

DIABETIC RETINOPATHY DETECTION BY MEANS OF DEEP LEARNING

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Abstract

Diabetic Retinopathy (DR) is a leading cause of blindness among diabetic patients. DR occurs due to prolonged high blood sugar levels that damage the retinal blood vessels. Early detection of DR is vital for timely intervention and preventing vision loss. This paper proposes an automated DR detection and classification model using deep learning techniques, specifically the InceptionV3 architecture. A publicly available dataset containing over 35,000 retinal images is used for training and validation. The model achieves a test accuracy of 97.3% and is capable of identifying five stages of DR: No DR, Mild, Moderate, Severe, and Proliferative DR. A Flask-based web interface facilitates the user-friendly deployment of the model for clinical use.

Keywords: Diabetic Retinopathy, Deep Learning, InceptionV3, Fundus Images, CNN, Medical Image Classification

I. INTRODUCTION

The integration of Artificial Intelligence (AI) in medical diagnostics has revolutionized traditional healthcare practices. Among the subfields of AI, Machine Learning (ML) has emerged as a transformative technology in image classification and medical imaging. Diabetic Retinopathy (DR) [1], a

microvascular complication caused by diabetes, affects millions globally and can lead to permanent vision impairment if not detected in time.

Manual diagnosis involves expert ophthalmologists analyzing fundus images, a process that is time-consuming, prone to error, and not scalable. The development of automated systems that leverage deep learning and computer vision techniques has become imperative. These systems offer high accuracy and efficiency in detecting DR at various stages.



Fig. 1. Diabetic Retinopathy Stages

Deep Convolutional Neural Networks (CNNs) have demonstrated remarkable performance in computer vision tasks. InceptionV3, a CNN architecture developed by Google, has been successfully applied to medical imaging due to its depth, efficient computation, and ability to capture hierarchical features. This research aims to build a robust, scalable, and high-performing DR

detection model based on InceptionV3, integrated with a web interface for real-world usability.

II. LITERATURE REVIEW

Several studies have explored DR detection using traditional image processing and machine learning techniques. Carrera et al. (2017) used SVM classifiers with extracted retinal features like microaneurysms and exudates, achieving 94.6% sensitivity. Chetoui et al.

(2018) employed Local Ternary Patterns (LTP) and Local Energy-based Shape Histograms (LESH) [2] for texture feature extraction, obtaining a 90.4% accuracy on the MESSIDOR dataset.

With the advent of deep learning, CNN-based models have become prevalent. Martina et al. implemented a 10-layer deep CNN for vessel segmentation on the DRIVE dataset, achieving a 94% accuracy. InceptionV3, MobileNetV2, DenseNet, ResNet, and Xception models have all been used for DR classification, often with transfer learning.

Recent research has focused on ensemble models and attention mechanisms to enhance detection. Tang et al. proposed a lesion-guided network using RetinaNet with ResNet-50 backbone. Gunasekaran et al. utilized a deep RNN [3], while others explored hierarchical multi-task networks, graph CNNs, and hybrid models like E-DenseNet and AD2Net.

Studies consistently show that transfer learning, data augmentation, and model regularization improve performance and generalization. Metrics such as accuracy,

precision, recall, F1-score, and AUC are used to evaluate model robustness. The reviewed literature highlights a growing consensus on the viability of CNNs for automated DR diagnosis.

III. PROPOSED SYSTEM

The proposed system uses InceptionV3, a deep CNN architecture optimized for image classification. The system is trained on a balanced dataset of DR fundus images [4] to classify the disease into five stages. Key features of the model include:

- **Input Processing:** Images are resized to 224x224 pixels and normalized.
- **Model Layers:** Convolutional, pooling, batch normalization, ReLU activation, and fully connected layers.
- **Output:** Softmax layer with five output nodes corresponding to each DR stage.

Advantages:

- Reduced need for manual diagnosis.
- High accuracy (97.3%) on the test dataset.
- Scalable and adaptable to different datasets.
- Integrated web interface for user interaction.

