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A Comprehensive Review of CNN-Based Framework for Multi-Sign Detection of Diabetic Retinopathy in Fundus Images Using Public Datasets

Umesh Kumar*

Abstract

Diabetic retinopathy (DR) is one of the main causes of vision impairment. Blindness prevention and effective treatment depend on early detection. A thorough deep learning-based framework for the automatic segmentation and simultaneous detection of exudates, hemorrhages, and microaneurysms – three important DR indicators – from retinal fundus images is presented in this work. These three pathological signs' corresponding annotated image patches, along with background (no-sign) areas, were used to train a ten-layer convolutional neural network (CNN). A post-processing algorithm is used to improve localization and remove noise from the probability maps that the network produces for each class. Receiver operating characteristic (ROC) curve analysis was utilized to determine the optimal classification thresholds. The proposed model was evaluated on two publicly available datasets, one for training and another for testing. It uses both patch-based and full-image analysis. To ensure reliability, the model's performance was tested across ten independent runs, consistently demonstrating high accuracy and reliable detection of all DR indicators. Furthermore, the approach was compared against several advanced models and techniques, including the tandem pulse coupled neural network (TPCNN), deep learning-based support vector machine (DLBSVM), synergic deep learning (SDL), and lesion-aware CNN (LACNN), using datasets, such as Messidor, DRIVE, CHASE_DB1, and OCT image databases. The proposed system exhibited competitive or superior results in terms of accuracy, specificity, and sensitivity. It confirms its potential as an effective and dependable tool for ophthalmologists in clinical DR screening.

Keywords: Diabetic retinopathy, fundus images, CNN, DR

INTRODUCTION

Our retina captures light and converts it into neural signals that helps brain to interpret images. In individuals with diabetic retinopathy (DR), the outer retinal layer becomes thickened and damaged, leading to the appearance of spots and deposits on the retina. Retinal vessel segmentation is a valuable tool in identifying changes in blood vessels, offering essential information about their condition [1].

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Diabetes has become a global health issue, largely due to elevated blood glucose levels. Prolonged high glucose concentrations can cause severe damage to blood vessels. Complications, like kidney disease, eye damage, gum disease, nerve problems, and cardiovascular issues, are more likely to occur in people with diabetes. The condition that arises due to prolonged elevated glucose levels is termed diabetes [2].

The number of people with diabetes increased significantly from 108 million in 1980 to 422 million in 2014. Diabetes directly causes approximately 1.6 million deaths annually. The prevalence among adults aged 18 and above increased from 4.7% in 1980 to 8.5% in 2014, with a 5% rise in premature mortality due to diabetes between 2000 and 2016.

Currently, retinal fundus images can be used to automatically identify DR by identifying specific abnormalities, such as microaneurysms (MA), hemorrhages (H), cotton wool spots (CWS), hard exudates (HE), and neovascularization. These indicators help determine whether a patient is healthy or affected by DR [3].

Fundus imaging which offers a broad view of the retina, like traditional indirect ophthalmoscopy, is widely used in DR detection systems to diagnose systemic conditions effectively [4]. Globally, one in every eleven people suffers from diabetes mellitus, a metabolic disorder that is projected to affect one in ten individuals by 2040 [5]. The worldwide prevalence of diabetes is expected to rise to 10.2% (578 million) by 2030 and further to 10.9% (700 million) by 2045.

