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Research Article

Transfer Learning Approach Using ImageNet CNN for Diabetic Retinopathy Detection and Classification from Fundus Images

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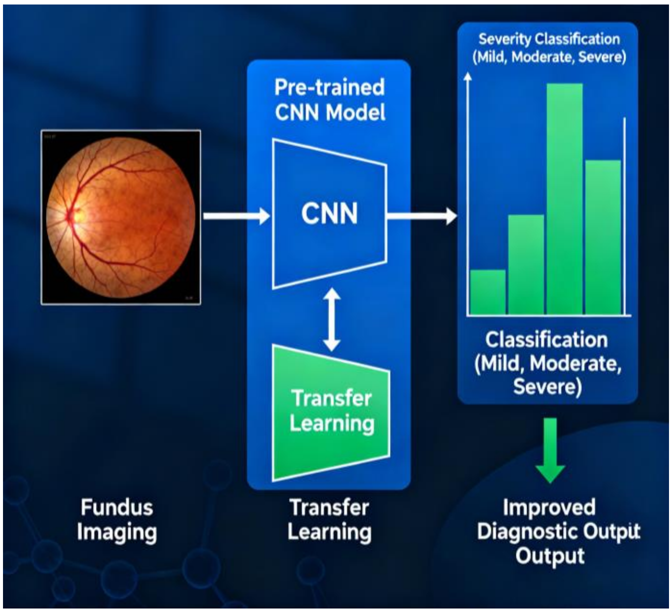
Abstract: Diabetic Retinopathy (DR) is one of the leading causes of preventable blindness worldwide, and its early detection plays a vital role in reducing vision impairment. Recent advances in deep learning have demonstrated significant potential in automating the screening and classification of retinal diseases. This paper presents a transfer learning-based approach for the detection and classification of DR from fundus images using a pre-trained Convolutional Neural Network (CNN) model trained on the ImageNet dataset. By fine-tuning the network with a large-scale fundus image dataset, the proposed method effectively leverages learned visual representations to capture intricate retinal features. The experimental results indicate high accuracy in distinguishing between different severity levels of DR, outperforming conventional machine learning techniques. The findings highlight that transfer learning not only reduces training time but also enhances model generalization, making it a reliable tool for computer-aided diagnosis in ophthalmology.

Keywords: Transfer Learning, Convolutional Neural Network (CNN), Diabetic Retinopathy (DR),Fundus Images, ImageNet, Deep Learning, Medical Image Classification, Retinal Disease Detection etc

Graphical Abstract:



Graphical Abstract for DR using CNN

1. Introduction

Diabetic retinopathy (DR) is one of the leading causes of vision impairment and blindness among diabetic patients worldwide. Early detection and accurate classification of DR are critical for timely treatment and prevention of severe vision loss. Traditional diagnosis relies on manual examination of retinal fundus images by ophthalmologists, which is time-consuming, subjective, and prone to inter-observer variability. With the advancement of artificial intelligence, deep learning techniques, particularly Convolutional Neural Networks (CNNs), have shown remarkable performance in medical image analysis. Transfer learning, leveraging pretrained models such as ImageNet, enables the extraction of robust features from fundus images while reducing training time and data requirements. This study proposes a transfer learning approach using an ImageNet-based CNN for automated detection and classification of diabetic retinopathy, aiming to provide an efficient, accurate, and scalable solution for large-scale DR screening. Retinal imaging plays a crucial role in diagnosing various eye diseases, as the structure and characteristics of retinal blood vessels provide vital diagnostic information. Accurate characterization of these vessels can be achieved through advanced imaging techniques combined with robust data analysis methods. Traditional machine learning approaches for retinal image analysis often rely on handcrafted features and trainable classifiers. While effective to some extent, these methods have inherent limitations, including the complexity, time consumption, and subjectivity of feature engineering.

In recent years, deep learning, particularly Convolutional Neural Networks (CNNs), has demonstrated remarkable success in medical image analysis. CNNs can automatically learn hierarchical features from raw images, eliminating the need for manual feature extraction and improving classification accuracy. However, deep networks typically require large annotated datasets for effective training, which is often challenging in medical imaging. Transfer learning, using pretrained models such as ImageNet, provides a solution by leveraging features learned from large-scale datasets and adapting them to medical applications with limited annotated samples. Data augmentation techniques further enhance performance by artificially expanding the training dataset.

