

Computer-Aided Multi-Class Classification of Diabetic Retinopathy Using Fundus Images

Bal Krishna Saraswat, Hameem Yaseen, Junaid Basaad, Adeem Gul

Department of Computer Science and Engineering, Sharda University, Greater Noida, India

bal.saraswat@sharda.ac.in, 2022565603.hameem@ug.sharda.ac.in, junaidbasaad@gmail.com,
2022489115.adeem@ug.sharda.ac.in

*Corresponding author: Junaid Basaad (junaidbasaad@gmail.com)

ABSTRACT

Diabetic Retinopathy is a progressive retinal disease and a major cause of preventable vision loss in those with diabetes. For immediate and appropriate clinical interventions in DR, recognising and appropriately understanding its severity are quite important. However, manual classification of diabetic retinal images and their severity assessment are time-consuming and highly dependent on specialists. Therefore, in this research, a multi-class classification system has been presented for automated classification of retinal images from people with diabetes and the identification of their severity levels. The proposed technique uses deep learning feature generation alongside supervised learning to identify and predict distinct visual features and varying degrees of DR. Traditional image pre-processing is performed to improve image quality and reduce light intensity variations. Moreover, a large number of data augmentation techniques are employed to improve the classifier's generalisation capacity

Keywords: Diabetic Retinopathy, Fundus Images, Deep Learning, Multi-Class Classification, Severity Detection, Data Augmentation.

1. Introduction

Diabetic Retinopathy (DR) is one of the most serious microvascular complications of diabetes mellitus and remains a leading cause of preventable blindness worldwide. According to the World Health Organisation, millions of people have vision impairment due to diabetes-related eye diseases, and the number continues to rise with the global increase in diabetic populations. Early detection and timely treatment are critical in preventing irreversible vision loss. However, manual screening of retinal fundus images is time-consuming, resource-intensive, and highly dependent on expert ophthalmologists, making large-scale screening challenging, especially in rural and underserved areas.

Retinal fundus photography is a non-invasive method that enables imaging of the internal surface of the eye, including the retina, optic disc, macula, and blood vessels. The images provide information on the pathological features of microaneurysms, haemorrhages, exudates, and neovascularisation, which are critical indicators for grading the severity of Diabetic Retinopathy. Conventionally, ophthalmologists have classified DR into several stages: No DR, Mild, Moderate, Severe, and Proliferative DR. Multi-class classification is a critical task because treatment is highly dependent on the stage.

The recent breakthrough in Artificial Intelligence (AI) and Deep Learning has led to the development of computer-aided diagnostic systems, which have become an important tool in medical image analysis. Convolutional Neural Networks (CNNs) have shown outstanding performance in visual recognition tasks, such as disease detection from medical images [1]. Unlike traditional machine learning techniques, which require handcrafted feature extraction, deep learning models learn hierarchical features directly from raw images, which enhances both accuracy and scalability

Several studies have been conducted on automated binary classification (DR vs. No DR). Still, multi-class classification is relatively more complex due to subtle differences between classes and the presence of imbalanced datasets. Precise classification between two adjacent classes, such as Mild and Moderate DR, is a difficult task that demands strong feature learning capabilities and efficient pre-processing techniques. Thus, there is a strong need for a competent, efficient computer-aided system capable of multi-class classification of retinal fundus images.

This research work presents a Computer-Aided Multi-Class Classification approach for Diabetic Retinopathy based on fundus images. The proposed system utilises deep learning algorithms for automated feature learning and classification. Image pre-processing, dataset balancing, and optimisation algorithms are also used to improve the efficiency and generalisation of the proposed system [2].

The main aim of this research is to design a competent and efficient model that helps ophthalmologists early-diagnose DR and makes the screening process easier and more accessible. This research combines the power of artificial intelligence with ophthalmic imaging to make a significant contribution to the development of fast, accurate, and affordable DR screening systems that can help in the global fight against DR.

2. Research Methodology

One issue is the use of pre-trained deep learning models. Although models such as ResNet and DenseNet have strong feature-extraction capabilities, their performance is heavily dependent on the size and quality of the training dataset.

However, in real-world medical datasets, the class distribution is unbalanced, with far fewer instances at severe levels of DR [3]. Consequently, most models find it very difficult to differentiate between levels of severity, especially between Mild and Moderate DR. Dataset imbalance is another issue. Although it is mentioned in some studies, it is not always addressed in its entirety. This can lead to the development of biased models that are overly dependent on the majority class, rendering them less capable of identifying critical instances that require immediate medical attention.