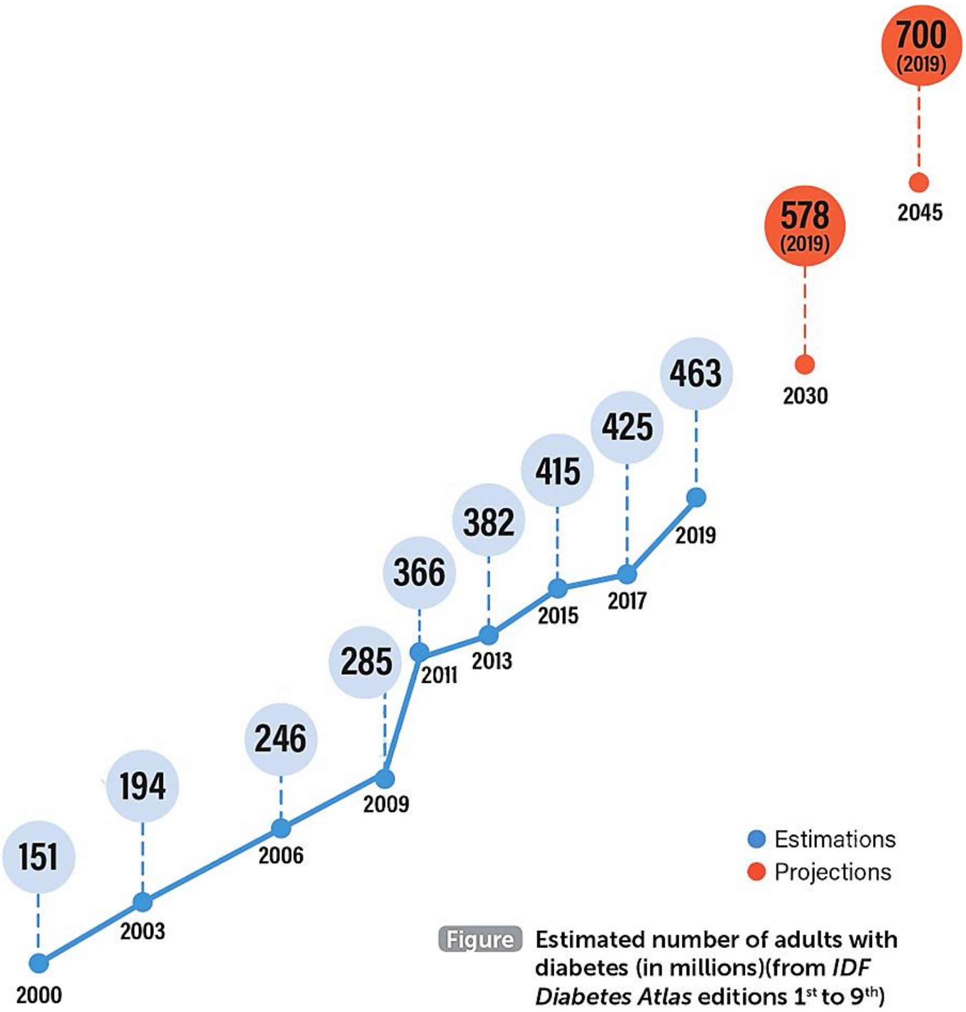

Figure 1. Estimated no. of adults with diabetes (in millions) (https://www.diabetesatlas.org/en/sections/worldwide-toll-of-diabetes.html).

Figure 1 illustrates the rapid global increase in diabetes cases. In 2000, approximately 151 million adults worldwide were living with diabetes. By 2009, this number had surged by 88% to reach 285 million. Currently, an estimated 463 million adults aged 20 to 79 – about 9.3% of the global adult population – are affected by diabetes. Back in 2010, it was predicted that diabetes would affect 438 million people by 2025. However, this estimate has already been exceeded by 25 million, well ahead of the expected year. The International Diabetes Federation (IDF) predicts that by 2030, 578 million adults will have diabetes, and by 2045, 700 million.

Diabetic retinopathy (DR) is a frequent complication of diabetes mellitus. It causes damage to the retina through the formation of lesions that impair vision. Diabetic retinopathy (DR) can lead to irreversible blindness if it is not detected and treated early [6]. While the condition cannot be cured, early diagnosis and appropriate treatment can greatly reduce the risk of significant vision loss [7].

China has the highest number of individuals with diabetes – around 110 million – although its prevalence rate ranks 78th globally at approximately 10%. India follows with about 69 million people affected, ranking 76th in prevalence with nearly 9%.