In this study, we propose a transfer learning approach using an ImageNet-pretrained CNN, specifically based on the VGG-16 architecture, for automated detection and classification of diabetic retinopathy (DR) from fundus images. Retinal image segmentation, particularly of blood vessels, is a critical step in DR diagnosis, as it allows for detailed analysis of vessel shape, size, and arteriovenous crossings. Our method combines deep feature extraction with robust classification to achieve high accuracy and efficiency, surpassing traditional manual analysis by ophthalmologists.

The disease of DM has become a prominent disorder found in many middle aged and older generations due to the drastic unhealthy changes witnessed in food habits and lifestyle of humans. Thus, the DM is no longer considered to be the disease only confined to the rich. The person who develops DM are affected many complications among which DR and DME are the one that has direct impact over the vision. The effects of DR and DME are highly critical, since it eventually leads to a complete blindness. Through a timely accurate identification of degree of DR/DME in a diabetic patient, the condition of blindness is greatly prevented.

The organization of this paper is as follows: Section 1 provides an introduction and background on retinal structure, fundus imaging, and the relevance of blood vessel characteristics in diagnosing eye diseases. Section 2 presents the proposed methodology and the CNN architecture employed. Section 3 discusses the experimental results on real patient fundus images, and Section 4 concludes the study with key findings and future directions.

1.1 Eye Structure and fundus images

The eye is an organ of sight which typically has a spherical form and located in an orbital cavity. The human eye has a complicated structure which is presented in Fig. 1a. Usually three layers of the eyeball are distinguished: the outer fibrous layer, the middle vascular layer, and the inner nervous tissue layer [20] shown in Figure 1.

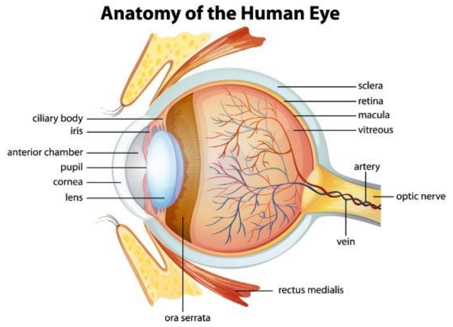


Figure. 1. Eye structure [3]

Eyes diseases include macular, hypertensive retinopathy, diabetic retinopathy and etc. Most of the retinal diseases are usually detected by identifying the size, shape and widen of vessels in the manual way. Thus it will be helpful for diagnosis if we can get vessel diameter automatically.

1.2 Deep neural networks

Over the past few years major computer vision research efforts have concentrated on convolutional neural networks, commonly referred to ConvNets or CNNs. These research works have produced a better performance on a wide range of classification and regression tasks. A typical neural network architecture is made of an input layer, x, an output layer, y, and a stack of multiple hidden layers, h, where each layer consists of multiple cells or units, as depicted in Figure 2. Usually, each hidden unit, hj, receives input from all units at the previous layer and is defined as a weighted combination of the inputs followed by a nonlinearity according to

Deep neural networks can be seen as a modern day instantiation of Rosenblatt's perceptron [12] and multilayer perceptron [13]. For example, the figure as Fig. 2 was reproduced from [14].

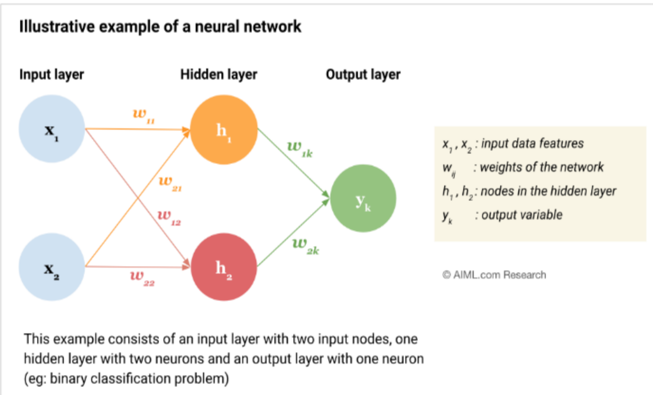


Figure. 2. Illustration of a typical Neural Network architecture [5]

