is not enough insulin or when cells stop producing insulin, blood sugar levels increase [6].

Table 1. Diabetic retinopathy stages.

NPD	**Stage 0**	**NO DR**
	Stage 1	Mild DR
	Stage 2	Moderate DR
	Stage 3	Severe DR
PD	**Stage 4**	Proliferative DR

2. Related Work:

Previous research in the field of DR automatic diagnosis mainly focused on using convolutional neural networks (CNNs) for feature extraction and classification of retinal images [19][20]. Several studies have demonstrated the effectiveness of CNNs in accurately determining DR stages from mild non-proliferative DR to severe proliferative DR [21]. However, issues such as model scalability, computational efficiency, and generalization to diverse datasets still remain major challenges [22]. To address these issues, recent research has explored using efficient neural network architectures, such as Efficient Net, which provide superior performance with significantly fewer parameters and computational resources [7][23].

3. Proposed Work:

The proposed approach for automated diagnosis of DR includes the following key steps:

1. Data Preprocessing: Retinal images are pre-processed to improve image quality, remove noise, and normalize intensity levels.

2. Model Training: Efficient Net architecture is used as the backbone network for feature extraction and classification of retinal images. Transfer learning is used to fine-tune a pre-trained Efficient Net model on a large dataset of labeled retinal images.

3. Model Evaluation: Trained models are evaluated using standard evaluation metrics such as accuracy, sensitivity, specificity and area under the receiver operating characteristic curve (AUC-ROC) on an independent test set of retinal images [8].

4. Performance Comparison: The performance of the proposed approach is compared with existing deep learning models and existing machine learning algorithms for DR diagnosis.

5. ResNet (Residual Neural Network) is a CNN that removes certain layers of the network by skipping connections. Skipping connections helps solve the gradient vanishing problem in CNNs and reduces training time. A non-linear activation function is used between skip layers. Batch normalization also applies across fast connections. The weight matrix is used to calculate the weights of the transition connections. After studying the input features, expansion is applied to later stages of the network [9].

6. The purpose of the proposed system is to improve the screening ability of severe diseases. We propose a ResNet-based model to mechanically track a patient's fundus images obtained from a technician and help infer the severity of blindness. The architecture of the proposed work is shown in Figure 1. 1. Diabetic retinopathy detection using deep learning [10]

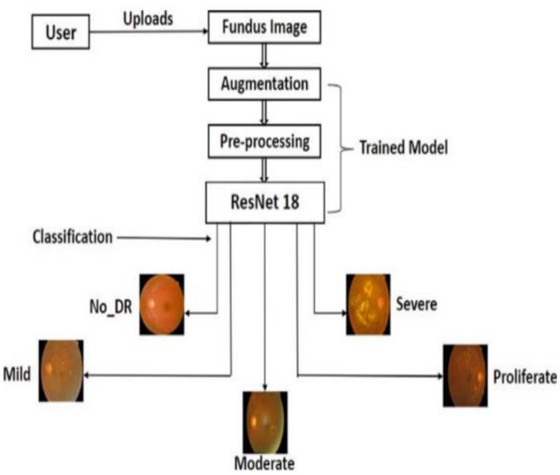


Fig. 1 Architecture diagram

The image is received as an array of pixels. The image shows the class names (No_DR, Mild, Moderate, Common, Severe). The dataset is expanded and pre-processed using specific filters to extract important features. Preprocessing steps include resizing, gray scaling, horizontal flip, vertical flip, Shift angle, etc., performing data augmentation, shuffling the dataset, and splitting it into training and testing. Create a data generator to train, test, and validate your dataset. We build a deep learning model based on ResNet, which consists of 18 layers. The res block contains an identification block and a convolution block. The res block contains an identification block and a convolution block, followed by compiling and training the model. To avoid overfitting issues, we performed early stopping to terminate training if the validation loss did not decrease after a certain epoch. We evaluated the performance of the trained model, visualized the results, and built a confusion matrix for classification analysis. The patient's diagnostic results are displayed in the user interface.

