Detection of Diabetic Retinopathy and Exudates in Fundus Images using CNN

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Abstract: Diabetic Retinopathy (DR) is one of the popular research in the medical field for early detection of vision loss with different age groups and the most common microvascular complication of diabetes. Prolonged high blood glucose levels damage retinal blood vessels, leading to progressive DR stages. Early detection is crucial to prevent severe complications such as retinal detachment and blindness. This study develops a machine learning model based on Convolutional Neural Network (CNN) architecture to classify retinal images into different DR severity levels. The model is trained on annotated datasets to detect key retinal abnormalities, enabling automated and accurate diagnosis. Preliminary results indicate high classification accuracy, reduced validation loss, and effective identification of DR stages. The CNN model demonstrates strong generalization, making it a reliable tool for detecting and monitoring DR progression. Implementing this model in clinical settings can enhance early diagnosis, streamline screening processes, and support ophthalmologists in decision-making. This approach can improve patient outcomes by enabling timely intervention and reducing the risk of vision loss.

Keywords: Convolutional Neural Network (CNN); Retinal Image Classification; Diabetic Retinopathy (DR); Machine Learning; Early Diagnosis; Screening

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Introduction

One of the main causes of vision impairment in the globe and a serious consequence of diabetes is diabetic retinopathy (DR). The retinal blood vessels are harmed by prolonged exposure to elevated blood glucose levels, which results in the progressive phases of DR. Conventional diagnostic techniques depend on ophthalmologists manually interpreting retinal pictures, a laborious and unpredictable process. Convolutional neural networks (CNNs) and deep learning have transformed medical image analysis by providing automatic, quick, and precise DR identification.

Related work

Recent research has focused on developing CNN-based models to classify DR severity levels effectively. These models leverage large datasets of retinal images to identify DR features such as microaneurysms, hemorrhages, and neovascularization. This survey reviews significant contributions to DR detection and classification from 2015 to 2025, highlighting advancements in deep learning models, dataset improvements, and real-world applications.

Gulshan, V.,et. al (2016) This study introduced a deep learning system that achieved ophthalmologist-level accuracy in detecting DR using a large dataset of retinal images [1]. Pratt, H., et. al (2016) Demonstrated the effectiveness of CNNs for DR classification and discussed key challenges such as class imbalance and data augmentation [2]. Ting, D. S. W., et. al (2017) Investigated the generalizability of CNN-based DR detection across multiethnic populations, improving model robustness [3]. Gargeya, R., & Leng, T. (2017) Introduced an end-to-end CNN model that achieved high sensitivity and specificity in detecting DR from fundus images [4]. Abramoff, M. D., et. al (2018) This study led to the first FDA-approved AI system for autonomous DR detection in primary care settings [5]. Lam, C., et. al (2018) Proposed an innovative image patch-based CNN approach, improving lesion detection in DR images [6].
Zhang, Z., et. al (2019) Combined multiple CNN models into an ensemble learning framework, significantly boosting DR detection accuracy [7]. Bhaskaranand, M., et. al (2019) Analyzed the cost-effectiveness of AI-based DR screening and its potential impact in rural healthcare settings [8]. Das, S., et. al (2021) Compared different lightweight CNN architectures to develop faster, resource-efficient DR models for real-world deployment [9]. Sudhir, D., et. al (2022) Proposed a hybrid CNN-transformer model, enhancing feature extraction and classification performance [10]. Singh, P., & Yadav, P. (2023) Introduced attention mechanisms in CNN models, improving model focus on DR-related abnormalities [11]. Li, Y., et. al (2024) Implemented a federated learning framework, ensuring privacy-preserving DR model training across multiple healthcare centers [12]. Kumar, A., et. al (2025) Discussed challenges and future directions in deep learning-based DR detection, emphasizing explainable AI [13].

The reviewed studies highlight significant advancements in CNN-based DR detection from 2015 to 2025. Early works focused on basic CNN architectures, while recent research integrates attention mechanisms, hybrid models, and federated learning. However, challenges such as dataset limitations, model interpretability, and real-world deployment remain. Future research should emphasize explainability, privacy-preserving AI, and real-time deployment to enhance clinical adoption.