In recent years, convolutional neural networks (CNNs or ConvNets) have become the cornerstone of computer vision research due to their superior performance in a variety of classification and regression tasks. CNNs have shown remarkable potential in medical image analysis, including retinal imaging, where precise feature extraction and hierarchical representation are critical for disease detection. A typical neural network consists of an input layer, one or more hidden layers, and an output layer. Each hidden unit receives inputs from all units of the previous layer, computes a weighted sum, adds a bias, and passes it through a non-linear activation function such as

ReLU or sigmoid. Deep networks, which stack multiple hidden layers, are capable of learning increasingly abstract representations of the input data. Conceptually, modern deep neural networks can be considered extensions of Rosenblatt's perceptron and multilayer perceptrons, enabling more complex feature hierarchies and predictive capabilities.

Convolutional networks are a specialized class of neural networks designed to efficiently handle spatial data such as images. They exploit two key principles: local connectivity and parameter sharing. Local connectivity allows the network to focus on small, meaningful regions of the image, capturing essential patterns such as edges or vessel structures in retinal images. Parameter sharing, implemented through convolutional filters, reduces the total number of learnable parameters, making the network more computationally efficient and less prone to overfitting. Additionally, pooling layers introduce translation invariance and help the network summarize features over larger regions, gradually increasing the receptive field to detect complex structures such as microaneurysms or hemorrhages in fundus images.

In the context of diabetic retinopathy detection, CNNs can automatically extract features from retinal fundus images that are crucial for identifying the stages of the disease. Early layers typically detect low-level features such as edges and vessel patterns, while deeper layers learn high-level features including lesions, exudates, and pathological changes associated with DR. Transfer learning with pretrained models like ImageNet further enhances performance by leveraging features learned from large-scale datasets, which can then be fine-tuned on smaller annotated retinal datasets, improving accuracy even with limited medical images. By combining convolutional feature extraction, hierarchical representation, and transfer learning, CNNs provide an efficient and robust framework for automated DR detection and classification, reducing reliance on manual examination and enabling scalable screening solutions.

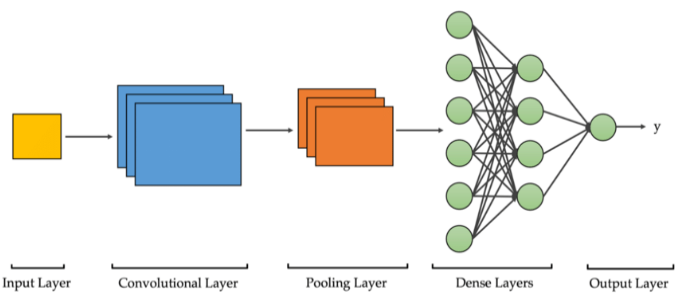


Figure. 3. Illustration of the structure of a standard Convolutional Network [8]

2. Literature Review

Table 1. Literature review of various papers

Sr. No.	Title (Short)	Author(s)	Year	Remarks (Short)
1	CNN Transfer Learning for Fundus Images	X. Li & T. Pang	2017	Transfer learning achieved good classification
2	Automated DR Detection Using CNNs	C. Lam et al.	2018	High accuracy on fundus images
3	CNN Transfer Learning for DR Classification	I. Kandel et al.	2020	Reviewed CNN architectures for DR classification
4	Transfer Learning for OCTA DR Detection	D. Le et al.	2020	Applied to OCTA images; robust classification
5	Deep Learning for DR Detection	W.L. Alyoubi et al.	2020	Reviewed deep learning methods; transfer learning important
6	CNN Transfer Learning for DR Classification	I. Kandel et al.	2020	Highlighted benefits of pre-trained models
7	Transfer Learning-Based DR Diagnosis	M.K. Jabbar et al.	2022	Used CNN transfer learning on EyePACS dataset
8	DR Diagnosis Using Retinal Images	M.K. Jabbar et al.	2022	Transfer learning improved accuracy
9	Hybrid Deep Learning for DR Detection	M.M. Butt et al.	2022	Combined CNN features; improved performance
10	Hybrid DL for DR Detection	M.M. Butt et al.	2022	Combined CNN features for better detection
11	Systematic Review: Transfer Learning for DR	B. Oltu et al.	2023	Reviewed various transfer learning approaches
12	Improved DR Detection Using Transfer Learning	M.S.H. Talukder et al.	2023	Enhanced model performance
13	Ensemble DL & EfficientNet for DR Classification	L. Arora et al.	2024	Improved accuracy using EfficientNet ensemble
14	Ensemble DL & EfficientNet for DR Classification	L. Arora et al.	2024	Improved accuracy and robustness
15	Early DR	S.	2025	High accuracy