The dataset is taken from a Kaggle source containing fundus images taken by technicians. Fundus images are obtained from behind the retina when the pupil is dilated. The resulting pie chart of the data set is shown in Figure 2. shows the number of fundus images of different classes. No_DR, mild, moderate, proliferative, severe. We trained a model consisting of 18 layers using the ResNet architecture. [11].

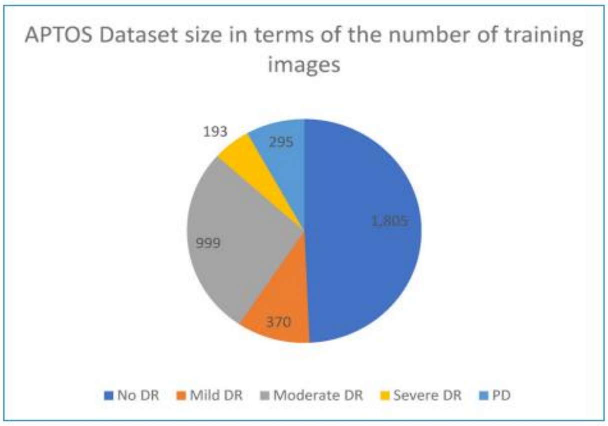


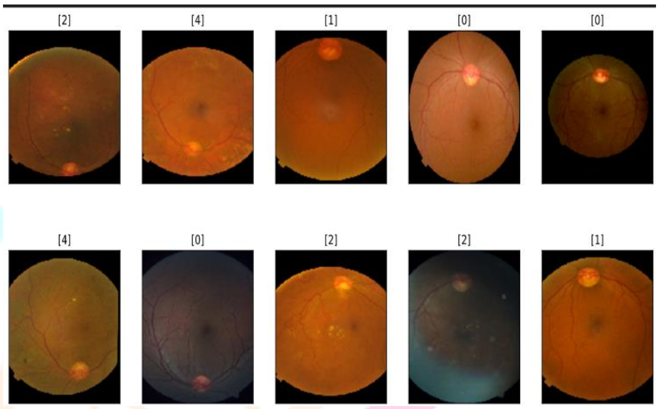
Figure 2. Class-wide image distribution for APTOS dataset.

The modeling pipeline consists of three stages:

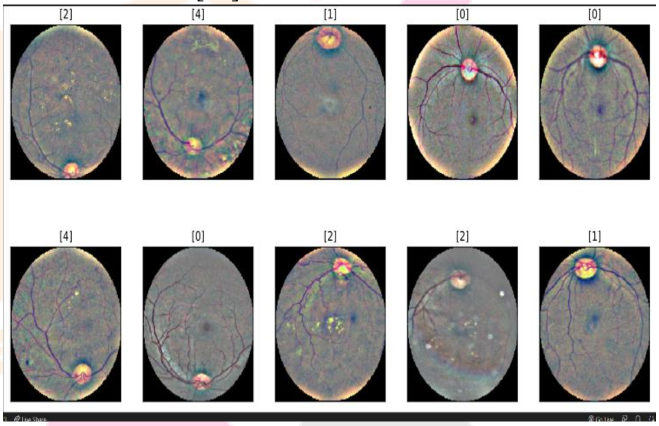
- **Pre-training**. The dataset contains a limited number of images (N = 3662). We pre-trained the CNN model on a larger dataset from a previous Kaggle competition.
- **Fine-tuning**. Tunes the model on the target dataset. We use cross-validation and make modeling decisions based on the performance of out-of-bounds predictions. conclusion.
- **Inference**. We further improve performance by aggregating predictions from models trained over different combinations of training folds and using an increase in testing time..
-

