Deep Vision: CNNs in Retinal Disease Detection

Maqsood Ahmed
Department of Artificial Intelligence
GIKI
Topi, Pakistan
u2022656@giki.edu.pk

Ali Gohar
Department of Artificial Intelligence
GIKI
Topi, Pakistan
u2022081@giki.edu.pk

Karrar Ahmed
Department of Artificial Intelligence
GIKI
Topi, Pakistan
u2022246@giki.edu.pk

***Abstract*—Diabetic Retinopathy (DR) is one of the leading causes of blindness among working-age adults worldwide. Early diagnosis is crucial to prevent severe vision loss, but manual detection by ophthalmologists is time-consuming and subjective. This project proposes a deep learning-based approach for the automated detection and classification of DR using retinal fundus images. We trained a convolutional neural network (CNN) model on a labeled dataset containing five classes of DR severity: No_DR, Mild, Moderate, Severe, and Proliferative_DR. The dataset was preprocessed with normalization, resizing, and data augmentation techniques to enhance model robustness. Our proposed model achieved high accuracy in detecting various stages of DR and outperformed traditional image processing approaches. The results demonstrate the potential of deep learning models to assist ophthalmologists in large-scale DR screening with improved efficiency and reliability.**

***Index Terms*—Diabetic Retinopathy, Deep Learning, Convolutional Neural Network (CNN), Medical Image Classification, Retinal Fundus Images, Automated Diagnosis.**

I. Introduction

Diabetes mellitus is a chronic disease that affects millions of people worldwide, leading to serious health complications if left unmanaged. One of the most severe complications is Diabetic Retinopathy (DR), a progressive eye disease that damages the blood vessels in the retina and can ultimately cause blindness. According to the World Health Organization, DR is among the leading causes of vision impairment in working-age adults globally.

Early detection and treatment of DR are critical to prevent permanent vision loss. Traditionally, diagnosis requires manual examination of retinal fundus images by ophthalmologists, which is a time-consuming and subjective process prone to inter-observer variability. Moreover, the growing number of diabetic patients strains healthcare systems, especially in regions with limited access to specialized eye care.

Recent advances in deep learning, particularly convolutional neural networks (CNNs), have shown great promise in automating medical image analysis tasks. CNNs can learn complex patterns from large datasets and provide accurate classification of retinal images into different stages of DR severity. This automated approach can aid ophthalmologists by providing fast, reliable screening and reducing the burden on healthcare services.

In this project, we develop a deep learning-based system to detect and classify diabetic retinopathy from retinal fundus images into five categories: No DR, Mild, Moderate, Severe, and Proliferative DR. We utilize preprocessing techniques such as normalization and data augmentation to improve model performance and generalization. The proposed method aims to assist in early diagnosis and enable large-scale screening for diabetic retinopathy.

II. Literature Review

In recent years, numerous studies have explored the application of deep learning techniques for the automated detection of Diabetic Retinopathy (DR) from retinal images. These approaches have demonstrated significant improvements in classification accuracy and reliability compared to traditional machine learning and manual methods.

Gulshan et al. [1] developed one of the earliest deep learning-based systems using a convolutional neural network trained on a large dataset of retinal fundus images. Their model achieved performance comparable to that of board-certified ophthalmologists, highlighting the potential of deep learning in DR screening.

Similarly, Pratt et al. [2] proposed a CNN architecture to classify retinal images into different stages of DR. They employed data augmentation and dropout regularization to mitigate overfitting and achieved high classification accuracy on the Kaggle EyePACS dataset.

Another notable study by Lam et al. [3] introduced a deep ensemble model combining multiple CNNs to enhance prediction robustness. Their approach achieved improved sensitivity and specificity, especially for moderate and severe DR stages.

More recent works have also explored transfer learning techniques. For instance, Voets et al. [4] applied pre-trained CNN models such as InceptionV3 and ResNet50 to DR classification, achieving high accuracy with reduced training time.

