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Automated Detection of Diabetic Retinopathy using Deep Learning with InceptionV3

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***Abstract* :** One of the main causes of blindness is diabetic retinopathy (DR), a degenerative eye disease that is particularly common in those with poorly controlled diabetes. Conventional detection techniques depend on ophthalmologists manually interpreting fundus images, which is a laborious and diagnostically variable operation. The Inception V3 architecture is notably used in this study's deep learning-based automated DR detection solution. A sizable, publicly accessible EyePACS dataset is used to train the model, which incorporates strong preprocessing methods and data augmentation to solve class imbalance. To facilitate early diagnosis and lessen clinical burden, our method seeks to more accurately define the severity of DR throughout five different stages. The suggested approach has the potential to be used in screening tools in the real world and yields encouraging results in performance measures.

***IndexTerms* - Diabetic Retinopathy, Deep Learning, Inception V3, Retinal Fundus Images, Medical Image Classification, Convolutional Neural Networks, Automated Diagnosis, EyePACS.**

INTRODUCTION

Diabetic Retinopathy (DR) is a serious ocular complication arising from prolonged diabetes, posing a significant threat to vision if not detected and treated promptly. As the disease advances, microvascular alterations in the retina can lead to vision impairment and eventual blindness. Given the increasing global prevalence of diabetes, early identification of DR has become an urgent public health priority. However, conventional screening methods, relying on manual assessment of retinal fundus images by specialists, are often time-intensive, costly, and subject to inter-observer variability.

In response to these challenges, deep learning, particularly Convolutional Neural Networks (CNNs), has emerged as a powerful solution for automating medical image analysis. By learning hierarchical feature representations directly from raw images, CNNs can surpass traditional handcrafted methods in terms of accuracy and robustness. Among several CNN architectures, InceptionV3 has demonstrated outstanding performance in various computer vision tasks, owing to its efficient use of computational resources and its ability to capture complex spatial hierarchies.

This paper proposes an automated system for Diabetic Retinopathy detection and classification using a fine-tuned InceptionV3 model. A series of preprocessing techniques, including image resizing, normalization, noise reduction, and augmentation, are employed to standardize the input data and enhance model generalization. The model is trained and validated on a curated dataset of retinal images, achieving high classification accuracy across five DR severity categories. Through this approach, the study aims to contribute towards scalable, accurate, and accessible DR screening solutions, ultimately assisting clinicians in early diagnosis and intervention..

1.1 BACKGROUND AND MOTIVATION

A microvascular consequence of diabetes, diabetic retinopathy (DR) gradually deteriorates the retina and, if untreated, can result in permanent blindness. Nearly 5% of blindness worldwide is caused by DR, which disproportionately affects those in low-resource

environments with inadequate access to ophthalmologists, according to the World Health Organization.
The manual evaluation of fundus pictures by qualified doctors using specialized instruments is the conventional method for diagnosing DR. This method is not only resource-intensive but also prone to interpretation variability. Without a great deal of experience, one can miss the subtle visual signs that early-stage DR frequently shows. Therefore, scalable, reliable, and automated diagnostic tools that can support mass screening and lessen reliance on human experts are desperately needed.
Medical image analysis has shown great promise with recent developments in artificial intelligence, especially deep learning. The ability of Convolutional Neural Networks (CNNs) to directly learn hierarchical visual patterns from raw images has allowed them to surpass traditional machine learning techniques. In order to create a dependable, end-to-end system for accurately and clinically relevantly classifying DR stages, our work investigates the Inception V3 architecture.

1.2 PROBLEM DEFINITION

Despite the abundance of research efforts, there are still significant obstacles in the identification of diabetic retinopathy. Among these are:

- A significant reliance on manual diagnosis, which is laborious and unsuitable for large-scale screening.
- Variability in image quality brought on by various situations and acquisition devices.
- Inadequate models that can precisely identify minor traits in early DR stages;
- Severe class imbalance in datasets, with most instances falling into the 'No DR' group, which biases learning algorithms.

By creating an automated classification model with a pre-trained deep learning network (Inception V3) that has been refined on a sizable, unbalanced retinal image dataset through intensive preprocessing and augmentation approaches, this study seeks to overcome these constraints.