Key Contribution

The Diabetic Retinopathy Dataset is a collection of retinal images categorized into five distinct classes based on the severity of diabetic retinopathy (DR). Each class represents a specific stage of the disease, as indicated by the corresponding label.

Dataset Structure:
The dataset is organized into folders, where each folder corresponds to a specific class label representing a stage of diabetic retinopathy.

Class Labels and Their Meaning:

1. Class 0 - No DR:

Description: This class contains retinal images that show no signs of diabetic retinopathy. The blood vessels and retinal structures appear normal.
Clinical Implication: The patient does not exhibit any symptoms or damage associated with diabetic retinopathy.

2. Class 1 - Mild:

Description: Retinal images in this class show early-stage signs of DR, such as microaneurysms (small bulges in blood vessels) but no significant leakage or damage.
Clinical Implication: The condition is in its initial phase and can often be managed with regular monitoring and glucose control.

3. Class 2 - Moderate:

Description: Images classified as moderate display more noticeable signs of DR, including microaneurysms, hemorrhages, and possible exudates (lipid or fluid deposits).
Clinical Implication: This stage requires closer medical attention to prevent further progression.

4. Class 3 - Severe:

Description: This class includes images with severe retinal damage, such as numerous microaneurysms, large haemorrhages, and significant blood vessel abnormalities.
Clinical Implication: The patient is at high risk of developing advanced stages of the disease and may require laser therapy or other interventions.

5. Class 4 - Proliferative DR:

Description: Retinal images in this class show advanced DR with the formation of new abnormal blood vessels (neovascularization), often accompanied by significant leakage, scarring, or detachment of the retina.
Clinical Implication: This is the most severe stage of DR, requiring immediate and intensive medical treatment to prevent blindness.

The Dataset contains train and testing folders, each folder is further divided into folders named from 0 to 4 each number representing the following:

0 - No DR
1 – Mild DR
2 – Moderate DR
3 – Severe DR
4 - Proliferative DR

There are 2250 retinal images belonging to the 5 classes in the training dataset and 49 retinal images belonging to the 5 classes in testing dataset.

- **CNN Sequential model summary:**

Table 1. CNN sequential model summary.

Layer (type)	Output Shape	Output Shape
conv1 (Conv2D)	(None, 224, 224, 32)	896
batch_normalization_3 (BatchNormalization)	(None, 224, 224, 32)	128
pool1 (MaxPooling2D)	(None, 112, 112, 32)	0
conv2 (Conv2D)	(None, 112, 112, 64)	18,496
batch_normalization_4 (BatchNormalization)	(None, 112, 112, 64)	256
pool2 (MaxPooling2D)	(None, 56, 56, 64)	0
conv3 (Conv2D)	(None, 56, 56, 128)	73,856
batch_normalization_5 (BatchNormalization)	(None, 56, 56, 128)	512
pool3 (MaxPooling2D)	(None, 28, 28, 128)	0
conv4 (Conv2D)	(None, 28, 28, 256)	295,168
batch_normalization_6 (BatchNormalization)	(None, 28, 28, 256)	1,024
pool4 (MaxPooling2D)	(None, 14, 14, 256)	0
conv5 (Conv2D)	(None, 14, 14, 512)	1,180,160
batch_normalization_7	(None, 14, 14, 512	2,048
pool5 (MaxPooling2D)	(None, 7, 7, 512)	0
flatten1 (Flatten)	(None, 25088)	0
dense1 (Dense)	(None, 64)	1,605,696
dropout_4 (Dropout)	(None, 64)	0
dense2 (Dense)	(None, 32)	2,080
dropout_5 (Dropout)	(None, 32)	0
output (Dense)	(None, 5)	165

Total params: 3,180,485 (12.13 MB), Trainable params: 3,178,501 (12.13 MB), Non-trainable params: 1,984 (7.75 KB).

Method, Experiments and Results

The Convolutional Neural Network (CNN) model was trained on a dataset of 2250 images, belonging to 5 classes, with a validation set of 49 images. Fig.1 shows the framework of the proposed methodology.