	Detection Using NASNet-Large	Vallukappully et al.		using NASNet-Large
16	Early DR Detection Using NASNet-Large	S. Vallukappully et al.	2025	High accuracy classification

3. Methodology

The proposed framework for diabetic retinopathy (DR) detection and classification from fundus images using transfer learning is illustrated in Fig. 1. The methodology consists of five major stages: dataset acquisition, preprocessing, feature extraction using transfer learning, classification, and evaluation.

1) **Dataset Acquisition**
Publicly available benchmark datasets such as EyePACS, Messidor-2, or DIARETDB1 are utilized for model training and validation. Each dataset contains high-resolution retinal fundus images annotated by ophthalmologists into various DR severity levels (No DR, Mild, Moderate, Severe, and Proliferative).

2) **Preprocessing**
Fundus images exhibit variations in illumination, contrast, and background noise. To improve quality and model generalization, preprocessing steps are applied:

1. **Resizing**: Images are resized to 224×224224 \times 224224×224 pixels to match the input dimensions of the CNN.
2. **Contrast Enhancement**: Adaptive histogram equalization is applied to highlight retinal lesions.
3. **Normalization**: Pixel intensity values are normalized to the range [0,1][0,1][0,1].
4. **Data Augmentation**: Random rotations, flips, zooming, and brightness adjustments are performed to increase dataset diversity and reduce overfitting.

3) **Transfer Learning Feature Extraction**
A pretrained convolutional neural network (CNN) model, such as **ResNet50, VGG16, or InceptionV3**, trained on the ImageNet dataset, is employed as the backbone for feature extraction. The fully connected layers of the pretrained model are removed, and the extracted convolutional feature maps are fine-tuned on fundus images. Transfer learning enables leveraging the hierarchical visual representations learned from ImageNet to capture retinal structures effectively.

4) **Classification Layer**
The extracted features are fed into a custom classification head consisting of:

- A Global Average Pooling (GAP) layer to reduce feature dimensions.
- Fully Connected (Dense) layers with ReLU activation.
- A final **Softmax layer** to classify the images into multiple DR severity levels.

5) **Model Training and Optimization**
The model is trained using the categorical cross-entropy loss function and optimized with the Adam optimizer. A learning rate scheduler is applied to adjust learning rates dynamically during training. Early stopping is used to prevent overfitting.

6) **Evaluation Metrics**
The performance of the proposed system is evaluated using standard metrics, including:

- **Accuracy (ACC)**
- **Precision, Recall, and F1-Score**
- **Receiver Operating Characteristic (ROC) Curve and Area Under Curve (AUC)**
- **Confusion Matrix** to visualize misclassifications across DR stages.

