# A Study on Diabetic Retinopathy Classification using Deep Learning Technique

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**ABSTRACT:**

Diabetic Retinopathy (DR) is a prevalent complication of diabetes mellitus, leading to retinal lesions that can cause vision impairment and even blindness if left undetected. The prevalence of diabetes worldwide has witnessed a significant increase in recent years, affecting individuals across all age groups. Early detection and treatment of DR are crucial to mitigate the risk of vision loss. However, the manual diagnosis of DR using retina fundus images is time-consuming, labor-intensive, costly, and prone to misdiagnosis. As a result, computer-aided diagnosis systems have emerged as promising alternatives. Among these, deep learning techniques, particularly convolutional neural networks (CNNs), have shown remarkable performance in various domains, including medical image analysis and classification. In this article, we present a comprehensive review and analysis of the state-of-the-art methods for the detection and classification of DR color fundus images using deep learning techniques. We highlight the effectiveness of CNNs in addressing the challenges associated with DR diagnosis. By leveraging large datasets, these deep learning models learn intricate patterns and features directly from the raw image data, enabling accurate classification of DR severity levels.

**Keywords:** Diabetic retinopathy grading; diabetic retinopathy detection; deep learning; convolutional neural network; retinal fundus images.

## 1. Introduction

The increasing global prevalence of diabetes over the past two decades has become a significant public health concern. According to the IDF Diabetes Atlas[2], nearly half a billion individuals of all age groups have been diagnosed with diabetes worldwide, with projections estimating this number to reach seven-hundred million by 2045. Alarmingly, it is predicted that one in three diabetes patients will develop Diabetic Retinopathy (DR) by 2040. DR is characterized by damage to the blood vessels behind the retina, leading to potentially severe complications, including vision loss if left undetected for extended periods. Currently, the assessment of DR severity relies on manual examination of fundus images by medical professionals, a process that is time-consuming and hindered by a shortage of available specialists relative to the increasing number of patients. Consequently, many patients do not receive timely medical care, resulting in delayed detection and treatment of the disease. Regular screenings of fundus images are advised for diabetic patients; however, a significant number of cases go undetected until the condition has progressed to an advanced stage. Therefore, the development of an automated system for DR detection is highly desirable we also provide an overview of the DL architectures employed by the various studies we analyzed. Figure 1 shows the healthy retina and unhealthy retina due to diabetes. [1].