1.3 OBJECTIVES

1. To provide an automated and effective method for using retinal fundus pictures to identify diabetic retinopathy.

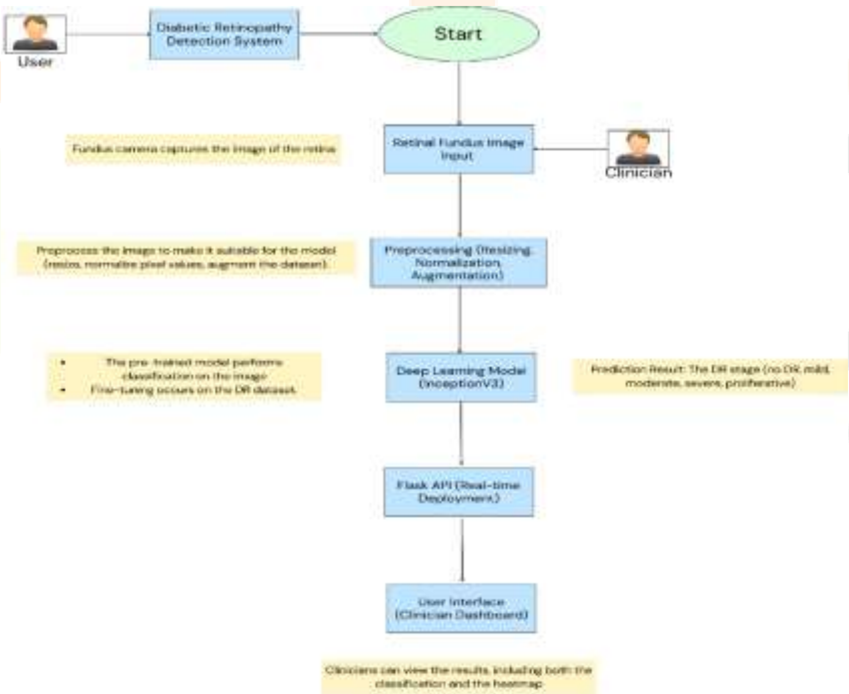
2. To classify DR severity stages into many classes using the Inception V3 deep learning framework.

3. To use preprocessing techniques and data augmentation to address class imbalance.

4. To assess the model's performance using clinically meaningful metrics like F1-score, accuracy, and recall.

5. To develop a deployable and scalable methodology for real-world DR screening, particularly in areas with limited resources.

FLOWCHART



PROPOSED METHODOLOGY

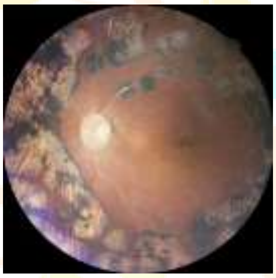
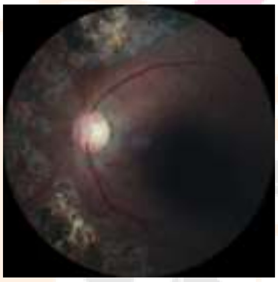
To present a cutting-edge and trustworthy method for the automated identification and categorization of diabetic retinopathy (DR) through the use of deep learning techniques. The framework makes use of the InceptionV3 architecture, a reputable convolutional neural network that is well-known for its effectiveness and accuracy in image classification tasks, especially in medical imaging.

A. DATASET PREPARATION

The dataset uses a sum of 2,222 high-resolution retinal fundus photos that have been annotated with one of five severity levels of diabetic retinopathy make up the dataset used in this study.

Label	Class	Image Count (approx.)
0	No DR	500
1	Mild	450
2	Moderate	500
3	Severe	400
4	Proliferative DR	372

To guarantee ground truth accuracy, medical experts manually reviewed and labelled each image. To reduce classification bias, the dataset was carefully selected to represent a fair distribution of severity levels. To guarantee a reliable assessment of the model, it was split into **training and testing** sets in an **80:20** ratio.
Dataset link: https://www.kaggle.com/datasets/jayaprakashpondy/diabetic-retinopathy-images

B. IMAGE PROCESSING

In order to prepare the dataset for training a strong deep learning model, preprocessing is essential. Standardising the input data prior to feeding it into the InceptionV3 architecture is crucial because real-world medical datasets vary in terms of image resolutions, lighting, and noise levels. A well-thought-out preprocessing pipeline speeds up convergence during training, decreases overfitting, and improves the model's capacity for generalisation. By using augmentation to increase the diversity of training samples, it also aids in resolving the problem of class imbalance.