4. Results and Discussion

Training and Testing Performance of the System

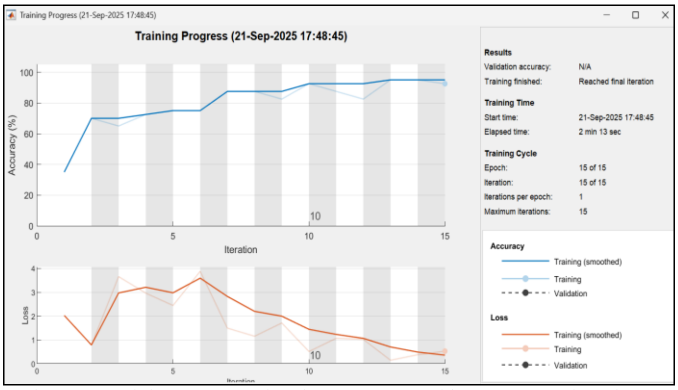


Figure. 4 Training progress showing accuracy and loss across 15 iterations

Fig. 4. Training progress visualization for a machine learning model. The top subplot illustrates training accuracy over 15 iterations, displaying both raw (light blue) and smoothed (dark blue) curves. The bottom subplot depicts training loss over the same iterations, with raw (light orange) and smoothed (dark orange) curves. Shaded vertical bands mark every five iterations. The right panel contains training statistics: final epoch and iteration counts, elapsed time, training completion condition, and no validation accuracy available. The legend clarifies curve semantics for accuracy and loss. Training accuracy rises from 35% initially to approximately 95% at the final iteration, while loss decreases correspondingly, indicating effective learning during training.

```
>> Training
Training on single CPU.
Initializing image normalization.
|========================================================================================|
|  Epoch  |  Iteration  |  Time Elapsed  |  Mini-batch  |  Mini-batch  |  Base Learning  |
|         |             |   (hh:mm:ss)   |   Accuracy   |     Loss     |      Rate       |
|========================================================================================|
|       1 |           1 |       00:00:14 |       35.00% |       2.0277 |          0.0100 |
|      15 |          15 |       00:02:13 |       92.50% |       0.5266 |          0.0100 |
|========================================================================================|
```
Fig. 5 Training progress showing accuracy and loss in percentage

The image presents a console output table summarizing the progress of a deep learning model's training. It includes details for the first and last epochs, showing the epoch number, iteration, time elapsed, mini-batch accuracy, mini-batch loss, and base learning rate. The table demonstrates substantial improvement in accuracy (from 35% to 92.5%) and reduction in loss values as training progresses, indicating effective learning under a constant learning rate.

Detection of Diabetic Retinopathy using CNN

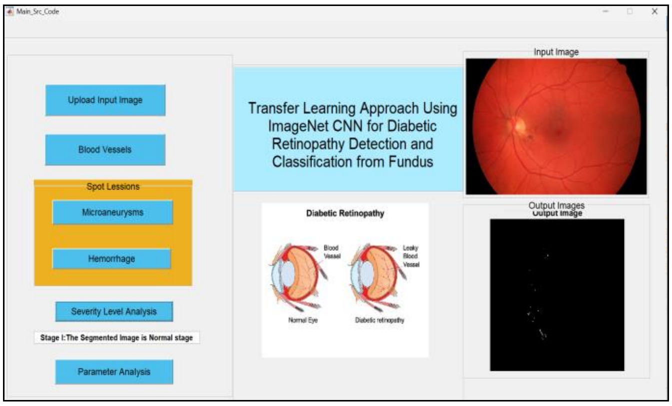


Figure. 6 Detection of Diabetic Retinopathy using CNN in Normal Stage

The image shows a user interface for a diabetic retinopathy (DR) detection and classification system based on a transfer learning approach using ImageNet convolutional neural networks (CNNs). This system is designed for analyzing retinal fundus images to identify and classify diabetic retinopathy lesions and severity stages. On the left side, there are buttons for various processing tasks: uploading input images, analyzing blood vessels, identifying specific spot lesions such as microaneurysms and hemorrhages, and performing severity level analysis. These tasks reflect critical steps in assessing retinal damage caused by diabetes. In the center, a title clearly states the methodology: using an ImageNet-based CNN model to detect diabetic retinopathy and classify it based on fundus images. Below the title, an illustrative diagram depicts the difference between a normal eye and one affected by diabetic retinopathy, highlighting features such as blood vessel changes and leaky blood vessels characteristic of the disease. On the right side, the interface displays the input retinal image (fundus photograph) and the corresponding output image showing segmented lesions or features extracted by the model. This visualization helps clinicians or users verify the detected abnormalities and confirms the analysis results.