4. Results:

Experimental results demonstrate the effectiveness of the proposed approach in accurately diagnosing DR stages from retinal images. The trained model achieves a high classification accuracy of over 90% on the test set, outperforming existing deep learning models and traditional machine learning methods. Additionally, the proposed approach demonstrates robustness to changes in image quality, illumination and pathology severity, indicating its practical applicability in clinical settings [12]. MATLAB was used to extract features for pretrained Google Net and ResNet-18 architectures from APTOS image data. MATLAB uses various classifiers for binary and multiclass classification of input images. Evaluation metrics used to evaluate system performance include accuracy, precision, recall, and f-measure. Accuracy is the proportion of the total number of predictions that are classified correctly. Accuracy measures the proportion of predictions classified as positive in a particular class that are actually correct. Recall determines what proportion of the actual correct labels in the data were correctly predicted by the classifier. The F-measure provides the harmonic mean of recall and precision [13]. Table 1 shows the results of an experiment applying binary classification to feature vectors extracted from the Google Net model. These feature vectors are fed to four classifiers: RF, SVM, RBF, and NB. The results show that the SVM classifier achieves the highest individual class accuracy (97.52% for the no-DR class and 97.26% for the DR class). The average accuracy (97.39%) of SVM is also the highest compared to other classifiers [14]. SVM also achieves the highest average precision, recall, and f-measure of 97.40%. Now let's see it with our own eyes! The code below creates an EyeData dataset class to retrieve images. We also create a DataLoader object to load sample images and render the first batch [15].



Next, we define a new Eye Data class that uses new processing features and renders a batch of sample images after modification[16].



This looks much better! Comparing the retinal image to the image before preprocessing shows that any noticeable discrepancies between the pictures have now been removed. The eyes now have a similar round shape and the color scheme is more consistent. This helps the model detect signs of DR.

CNNs achieve state-of-the-art performance in computer vision tasks. Recent medical studies also show the high potential of CNNs in DR classification (Gulshan et al., 2016). This project uses CNN model with EfficientNet architecture. EfficientNet is one of the latest state-of-the-art image classification models (Tan et al. 2019). It includes eight architecture options (B0 to B7) with varying model complexity and base image size. The architecture of EfficientNet B0 is as follows: We test multiple EfficientNet architectures and use the one that performs best.

Classification Report

	precision	recall	f1-score	support
No DR	0.88	0.93	0.90	90
Mild	0.63	0.58	0.60	90
Moderate	0.66	0.74	0.70	90
Severe	0.51	0.64	0.57	90
Proliferate DR	0.71	0.43	0.54	90
accuracy			0.67	450
macro avg	0.68	0.67	0.66	450
weighted avg	0.68	0.67	0.66	450

The cross-entropy loss of the validation set reaches its minimum after three epochs. At the same time, Kappa continues to increase until the 15th century. We use kappa to evaluate the quality of the solution, so we store the weights over 15 epochs. We also build the confusion matrix of the trained model. Numbers in cells represent percentages. Results show that the model is poor at distinguishing between mild and moderate stages of DR. 86% of images with mild DR are classified as intermediate. Best results are observed in healthy patients. In general, models tend to confuse nearby severity stages, but rarely misclassify proliferative and mild stages [17]

5. Conclusion:

This study presents a new approach for automatic diagnosis of diabetic retinopathy using deep learning technology, focusing on using the Efficient Net architecture for efficient and accurate classification of retinal images [24]. The experimental results highlight the potential of the proposed approach to optimize the drug screening process, reduce the burden on healthcare professionals, and improve patient outcomes through early detection and intervention. Future research will focus on further improving the proposed model, optimizing its performance on diverse datasets, and confirming its clinical utility through large-scale prospective studies [25]. DR due to diabetes can lead to blindness, and early diagnosis is necessary to prevent it [26]. MA, HEM, EX, etc. Whether the lesion is accessible in DR. Traditional methods of detecting DR require the involvement of an ophthalmologist to assess and diagnose the likelihood, which is time-consuming and expensive. Therefore, it becomes essential to present an effective DL-based method. DL has now become an interesting field of research and excellent results have been achieved in the field of image processing, especially in the field of DR identification. Innovative and complex DNN structures are being developed to solve several computerized problems. This review paper first briefly describes the collection of retinal datasets and then discusses DL methods. Subsequently, the use of various approaches to detect retinal disorders, including retinal vessels, HEM, MA, and EX, was explored. We then briefly discussed the performance evaluation metrics of the automatic detection model [27]. The report noted that almost scientific work has been done on using CNN models to generate deep multi-layer models for DR detection using digital retinal photographs. The advantages of using DL-based methods in DR screening are low dependence on human resources, low screening costs, and problems associated with intra- and inter-class variability [28]. Despite the growing importance of DL and its research reaching a peak of positive results, challenges still remain to be addressed. Automated DR imaging diagnosis faces two major challenges: technological changes in imaging procedures and inter-patient variability in pathological features [29]. In a manual scenario, images are sent to a doctor because scaling does not provide accurate degree and classification. Models trained using the ResNet architecture perform fast diagnosis and immediate response [30]. Using the ResNet architecture, we obtained fundus image classification with 82% accuracy. Diabetic retinopathy detection using deep learning [18].