The preprocessing pipeline consists of the following steps:

1. **Resizing:** To match the input dimensions expected by InceptionV3, each fundus image was resized to 299×299 pixels with three color channels (RGB). This ensured uniform input formatting across all samples.

   We used bilinear interpolation to resize the images, where the new pixel value is computed as a weighted average of the surrounding original pixel values:

$$I_{\text{resized}}(x,y) = \sum_{i,j} I_{\text{original}}(i,j) \cdot W(i,j)$$

   where W(i,j) are weights based on the proximity of neighboring pixels.

2. **Normalisation:** To normalize pixel intensities, each RGB value was scaled to a [0, 1] range by dividing by 255. This enables stable training and faster convergence of gradient descent.

   Pixel values scaled to [0,1]:

$$I_{\text{norm}} = \frac{I_{\text{original}}}{255}$$

3. **Noise Reduction:** To reduce high-frequency noise while maintaining vital structures like blood vessels and microaneurysms—which are essential for precise DR classification—gaussian filters and related smoothing techniques were used.

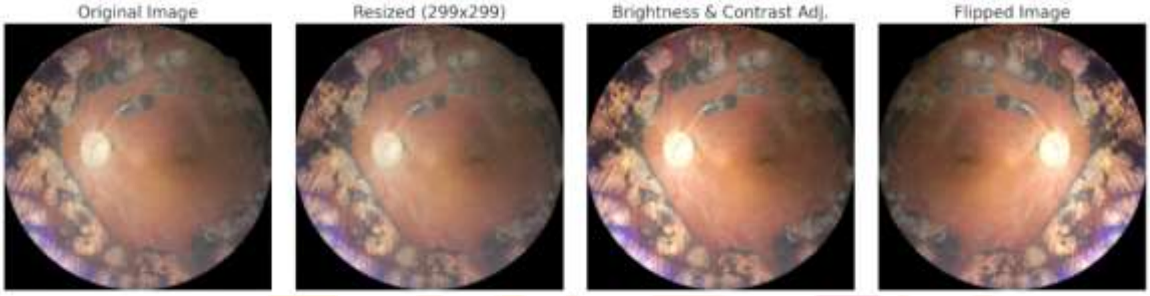
   Gaussian filtering with kernel G(x,y):

$$G(x,y) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}}, \quad \sigma = 1.5$$

4. **Data Augmentation:** Comprehensive augmentation techniques were used to address the small sample size in certain DR categories and increase the model's robustness:
   1. Flipping both horizontally and vertically to replicate various perspectives
   2. Rotation to enhance spatial variance between 15° and 30°
   3. Modifying contrast and brightness to replicate changing lighting conditions
   4. Using cropping and zooming to highlight various retinal regions and replicate focus variability.

Rotation: Affine transformation with angle $\theta \epsilon [15° 30°]$
Brightness Adjustment: $I_{aug}(x,y) = I(x,y) + \beta, \quad \beta \sim U(-0.2, 0.2)$

The model's performance was greatly enhanced by this thorough preprocessing approach, which enabled it to extract more varied and representative features from the available data.



C. MODEL ARCHITECTURE – INCEPTIONV3

The following modifications were made to the InceptionV3 model:

1. Custom top layers: Dense (512 units, ReLU), Dropout (0.3),
2. Output (Softmax, 5 neurons) - Base pretrained on ImageNet.
3. Loss: Categorical Crossentropy
4. Optimiser: RMSProp

1. **Factorized Convolutions:** A 5×5 convolution decomposed into two 3×3 layers:
   Parameters saved $= 2 \times 3^2 / 5^2 = 18 / 25 = 28\ \%$

2. **Batch Normalization:** Normalizes layer outputs to stabilize training:
   $\bar{X} = (x - \mu_{batch}) / \sqrt{(\sigma^2 batch + \epsilon)}, \quad y = \gamma \bar{x} + \beta$