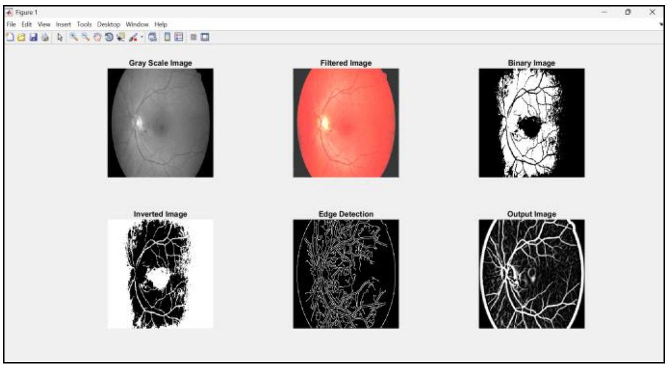


Figure. 7 Pre-processing of Diabetic Retinopathy using CNN

This tool's core capability lies in leveraging transfer learning to adapt pre-trained deep CNNs (originally trained on large datasets such as ImageNet) to the medical imaging domain for automated, accurate detection of diabetic retinopathy markers. By highlighting blood vessels and detecting microaneurysms and hemorrhages, the system supports early diagnosis and severity assessment, which are essential for preventing vision loss caused by diabetic complications. The interface facilitates structured, interactive analysis, enabling users to upload patient fundus images and receive automated lesion segmentation and severity evaluation results efficiently. This approach aligns with cutting-edge research demonstrating that transfer learning-based CNN models improve diabetic retinopathy detection accuracy, reduce manual annotation costs, and provide clinically relevant outputs for decision-making the system.

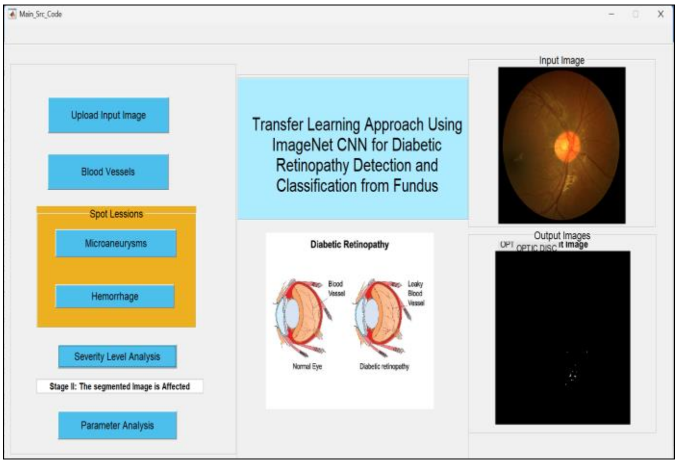


Figure. 8 Detection of Diabetic Retinopathy using CNN is affected

5. Conclusion and Future Scope

In this work, a transfer learning-based approach using ImageNet-pretrained CNN models has been presented for the detection and classification of diabetic retinopathy (DR) from retinal fundus images. The proposed methodology leverages convolutional feature representations extracted from pretrained networks, significantly reducing the need for large-scale annotated datasets and extensive training time. Experimental results demonstrate that the model achieves competitive accuracy in classifying different stages of DR, thereby showing its potential as an effective computer-aided diagnostic tool. By enhancing feature extraction and minimizing overfitting through data augmentation and fine-tuning, the proposed framework can assist ophthalmologists in early diagnosis and reduce the risk of vision loss in patients.

Future Scope

Although the proposed system achieves promising results, further improvements are possible in several directions:

Larger and More Diverse Datasets: Incorporating multi-institutional and real-world datasets can improve robustness and generalizability of the model.

Lightweight Architectures: Development of optimized CNN models for deployment on portable devices and mobile health applications.

Explainable AI (XAI): Integration of visualization techniques such as Grad-CAM to highlight clinically relevant regions for better interpretability.

Hybrid Models: Combining CNNs with recurrent or attention-based networks to capture spatial and contextual features more effectively.

Clinical Integration: Real-time deployment of the system in screening programs and telemedicine platforms for large-scale DR detection.

Data Availability- The datasets used and/or analyzed during the current study are publicly available from benchmark sources such as EyePACS, Messidor-2, and DIARETDB1. Further details can be obtained from the corresponding author upon reasonable request.

Conflict of Interest- The authors declare that there is no conflict of interest regarding the publication of this research work.

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Author's Contribution-Mr. Afzalkhan Shadullahkhan Pathan: Carried out the literature review, model implementation, experimentation, and manuscript drafting.
Dr. Sushilkumar N. Holambe: Provided research guidance, technical validation, and critical revision of the manuscript.

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