IJIRMET ISSN (Online): 2456-0448
International Journal Of Innovative Research In Management, Engineering And Technology
Vol. 11, Issue 3, March 2026

Diabetic Retinopathy Detection Using Deep Learning

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Abstract: ***Diabetic retinopathy (DR) is a leading cause of visual impairment and preventable blindness worldwide. Early detection through retinal fundus imaging is critical for timely intervention. Deep learning (DL) methods, especially convolutional neural networks (CNNs), have shown outstanding potential for automating DR screening. Diabetic retinopathy is a retinal vascular complication of diabetes, causing damage to small blood vessels, microaneurysms, hemorrhages, exudates, and, in advanced stages, neovascularization. Globally, over 30% of people with diabetes show signs of DR, with one-third of those requiring urgent care to prevent vision loss. The condition evolves from early non-proliferative stages (mild to severe) to proliferative DR (PDR), which can lead to blindness if untreated. Early detection and timely treatment can reduce vision loss by over 90%. Unlike traditional CAD (computer-aided diagnosis) systems relying on feature engineering (e.g., manual lesion segmentation or vessel analysis), CNNs learn hierarchical features directly from data with minimal preprocessing. Deep learning models leveraging DenseNet, rigorous preprocessing, and auxiliary modules (attention, lesion segmentation, auxiliary heads) are highly effective for DR detection from fundus images. These systems deliver near-human performance in grading severity, offer interpretable output through visual attention/segmentation maps, and hold promise for scalable, low-cost DR screening—especially in telemedicine and underserved settings.***

Key Words: Diabetic retinopathy, Deep learning, computer-aided diagnosis, proliferative DR

I. INTRODUCTION

Diabetic retinopathy (DR) is a progressively debilitating microvascular complication of diabetes mellitus, resulting from prolonged hyperglycemia that compromises the retinal blood vessels. Typically developing silently during the early non-proliferative phase marked by microaneurysms, intraretinal hemorrhages, and cotton-wool spots DR eventually advances to proliferative retinopathy, where ischemia-driven neovascularization causes fragile vessel growth, hemorrhages, and tractional retinal detachment. A significant subset of patients also develop diabetic macular edema (DME), in which leakage into the macula leads to central vision distortion, often representing the primary reason for vision impairment in DR cases. According to WHO, Diabetic Retinopathy is an intense eye disease that requires urgent contemplation at an international level. According to a report, in India there are about 12000 ophthalmologists for 60 million diabetics with eye disorder. The main reason for such an alarming number of patients is the result of the fact that mostly people are obvious that they are suffering from this disorder. They also show insensitivity and an incautious attitude towards this disease.

Globally, DR affects roughly 22–35 % of people living with diabetes, with an estimated 103 million individuals in 2024 and projected to escalate to 160 million by 2045. Vision-threatening forms, including proliferative DR and clinically significant macular edema, impact about 6–7 % of diabetic patients. Rates of visual impairment and progression have declined in high-income countries thanks to early diagnosis and better systemic management, but low-resource areas continue to bear the brunt of the ongoing epidemic. Thus to detect Diabetic Retinopathy at an early stage is pivotal in averting the complexities of this disorder. In Key risk factors include longer diabetes duration, poor glycemic control, hypertension, dyslipidemia, obesity, and nephropathy. Ethnic disparities also persist higher rates appearing among Hispanic, African American, and South Asian populations, emphasizing socio-economic and healthcare inequities.

Clinically, early DR is often asymptomatic, making regular screening critical, typically beginning at diagnosis of type 2 diabetes or five years after type 1 onset, followed by annual dilated fundus examinations. As the disease advances, patients may experience floaters, blurred vision, dark or blank spots, and eventual vision loss if untreated.

Treatment strategies range from tight glycemic and blood pressure control to intravitreal anti-VEGF injections, focal or pan-retinal laser photocoagulation, and vitrectomy in advanced stages such as non-clearing vitreous hemorrhage or tractional detachment—significantly reducing the risk of severe vision loss when applied timely