IV. SYSTEM IMPLEMENTATION

A. Dataset

- **Source:** EyePACS (Kaggle)
- **Total Images:** 35,126
- **Classes:** No DR, Mild, Moderate, Severe, Proliferative DR
- **Preprocessing:** Grayscale conversion, histogram equalization, CLAHE, noise reduction

B. Model Development

- **Framework:** TensorFlow & Keras
- **Architecture:** InceptionV3 pre-trained on ImageNet
- **Optimizer:** RMSProp
- **Loss Function:** Categorical cross-entropy
- **Batch Size:** 10
- **Epochs:** 30
- **Validation Split:** 20%

C. Evaluation Metrics

- **Training Accuracy:** 97.3%
- **Validation Accuracy:** 95.6%
- **Test Accuracy:** 97.3%
- **Confusion Matrix:** Used to visualize true positives, false positives, and misclassifications

D. Web Interface

- **Frontend:** HTML, Bootstrap
- **Backend:** Flask (Python)
- **Functionality:**
 - Upload retina image
 - Predict DR stage
 - Display result with probability score

TABLE I
BIASED DATA

Class	Count
No DR	25810
Mild NPDR	2443
Moderate NPDR	5292
Severe NPDR	873
Proliferative	708

V. SYSTEM DESIGN

A. UML Diagrams

- **Use Case Diagram:** Describes user interaction for image upload and prediction

- **Class Diagram:** Shows system components including image preprocessing, model, and output layer
- **Sequence Diagram:** Workflow from image input to prediction output
- **Activity Diagram:** Step-by-step process from image preprocessing to classification

B. Data Flow Diagram

- Describes flow from input images through preprocessing, feature extraction, classification, and result display

Layer (type)	Output Shape	Param #
conv2d_1 (Conv2D)	(None, 253, 253, 32)	1568
conv2d_2 (Conv2D)	(None, 250, 250, 32)	16416
max_pooling2d_1 (MaxPooling2D)	(None, 31, 31, 32)	0
flatten_1 (Flatten)	(None, 30752)	0
dense_1 (Dense)	(None, 2048)	62982144
dropout_1 (Dropout)	(None, 2048)	0
dense_2 (Dense)	(None, 2048)	4196352
dropout_2 (Dropout)	(None, 2048)	0
dense_3 (Dense)	(None, 5)	10245
Total params: 67,206,725		
Trainable params: 67,206,725		
Non-trainable params: 0		

Fig. 2. Model Summary

VI. RESULTS & DISCUSSION

The model was evaluated using unseen test data and demonstrated a high degree of accuracy. It correctly predicted all five stages of DR in most cases [5]. The performance metrics indicate reliable classification and minimal overfitting.

TABLE II
CONFUSION MATRIX

	0	1	2	3	4
0	2375	125	24	48	9
1	226	270	93	142	2
2	248	304	773	185	77
3	2	21	51	151	37
4	3	17	29	62	101

TABLE III
PRECISION AND RECALL

Class	Precision	Recall
0	0.832	0.92
1	0.366	0.368
2	0.796	0.462
3	0.256	0.576
4	0.447	0.476

Graphical Outputs:

- Accuracy and Loss curves show model stability
- Confusion matrix reveals excellent differentiation between DR stages

Screenshots:

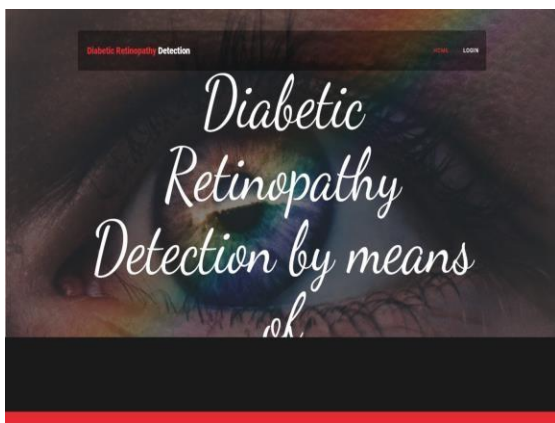


Image – I (Home Page)

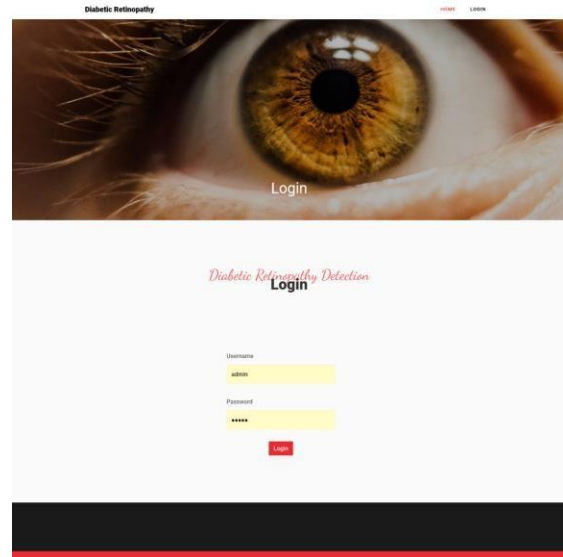


Image – II (Login Page)

