



RESEARCH ARTICLE

OPEN ACCESS

MULTI-STAGE DIABETIC RETINOPATHY CLASSIFICATION USING DEEP LEARNING: TRENDS, CHALLENGES, AND FUTURE DIRECTIONS

Shreya Dubey¹, Mahesh Goyani^{*2}, Pinal Patel³, Safvan Vahora⁴, Uttam Chauhan⁵, Mahendra Patel⁶

^{1, 2, 3, 4, 5, 6}Department of Computer Engineering, Government Engineering College, Modasa, India

¹<http://orcid.org/0009-0006-5350-5215> , ²<http://orcid.org/0000-0002-7269-1176> , ³<http://orcid.org/0000-0003-1086-8906>

⁴<http://orcid.org/0000-0002-8051-8429> , ⁵<http://orcid.org/0000-0003-4373-2132> , ⁶<http://orcid.org/0000-0002-4342-1070>

E-mail: shreya4dubey@gmail.com, *mgoyani@gmail.com, pinal.patel@gecmmodasa.ac.in, safvan465@gmail.com, uttam.chauhan@gecmmodasa.ac.in, mnpatel32@gmail.com

ARTICLE INFO

Article History

Received on: March 03, 2026

Reviewed on: April 03, 2026

Accepted on: May 01, 2026

Published on: July 31, 2026

Keywords:

Diabetic Retinopathy,
Symptoms,
Microaneurysms,
Hemorrhages,
Exudates

ABSTRACT

Diabetic Retinopathy (DR) is a primary cause of vision loss globally in patients suffering from diabetes. Timely detection of the disease can reduce the chances of blindness. Fundus images are studied by the Ophthalmologists for any signs of the disease. Existing methods for detecting DR include manual study by the experts or usage of Artificial Intelligence-based models. But these methods encounter several issues like inaccurate detection, time-consuming, costly including the lack of stable datasets and consistent image processing techniques. Owing to the damage these lesions do to the retina it becomes essential to look for an efficient and accurate model for diagnosing DR. Deep Neural Networks help us to segment the fundal images to focus on the retinal areas helping us to look for early signs of the disease. If DR is detected at an earlier stage, the risk of complete blindness can be reduced. This paper presents a comprehensive survey of existing models for Diabetic Retinopathy detection, with an intention of identifying opportunities for improvement to develop a more robust and stable model which can efficiently and accurately perform the classification. It also includes detailed discussion on various datasets used for detection/classification of the disease.



Copyright ©2026 by authors and Galileo Institute of Technology and Education of the Amazon (ITEGAM). This work is licensed under the Creative Commons Attribution International License (CC BY 4.0).

I. INTRODUCTION

Prolonged high blood sugar levels due to low amount of insulin produced by pancreas leads to Diabetes Mellitus commonly known as *Diabetes*. There are mainly two categories of it: Type-1 whose root cause is not known and Type-2 which can be identified by the symptoms like Microaneurysms, Hemorrhages, Exudates, etc. This when left untreated for longer duration can lead to lesions on the retina and ultimately leading to blindness [1]. DR mainly occurs due to retinal vascular disease and abnormal flow of blood through retina which could eventually lead to blood or fluid leakage [2]. In a survey conducted in 2021, it was found that around 26% of diabetic patients in the United States had suffered from DR and around 5% of diabetic patients had reported severe case of DR that could lead to vision-loss. According to World Health Organization, issues related to diabetes will cross 700 million by 2045 and out of this approximately 1/3rd will face issue of this disease [3]. It is one of the five leading causes of vision loss along with glaucoma, refractive errors, age-related macular degeneration (AMD) and cataract. A study showed that some of the leading causes for DR include poor renal function, elevated blood glucose levels, liver disease, hematonosis (blood disorders), and high blood pressure [4]. The common symptoms for DR include frequent vision blurriness or difficulty while reading later on when severity increases it can include dark spots in vision, fluctuated or disorientated vision or retinal detachment ultimately leading to blindness. Although DR is irreversible but detecting it in early stages can help control the damage by controlling the factors like hypertension and hyperglycemia. DR can be detected either manually or automatically by using techniques such as laser treatment, anti-VEGF injections, or vitrectomy [1]. Figure 1 describes the various stages of DR, which are classified into namely - Normal, Mild Non-Proliferative Diabetic Retinopathy (NPDR), Moderate NPDR, Severe NPDR and Proliferative Diabetic Retinopathy (PDR). The main classification being Normal vs NPDR vs PDR. NPDR further being classified as Mild, Moderate, and Severe based on the type and amount of lesions present.