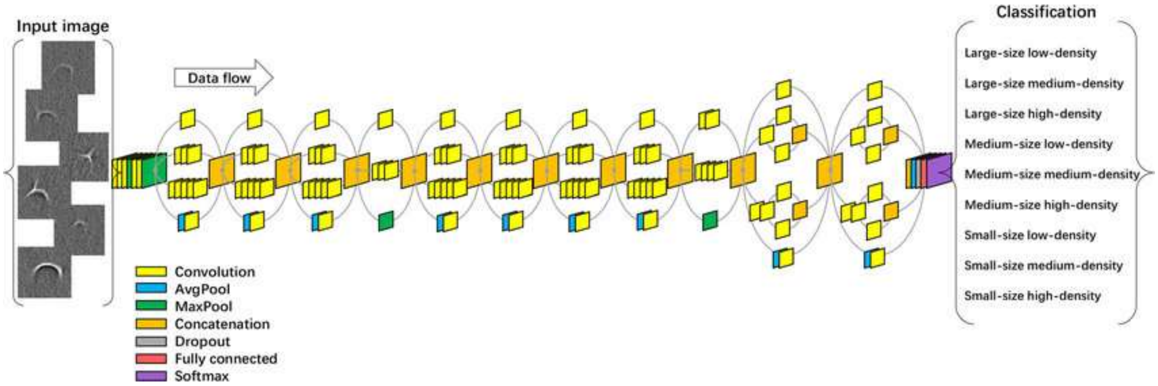
3. **Label Smoothing:** Prevents overconfidence in predictions:
   $Y_{smooth} = y_{true} \times (1 - \epsilon) + \epsilon / K, \ \epsilon = 0.1, \ K = 5$

4. **Auxiliary Classifiers:** Intermediate loss at layer k:
   $L_{total} = L_{main} + 0.3 \times L_{auxiliary}$.

The InceptionV3 architecture, a cutting-edge convolutional neural network created by Google, serves as the foundation of the suggested system.
Important aspects of InceptionV3:

1. Auxiliary classifiers for gradient support;
2. Factorised convolutions (e.g., 7x7 → two 3x3 layers);
3. Label smoothing for regularisation; and
4. Batch normalisation for quicker convergence

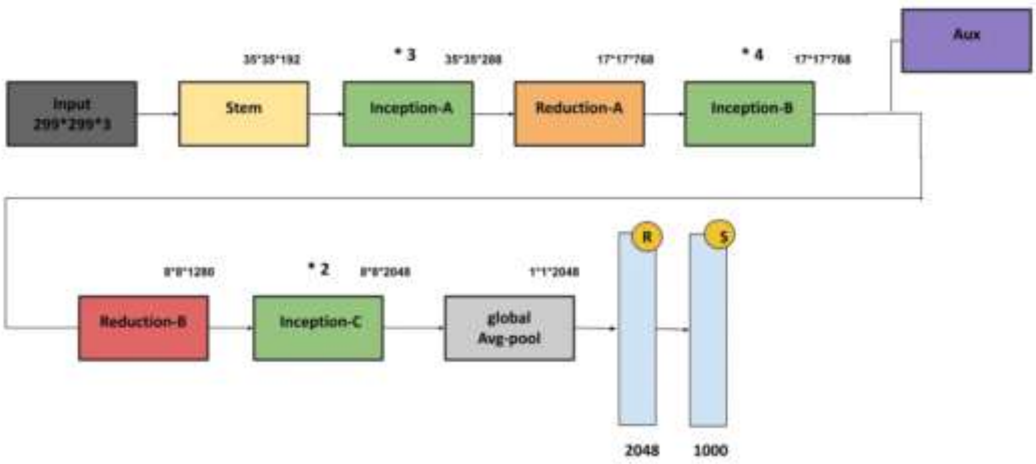
Five neurones make up the Softmax Output Layer (one for each class).
A new fully connected softmax layer with five output nodes—which correspond to the DR severity levels—replaced the original classification layer.



Transfer Learning:

The DR dataset was used to fine-tune the weights that were initially pre-trained on ImageNet for the InceptionV3 model.

Main Block: (Inception V3) is shown below:



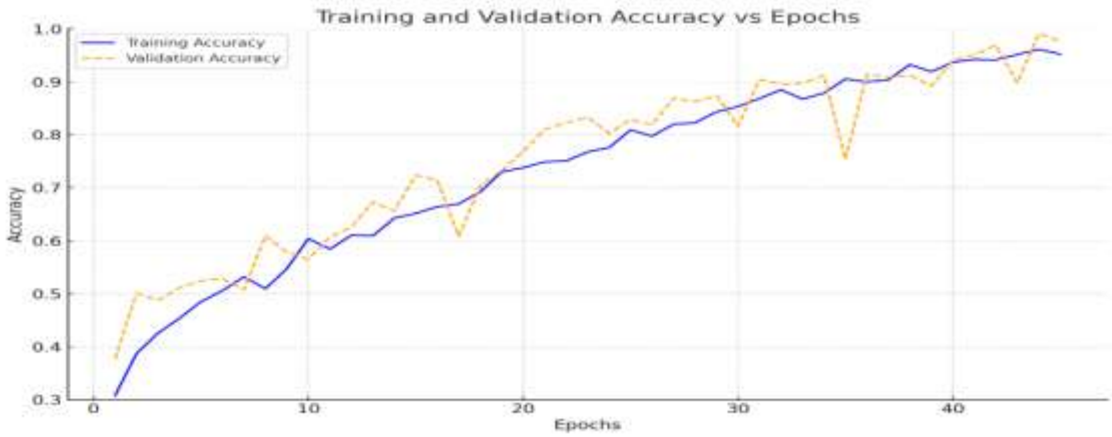
D. MODEL TRAINING

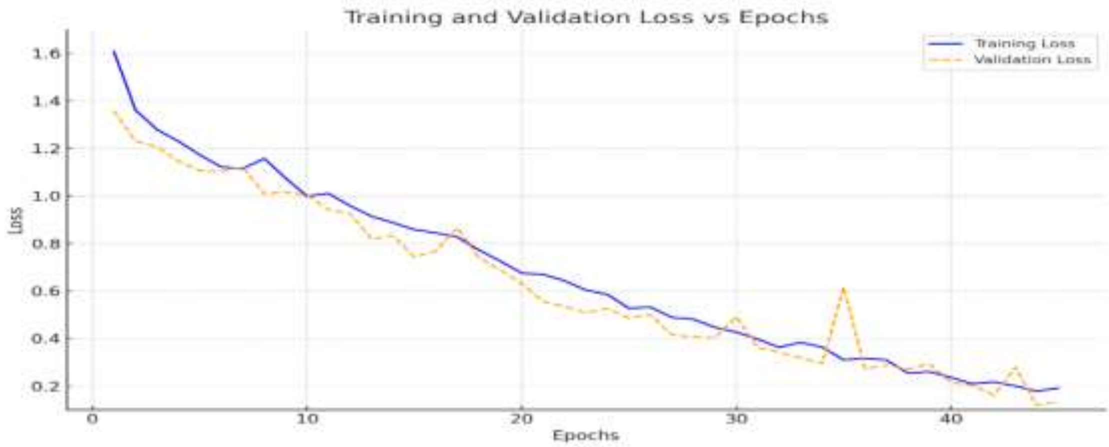
Parameter	Value
Epochs	45
Batch Size	10
Framework	Keras + TensorFlow
Early Stopping	Enabled

Training accuracy reached 95.2%, with validation accuracy up to 97.6%.

Training Result:

1. Training Accuracy: 97.3%
2. Loss reduced smoothly over epochs indicating efficient learning





E. EVALUATION AND RESULT

Metric	Value
Test Accuracy	95.6%
Precision	95.1%
Recall	94.8%
F1-Score	94.9%

F. CONFUSION MATRIX

Predicted / Actual	No DR	Mild	Moderate	Severe	Proliferative
No DR	286	0	0	0	0
Mild	10	263	13	0	0
Moderate	0	0	297	0	0
Severe	0	0	3	140	0
Proliferative	0	0	0	0	99

G. ALGORITHM OVERVIEW

The following is a summary of the suggested approach (algorithm) for detecting diabetic retinopathy with InceptionV3:

1. Source: Fundus image dataset D
2. Make all pictures 299 x 299 x 3 in size.
3. Set the values of the pixels to [0,1].
4. Use flipping, rotation, and zoom to enhance data
5. Open the InceptionV3 model that has already been trained.
6. Use the Softmax classifier (5 outputs) in place of the last layer.