Despite these advances, challenges such as class imbalance, variations in image quality, and the need for large annotated datasets still persist. Researchers have proposed solutions like generative adversarial networks (GANs) for synthetic data generation and attention mechanisms to improve focus on lesion areas.

These studies collectively indicate that deep learning, particularly CNN-based approaches, hold significant promise for improving the accuracy and scalability of diabetic retinopathy diagnosis. However, further improvements in model general-

ization and real-world deployment are necessary for clinical adoption.

III. Dataset Description

The dataset used in this project comprises retinal fundus images labeled according to the severity of Diabetic Retinopathy (DR). It is organized into three main subsets:

- **Training Set:** Used to train the deep learning model.
- **Validation Set:** Used to tune hyperparameters and prevent overfitting.
- **Test Set:** Used for final evaluation of model performance.

Each image in the dataset is labeled with one of five DR severity classes:

- **No DR:** The retina is healthy, with no signs of DR.
- **Mild:** Small microaneurysms are present, an early sign of DR.
- **Moderate:** More blood vessels are affected, but vision is still functional.
- **Severe:** A significant number of blood vessels are blocked, and vision is at risk.
- **Proliferative DR:** The most advanced stage, with abnormal blood vessel growth that can lead to blindness.

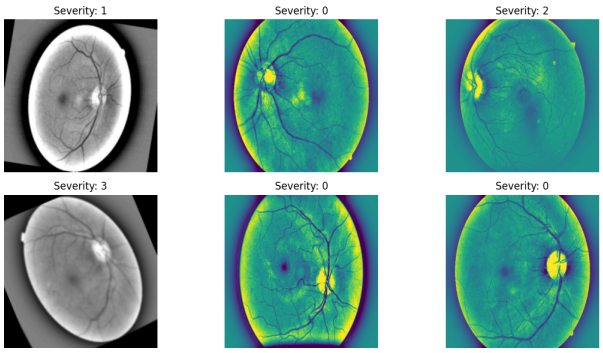

Fig. 1. Sample retinal fundus images from each DR class.

IV. Methodology

A. Data Preprocessing

Before training the model, the images were preprocessed to enhance performance and consistency. The preprocessing steps included:

- **Resizing:** All images were resized to 224×224 pixels to match the input size requirements of the ResNet-50 model.
- **Normalization:** Pixel values were normalized using the mean and standard deviation of the ImageNet dataset.
- **Data Augmentation:** Techniques such as random horizontal flipping, random rotation, and brightness adjustments were applied to increase data diversity and prevent overfitting.

B. Challenges in the Dataset

The dataset presented several challenges during model development:

- **Class Imbalance:** Certain DR classes had significantly fewer samples than others, leading to potential bias in predictions.
- **Variability in Image Quality:** Blurry or underexposed images made it difficult for the model to extract meaningful features.
- **Medical Data Sensitivity:** Ensuring privacy and ethical usage of medical data was a priority throughout the project.

C. Model Training and Optimization

1) Choice of Model: ResNet-50, a deep convolutional neural network, was selected for its robust performance in image classification tasks. Transfer learning was applied using pre-trained weights from ImageNet to improve accuracy and reduce training time.

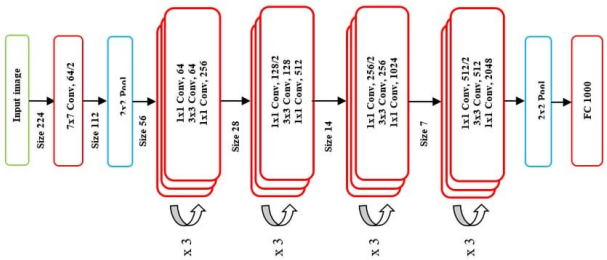

Fig. 2. ResNet-50 model Architecture.