It also shows the vital symptoms which show the presence of DR. Ophthalmologists target these lesions to check for the presence of the disease and understand its severity. Normal grade also known as NO-DR stage is a condition where the eye is normal and retina shows no signs of the lesions. The vision of the patient remains unaffected. Mild NPDR is the earliest stage of the disease where microaneurysms begin to generate. There are no to very least chances of vision loss at this stage, and the retina remains intact. In the Moderate NPDR stage more microaneurysms begin to appear and other lesion structures like hemorrhages, and hard exudates also start to generate. Veins and capillaries begin to get blocked, reducing blood flow. Blood leakage starts which leads to the issue of Macular Edema. Severe NPDR stage witnesses lesions like cotton-wool spots and venous beading. The issue of vein blockage increases after which blood supply to the retina almost stops hence level of oxygen reduces in the retina. PDR stage faces Neovascularization i.e., the new and abnormal blood vessels begin to appear on retina and optic disc. The vessels being weak tend to burst and lead vitreous hemorrhage. If not attended on time, it can lead to significant blood loss.



Figure 1: Different classes of Diabetic Retinopathy.

Source: [5].

The common symptoms of DR include *microaneurysms* which are usually seen in people suffering from diabetes when the capillary walls widen. They are usually seen in the form of small red dotlike structures when captured in colored fundus images and bright hypersensory spots when looked through fluorescein angiography. They are usually found in the early stages of DR [6]. *Hemorrhages* are the initial indicators used to detect DR when it enters in severe stages. Hyperglycemia causes damage to the blood vessels which results in their bursting, causing hemorrhages. There are different types of hemorrhages like *flame-shaped* hemorrhages found in the top layers and *dot-blot* hemorrhages found in the lower layers. Non-proliferative retinopathy is caused by the presence of large numbers of hemorrhages [7]. *Exudates* occur due to an increased blood sugar levels damaging the blood vessels, leading to leakage of yellow-white lipid and protein deposits. They are mainly categorized into - soft exudates and hard exudates. Soft exudates are the yellow-white colored lesions also known as the cotton wool spots generally found in the nerve fiber layer. They are fluffy in texture [8]. Hard exudates are comparatively brighter and reflective in nature. Found in different sizes, they are generally white- or cream-colored lesions. They are a strong indicator of diabetic macular edema (DME) and affect the central vision [9]. They are marked with sharp boundaries and have a waxy, shiny texture located into the outer layer of the retina.

Medical equipment like ophthalmoscope and fundus cameras are used during eye-checkups. But using these traditional method is time-consuming as well as expensive, the doctor and patient ratio is 1:10,000 making it difficult to give personal attention to each patient. Thus it creates a need for an automated detection method which can easily, accurately and consume less time to classify the disease. Although it is not curable but if detected timely we can slow down its progress and save eyesight of the affected. Ophthalmologists study the fundus images for finding any abnormalities or lesions in the retina. Along with fundus images - Slit lamp Images, Ultrasonic Images and Digital Images are used for DR detection [10]. It can become difficult to detect DR in earlier stages as the symptoms are minor and can be missed by the human eye. So there is a need for Machine Learning-Deep Learning based models which can easily process images to detect and segment affected areas. It can also help in predicting the severity of disease [11]. Thus models trained using DL are used in modern-day medical analysis to analyze the fundus images, focusing on studying retina's blood vessels. The data is processed through numerous layers aimed for automatic recognition of patterns and extraction of complex features which is a fundamental requirement for classification of Diabetic Retinopathy using fundus images [12]. Along with DR detection technique the dataset also plays an important role in this. The symptoms may vary according to the demographic variety or factors like age, gender or previous medical conditions. So a stable dataset covering different varieties of patient is required to train the model in order to get accurate and unbiased results [13]. Table 1 discusses about the existing commercial systems used for DR detection and the limitation faced by the systems.