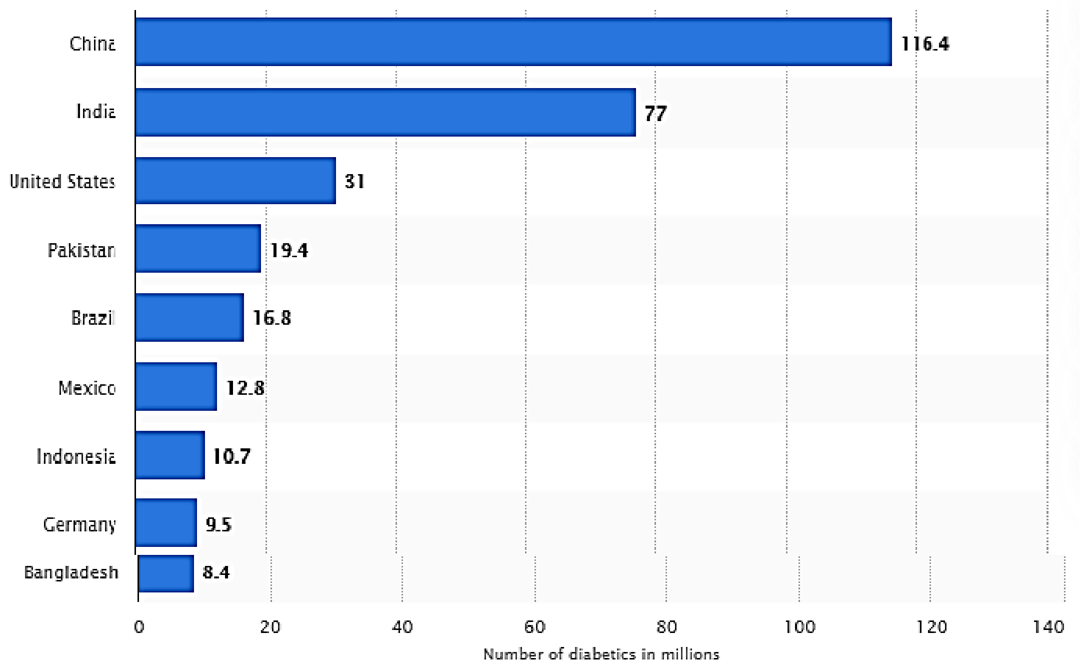

Figure 2. The nations with the largest global diabetes in 2019 (https://www.statista.com/statistics/281082/countries-with-highest-number-of-diabetics/#statisticContainer).

Figure 2 highlights that China currently has the highest number of individuals diagnosed with diabetes, with approximately 116 million cases. By 2045, it is projected that India will surpass this figure, reaching an estimated 134 million people living with the disease. About 1.6 million people died from diabetes in 2016, making it one of the worlds' leading causes of death. In 2019, South-East Asia recorded the highest regional death toll from diabetes, with around 592,000 fatalities. Additionally, obesity which is one of the primary risk factors for diabetes, has been rising significantly in many countries around the world.

Although diabetes has no known cure, its progression and complications can be managed or delayed through early detection and proper monitoring, such as screening methods recommended by the American Academy of Ophthalmology. One critical sign of diabetic eye disease is *IRMA* (Intraretinal Microvascular Abnormalities), which refers to abnormal blood vessels that form near the retina. IRMA is recognized as an early warning sign of potential retinal neovascularization. In this abnormal condition, fragile blood vessels grow in unsuitable areas of the eye, increasing the risk of vision loss or blindness.

Researchers, including those from the University of North Sumatra, have identified six critical retinal features essential for diagnosing diabetes-related vision loss. These are optic disc, macula, retinal blood vessels, microaneurysms (tiny swellings in blood vessels), exudates (fluid deposits without protein), and hemorrhages (bleeding inside the eye). By collectively analyzing these features, intelligent diagnostic systems can accurately detect diabetes-induced blindness. It can also determine its specific type.

To improve diagnostic precision, a deep learning technique convolutional neural networks (CNNs) which is widely used for image analysis, is applied. CNNs excel at interpreting medical images and detecting patterns that may signal disease. Their integration enhances the prediction and classification of diabetes-related blindness. Machine learning systems are becoming increasingly powerful and efficient, enabling faster and more accurate analysis of complex medical data. This is due to ongoing technological advancements, particularly in hardware, such as graphics processing units (GPUs).

A major challenge in applying the CNNs algorithm lies in accurately identifying the specific type of vision loss experienced by diabetic patients. The goal of the study is to enhance diagnostic precision through advanced technology. According to research, diabetic-related eye conditions can be categorized into five main stages:

- *No Diabetic Retinopathy (No DR):* No signs of vision impairment are present.
- *Mild DR:* Characterized by the presence of microaneurysms, minor intra-retinal hemorrhages, or hard/soft exudates.
- *Moderate DR:* Involves intra-retinal bleeding along with early signs of IRMA (Intraretinal Microvascular Abnormalities).
- *Severe DR:* Identified by extensive bleeding and microaneurysms across four retinal quadrants, dilated veins in two quadrants, or IRMA confined to at least one quadrant.
- *Proliferative DR:* Anywhere on the retina, new, aberrant blood vessels will form, marking the condition.