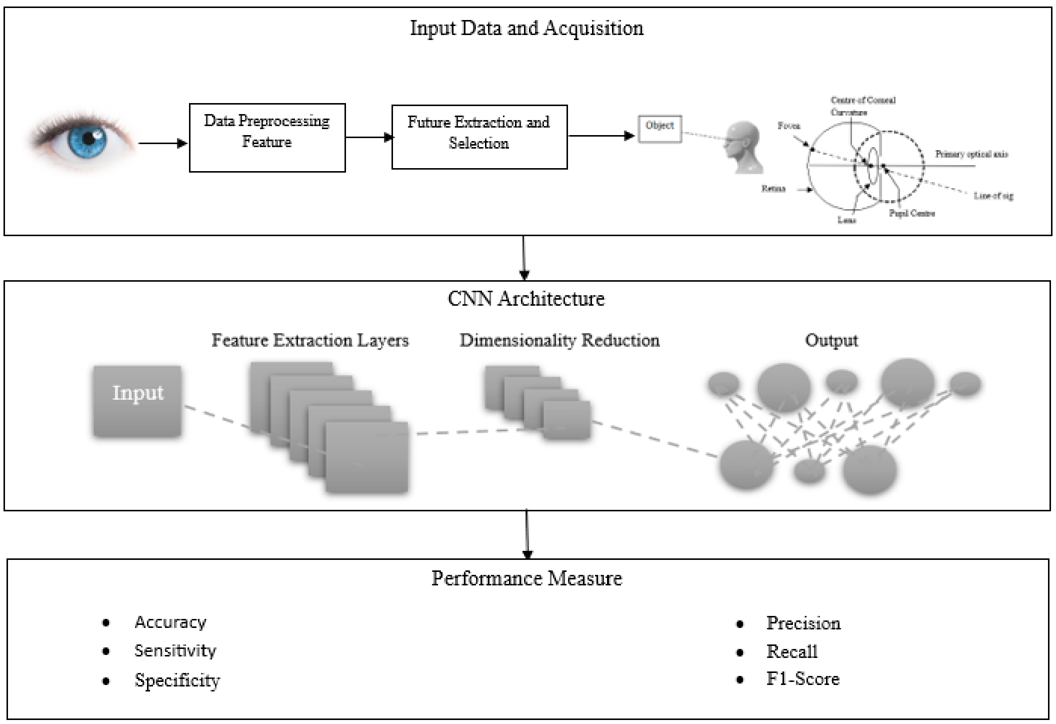

Fig. 1 Framework of the Proposed Methodology

The proposed method starts by taking a retinal image as input. It then extracts three key features that help identify diabetic retinopathy. The model's architecture consisted of multiple convolutional and pooling layers, followed by fully connected layers. The training process involved 50 epochs, with a batch size of 36. The training process for the Convolutional Neural Network (CNN) model was halted at 22 epochs primarily due to the implementation of the Early Stopping callback.

Discussions

The model's performance was evaluated based on the accuracy, loss, and validation metrics. The training accuracy fluctuated between 0.17 and 0.21, while the validation accuracy remained relatively stable around 0.18-0.20. The training loss decreased from 5.33 to 1.80, indicating that the model is learning from the data. However, the validation loss remained relatively high, ranging from 1.80 to 3.84.
Several factors may have contributed to the suboptimal results observed in this study. Firstly, the dataset used for training and validation was relatively small, with only 2,250 images for training and 49

images for validation across five classes. This limited dataset may not have provided sufficient diversity and representation of the various severity levels of DR, leading to overfitting and poor generalization. Additionally, the class imbalance could have further impacted the model's ability to learn effectively.