Table 1: Comparative Analysis of Commercial Diabetic Retinopathy (DR) Detection Systems.

System	Approval	Staging Capacity	Image Quality Dependency	Major Limitation
IDx-DR	FDA	Only referable DR	High	No detailed DR
EyeArt	FDA, CE	DR + DME	High	High false positives
RetmarkerDR	CE	Early DR focus	Moderate	Limited to detecting microaneurysms
Google DR AI	Clinical use	Multi-stage DR	High	Limited availability
EyePACS	Clinical use	Multi-stage DR	Moderate	Depends on graders
RetinaLyze	CE	Limited	Moderate	Not autonomous
Bosch DR AI	Clinical use	Referral-based	Moderate	Limited published validation
Remidio DR AI	CE	Limited	High	Smartphone image limitations

Source: Authors, (2026).

In this paper we have studied various state-of-the-art-methods implemented by multiple researchers in the domain of DR classification on various performance parameters based on the methodology used for classification task and symptom specific methods too. We have also identified the research gaps from the previous work and tried to highlight challenges in existing methods. The paper also includes the detailed discussion about the symptoms and types of diabetic retinopathy. The remainder of the paper is structured as follow. Section I discusses the literature review of the previous work, divided further according to the technology used for the model. It also discusses the works done for DR detection based on the symptoms of disease. The section also includes a detailed discussion on various datasets giving us an insight about the kind of data available to DR classification. In section II we will be discussing the challenges and future scopes faced by the researchers while developing a mode for DR classification. Section III concludes the survey done by summarizing the importance of DR detection and the ways used for the same.

II. LITERATURE REVIEW

Analyzing previous work can help us build a model by filling their research gaps and creating a more efficient, accurate, and reliable one. In this section, we will be discussing the works of various authors who have carried out research in this field and trying to understand the gaps present between their research and limitations faced by them. There have been several studies carried out for the classification of DR using algorithms based on Machine Learning, Deep Learning, and Hybrid Learning. Along with that, we can also focus on symptom-wise classification techniques of DR. Figure 2 is used to visually showcase the broader categorization of DR-detection techniques.

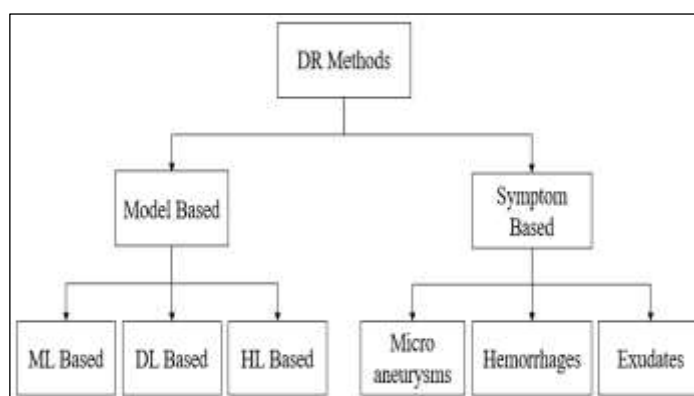


Figure 2: Taxonomy for Diabetic Retinopathy Detection.

Source: Authors, (2026).

II.1 ML-BASED TECHNIQUES FOR DR CLASSIFICATION

Machine learning is a widely used technology among researchers for medical diagnosis of any disease owing to accuracy and wide adaptability. We can further classify the ML techniques based on the kind of classification it does - binary classification usually indicates the absence or presence of the disease whereas the multi-class classification is used to grade the disease severity.