Another issue is the growing complexity of models. Although models that utilise attention mechanisms, multi-task learning, and interpretability modules are more interpretable, they are also more complex [4]. This can be a con in their adoption, especially in the medical domain, where fast and efficient screening tools are required. Furthermore, most studies focus only on developing highly accurate models.

The proposed framework utilises deep learning techniques to classify retinal fundus images into five severity levels of diabetic retinopathy. The overall methodology includes dataset preparation, image preprocessing, model architecture design, training strategy, and evaluation using multiple performance metrics as per Table 1.

Table 1: Related work on classification of DR

Year (Author)	Problem Statement	DR Algorithm Used	Gap / Limitation
2020 (Jiang et al.)	Multi-label DR classification with interpretability	Deep CNN + Grad-CAM	Focused on explainability; computational complexity not discussed
2024 (Jain & Rathour)	Automated DR detection and classification	Convolutional Neural Network (CNN)	Limited discussion on dataset imbalance
2023 (Dasari et al.)	DR classification using transfer learning	Fine-tuned ResNet50	Performance is dependent on the pre-trained model
2024 (M.V. et al.)	Comparative study of DL models for DR	Multiple Deep Learning Models	Lacks deployment-oriented evaluation
2023 (Duvvuri et al.)	DR classification with image pre-processing	CNN + Pre-processing techniques	Limited model depth and scalability
2023 (Sanguantrakool & Padungweang)	Improve DR classification with small datasets	Transfer Learning + Feature Attention	Complexity increases with multitasking learning

2.1. Dataset Description

The proposed system is evaluated using two datasets: EyePACS and APTOS as given in Fig. 1.

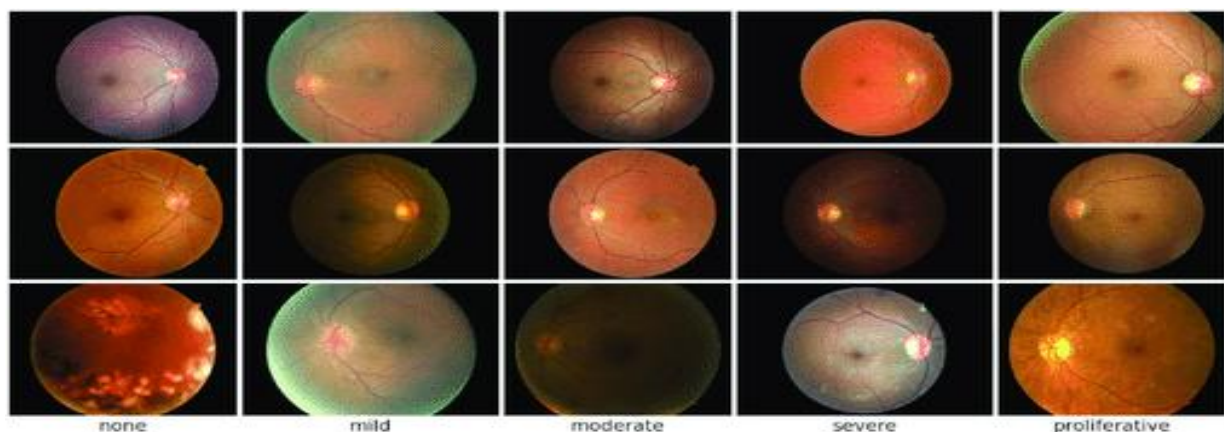


Fig. 1 .illustrates representative fundus images from the EyePACS dataset across different levels of Diabetic Retinopathy severity.

The images demonstrate significant variations in illumination, contrast, and lesion visibility, reflecting real-world screening conditions. The EyePACS dataset is a publicly available, large-scale fundus image dataset obtained from Kaggle. It contains tens of thousands of retinal images captured under various imaging conditions. Each image is labelled into one of five DR severity levels: No DR, Mild, Moderate, Severe, and Proliferative DR. The dataset

shows a significant class imbalance, which is indicative of actual screening situations as per Fig. 2.