This classification system has been adopted to support the integration of machine learning and computer vision technologies, with the aim of enabling early detection of IRMA and minimizing the risks associated with diabetic blindness. By leveraging CNN-based models, healthcare professionals can enhance screening and preventive strategies, ultimately reducing the impact of DR on affected populations.

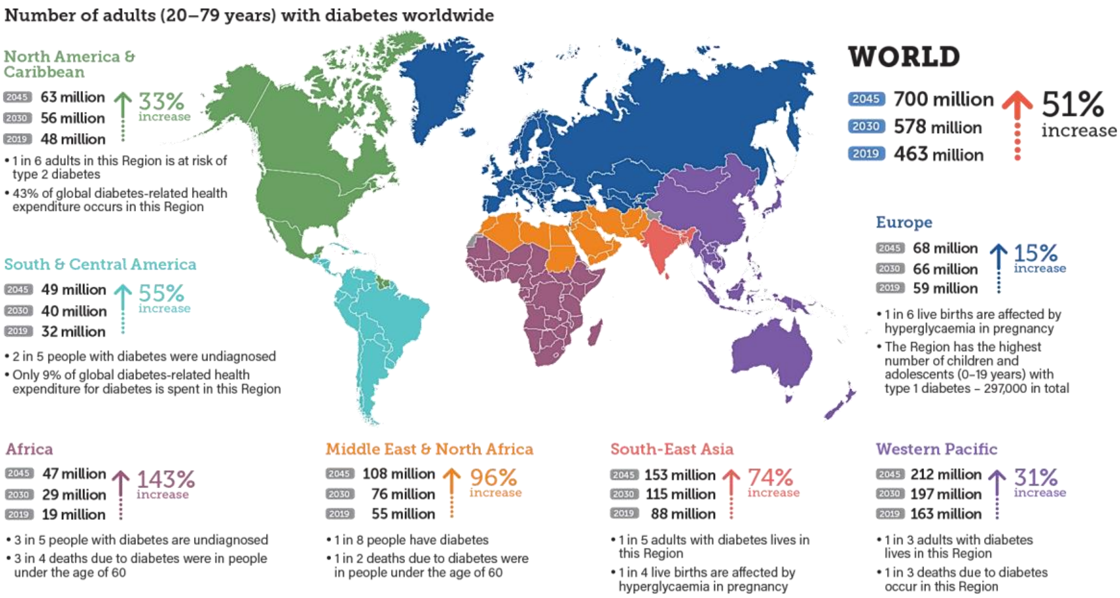

Figure 3. Diabetes patients in worldwide 2010-2045 (https://diabetesatlas.org/data/en/world/).

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Figure 3 illustrates the steady global increase in diabetes cases over time. As of 2020, there were approximately 578 million people worldwide living with diabetes, and this number is projected to reach 700 million by 2045. In North America and the Caribbean, around 56 million individuals were living with diabetes in 2020. This figure is expected to rise to 63 million by 2045, with 1 in 6 adults in the region at risk of developing type 2 diabetes. In South-East Asia, an estimated 115 million people had diabetes in 2020. This number is predicted to grow to 153 million by 2045, and currently, 1 in every 5 adults with diabetes resides in this region. By 2045, the Middle East and North Africa regions are projected to have 108 million diabetes cases. In Europe, approximately 66 million people were living with diabetes in 2020. The Western Pacific region is also expected to experience a sharp rise, with diabetes cases reaching 212 million by 2045. In Africa, the number of individuals with diabetes grew from 19 million in 2009 to 29 million in 2020, and this figure is anticipated to climb to 47 million by 2045.

LITERATURE REVIEW

Jebaseeli TJ, et al. (2019) [1] presented a Deep Learning-Based Support Vector Machine (DLBSVM) for the classification and extraction of blood vessels and suggested a Tandem Pulse Coupled Neural Network (TPCNN) model for the automatic generation of feature vectors. They used fundus images from publicly available datasets like STARE, DRIVE, HRF, REVIEW, and DRIONS. Image quality was improved by applying Contrast Limited Adaptive Histogram Equalization (CLAHE), which increased contrast and reduced noise from shifting lighting conditions. The TPCNN model, which combines two source images to generate feature vectors, facilitates segmentation of the retinal vasculature. The experimental results demonstrated the effectiveness of the proposed methods with a sensitivity of 80.61%, specificity of 99.54%, and accuracy of 99.49%.