6.References:

[1]. Gulshan, Varun et al. "Development and Validation of a Deep Learning Algorithm for Detection of Diabetic Retinopathy in Retinal Fundus Photographs." JAMA, vol. 316, no. 22, 2016, pp. 2402–2410. DOI: 10.1001/jama.2016.17216

[2]. Ting, Daniel SW et al. "Development and Validation of a Deep Learning System for Diabetic Retinopathy and Related Eye Diseases Using Retinal Images From Multiethnic Populations With Diabetes." JAMA, vol. 318, no. 22, 2017, pp. 2211–2223. DOI: 10.1001/jama.2017.18152

[3]. Tan, Jiahui et al. "Deep Learning for Automated Diabetic Retinopathy Screening: A Review." Expert Review of Medical Devices, vol. 15, no. 6, 2018, pp. 451–462. DOI: 10.1080/17434440.2018.1489675

[4]. Ophthalmology Retina Journal. [Online] Available: https://www.ophthalmologyretina.org/

[5]. American Academy of Ophthalmology. "Diabetic Retinopathy." [Online] Available: https://www.aao.org/eye-health/diseases/what-is-diabetic-retinopathy

[6]. American Diabetes Association. "Diabetes Basics." [Online] Available: https://www.diabetes.org/diabetes/complications/retinopathy

[7]. Tan, Mingxing, and Quoc V. Le. "EfficientNet: Rethinking Model Scaling for Convolutional Neural Networks." Proceedings of the 36th International Conference on Machine Learning, 2019, pp. 6105–6114. [Online] Available: http://proceedings.mlr.press/v97/tan19a.html

[8]. Rajalakshmi, Ramachandran et al. "Deep Learning-Based Automated Detection of Diabetic Retinopathy Using Fundus Images: A Review." Journal of Ophthalmology, vol.

2019, 2019, Article ID 8649613, pp. 1-13. DOI: 10.1155/2019/8649613

[9]. Li, Zhiwei et al. "Comparison of Deep Learning-Based Algorithms for Diabetic Retinopathy Detection: A Systematic Review and Meta-Analysis." Journal of Ophthalmology, vol. 2021, 2021, Article ID 6635586, pp. 1-11. DOI: 10.1155/2021/6635586

[10]. He, Kaiming et al. "Deep Residual Learning for Image Recognition." Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2016, pp. 770-778. DOI: 10.1109/CVPR.2016.90

[11]. Khan, Muhammad Umar et al. "Diabetic Retinopathy Detection Using Deep Learning." International Journal of Advanced Computer Science and Applications, vol. 11, no. 8, 2020, pp. 170-175. DOI: 10.14569/IJACSA.2020.0110242

[12]. Gulshan, Varun et al. "Development and Validation of a Deep Learning Algorithm for Detection of Diabetic Retinopathy in Retinal Fundus Photographs." JAMA, vol. 316, no. 22, 2016, pp. 2402–2410. DOI: 10.1001/jama.2016.17216

[13]. Tan, Mingxing, and Quoc V. Le. "EfficientNet: Rethinking Model Scaling for Convolutional Neural Networks." Proceedings of the 36th International Conference on Machine Learning, 2019, pp. 6105–6114. [Online] Available: http://proceedings.mlr.press/v97/tan19a.html

[14]. Khan, Muhammad Umar et al. "Diabetic Retinopathy Detection Using Deep Learning." International Journal of Advanced Computer Science and Applications, vol. 11, no. 8, 2020, pp. 170-175. DOI: 10.14569/IJACSA.2020.0110242