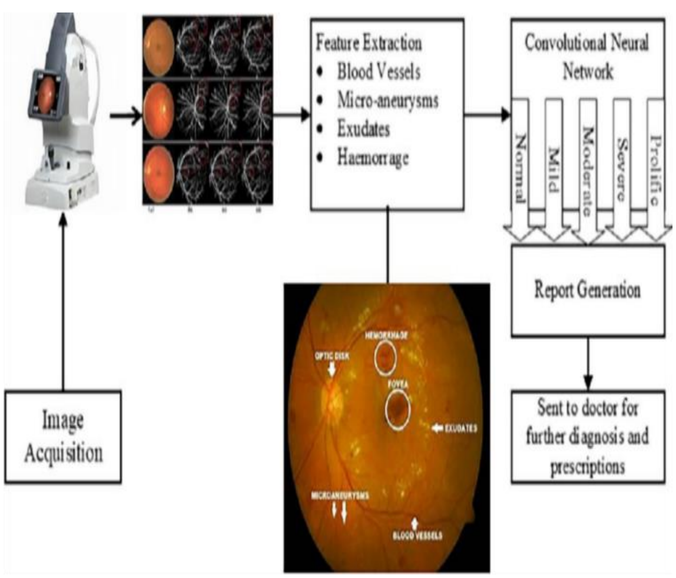
Diabetic retinopathy (DR) begins with chronic hyperglycemia that triggers a cascade of microvascular damage. The below figure illustrates hallmark DR lesions, including microaneurysms, cotton-wool spots, exudates, hemorrhages, and neovascularization and visually emphasizes how they reflect underlying vascular damage and ischemia. This figure anatomically highlights the primary pathological signs observed in fundus images and serves as a visual summary of the disease's progression and clinical features.

II. LITERATURE SURVEY

Diabetic Retinopathy (DR) is an ophthalmic disease that damages retinal blood vessels. DR causes impaired vision and may even lead to blindness if it is not diagnosed in early stages. DR has five stages or classes, namely normal, mild, moderate, severe and PDR (Proliferative Diabetic Retinopathy) . Normally highly trained experts examine the colored fundus images to diagnose this fatal disease. This manual diagnosis of this condition (by clinician) is tedious and error-prone. Therefore, various computer vision- based techniques have been proposed to automatically detect DR and its different stages from retina images. However, these methods are unable to encode the underlying complicated features and can only classify DR's different stages with very low accuracy particularly, for the early stages.

Visually impaired and blind people due to diabetic retinopathy were 2.6 million in 2015 and estimated to be 3.2 million in 2020 globally. Though the incidence of diabetic retinopathy is expected to decrease for high-income countries, detection and treatment of it in the early stages are crucial for low- income and middle-income countries. Due to the recent advancement of deep learning technologies, researchers showed that automated screening and grading of diabetic retinopathy are efficient in saving time and workforce. However, most automatic systems utilize conventional fundus photography, despite ultra-wide-field fundus photography provides up to 82% of the retinal surface. In this study, we present a diabetic retinopathy detection system based on ultra-wide-field fundus photography and deep learning. In experiments, we show that the use of early treatment diabetic retinopathy study 7-standard field image extracted from ultra-wide-field fundus photography outperforms that of the optic disc and macula centered image in a statistical sense.

Diabetic retinopathy (DR) is a potentially blinding complication affecting individuals with diabetes, where early diagnosis and treatment are crucial to preventing vision loss. Recent advances in deep learning have shown promise in automating DR diagnosis, offering faster, more reliable, and cost- effective solutions. Our study employed convolutional neural networks (CNNs) to classify the severity of DR using retinal images from the EyePACS dataset, which includes 35,155 images categorized into five classes. Building on previous research that often classified DR into two classes, such as no DR and varying levels of DR, we found that while these studies typically used models like Inception V3, VGGNet, and ResNet, they focused on simplifying the diagnostic process by reducing the number of classes. However, our approach utilized a smaller, more flexible CNN architecture, allowing for a more detailed classification into five stages of DR. We employed



various image preprocessing techniques, including grayscale conversion, background removal, and data augmentation, with our findings indicating that background removal significantly enhanced model performance, achieving a validation accuracy of 90.60%. This underscores the importance of sophisticated data preprocessing in medical imaging, and our study contributes to the ongoing development of automated DR diagnosis, potentially easing the burden on healthcare systems and improving patient outcomes.

Timely or early treatment is necessary to prevent some DR complications and control blood glucose. DR is very difficult to detect in time- consuming manual diagnosis because of its diversity and complexity. This work utilizes a deep learning application, a convolutional neural network (CNN), in fundus photography to distinguish the stages of DR.The images dataset in this study is obtained from Xiangya No. 2 Hospital Ophthalmology (XHO), Changsha, China, which is very large, little and the labels are unbalanced. Thus, this study first solves the problem of the existing dataset by proposing a method that uses preprocessing, regularization, and augmentation steps to increase and prepare the image dataset of XHO for training and improve performance. Then, it takes the advantages of the power of CNN with different residual neural network (ResNet) structures, namely, ResNet-101, ResNet-50, and VggNet-16, to detect DR on XHO datasets. ResNet-101 achieved the maximum level of accuracy, 0.9888, with a training loss of 0.3499 and a testing loss of 0.9882. ResNet-101 is then assessed on 1787 photos from the HRF, STARE, DIARETDB0, and XHO databases, achieving an average accuracy of 0.97, which is greater than prior efforts. Results prove that the CNN model (ResNet- 101) has better accuracy than ResNet-50 and VggNet-16 in DR image classification.