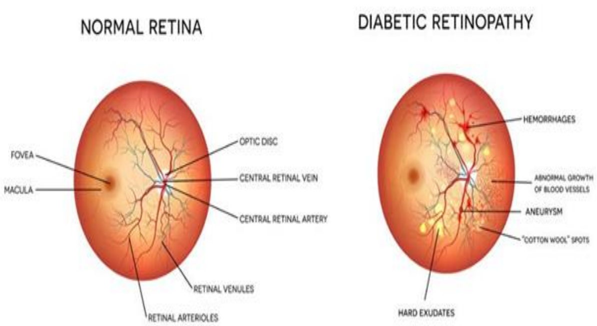


**Figure 1: Healthy retina and unhealthy retina**

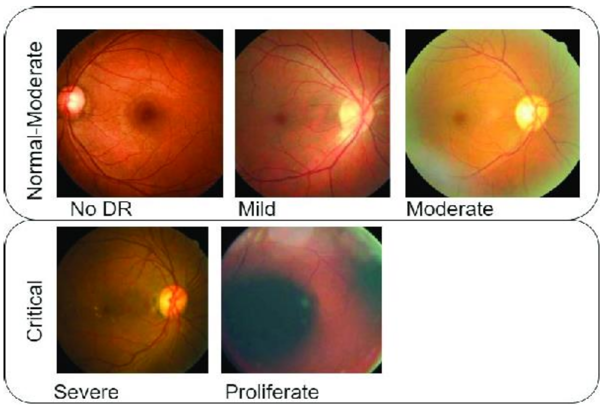


**Figure 2: diabetic retinopathy stages, ranked by severity**

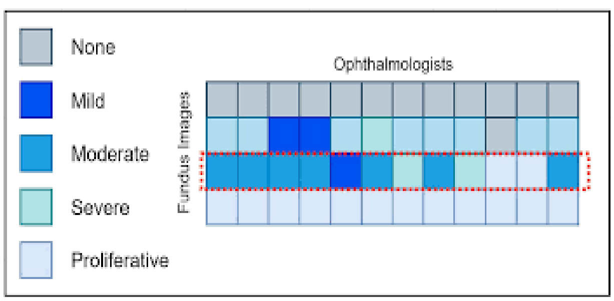


**Figure 3: diabetic retinopathy classification**

With the rapid advancement of AI techniques, particularly machine learning and deep learning, there have been significant developments in the detection and grading of retinal images for the identification and segmentation of affected regions. Machine learning approaches have played a pivotal role in diabetic retinopathy (DR) classification and grading. For instance, Nazir et al. [3] introduced a novel representation of fundus images known as the "tetragonal local octa pattern (T-LOP) features" and employed an extreme learning machine for classification. Another study [4] utilized three machine learning classifiers-support vector machine (SVM), random forest, and J48—for DR classification. In [5], the authors employed the Gabor wavelet method followed by the AdaBoost classifier for DR grading.

In recent years, deep learning techniques have gained prominence in the field of DR detection and grading. Deep learning is a subset of AI that utilizes artificial neural networks with multiple layers to extract progressively higher-level features from the input data. Numerous studies have applied deep learning techniques for these tasks. In this paper, we provide a comprehensive review of the current literature in this area, focusing on the utilization of deep learning for DR detection and grading from fundus images. Furthermore, we summarize the various deep learning architectures employed in the reviewed studies.

By leveraging the power of deep learning, researchers have achieved remarkable results in automated DR diagnosis. The ability of deep learning models to learn complex patterns and features directly from raw data has significantly improved the accuracy and efficiency of DR detection and grading systems. This review aims to consolidate the knowledge and advancements in deep learning-based approaches for DR diagnosis, providing insights into the effectiveness of different architectures and techniques utilized in the field.

## 2. LITERATURE REVIEW

Adoption of Deep Learning: Many studies during this period embraced deep learning techniques, particularly convolutional neural networks (CNNs), for retinopathy grading. Various architectures such as VGG-16, VGG-19, AlexNet, InceptionV3, ResNet, DenseNet, and EfficientNet were extensively employed, showcasing the effectiveness of deep learning in this domain. The classification of diabetic retinopathy can be divided into two categories: binary classification, which seeks to determine if DR is present or absent, and multi-class classification, which determines the precise stage of DR. As a result, new techniques concentrating on lesion-based classification were created. In the following sections of the paper, such classification problems are examined under supervised and self-supervised learning.

Transfer Learning: Transfer learning, a technique that utilizes pre-trained models was widely utilized in retinopathy grading studies. Researcher's often leveraged models trained on large-scale image datasets like ImageNet and fine-tuned them on retinal images to enhance performance.

Diverse Datasets: Multiple datasets were used for training and evaluation purposes. Popular datasets included Kaggle EyePACS, Kaggle APTOS, Kaggle DR, MESSIDOR, IDRiD, and DIARETDB1. This diversity of datasets allowed for robust evaluation and comparison of different methods across different populations and imaging conditions.

Ensemble Approaches: Several studies explored ensemble methods, combining multiple deep learning models or architectures to improve the accuracy and generalization of retinopathy grading systems. Ensemble techniques help mitigate the limitations of individual models and provide more reliable predictions.

Incorporation of Novel Architectures: Newer architectures such as SE-MIDNet, SAGN, HA-Net, DCNN, DRNet, and others were introduced, showcasing the continuous evolution and experimentation within the field. These architectures aimed to improve the detection and grading performance by incorporating novel features and design choices.

Dataset Expansion: Researchers made efforts to expand available datasets by collecting data from different sources, including hospitals and medical centers in various countries. This expansion helped in building more diverse and representative datasets, leading to more robust and generalizable models.

Exploration of Semi-Supervised and Generative Models: Some studies explored the utilization of semi-supervised learning and generative adversarial networks (GANs) to address the scarcity of labeled data in retinopathy grading. These approaches aimed to leverage unlabeled data and generate synthetic samples to enhance model performance.

Overall, the literature survey during the mentioned period demonstrates the progress made in leveraging deep learning techniques, diverse datasets, and innovative approaches to improve the detection and grading of diabetic retinopathy. These advancements have the potential to positively impact clinical practice by enabling earlier detection and intervention for patients at risk of vision loss.

The below table provides an overview of the available DR datasets with their respective image counts, distribution of severity levels, and image sizes. Additional details such as the specifics of each dataset's characteristics and sources should be included in the research paper along with appropriate citations.