In their 2020 study, K. Shankar and colleagues [2] proposed a complete method for analyzing diabetic retinopathy (DR) using fundus images. Their approach includes three key steps: preprocessing, segmentation, and classification. First, they cleaned up the images by removing unwanted noise, especially around the edges, to improve overall image quality. Next, they used a histogram-based segmentation technique to highlight the important areas within the images. Finally, they applied a synergic deep learning (SDL) model to classify the images based on how severe the DR was. The team tested their model using the Messidor DR dataset, and the results were impressive. For stage 1 DR images, the model achieved 98.93% accuracy, 97.39% sensitivity, and 99.04% specificity. For stage 2 images, the performance was even better, with 99.33% accuracy, 98.38% sensitivity, and 99.58% specificity. This shows clear improvements over existing methods.

In 2017, Ruchir Srivastava and his team [3] introduced an innovative filtering technique to help distinguish between blood vessels and red lesions in retinal images. Their method takes advantage of the fact that blood vessels often appear as circular, blob-like shapes in these images. To handle the challenge of lesions coming into different sizes, the researchers did not process the entire image all at once. Instead, they divided the image into smaller patches using a grid, with the grid size determining the size of each patch. This allowed them to apply their filters more effectively to different areas of the image. To bring together the detection results from the various patch sizes, they used a Multiple Kernel Learning (MKL) approach, which helped improve the accuracy of identifying lesions.

The study was carried out using a set of 143 retinal fundus images taken from two publicly available sources: DIARETDB1 and MESSIDOR databases. The DIARETDB1 database contributed 89 images, with 5 showing healthy eyes and the remaining 84 containing at least one red lesion. These images had a resolution of 1152 × 1500 pixels and covered a 50° field of view (FOV). Ground truth labels were provided, indicating whether microaneurysms (MAs) or hemorrhages (Hs) were present. The results showed that the proposed filtering technique could accurately detect both MAs and Hs, even when they appeared close to blood vessels. The model performed exceptionally well, achieving an area under the

ROC curve of 0.97 for microaneurysms and 0.92 for hemorrhages – both results surpassing those of existing approaches.

In 2019, Xuechen Li and colleagues [4] developed and tested their method using a dataset of Optical Coherence Tomography (OCT) images provided by Wenzhou Medical University (WMU). The images were captured with a specially designed spectral domain OCT (SD-OCT) system equipped with a CCD camera, capable of scanning up to 70,000 A-lines per second. To strike a balance between image quality and scanning speed, they set the scan rate to 50 kHz. The system captured detailed images with an 8 mm scan width, recording 2048 A-lines and 32 B-scans per eye.

In total, the dataset included 4,168 OCT images from 155 patients. Of these, 1,112 images from 45 patients were diagnosed with grade 1 diabetic retinopathy (DR 1), 1,856 images from 64 diabetic patients showed no visible retinal abnormalities (classified as grade 0 DR), and 1,200 images came from 46 healthy individuals with no history of diabetes. Diagnoses for grade 1 DR were made through clinical evaluation using seven-field stereo fundus photography, and any disagreements were resolved by consulting a senior expert. All images were stored in 8-bit grayscale format. The researchers also ensured that the age distribution across the three groups – healthy, grade 0 DR, and grade 1 DR – was similar, reducing the risk of age-related bias in the classification results. Their proposed method achieved impressive performance, with 92% accuracy, 90% sensitivity, and 95% specificity for distinguishing between the three groups.

In the same year, Ramon Pires and his team [5] introduced a method that showed strong generalization ability, achieving an impressive area under the ROC curve (AUC) of 98.2% (with a 95% confidence interval between 97.4% and 98.9%). Their model was tested under strict cross-dataset conditions – trained on the Messidor-2 dataset and evaluated on the Kaggle DR dataset. They used a 5 × 2-fold cross-validation approach, which consistently delivered high performance on both Messidor-2 and DR2 datasets. Remarkably, their method reduced classification errors by more than 44% compared to several previously published techniques.

The model was developed step by step, starting with a Convolutional Neural Network (CNN) backbone and gradually adding improvements like advanced feature extraction, data augmentation, patient-level analysis, and multi-resolution training. Each of these additions was carefully tested to see how much they contributed to boosting performance. Even when the model was trained on the Kaggle dataset and tested on the Messidor-2 dataset, it still achieved an impressive area under the ROC curve (AUC) of 98.2% (95% confidence interval: 97.4%–98.9%). These results suggest that directly detecting lesions may not always be necessary for reliable DR screening.