III. SYSTEM METHODOLOGIES

IMAGE ACQUISITION

Image acquisition for diabetic retinopathy (DR) detection involves taking images of the retina and using them to identify signs of the disease. This involves the process of capturing high-quality fundus (retina) photographs that clearly show central structures like the macula, optic disc, and blood vessels essential for detecting DR lesions such as microaneurysms and hemorrhages.

DATA PREPROCESSING

In deep learning pipelines for diabetic retinopathy detection using DenseNet architectures, image preprocessing plays an indispensable role in enhancing lesion visibility and model robustness. By applying a coherent sequence of illumination normalization → contrast enhancement → green-channel extraction → noise removal → resizing & normalization → augmentation, DenseNet-based DR detection systems gain robustness, enhanced lesion visibility, and improved accuracy—especially in detecting subtle lesions like microaneurysms.

ILLUMINATION NORMALIZATION

Illumination normalization is a critical preprocessing step in diabetic retinopathy (DR) detection pipelines. It addresses uneven lighting and contrast variation in retinal fundus images, which can significantly impact the performance of deep learning models like DenseNet by masking subtle lesions such as microaneurysms and exudates. Illumination normalization is foundational in preparing retinal fundus images for DenseNet-based DR detection. Whether implemented via classical filters or embedded as adaptive layers, this preprocessing step significantly enhances downstream segmentation and classification accuracy.

CONTRAST ENHANCEMENT

Contrast enhancement is a preprocessing technique used to amplify local differences in pixel intensities in fundus images. It makes subtle retinal features such as microaneurysms, hemorrhages, and exudates more visually distinguishable, thereby enabling both human graders and CNN models like DenseNet to detect them more reliably. Contrast enhancement operations generally improve micro-lesion detection by exposing vessel boundaries and small hemorrhages more clearly for CNN feature learning.

GREEN CHANNEL EXTRACTION

Green channel extraction involves isolating the green component from RGB fundus images. Unlike the red or blue channels, the green channel exhibits the highest contrast between retinal lesions (like hemorrhages and exudates) and the surrounding tissue making it an ideal basis for further analysis and feature extraction. By focusing on the green channel early in your preprocessing pipeline, it allows the model to learn more effectively from highly contrasted, clinically relevant retinal structures ultimately improving classification and lesion detection in diabetic retinopathy.

NOISE REMOVAL

Noise removal methods include a median filter, Gaussian filter, and Non Local Means Denoising methods respectively. The median filter is a nonlinear digital filtering technique, often used to remove noise from an image or signal. Such noise

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reduction is a typical preprocessing step to improve the results of later processing (for example, edge detection on an image). Median filtering is very widely used in digital image processing because, under certain conditions, it preserves edges while removing noise, also having applications in signal processing.

RESIZING AND NORMALIZATION

Fundus images often come in varied resolutions (e.g. 3,500×2,500 pixels). Resizing ensures consistent input shape and manageable computation. For example, cropping the retinal area followed by resize preserves the region of interest while standardizing input size. Many studies show that cropping then resizing results in significantly better training performance, with up to 15% improvement in Kappa score metrics, compared to using full uncropped images

AUGMENTATION

Data augmentation plays a vital role in improving deep learning–based diabetic retinopathy (DR) detection pipelines especially when using a DenseNet backbone by expanding data diversity, reducing overfitting, and helping the model generalize across real-world variability.