**Table1: provides an overview of the available DR Datasets**

| Dataset | Number of Images | Normal Image | Mild DR | Moderate and Severe Non-Proliferative DR | Proliferative DR | Training Sets | Test Sets | Image Size |
|---|---|---|---|---|---|---|---|---|
| DiaretD | 89 | 27 | 7 | 28 | 27 | 28 | 61 | 1500X1 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| B1 | | | | | | | | 152 pixels |
| Kaggle | 88702 | - | - | - | - | 35126 | 53576 | Different Resolutions |
| DRIVE | 40 | 33 | 7 | - | - | 20 | 20 | 565X584 pixels |
| E-Ophtha | 82 | - | - | - | - | EX:35 MA:381 | EX:233 MA:233 | Different Resolutions |
| HRF | 45 | 15 | 15 | - | - | - | - | 3504X2336 pixels |
| DDR | 13673 | 6266 | 630 | 4713 | 913 | 6835 | 4105 | Different Resolutions |
| Messidor | 1200 | - | - | - | - | - | - | Different Resolutions |
| Messidor-2 | 1748 | - | - | - | - | - | - | Different Resolutions |
| STARE | 20 | 10 | - | - | - | - | - | 700X605 pixels |
| CHASE DB1 | 28 | - | - | - | - | - | - | 1280X2848 pixels |
| IDRiD | 516 | - | - | - | - | 413 | 103 | 4288X2848 pixels |
| RBC | 100 | - | - | - | - | 50 | 50 | Different Resolutions |
| DR2 | 435 | - | - | - | - | - | - | 857X569 pixels |

## 3. Diabetic retinopathy (DR) classification methodologies

DR classification methodologies involve analyzing retinal images to determine the severity and stage of the disease. These methodologies utilize various techniques, including machine learning and image analysis algorithms. Here are some commonly used classification methodologies for diabetic retinopathy:

1. *Manual Grading:* Manual grading involves trained ophthalmologists or optometrists visually examining retinal images and categorizing the severity of diabetic retinopathy based on established grading scales, such as the Early Treatment Diabetic Retinopathy Study (ETDRS) or the International Clinical Diabetic Retinopathy (ICDR) classification. This method is subjective and can be time-consuming.

2. *Automated Image Analysis:* Automated image analysis methods employ computer algorithms to analyze retinal images and classify diabetic retinopathy. These algorithms can detect and quantify various features associated with the disease, such as microaneurysms, hemorrhages, exudates, and neovascularization. Machine learning techniques, such as convolutional neural networks (CNNs), are often used to train models on large datasets of labeled retinal images for accurate classification.

3. *Deep Learning:* Deep learning is a subset of machine learning that involves training deep neural networks to automatically learn hierarchical representations from data. Convolutional neural networks (CNNs) have been widely used for the automatic classification of diabetic retinopathy. Deep learning models can extract intricate features from retinal images, enabling accurate classification and staging of the disease.

4. *Ensemble Methods:* Ensemble methods combine multiple classification models to improve the accuracy and robustness of the classification process. By aggregating the predictions of individual models, ensemble methods can provide more reliable and consistent results in diabetic retinopathy classification.

5. *Hybrid Approaches:* Hybrid approaches combine both manual grading and automated image analysis techniques. They leverage the expertise of ophthalmologists or optometrists in interpreting retinal images while incorporating computer-aided analysis to enhance accuracy and efficiency.

It's important to note that these methodologies are continually evolving as new techniques and technologies emerge. The ultimate goal is to develop accurate, reliable, and efficient methods for the early detection and classification of diabetic retinopathy to guide appropriate treatment and management strategies.

## 4. DISCUSSION

Examining the outcomes and methodology of each approach, this paper evaluates 11 supervised papers, 3 self-supervised papers, and 4 transformer papers. The purpose of this paper is to evaluate DR grading and classification procedures from a qualitative perspective, so that researchers in the future can benefit from knowing about the progress made in the DR field.

Of the supervised approaches, 46% categorize DR by severity levels from mild to severe, while 54% employ binary classification for DR detection. The majority of unsupervised approaches (67%), although not all (33%), utilise multi-class detection. Dataset-wise, a few researches attempted to use self-developed private sets for total control; this generally produced improved outcomes, but no association can be drawn due to varied data distributions. Of the studies, roughly 57.2% use more than one dataset to train their models, whereas the remaining 42.8% only use one. The data has been compiled and is displayed in Figure 4. For certain applications, supervised models are robust and effective. The extremely long time required to train new models each time is a drawback that is rarely mentioned in the articles. The process of annotating and organising the data to make it "model ready" almost defeats the purpose of mission-critical models that are constantly being inundated with fresh data. It is important to promote DL ensemble learning pipelines in the supervised learning setting because they are so effective at dealing with features in data distributions that are very non-normal.