In 2018, Kemal Adem [6] proposed a method to automatically detect exudates in retinal images using three publicly available datasets: DiaretDB0, DiaretDB1, and DrimDB. His approach began with standard preprocessing steps, followed by segmenting the optic disc (OD) using circular Hough transformation to exclude OD regions from the analysis. At the heart of the system was a CNN-based model designed to identify exudates in retinal fundus images automatically. The images were captured with digital fundus cameras. For DiaretDB0 and DiaretDB1, images had a resolution of 1500 × 1152 pixels, 24-bit color depth, and a 50° field of view. DrimDB images had a 60° field of view with a resolution of 570 × 760 pixels, also with 24-bit color depth. DiaretDB0 included a total of 130 fundus images.

The model was trained and tested separately on each dataset, and the results were outstanding. In DiaretDB0, it achieved 100% sensitivity, 98.41% specificity, and 99.17% overall accuracy. For DiaretDB1, it delivered 99.2% sensitivity, 97.97% specificity, and 98.53% accuracy. The results remained impressive on the DrimDB dataset, with 100% sensitivity, 98.44% specificity, and 99.18% accuracy.

Later, in 2020, Wejdan L. Alyoubi and her team [7] discussed the limitations of diagnosing DR manually using retinal fundus images. This traditional process is often time-consuming, expensive, and prone to human error. In comparison, computer-aided diagnostic systems – especially those powered by deep learning – have shown great promise in improving both the speed and accuracy of DR diagnosis. Deep learning has become an increasingly popular tool for analyzing and classifying medical images, offering significant advantages over conventional methods.

Segmenting retinal blood vessels and detecting DR often relies on publicly available retinal image datasets [8]. These datasets are essential for training, validating, and benchmarking the performance of automated diagnostic systems. Retinal imaging typically involves fundus color photography and Optical Coherence Tomography (OCT), which together provide both 2D and 3D views of the retina using low-coherence light. This helps capture detailed information about retinal structure and thickness.

In one such method, segmentation maps were generated through two separate processing paths and then combined to produce the final output. This approach delivered excellent results, achieving an accuracy of 95.80% on the DRIVE dataset and 96.01% on CHASE_DB1, with AUC scores of 0.9560 and 0.9577, respectively.

Many researchers have focused on detecting specific DR indicators like hemorrhages, microaneurysms, and exudates. For example, in 2003, Sánchez et al. [9] used a statistical mixture model with dynamic thresholding to isolate exudates from the background. Later, in 2012, Giancardo et al. [10] developed a method using color and wavelet-based features, achieving strong results with an SVM classifier and reporting AUC values ranging from 0.88 to 0.94, depending on the dataset.

In 2017, Fraz et al. [11] introduced a multiscale segmentation technique using morphological reconstruction and Gabor filters to extract features, followed by classification with a bootstrap decision tree, specifically targeting exudate regions. Similarly, Kaur and Mittal (2018) [12] used dynamic thresholding to outline exudate boundaries, achieving sensitivity scores of 88.85% for image-level detection and 94.62% for lesion-level detection.

For hemorrhage detection, Tang et al. (2017) [11] divided retinal images into smaller regions called "splats" and extracted features like texture, area, and color. Their approach achieved AUC scores of 0.96 for patch-level analysis and 0.87 for full image-level analysis.

Walter et al. (2007) [13] addressed microaneurysm detection using kernel density estimation and morphological operations to create feature vectors, which were classified using KNN, Gaussian, and Bayesian models. Their method achieved an accuracy of 88.5%.

Grinsven et al. (2016) [14] proposed a nine-layer CNN trained on misclassified negative samples to detect hemorrhages, achieving AUC scores of 0.89 and 0.97 across two datasets. Similarly, Shan and Li (2016) [15] used a patch-based method with stacked sparse autoencoders for microaneurysm detection, reaching an accuracy of 91.38%.

For accurate DR diagnosis, it's essential to detect exudates, hemorrhages, and microaneurysms together, yet many studies have only focused on identifying these features separately. Few have succeeded in integrating all three into a single, reliable system.

To differentiate between individuals with and without DR, Agurto et al. (2007) [16] used a multiscale amplitude-modulation frequency-modulation (AM-FM) method to extract texture features from segmented retinal images. They calculated distance metrics based on these features to separate the two groups. While the approach successfully detected DR-affected regions, it couldn't distinguish between the specific lesion types – exudates, hemorrhages, and microaneurysms – which is critical for effective treatment planning.