II.1.1 Binary-Class-Classification

Ashim Chakraborty [14] created a model focused on detecting the three early signs of the Diabetic Retinopathy namely the Hard Exudates (HE) - the yellowish spots, Microaneurysms - the tiny red dots and Blood Vessels - the abnormal vessel growth. Then binary classifier 6 was used to detect if these features indicated presence of DR or not. Multiple datasets like DIARETDB0, DIARETDB1, Messidor, Kaggle DR dataset were used. Accuracy for DR detection based on the lesion is HE with 95.7%, MA with 93.45% and BV with 90% accuracy. But the model had several issues like dataset imbalance, risk of false positives. Krishnendu Barik and Anil Kumar studied the biomarker genes found in blood samples to check for the presence of DR using RNA sequencing dataset-GSE221521 containing 69 DR and 50 Healthy-controls (Non-DR) patient data for the identification of Differentially Expressed Genes(DEGs). They trained multiple ML-based models like SVM, Logistic Regression, Random Forest, Gradient Boosting, Neural Network on the 7-Key genes selected through Elastic Net regularization out of which SVM performed the best with an accuracy of 86% [15]. Researcher Hassaballah and Hameed introduced a metaheuristic algorithm combining standard Golf Optimization Algorithm (GOA) with genetic operators. They introduced three hybrid models - mGOA-SVM, mGOA-radial SVM, and mGOA-kNN developed for both binary and multi-class classification on Messidor and EyePACS dataset respectively. [16]. Michal Gandor et al. adopted feature engineering technique combining multiple data preprocessing techniques along with several feature extraction algorithms to develop a model for the early diagnosis of the disease. On the basis of the preprocessing techniques applied four variants were created - pure, no-vessels, no-vessels-no-optic-disk and no-optic-disk. They experimented with an aggregated dataset of 8 public datasets and 1 private dataset making the results non-biased and more accurate. Random forest and XgBoost were the two classifiers used for detecting DR. [17]. Penikalapati Pragathi et al. developed an integrated approach using SVM, PCA and Moth-Flame Optimization for detecting DR and achieved an accuracy of 86.3%. Usually using PCA reduces the performance of the algorithm and to balance it out Moth-flame optimization technique is used. It selects the optimal features improving the performance. The model was trained and tested on the Diabetic Retinopathy Debrecen dataset from the UCI ML repository [18]. Michele Bernardini et al. developed a model for Task 1 - Risk of DR and Task 2 - temporal stratification of DR risk in 0-2 years vs. 2-5 years creating a Clinical Decision Support System. The paper used 120K dataset from multiple Italian diabetologic centers consisting of EHR: demographics, pathology codes, and lab tests. Among the various ML algorithms used Random Forest (RF) achieved the highest accuracy [19].

II.1.2 Multi-Class Classification

Xiaoli Li et al. [20] used clinical data and OCTA (Optical Coherence Tomography Angiography) images to develop a model to grade DR into 3 classes each with a binary classification - DR Identification (Non-DR and DR), Referable DR (RDR) - Identification (Non-RDR and RDR), Vision-Threatening DR (VTDR) – Identification (Non-VTDR and VTDR). The paper focused on four ML models - Random Forest (RF), Gradient Boosting Machine (GBM), Logistic Regression (LR) and Deep Learning DL. Xu Wang et al. [4] focused on following a white-box approach by adopting SHAP (SHapley Additive exPlanations) interpretability model to reason out the findings hence increasing model's reliability. The model used 1000 records from diabetes complications early warning dataset and compared 5 distinct ML-algorithms Support Vector Machine(SVM), Random Forest, XGBoost, Gradient Boosting Tree and CatBoost. Researcher Gigi Tabacaru et al. [21] used PyCaret library to select the best performing model out of the 15 available models and found that the Gradient Boosting Classifier (GBC) is the best performer with an accuracy of 92.9%. They used Indian Diabetic Retinopathy Image Dataset (IDRID) to classify the results at different severity level - NoDR/Mild, NoDR/Moderate, and NoDR/Severe. Eman Abdelmaksoud et al. [22] proposed Multi-Label Computer-Aided Diagnosis (ML-CAD) system initially performing binary classification using SVM and GLRLM features to filter the cases then using the U-Net model to segment the pathological variations and lastly using a Multi-Label SVM (MLSVM) based on a Classifier Chain (CC) for grading the disease. Multiple datasets - DRIVE, HRF, STARE, CHASEDB1, DIARETDB0, IDRID, DIARETDB1, and Messidor were used for the experiment. Aqib Ali et al. [23] developed an image segmentation method called Center-Based Irregular Polygon Region-Growing Segmentation(CARGS) for isolation of lesions before performing feature extraction. An irregular polygon shaped seed is used to circumference the lesion boundary then using K-Means clustering these pixels are separated into 3 clusters - background, normal retina and lesions affected areas. Features like GLCM, histogram, wavelets, etc. are extracted and fed to ML classifiers like Sequential Minimal Optimization, Logistic Model Tree, Multilayer Perceptron classifier. Table 2 some of the top ML models reviewed and their features.