Fine-tuning on new data sets is an area where self-supervised models excel. Training on a massive dataset like Messidor or EYEPACS, as all three articles predicted, would improve the model's ability to generalize to smaller datasets like DRIVE and GTest. The given results confirmed this to be the case. However, knowing how SSL models interpret the data fed into them is essential for making sense of them. Luo uses t-SNE plots to explain how SFCN can distinguish between typical and abnormal photos. To illustrate the features that the model is concentrating on, A. employs attention maps. The heatmaps show how CABNet's attention block selects only the most relevant features. This has the potential to drastically decrease the size of generalization-required embeddings. While research shows that SSL methods can be effective, it does not indicate how they can be less prone to inductive bias in the long run. When choosing a model for mission critical applications, advantages like SSL techniques' ability to handle cross-domain inputs are vital. The publications also don't address whether or not SSL approaches are robust when dealing with smaller datasets.

While most of the latest DL developments attain encouraging scores in classification, several still lack the ability to discriminate damaged lesions, and DR screening remains an open topic because of the scarcity of publicly available datasets.

The 5 DR phases, widely regarded as essential for assessing the gravity of the condition, are simply disregarded by alternative methodologies. This kind of variation in approach indicates yet another stumbling block. Researchers in the field may still have diverse viewpoints on the validity of the data because there are no standard techniques that agree on a common set of DR phases. However, most outcomes are merely useful for diagnosis and are seldom considered conclusive.

More research needs to be done in the direction of employing SSL approaches to build fresh fundus images based on the learnt characteristics using generative networks, which can then be used for generalization. By combining preexisting networks with generative adversarial networks (GANs) and variational auto-encoders (VAEs), we may generate a wide variety of improved fundus images for use in training. For instance, Ramesh et al.'s [69] DALL-E can generate images from text, suggesting that a model with this capability may produce enormous collections of DR fundus images for use in training and testing.

To encode better features when large-scale DR sets are available, another way might be to use self-supervised vision transformers like DINO described. Since the accuracy of transformers increases with the number of trainable parameters, they are resistant to saturation as the set size and distribution of the training data change. The complexity of CNN layers grows in proportion to the size of the filters, but this issue could be mitigated with the use of vision transformers. Due to the possibility that visual characteristics would be lost in the network, CNNs are unable to acquire an overall comprehension of the image. Vision transformers, on the other hand, are able to use their attention mechanisms to their advantage and discover connections within rearranged feature sequences.

Recent research indicates that attention mechanisms significantly altered the contextualization and interpretation of visuals. The reviewed transformer-based models perform well in binary and multi-class categorization of DR illness in the medical imaging domain. The capacity to more precisely differentiate tiny lesions as a result of the improved explain ability provided by these transformer investigations is a major step forward. While the outcomes show promising performance and gains over CNNs, more research is needed to benchmark models in production settings. When put to use in the actual world, most vision models end up failing.

## 5. CONCLUSION

Diabetic retinopathy (DR) poses a significant threat to individuals with diabetes, potentially causing vision impairment and blindness if not detected in time. The manual grading of retinal images for DR diagnosis is a cumbersome and error-prone process, leading to the emergence of computer-aided diagnosis systems as promising alternatives. Deep learning techniques, particularly convolutional neural networks (CNNs), have demonstrated impressive capabilities in the detection and classification of DR. The adoption of deep learning in the field of DR detection and grading has been widespread, with various architectures like VGG-16, VGG-19, AlexNet, InceptionV3, ResNet, DenseNet, and EfficientNet showcasing their effectiveness. Transfer learning, which involves fine-tuning pre-trained models on retinal images, has been extensively employed to boost performance. Apart from deep learning, other classification methodologies for DR include manual grading by ophthalmologists or optometrists, automated image analysis algorithms, ensemble methods, and hybrid approaches that combine manual grading with automated analysis. Overall, the utilization of deep learning techniques, diverse datasets, and innovative approaches has significantly advanced the detection and grading of diabetic retinopathy. These advancements have the potential to positively impact clinical practice by enabling earlier detection and intervention for patients at risk of vision loss. The field continues to evolve with the ultimate goal of developing accurate, reliable, and efficient methodologies for the early detection and classification of diabetic retinopathy.

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