Tan et al. (2016) [17] designed a ten-layer CNN model to detect DR-related features. Their system showed good sensitivity (0.87) for exudates but struggled with hemorrhages and microaneurysms, achieving sensitivities of only 0.62 and 0.46, respectively. One key limitation was its patch-based design, which analyzed small parts of the image rather than the entire fundus. This likely caused background areas to be misclassified, reducing overall detection performance.

Patch-based methods are frequently used in CNN-driven retinal image analysis [18], but they often suffer from inconsistencies due to variable lesion sizes and lack of contextual awareness. These limitations stem from evaluating pathological features in isolation, without accounting for surrounding tissue or background information. Although some studies have succeeded in separating microaneurysms from the background or precisely outlining exudates, most of them focus on detecting a single type of lesion at a time.

This single-sign detection approach can result in overlapping identifications among exudates, hemorrhages, and microaneurysms, reducing diagnostic accuracy. Moreover, while various techniques exist for enhancing image quality and identifying DR signs, there is still no comprehensive framework that integrates detection, classification, and contouring of all three lesion types in a unified system.

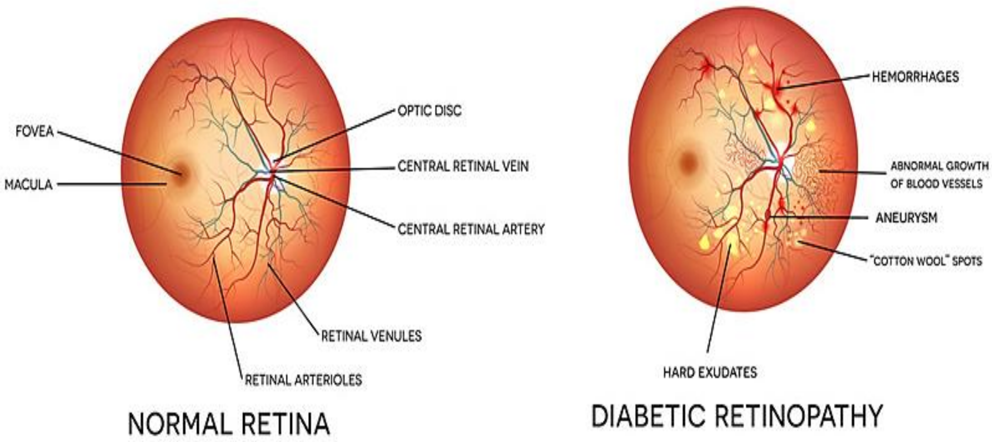

Figure 4. Normal retina and patients with diabetic retinopathy (https://medsurgeindia.com/cost/diabetic-retinopathy-treatment-cost-in-india/).

Figure 4 illustrates how DR develops in individuals with diabetes due to damage to the blood vessels of the retina. This condition can arise particularly in patients with consistently high blood sugar levels. Initially, DR may cause mild vision problems, but if left untreated, it can progress to severe vision loss or even blindness. Chronically elevated blood glucose levels can block normal retinal blood vessels. In response, the eye attempts to form new, but abnormal, blood vessels. These fragile vessels are prone to leaking blood and fluid, leading to a condition called macular edema, which results in blurred vision. As DR progresses, scar tissue can form and block the fragile new blood vessels that develop in the retina. This increases pressure on the retina, which can eventually lead to retinal detachment. In more severe cases, it can cause serious complications like glaucoma or even permanent vision loss.

In response to this, the study presents a comprehensive framework based on CNNs to help detect early signs of DR from retinal fundus images. The system is designed to segment exudates and detect both hemorrhages and microaneurysms – three key indicators of DR. A ten-layer CNN model was built and trained using image patches that were carefully labeled to represent exudates, hemorrhages, microaneurysms, and healthy areas.

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Once trained, the model generates probability maps to highlight where these signs of disease are present. To improve accuracy, a post-processing step filters out irrelevant pixels that may look like real lesions but aren't pathological. The researchers also used Receiver Operating Characteristic (ROC) curve analysis to find the optimal threshold values for detecting each type of abnormality.

The system was evaluated using two publicly available datasets – one for training and both for testing – through patch-level and full-image analysis. To make sure the results were consistent and reliable, the experiments were repeated ten times, and the performance was averaged across these runs.