Table 2: Comparison of ML approaches for diabetic retinopathy diagnosis.

Ref	B/M	Preprocessing	Model	Dataset	Performance
[16]	B	Data Cleaning, Formatting	m-GOA radial SVM	Messidor, EyePACS	A: 99.12%, P: 99.15% A: 98.91%, P: 98.87%
[14]		CLAHE, Grey Scaling	Supervised ML model	Messidor, DiaretB0	A: 95.70%, P: 96.64%, F1: 96.37%, S: 96.11%
[15], [18]		PCA, Denoise, Normalization	SVM	Debrecen	A: 86.30%, P: 86.00%, F1: 86.00%, S: 94.20%
[15]		Normalization, Regularization	SVM	GSE221521	A: 86.36%, P: 100.00%, F1: 86.96%, S: 76.92%
[20]	M	Data Clean, Missing Data	RF	Clinical + OCTA	AUC: 96.65%
[23]		Grayscale, HE, CARGS	LMT + SLg	Private dataset	A: 99.73%, AUC: 100.00%
[22]		Filtering, HEBPDS	MLSVM + U-Net	Multiple datasets	A: 95.05%, S: 86.11%, AUC: 91.85%
[21]		Gamma Correction	M11 + GBC	IDRID	A: 92.90%, F1: 90.20%, AUC: 94.10%

B: Binary DR classification, M: Multi class DR classification, A: Accuracy P: Precision F1: F1 Score S: Specificity AUC: Area under Curve.

Source: Authors, (2026).

II.2 DL - BASED TECHNIQUES FOR DR CLASSIFICATION

Deep Learning provides us with several models implemented using neural networks utilizing which we can easily analyze and study the images. Image analysis is an integral part of healthcare, and DL allows us to do that very efficiently by using variants of model like CNN.

II.2.1 Binary-Class Classification

In a study conducted by SamiaAkhtar et al., he created custom Convolutional Neural Network (CNN) model called RSG-Net (Retinopathy Severity Grading) used for both multi-class and binary classification with accuracy being 99.36% and 99.37% respectively. Gaussian Blur technique was used for reducing the noise in the image, Histogram equalization for enhancing the contrast and brightness of the image. The images were resized and augmented as well. The model was trained and tested for the Messidor-1 dataset with split ration of 70% Training, 10% Validation, 20% Testing. The limitation of the model being that it can be prone to issue of over-fitting and generalization to diverse dataset as it was tested only for Messidor-1 [24]. Amad Zafar developed a two-stage deep learning framework for the detection as well as the classification of the severity of the disease. A lightweight network was designed for binary classification. And if the disease is detected then in the next phase a transfer learning approach was implemented wherein the model trained in earlier staged is re-used and fine-tuned for the multi-class classification for the severity level. The primary dataset for the model being APTOS2019 and FairVision and DDR dataset for the validation purpose. The pre-processing techniques used were Data Augmentation, Normalization and Image Cropping [25]. M. Mutawa proposed a framework following randomized-based learning approach in traditional image processing techniques.