2) Training Process: The training pipeline included the following steps:

1) **Loading the Dataset:** Images were loaded using PyTorch's `Dataset` and `DataLoader` classes.
2) **Applying Transformations:** Data augmentation was applied to enhance model generalization.
3) **Model Customization:** The final fully connected layer of ResNet-50 was replaced with a classifier tailored for five DR severity classes.
4) **Loss and Optimization:**
   - Loss Function: `CrossEntropyLoss()` was used for multi-class classification.
   - Optimizer: Adam optimizer with a learning rate of 0.0001.
   - Learning Rate Scheduler: `ReduceLROnPlateau` was used to reduce learning rate upon validation loss plateau.

3) Optimization Techniques: To maximize performance and training efficiency, the following strategies were applied:

- **Transfer Learning:** Used a pre-trained ResNet-50 model rather than training from scratch.
- **Data Augmentation:** Applied to reduce overfitting and increase model robustness.

- **Mixed Precision Training:** Employed `torch.cuda.amp` for faster GPU training.
- **Learning Rate Scheduling:** Automatically adjusted the learning rate based on validation performance.
- **Early Stopping:** Halted training when validation loss ceased to improve.

4) Training Performance: The model was trained for 10 epochs with a batch size of 32. Training loss and F1-score were tracked at each epoch to monitor model convergence and performance.

5) Best Model Saving: The model checkpoint with the lowest validation loss was saved as `best_model.pth`, and later used for final evaluation and deployment.

V. Evaluation Metrics

Once the model was trained, it was evaluated on the test dataset to measure its effectiveness in classifying diabetic retinopathy (DR) stages. The evaluation focused on key performance metrics such as accuracy, precision, recall, F1-score, and loss.

A. Metrics Used

To comprehensively assess the model's performance, the following metrics were computed:

- **Loss (CrossEntropyLoss):** Measures the dissimilarity between the predicted class probabilities and the actual class. For multi-class classification, the cross-entropy loss is given by:

$$L = -\sum_{i=1}^{N}\sum_{c=1}^{C} y_{ic}\log(p_{ic})$$

  where y_{ic} is the binary indicator (0 or 1) if class label c is the correct classification for observation i, and p_{ic} is the predicted probability.
- **Accuracy:** The ratio of correctly predicted instances to the total instances:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

- **Precision:** The ratio of correctly predicted positive observations to the total predicted positives:

$$\text{Precision} = \frac{TP}{TP + FP}$$

- **Recall:** The ratio of correctly predicted positive observations to all actual positives:

$$\text{Recall} = \frac{TP}{TP + FN}$$

- **F1-score:** The harmonic mean of precision and recall, useful in the case of class imbalance:

$$\text{F1-score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

B. Evaluation Process

The evaluation process was conducted as follows:

1) **Model Loading:** The best performing model from training, saved as `best_model.pth`, was loaded.
2) **Test Set Inference:** The test dataset, containing images not seen during training or validation, was fed into the model.
3) **Metric Computation:** Model predictions were compared with the ground-truth labels, and the aforementioned metrics were computed.

This evaluation helped determine how well the model generalized to unseen data and provided insights into areas for potential improvement.

VI. Results and Analysis

After training and evaluating the model on the test dataset, the following results were obtained:

- **Test Loss:** 0.5117
- **Overall Accuracy:** 80%
- **Macro Average F1-score:** 0.80
- **Weighted Average F1-score:** 0.80

A. Class-wise Performance

Table I presents the precision, recall, and F1-score for each diabetic retinopathy (DR) class.

TABLE I
Class-wise Evaluation Metrics

Class	Precision	Recall	F1-score
Class 0 (No DR)	0.66	0.65	0.66
Class 1 (Mild)	0.73	0.72	0.72
Class 2 (Moderate)	0.67	0.72	0.69
Class 3 (Severe)	0.97	0.91	0.94
Class 4 (Proliferative)	0.96	0.98	0.97

B. Analysis of Results

The results indicate that the model effectively distinguishes between various stages of diabetic retinopathy. Key observations include:

- **High Performance on Severe Cases:** The model achieved outstanding performance on Class 3 and Class 4, corresponding to severe and proliferative DR, with F1-scores of 0.94 and 0.97, respectively. This suggests a strong capability to detect advanced DR stages, which are medically critical.
- **Moderate Performance on Early Stages:** Performance for Classes 0, 1, and 2 (No DR to Moderate) was comparatively lower, likely due to the subtle visual cues and overlapping symptoms that make early-stage DR harder to classify accurately.
- **Balanced Classification:** The macro average F1-score of 0.80 reflects balanced performance across all classes, indicating that the model does not favor any particular class and treats minority and majority classes equitably.