The table below explains several recent DR detection methods and their performance:

- Jebaseeli TJ, et al. (2019) [1] utilized the Tandem Pulse Coupled Neural Network (TPCNN) and a Deep Learning-Based Support Vector Machine (DLBSVM). It uses datasets, such as STARE, DRIVE, HRF, REVIEW, and DRIONS. Their model achieved 99.49% accuracy, 80.61% sensitivity, and 99.54% specificity.
- K. Shankar et al. (2020) [2] employed the Synergic Deep Learning (SDL) model on the Messidor DR dataset. This reported 98.93% accuracy, 97.39% sensitivity and 99.04% specificity.
- Xuechen Li et al. (2019) [4] introduced the Lesion-Aware Convolutional Neural Network (LACNN) using a proprietary OCT image dataset. The model reached 92% accuracy, 90% sensitivity and 95% specificity.
- Ramon Pires et al. (2019) [5] developed a CNN-based solution evaluated on the Kaggle competition dataset. This was tested on Messidor-2, achieving an AUC of 98.2% (95% CI: 97.4–98.9%).
- Kemal Adem (2018) [6] used a CNN model with the DiaretDB0, DiaretDB1, and DrimDB datasets. The performance results were:
    - *DiaretDB0:* 100% sensitivity, 98.41% specificity, 99.17% accuracy.
    - *DiaretDB1:* 99.2% sensitivity, 97.97% specificity, 98.53% accuracy.
    - *DrimDB:* 100% sensitivity, 98.44% specificity, 99.18% accuracy.
- Wejdan L. Alyoubi et al. (2020) [7] applied deep learning and CNNs. This used the DRIVE and CHASE_DB1 datasets. It achieved accuracies of 95.80% and 96.01%. It achieved corresponding AUCs of 0.9560 and 0.9577.

Table 1. Summary of techniques in DR detection.

S. N.	Authors (Year)	Methodology	Dataset(s) Used	Performance Metrics
1	Jebaseeli TJ, et al. (2019) [1]	Tandem Pulse Coupled Neural Network (TPCNN) combined with Deep Learning-Based Support Vector Machine (DLBSVM)	STARE, DRIVE, HRF, REVIEW, and DRIONS	Achieved 99.49% accuracy, 80.61% sensitivity, and 99.54% specificity.
2	Shankar K. et al. (2020) [2]	Synergic Deep Learning (SDL) framework	Messidor DR	Recorded 98.93% accuracy, 97.39% sensitivity, and 99.04% specificity.
3	Xuechen Li et al. (2019) [4]	Lesion-Aware Convolutional Neural Network (LACNN)	OCT image dataset	Reported accuracy of 92%, sensitivity of 90%, and specificity of 95%.
4	Ramon Pires et al. (2019) [5]	Deep CNN model evaluated under cross-dataset protocol	Kaggle DR dataset (training), Messidor-2 (testing)	Achieved an AUC of 98.2% (95% Confidence Interval: 97.4%–98.9%).
5	Kemal Adem (2018) [6]	CNN-based Exudate Detection System	DiaretDB0, DiaretDB1, and DrimDB	DiaretDB0: Accuracy 99.17%, Sensitivity 100%, Specificity 98.41%; DiaretDB1: Accuracy 98.53%, Sensitivity 99.2%, Specificity 97.97%; DrimDB: Accuracy 99.18%, Sensitivity 100%, Specificity 98.44%.
6	Wejdan L. Alyoubi et al. (2020) [7]	Deep Learning using CNNs for vessel and DR segmentation	DRIVE and CHASE_DB1	Achieved accuracy of 95.80% (DRIVE) and 96.01% (CHASE_DB1); AUC values of 95.60% and 95.77%, respectively.

CONCLUSIONS

To enhance image clarity and reduce noise, especially in photos taken under different lighting conditions, the CLAHE technique is applied. Next, the TPCNN model combines two input images and extracts key features that help in identifying retinal blood vessels. These features are then passed to the DLBSVM system, which classifies each pixel as either part of a blood vessel or not. DLBSVM uses multiple layers to boost classification accuracy and minimize mistakes when separating vessels from the background. To further fine-tune the process, the Firefly Algorithm is used to optimize the classification settings. Altogether, this approach provides ophthalmologists with reliable tools to analyze the structure of retinal blood vessels, aiding in the accurate diagnosis of diabetic retinopathy.

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