ROI & LESION SEGMENTATION

ROI Detection (Region of Interest Localization)

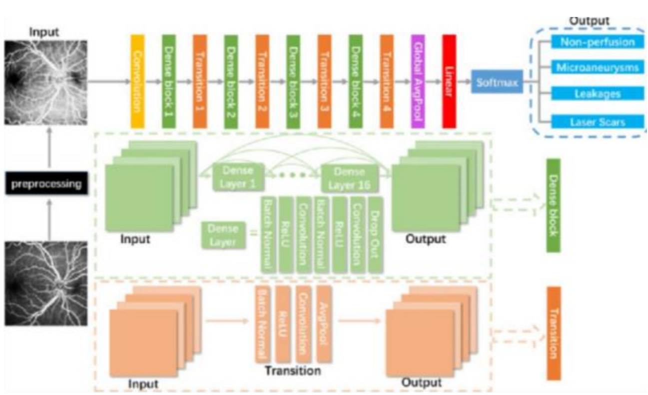
Region localization is commonly achieved using object detection networks such as Faster R-CNN or Mask R-CNN, which generate bounding boxes or segmentation masks around suspicious lesions (e.g., hemorrhages, exudates). In multi-stage pipelines, ROI detectors precisely identify candidate lesion regions, enabling focused analysis at a smaller patch scale for finer classification.

Lesion Segmentation (Pixel-Level Classification)

Once ROI regions are located, semantic segmentation networks such as U- Net, R2U-Net, DeepLabv3+, or multi-scale FCNs are employed to produce pixel- level masks delineating lesion boundaries. These models are often trained on datasets which provide detailed pixel-level annotations for lesions including microaneurysms (MA), hemorrhages (HM), hard exudates (HE), and soft exudates.

FEATURE EXTRACTION WITH DENSENET

DenseNet is a convolutional neural network architecture known for its dense connectivity each layer receives as input the feature maps of all preceding layers and passes its own feature maps to all subsequent layers. This architecture enables strong feature propagation, efficient gradient flow, and feature reuse, ultimately helping the model extract robust representations even with fewer parameters and limited training data.



6.1.1 S CLASSIFICATION HEAD

After DenseNet processes a preprocessed fundus image, feature extraction is completed and the resulting feature tensor must be translated into a clinical diagnosis this is the job of the classification head. Many pipelines fine-tune the DenseNet on retinal fundus datasets using transfer learning, which accelerates convergence and improves generalization even with limited

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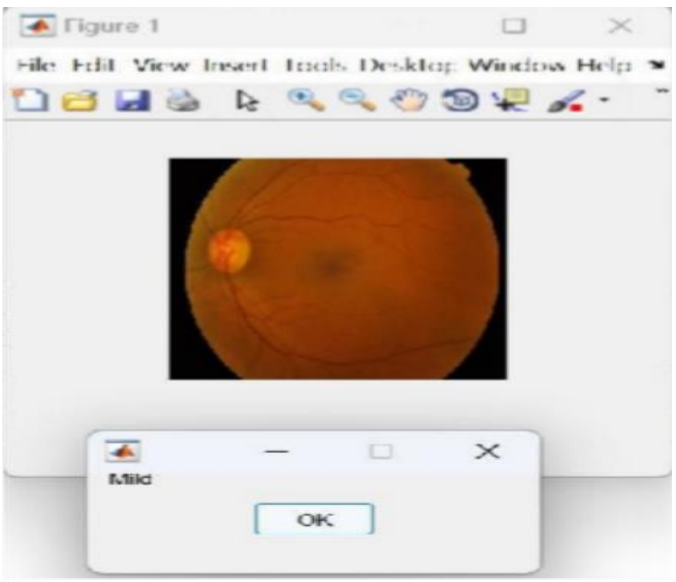
training data. Some systems incorporate auxiliary classifier heads similar to Inception architecture to provide deep supervision and improve gradient flow, though DenseNet typically handles this through its dense connectivity. With thisclassification head design, DenseNet - based DR detection systems are both compact and powerful allowing efficient fine-tuning, severity prediction, and integration of attention-based enhancements.

DenseNet Backbone and Global Pooling

The DenseNet backbone comprises multiple dense blocks connected by transition layers. Each block implements concatenated feature reuse, promoting strong gradient flow and multi-scale feature representation. After the final dense block, a Global Average Pooling (GAP) layer aggregates the spatial feature maps into a fixed-length vector, summarizing the rich hierarchical features generated from the retina image

4. EXPERIMENTAL RESULTS

Image with Mild DR




```
Class List in given sample 1 2 3 4 5
Total Instance = 3662
class1==>1 class2==>2 class3==>3 class4==>4 class5==>5
Confusion Matrix
predict_class1   predict_class2   predict_class3   predict_class4   predict_class5

    Actual_class1        65          4          0          5
    Actual_class2        13        116         10         43
    Actual_class3        11         16       1732         59
    Actual_class4        87        145         56        859
    Actual_class5        17         14          7         33

Getting Values

TP = 65 TN = 13 FN = 4 FP = 116
Accuracy = 0.9696 Error = 0.0304 Sensitivity = 0.9627 Specificity = 0.9836 Precision = 0.9627
FalsePositiveRate = 0.0164
F1_score = 0.9627
MatthewsCorrelationCoefficient = 0.9464
Kappa = 0.9316
```