The preprocessing included techniques like Green channel extraction to reduce the noise, CLAHE for noise reduction and contrast enhancement and morphological operations to focus on the blood vessels and Otsu's thresholding for image binarization and segmentation of blood vessels. After that feature extraction is done on the preprocessed images using two parallel methods: Multi-Scale Discriminative Robust Local Binary Pattern (MS-DRLBP) responsible for capturing the local texture and edge patterns and CNN model (VGG16) responsible for automatically analyzing the complex features from the images. After that classification done using a hybrid CNN model - Radial Basis Function (CNN-RBF). It takes the combined features from both MS-DRLBP and VGG16 for the binary classification of the dataset. Randomization in framework was applied by the non-iterative nature of Otsu's method for thresholding and random initialization of RBF centres this reduced the complexity of computation and simplified the learning process. The model achieved an accuracy of 96.1%. A combined dataset of STARE, HRF, and FFA was used with a split of 60% for training and 40% for testing [12]. Saad Alanazi proposed a model called the FedCNN with VGG19 for segmentation and SMOTE with its core being the Federated learning (FedCNN) to maintain privacy of the patient's data by only sharing the local updates from each hospital's AI model learning instead of sharing the raw patient data. The CNN model VGG19 was employed for recognizing the intricate patterns and features in the images. Its primary work is to segment the important areas of the retinal images and after that extract detailed information of the features from the segmented areas. SMOTE(Synthetic Minority Oversampling Technique) was also used to create synthetic data to balance the model training. He worked on the EyePACS dataset from Kaggle. Pre-processing techniques like Weinmed Filtering(Weiner and Median Filter) and SMOTE were used to enhance the dataset achieving an accuracy of 98.0% [26].

Yixiao Li introduced an improved framework on an existing network KiU-Net making it more accurate and efficient at segmenting the HRF. HRF(hyperreflective foci) are the tiny, bright spots in OCT images used for detection DR. KiU-Net is a combination of two kinds of model called the Kite-Net branch for upscaling of the images to detect even the small lesions like the HRF. This allows us to extract more fine-tuned and detailed knowledge about the small structures. Another model being the U-Net branch used for extract the high-level of semantic information unlike the Kite-Net in downscales the images to get a broader view of the image and analyze the larger patterns. Further it uses the Cross-Attention Block(CAB) to combine the results of both of these to get the final information about the images. The dataset used here was 173 OCT images from 50 patients, obtained from the Department of Ophthalmology, Qilu Hospital affiliated with Shandong University, China. Common techniques like the Denoising the OCT images along with Bilateral Filtering and Augmentation were used to get the best of the dataset. For pixel-level segmentation using Kite-Net, the model achieved a Dice Similarity Coefficient (DSC) of 66.84% and for HRF number detection, the model achieved a Dice Similarity Coefficient (DSC) of 71.32% [27]. K. K. Mujeeb Rahman et al. gathered 560 fundal images combining Kaggle, DDR, Mendeley data and Zenodo datasets. The study involved both the SVM and DNN models with DNN getting an edge with an accuracy of 95.77%. The model was fed with features extracted using the GLCM(Gray Level Co-occurrence Matrix) technique [28].

Fasmin Shi, developed a technique called the Fair Adaptive Scaling(FAS) module which can be used as an add-on to other existing models. Its main focus is to reduce the difference of performance rates among different demographic groups like Whites and Blacks. FAS works on Individual and Group Scaling. Individual scaling focuses on giving more attention to the individual images who are having difficult time to be analyzed like if they giving wrong or uncertain results during the training stages. Group scaling focuses on the overall performance of the model for a particular demographic group. If a group shows higher error rate or is underrepresented its samples are given more weight. FAS is integrated with several Backbone models like the EfficientNet and ViT-B for 2D OCT images and ResNet18 and DenseNet121 for 3D OCT images. These backbone models are responsible for extracting complex features and patterns from the eye images. The study included both the private datasets from Massachusetts Eye and Ear - MEE like MEE In-House Color Fundus Dataset and MEE In-House Color Fundus Dataset and public datasets like ODIR-5K and Harvard-FairVision30k [29]. In a study by Manish Bali et al., a hybrid model was introduced called QuantumNet combination of a pre-trained ResNet-50 model and a Variational Quantum Classifier(VQC). The ResNet-50 model was responsible for extraction of features from the images of retina and VQC was tasked with classification of data from ResNet by encoding it into quantum states. The VQC uses a 4-qubit dressed quantum circuit to classify the 2048-dimensional feature vector into 4 dimensions. APTOS2019 dataset was split into 70% training, 15% validation and 15% testing set. Pre-processing techniques like Re-scaling and Image augmentation were employed. The model achieved an accuracy of 94.11%. The model faced limitations like requirement of advanced error correction techniques in quantum devices. Limited qubit counts and higher error rates in current quantum computers [30].