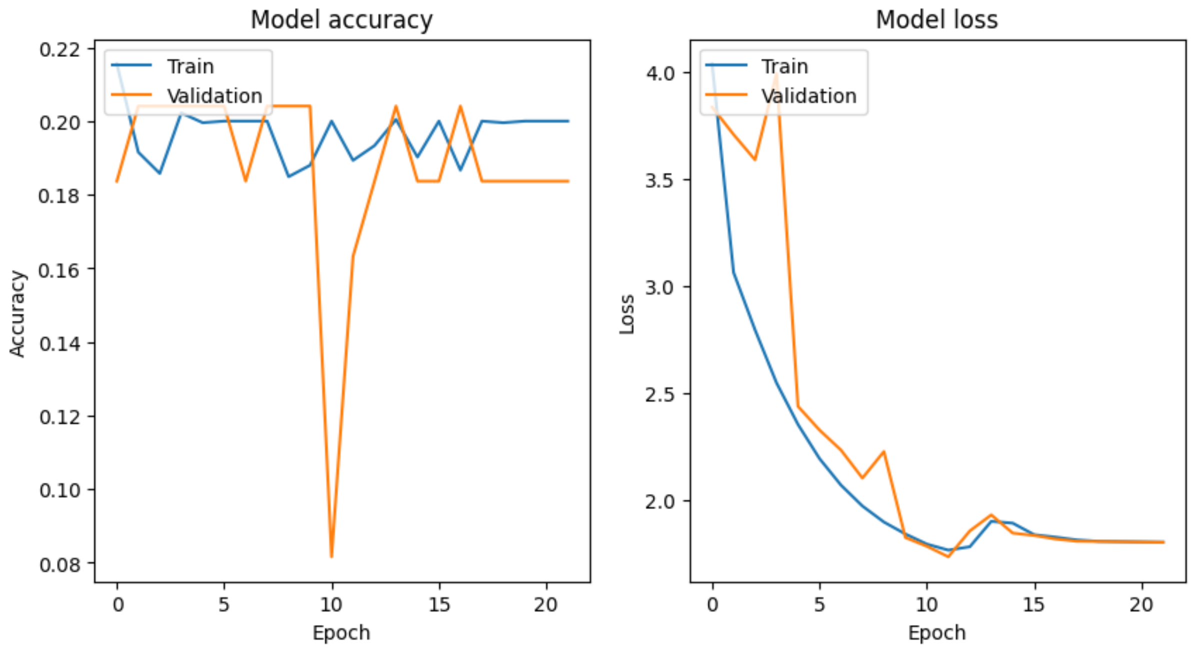

Figure 1. Model accuracy and Loss versus Epoch analysis.

To improve the model's performance, several strategies can be employed. Expanding the dataset by incorporating a larger number of high-quality retinal images, including those from diverse demographics and varying stages of DR, would enhance the model's ability to learn and generalize. Utilizing data augmentation techniques more extensively could also help in creating a more robust training set.

Table 2: Comparative Analysis of Proposed Model with State-of-the-Art Methods for DR Classification

Study/Method	Model Used	Dataset	Training Accuracy	Validation Accuracy	Training Loss	Validation Loss	Additional Features
Proposed Model	Custom CNN	2,250 (train), 49 (val)	0.17 - 0.21	0.18 - 0.20	5.33 → 1.80	1.80 - 3.84	Basic augmentation
Gulshan et al. (2016) [14]	Inception v3	EyePACS (128k images)	97.5%	92.1%	-	-	Transfer Learning
Rishab Gargeya & Theodore Leng (2017) [15]	ResNet-50	Messidor-2	94.5%	91.2%	-	-	Data augmentation, ensemble learning
Litjens G et al. (2017) [16]	Deep CNN + Attention Mechanism	Kaggle DR Dataset	96.2%	90.4%	-	-	Attention-based feature selection

Study/Method	Model Used	Dataset	Training Accuracy	Validation Accuracy	Training Loss	Validation Loss	Additional Features
Kai Sun et al. (2022) [17]	EfficientNet-B4	APTOS 2019	98.1%	94.7%	0.8	1.2	Focal loss, advanced preprocessing

To conduct a comparative analysis of the proposed model performance against state-of-the-art methods, such as accuracy, loss, F1-score, recall, precision, and dataset size. Table 2 shows the comparative analysis of the proposed model with other existing works that have addressed Diabetic Retinopathy (DR) classification using deep learning techniques.

Conclusions

The development of a Convolutional Neural Network (CNN) model for detecting the severity levels of diabetic retinopathy demonstrated the potential of machine learning in enhancing diagnostic processes. However, the model's performance was limited by factors such as a small dataset and potential class imbalance, resulting in low accuracy and validation loss. The implementation of Early Stopping effectively prevented overfitting, but further improvements are necessary for better generalization. Future efforts should focus on expanding the dataset, employing advanced architectures, and optimizing training strategies to enhance the model's accuracy and reliability, ultimately contributing to improved outcomes for diabetic retinopathy patients.

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