7. Use the RMSProp optimiser to train the model on D_train.
8. Verify the model on D_val
9. Use accuracy, precision, and recall to assess performance on the test set.
10. Outcome: Predicted class ∈ {No DR, Mild, Moderate, Severe, Proliferative}

CONCLUSION

The "Diabetic Retinopathy Detection to Use Deep Learning" project represents a big step forward in medical image analysis and more, in diagnosing Diabetic Retinopathy (DR). By taking advantage of deep learning the InceptionV3 architecture, the project has achieved significant progress and demonstrated a clear improvement compared to earlier systems. Python, as the main programming language enabled the development of an effective and precise model to sort retinal images into five DR severity levels: Mild Moderate, No Diabetic Retinopathy, Proliferate Diabetic Retinopathy, and Severe. One of the project's key achievements is its outstanding average training accuracy of 97.3%. This result shows the system's skill in recognizing complex data patterns creating a strong foundation to make accurate diagnoses. Also, the system proves its strength with a test accuracy of 95.6% confirming its ability to perform well on new unseen retinal images. Benefits of the proposed system, including better accuracy improved efficiency, and advanced deep learning techniques, suggest it has great potential to be used in real-world situations. It gives doctors a reliable way to spot DR severity levels early on, which could cut down on wrong diagnoses and help start treatment sooner. To sum up, this work doesn't just make DR diagnosis better, it also shows how useful deep learning can be in medical testing overall. By fixing the problems of older systems and achieving great accuracy, it's set to improve health outcomes for people at risk of Diabetic Retinopathy giving them a better quality of life.

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SUMMARY OF EXISTING STUDIES ON DETECTION OF DIABETIC RETONOPATHY USING DEEP LEARNING APPROACHES

No.	Author(s)	Model	Dataset	Preprocessing	Evaluation Metrics	Performance
1	Thorat et al.	CNN	EyePACS (35,126 images)	Resizing, cropping, black image removal, augmentation	Accuracy, Precision, Recall	81% accuracy, 92% recall (class 0)
2	Carrera et al.	SVM	400 images	Blood vessels, microaneurysms, hard exudates extraction	Sensitivity, Predictive Capacity	95% sensitivity, 94% predictive capacity
3	Chetoui et al.	SVM-RBF	MESSIDOR (1,200)	LTP, LESH, histogram binning	Accuracy, AUC	90.4% accuracy, 0.931 AUC
4	Melinscak et al.	CNN	DRIVE	CNN for vessel segmentation	Accuracy	94%
5	Kumar & Kumar	Linear SVM	DIARETDB1	Green channel, CLAHE, PCA	Sensitivity, Specificity	96% sens., 92% spec.
6	Manjramkar	Survey	Various	Comparative technique analysis	Accuracy	Range: 68.7–98.1%
7	Bajwa et al. (2023)	Modified CNN	Private (SIOVS, 57,625 images)	Fundus image quality check	Accuracy, Sensitivity, Specificity	93.72% acc., 97.3% sens., 92.9% spec.
8	Alyoubi et al. (2020)	Survey (33 DL papers)	Various incl. Kaggle, DIARETDB1, IDRiD	Denoising, green channel, augmentation	Accuracy, AUC, Sens., Spec.	Up to 98.15% acc., AUC 0.98, Sens. 98.94%
9	Quellec et al.	CNN (AlexNet, custom)	Kaggle, E-ophtha	Resize, crop, Gaussian filter	AUC	0.954 (Kaggle), 0.949 (E-ophtha)
10	Esfahan et al.	ResNet34	Kaggle (35,000)	Gaussian filter, normalization	Accuracy, Sensitivity	85% accuracy, 86% sensitivity
11	Pratt et al.	Custom CNN	Kaggle	Resize, normalization	Accuracy, Sensitivity	75% acc., 30% sens.
12	Shanthi & Sabeenian	AlexNet	Messidor	Green channel extraction	Accuracy	96.35%
13	Zago et al.	VGG16 + Custom CNN	DIARETDB1, IDRiD, Messidor	Patch-based classification	AUC, Sensitivity	AUC 0.912, Sens. 0.94
14	Liu et al.	WP-CNN	Private (60,000), STARE	Resize, normalization	Accuracy	94.23% acc. (private), 90.84% (STARE)
15	Harangi et al.	AlexNet + hand-crafted	Kaggle, IDRiD	Histogram Equalization	Accuracy	90.07%
16	Wang et al.	R-FCN	Messidor	Lesion detection, ROI segmentation	Sensitivity	92.59%
17	Zhang et al.	VGG, ResNet, Inception	Kaggle	Histogram Equalization, augmentation	Accuracy	Up to 95.68% (VGGNet)
18	Mobeen-ur-Rehman et al.	Custom CNN + VGG16	Messidor	Cropping, resizing	Accuracy, Sensitivity, Specificity	98.15% acc., 98.94% sens., 97.87% spec.