Class List in given sample

1 2 3 4 5

Total Instance = 3662

class1==>1 class2==>2 class3==>3 class4==>4 class5==>5

Confusion Matrix

	predict_class1	predict_class2	predict_class3	predict_class4	predict_class5
Actual_class1	65	4	0	5	1
Actual_class2	13	116	10	43	28
Actual_class3	11	16	1732	59	35
Actual_class4	87	145	56	859	113
Actual_class5	17	14	7	33	193

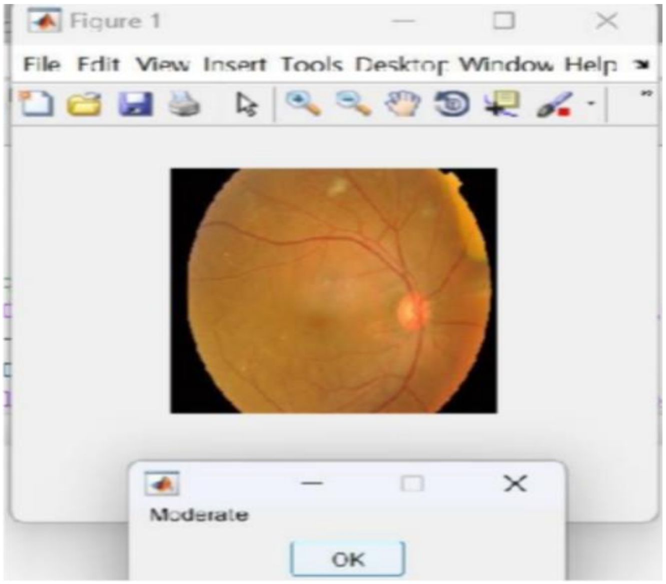
Getting Values

TP = 65 TN = 13 FN = 4 FP = 116 Accuracy = 0.9077 Error = 0.0923 Sensitivity = 0.9468

Specificity = 0.8056 Precision =0.9271 FalsePositiveRate =0.1944 F1 score = 0.9368

MatthewsCorrelationCoefficient =0.7661 Kappa = 0.7655 >>

Image with Moderate DR



Class List in given sample

1 2 3 4 5

Total Instance = 3662

class1==>1 class2==>2 class3==>3 class4==>4 class5==>5

Confusion Matrix

	predict_class1	predict_class2	predict_class3	predict_class4	predict_class5
Actual class1	65	4	0	5	1
Actual_class2	13	116	10	43	28
Actual_class3	11	16	1732	59	35
Actual_class4	87	145	56	859	113
Actual_class5	17	14	7	33	193

Getting Values TP = 65 TN = 13 FN = 4 FP = 116 Accuracy = 0.9077 Error = 0.0923

Sensitivity = 0.9468 Specificity =0.8056 Precision =0.9271 FalsePositiveRate = 0.1944

F1_score = 0.9368 MatthewsCorrelationCoefficient = 0.7661 Kappa = 0.7655 >>

CONCLUSION

The traditional method detection of diabetic retinopathy is prolonged, challenging and costly, thus many researchers were brought up to automate the detection process by using machine learning and deep learning approaches. In this work, we presented a comprehensive study of various methodologies for detecting diabetic retinopathy automatically and attempted to propose our own deep learning approach for the early diagnosis of retinopathy by using a DenseNet (which is a new CNN architecture, having many deep layers). A lot of preprocessing and augmentation was done to standardize the data in a desired format and to remove the unwanted noise, where the best accuracy among all was obtained by the proposed model and it also classifies the images into more number of classes. Our proposed model performed better than the regression model by achieving the accuracy yielded by the other model

FUTURE ENHANCEMENT

The effective screening of retinal images of Diabetic patients for the detection of Diabetic Retinopathy and classification of different stages of Diabetic Retinopathy can reduce the possibilities of sudden vision loss in affected patients. As the existing systems are quite slow in operation, a real time implementation of screening system can provide the better performance. Processing of Retinopathy images is very essential to get proper features. Statistical values can predict level of severity properly but in case of noisy images the chances of getting poor data will lead to lower accuracy. For getting better result selecting for proper features out of the image also important. Both CNN and DenseNet models are effective in term for image, because of CPU training time of CNN getting affected in the study, in this case DNN

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