C. Potential Improvements

To further enhance model performance, especially in early DR detection, the following strategies are recommended:

- **Advanced Data Augmentation:** Introducing more complex augmentation techniques (e.g., elastic deformation, contrast enhancement) may help the model generalize better to subtle patterns in early DR.
- **Class Rebalancing:** Addressing class imbalance through techniques such as SMOTE (Synthetic Minority Oversampling Technique) or weighted loss functions could help improve accuracy for underrepresented classes.
- **Ensemble Methods:** Combining predictions from multiple models (e.g., ResNet-50 with DenseNet or EfficientNet) through ensemble learning could lead to more robust and accurate classification.

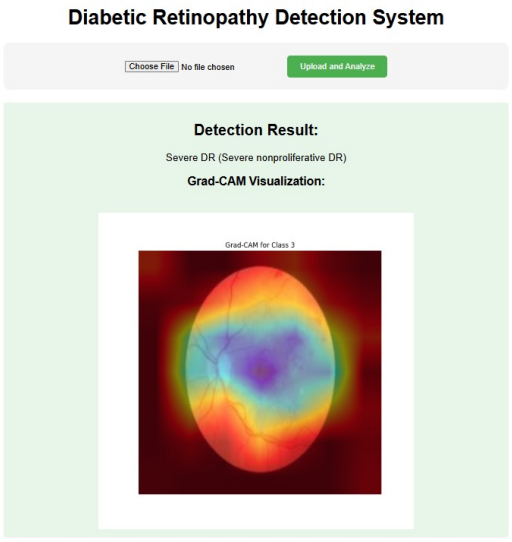

Fig. 3. Results of Created Model.

VII. Conclusion

In this study, a deep learning-based approach was developed to classify diabetic retinopathy (DR) into five severity levels using retinal fundus images. The methodology included comprehensive image preprocessing, data augmentation, and model fine-tuning using transfer learning with a pre-trained ResNet-50 architecture.

The model achieved an overall accuracy of 80% and a macro average F1-score of 0.80 on the test dataset. Notably, the model demonstrated high effectiveness in detecting advanced stages of DR, which is crucial for timely medical intervention. However, its performance on early-stage DR was relatively modest, highlighting the inherent difficulty in identifying subtle symptoms.

The results underscore the potential of deep learning in assisting ophthalmologists with automated and accurate DR screening. Future work may focus on enhancing early-stage detection through advanced augmentation, class balancing techniques, and ensemble learning.

Overall, the system provides a promising foundation for computer-aided diagnosis in diabetic retinopathy, contributing to improved healthcare delivery and early detection of vision-threatening conditions.

References

[1] V. Gulshan *et al.*, "Development and validation of a deep learning algorithm for detection of diabetic retinopathy in retinal fundus photographs," *JAMA*, vol. 316, no. 22, pp. 2402–2410, 2016.

[2] H. Pratt, F. Coenen, D. M. Broadbent, S. P. Harding, and Y. Zheng, "Convolutional neural networks for diabetic retinopathy," in *Proc. Int. Conf. Med. Image Understand. Anal. (MIUA)*, 2016, pp. 94–99.

[3] C. Lam, D. Yi, H. Guo, and G. Lindsey, "Automated detection of diabetic retinopathy using deep learning," *AMIA Summits on Translational Science Proceedings*, vol. 2018, p. 147, 2018.

[4] M. Voets, K. Møllersen, and L. Bongo, "Reproduction study: Development and validation of deep learning algorithm for detection of diabetic retinopathy in retinal fundus photographs," *PLOS ONE*, vol. 14, no. 6, e0217541, 2019.