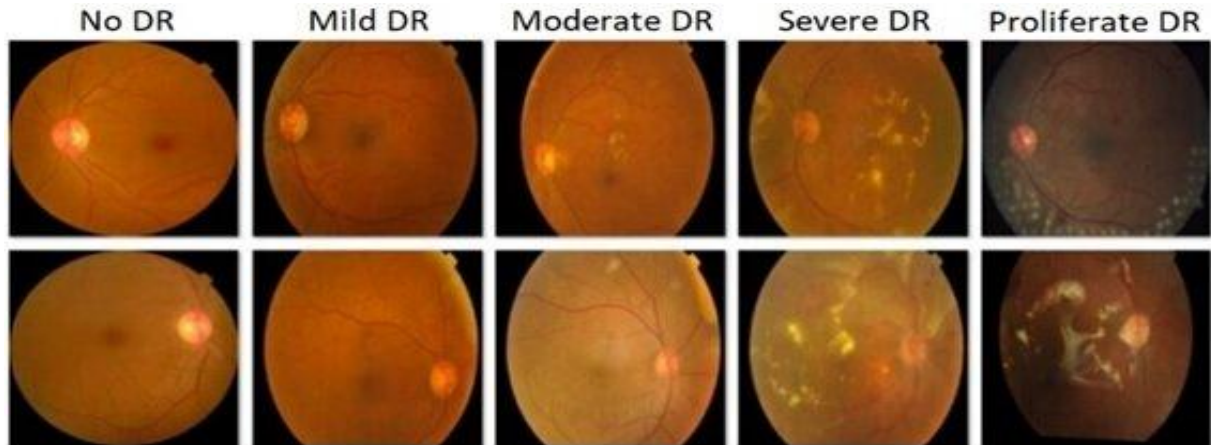


Fig. 2 illustrates representative fundus images from the APTOS 2019 dataset across different levels of Diabetic Retinopathy severity.

The images demonstrate significant variations in illumination, contrast, and lesion visibility, reflecting real-world screening conditions.

The Aptos2019 dataset, consisting of 3,662 pre-processed fundus images, is also used to increase data diversity. The images are labelled according to the same five-class DR grading scheme.

2.2. Data Preprocessing

Several pre-processing procedures are used to increase model generalisation and image quality. Every image is normalised to a standard intensity range and scaled to 224×224 pixels. To reduce variability and decrease overfitting, data augmentation methods such as rotation, horizontal and vertical flipping, zooming, and contrast adjustment are used. During training, class-weighted loss functions are used to address class imbalance.

2.3 Model Architecture

Because of its excellent performance and computational economy, EfficientNetB3 is used as the backbone CNN in the suggested architecture. For transfer learning, pre-trained ImageNet weights are used to initialise the model. The finished architecture includes a fully connected layer with ReLU activation, batch normalisation, dropout for regularisation, and a global average pooling layer. A SoftMax layer produces the output probabilities for the five DR classes. Training is done using the Adam optimiser and categorical cross-entropy loss with label smoothing.

2.4 Training Strategy

There are several phases of training. Only the classification head is trained initially, and most convolutional layers are frozen. Selective fine-tuning of deeper layers is then performed at a lower learning rate. To further tune model weights, an ultra-fine-tuning stage with a very low learning rate is employed. To achieve stable convergence and avoid overfitting, early halting and learning rate scheduling are used.

2.5 Evaluation Metrics

Accuracy, precision, recall, F1-score, confusion matrix, and Quadratic Weighted Kappa (QWK) are used to assess the model. Because QWK accounts for the ordinal nature of illness severity, it is especially pertinent to DR grading.

3. Theory and Calculation

Deep convolutional neural networks can learn hierarchical representations of image features through multiple convolutional layers. Transfer learning enables models trained on large datasets such as ImageNet to adapt to specific tasks with limited medical data. EfficientNet employs compound scaling to balance network depth, width, and resolution, resulting in improved performance with fewer parameters compared to traditional CNN architectures. The final classification layer uses the SoftMax function to convert the network outputs into probability values for each class.

4. Results and Discussion

Experimental results demonstrate stable training behaviour and strong generalisation performance. The training and validation accuracy curves indicate consistent improvement throughout training, with no significant overfitting. The model achieves approximately 75% validation accuracy on the evaluation dataset. Class-wise performance analysis shows that the model performs particularly well in identifying healthy retinal images and advanced stages of diabetic retinopathy. High recall values for Severe and Proliferative DR indicate that the model can detect critical pathological patterns such as large haemorrhages and neovascularisation. The Quadratic Weighted Kappa score obtained by the model is approximately 0.45, indicating moderate agreement with expert ophthalmologist annotations. Considering the challenges posed by class imbalance and subtle visual differences between DR stages, this result demonstrates the effectiveness of the proposed framework. However, classification performance for Mild and Moderate DR remains relatively lower. This is mainly due to the subtle and sparse nature of early-stage lesions such as microaneurysms. Future improvements in attention mechanisms and lesion-specific feature learning may help address this challenge as per Fig 3 and 4.