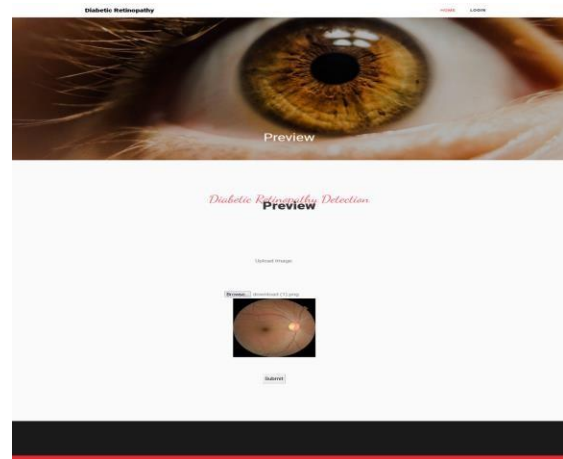


Image – III (Upload Eye Retina Image.)

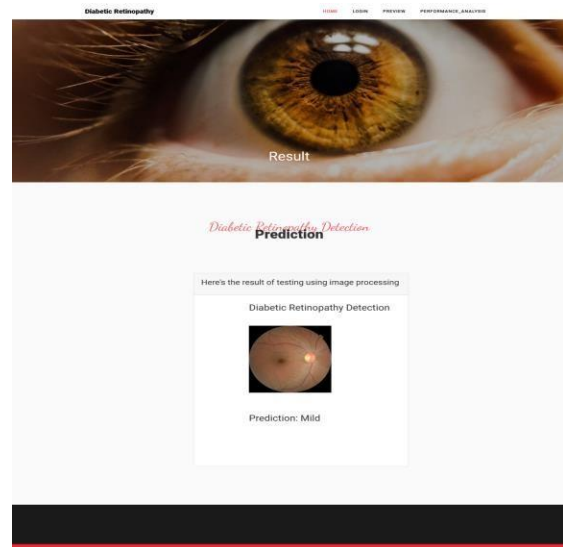


Image – IV (Upload Eye Retina Image.)

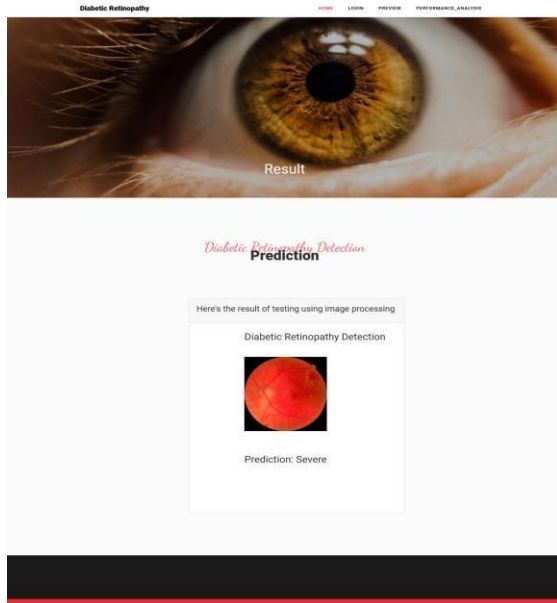


Image – V (Result Page Prediction Diabetic Type –Severe.)

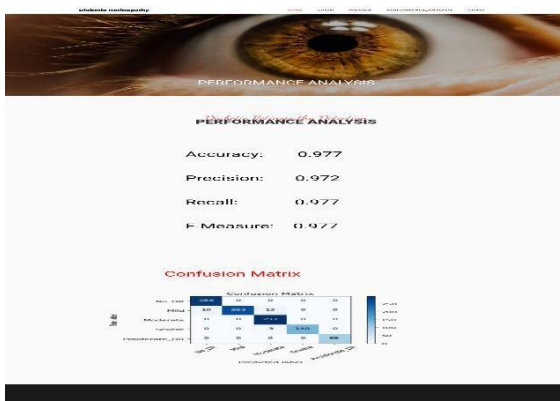


Image – VI (Performance Analysis and Confusion Matrix.)

VII. CONCLUSION & FUTURE SCOPE

Conclusion

This research demonstrates the feasibility of deep learning models, specifically InceptionV3, for automated DR detection and classification. The proposed system achieves over 97% accuracy and classifies five stages of DR, reducing dependency on manual diagnosis [6]. The integrated web interface enhances usability and practical deployment.

Future Scope

- Multilingual voice alerts for accessibility
- Integration with hospital EHR systems.
- Expansion to include other retinal diseases
- Mobile-based version for rural deployment
- Use of ensemble models for further accuracy improvements
- Incorporation of patient medical history for personalized predictions

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