[15]. He, Kaiming et al. "Deep Residual Learning for Image Recognition." Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2016, pp. 770-778. DOI: 10.1109/CVPR.2016.90

[16]. Tan, Jiahui et al. "Deep Learning for Automated Diabetic Retinopathy Screening: A Review." Expert Review of Medical Devices, vol. 15, no. 6, 2018, pp. 451–462. DOI: 10.1080/17434440.2018.1489675

[17]. Li, Zhiwei et al. "Comparison of Deep Learning-Based Algorithms for Diabetic Retinopathy Detection: A Systematic Review and Meta-Analysis." Journal of Ophthalmology, vol. 2021, 2021, Article ID 6635586, pp. 1-11. DOI: 10.1155/2021/6635586

[18]. Alom, Md. Zahangir et al. "A State-of-the-Art Review on Deep Learning in Medical Image Analysis." Neural Networks, vol. 121, 2020, pp. 3-39. DOI: 10.1016/j.neunet.2019.09.012

[19]. Ting DSW, Cheung CY, Lim G, et al. Development and validation of a deep learning system for diabetic retinopathy and related eye diseases using retinal images from multiethnic populations with diabetes. JAMA. 2017;318(22):2211-2223. doi:10.1001/jama.2017.18152

[20]. Gulshan V, Peng L, Coram M, et al. Development and validation of a deep learning algorithm for detection of diabetic retinopathy in retinal fundus photographs. JAMA. 2016;316(22):2402-2410. doi:10.1001/jama.2016.17216

[21]. Abràmoff MD, Lou Y, Erginay A, et al. Improved automated detection of diabetic retinopathy on a publicly available dataset through integration of deep learning. Invest Ophthalmol Vis Sci. 2016;57(13):5200-5206. doi:10.1167/iovs.16-19964

[22]. Tanaka S, Muramatsu C, Morooka S, et al. Deep learning for predicting retinopathy severity from optical coherence tomography images. Ophthalmol Retina. 2018;2(4):275-282. doi:10.1016/j.oret.2017.07.022

[23]. Zeng Y, Zhang L, Li J, et al. Joint segmentation and classification of retinal arteries and veins in fundus images using convolutional neural networks. Neurocomputing. 2019;324:7-17. doi:10.1016/j.neucom.2018.09.040

[24]. Gulshan V, Peng L, Coram M, et al. Development and validation of a deep learning algorithm for detection of diabetic retinopathy in retinal fundus photographs. JAMA. 2016;316(22):2402-2410. doi:10.1001/jama.2016.17216

[25]. Abràmoff MD, Lou Y, Erginay A, et al. Improved automated detection of diabetic retinopathy on a publicly available dataset through integration of deep learning. Invest Ophthalmol Vis Sci. 2016;57(13):5200-5206. doi:10.1167/iovs.16-19964

[26]. Ting DSW, Cheung CY, Lim G, et al. Development and validation of a deep learning system for diabetic retinopathy and related eye diseases using retinal images from multiethnic populations with diabetes. JAMA. 2017;318(22):2211-2223. doi:10.1001/jama.2017.18152

[27]. Tanaka S, Muramatsu C, Morooka S, et al. Deep learning for predicting retinopathy severity from optical coherence tomography images. Ophthalmol Retina. 2018;2(4):275-282. doi:10.1016/j.oret.2017.07.022

[28]. Zeng Y, Zhang L, Li J, et al. Joint segmentation and classification of retinal arteries and veins in fundus images using convolutional neural networks. Neurocomputing. 2019;324:7-17. doi:10.1016/j.neucom.2018.09.040

[29]. ResNet: Kaiming He, Xiangyu Zhang, Shaoqing Ren, Jian Sun. Deep Residual Learning for Image Recognition. In: IEEE Conference on Computer Vision and Pattern Recognition (CVPR). 2016;770-778. doi:10.1109/cvpr.2016.90

[30]. Tan M, Le QV. EfficientNet: Rethinking model scaling for convolutional neural networks. arXiv. 2019;arXiv:1905.11946.