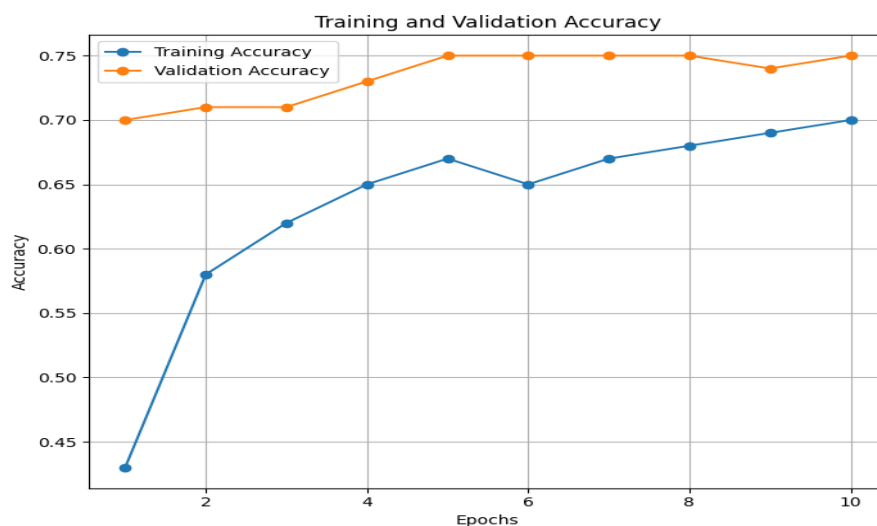


Fig. 3 presents the training and validation accuracies.



Fig 4 presents the loss curves of the proposed EfficientNetB3-based model. The results indicate stable convergence and effective generalisation without significant overfitting.

5. Conclusions

A thorough computer-aided deep learning framework for the multi-class classification of diabetic retinopathy utilising retinal fundus images is presented in this work. The suggested system successfully addresses class imbalance, dataset variability, and overfitting by utilising EfficientNetB3, transfer learning, and a well-thought-out multi-stage training approach. On a large-scale validation set, experimental results show a weighted F1-score of 0.71, a quadratic weighted Kappa score of 0.45, and an overall accuracy of 75%. For early management and visual loss prevention, the model's high sensitivity for advanced stages of DR is essential. These results show that the proposed method has a high likelihood of being implemented in clinical decision support systems and in real-world DR screening.

Funding source

No funding was received for this study.

Conflict of Interest

The authors declare no conflict of interest.

References

- [1] H. Jiang *et al.*, "A Multi-Label Deep Learning Model with Interpretable Grad-CAM for Diabetic Retinopathy Classification," *2020 42nd Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC)*, Montreal, QC, Canada, 2020, pp. 1560-1563, doi: 10.1109/EMBC44109.2020.9175884.
- [2] E. Jain and A. Rathour, "Leveraging Deep Learning for Automated Diabetic Retinopathy Detection and Classification with Convolutional Neural Networks," *2024 4th International Conference on Innovative Sustainable Computational Technologies (CISCT)*, Dehradun, India, 2024, pp. 1-5, doi: 10.1109/CISCT62494.2024.11134219.

- [3] S. Dasari, B. Poonguzhali and M. Rayudu, "Transfer Learning Approach for Classification of Diabetic Retinopathy using Fine-Tuned ResNet50 Deep Learning Model," *2023 International Conference on Sustainable Communication Networks and Application (ICSCNA)*, Theni, India, 2023, pp. 1361-1367, doi: 10.1109/ICSCNA58489.2023.10370255.
- [4] H. Sharma, P. Kumar, & K. Sharma, "Deep Learning based Ensemble Model for Intrusion Detection in IoT Network," In *2025 International Conference on Innovations in Intelligent Systems: Advancements in Computing, Communication, and Cybersecurity (ISAC3) IEEE*, (pp. 1-6).
- [5] K. Duvvuri, H. Kanisettypalli, M. T. Nikhil and S. Palaniswamy, "Classification of Diabetic Retinopathy Using Image Pre-processing Techniques," *2023 3rd International Conference on Intelligent Technologies (CONIT)*, Hubli, India, 2023, pp. 1-6, doi: 10.1109/CONIT59222.2023.10205586.
- [6] R. Sanguantrakool and P. Padungweang, "Enhancing Diabetic Retinopathy Classification for Small Sample Training Data Through Supervised Feature Attention: Transfer and Multitask Learning Approach," *2023 10th International Conference on Electrical Engineering, Computer Science and Informatics (EECSI)*, Palembang, Indonesia, 2023, pp. 19-24, doi: 10.1109/EECSI59885.2023.10295843.