II.2.2 Multi-Class Classification

Lein Sun et al. developed MAFNet(Multi-Scale Adaptive Fine Grained Network) model for fine grading of the disease into all 5 stages and not only limiting to the binary prediction. The main crux of the model was ConvNeXt CNN and it consisted of three modules: HGCM(Hierarchical Global Context Module), MSAM(Multi-scale Adaptive Attention Module) and RMA(Relational Multi-head Attention). HGCM responsible for analyzing both the global region(big picture) and local region(small lesions) simultaneously. MSAM was tasked to focus on the most essential lesion areas of the retina. RMA focusing on finding relationships between different lesions. The model was trained for the purpose of both classification and regression. It used multiple datasets like the DDR, Messidor-2 and APTOS2019 split into a ratio of 6:2:2(train:validation:test). The model received highest accuracy of 88.2% on DDR dataset followed by APTOS with 87.4% and last Messidor-2 having 82.2% accuracy [2]. Amina Zedadra et al. developed a model called DRdiag which was an integration of CNN and GNN. The CNN model uses the DenseNet121 pre-trained on ImageNet dataset and the GNN model is a two layer Graph Convolutional Network (GCN). The CNN model focused on extracting the intrinsic feature from the fundus images whereas the GNN model was used to understand the complex relationship between the patients. The outputs of both the models were combined using the adaptive fusion mechanism. The two publicly available datasets Messidor-2 and APTOS2019 were used by the model. The model achieved an accuracy of 98% for the APTOS dataset and 97.6% for the Messidor-2. The limitation of the model being that it only considered one clinical risk factor i.e., the duration of diabetes for analysis and avoided other essential features [31]. A study by Hussain et al. proposed an enhanced P-EDR (Diabetic Retinopathy) method based on a Convolutional Neural Network (CNN) to diagnose diabetic retinopathy (DR) using retinal images.

It uses dataset of retinal images from the Kaggle DR. The data was preprocessed through normalization, augmentation, and resizing to improve image quality and feature extraction. The images were standardized to 224x224 pixels to ensure uniform input size for the machine learning models. The results showed that the CNN-based P-EDR model outperformed the other models. It achieved an accuracy of 93% [32]. S Jahangeer Sidiq, proposed an ensemble deep learning model for detecting and classifying the 5 different stages of Diabetic Retinopathy. The authors divided the classification of disease into a 12 multiple simpler binary classification task using a One-Versus-One (OVO) mechanism. It used pre-trained, lightweight models in the form of base learners and for the final result majority voting was used by combining their outcomes. Among the other base learners MobileNet, InceptionV3, and DenseNet121 were found to be achieving highest performance. The model worked on the APTOS2019 with MobileNet as the base learner, IDRID with InceptionV3 as the base learner, Messidor-2 using DenseNet121 base learner and DDR with MobileNet as the base learner. The images were pre-processed using the resizing and data augmentation process. The model achieved an accuracy of 92% for the APTOS2019 dataset, 85% for IDRID, 86% for Messidor-2 and 88% on the DDR dataset [33]. Omar Dib proposed a secure server-less framework called FL-BC-SMPC-SMOTE to avoid the risk of security breach of patient data. The model trains AI models with their patient data kept private from other hospitals by sharing only the encrypted updated data on a global model. Block-chain(Hyperledger Fabric) keeps track of the updates securely and SMPC (Secure Multi-Party Computation) is tasked to ensure that no user can see the actual changes of others data to strengthen the privacy of the model.

IPFS (InterPlanetary File System) is used to efficiently store the encrypted parts of AI model. SMOTE(Synthetic Minority Over-sampling Technique) is used for creating synthetic data for rare disease cases so as to avoid issue of under-fitting. Several CNN-based models like EfficientNet-B0, ResNet-18, SqueezeNet, Custom CNN were trained on the APTOS2019 dataset with the 80% - 20% training-testing split. The model achieved an accuracy of 90% with individual being ResNet-18: 91.65%, EfficientNet-B0: 90.08%, Custom CNN: 87.93% and SqueezeNet: 80.09% [34]. Sarra Guefrachi proposed a Multistage framework combining the feature extracting and fine-tuning techniques using multiple pre-trained CNNs. A custom classifier head was developed and added to base CNN models. Models like InceptionResnetV2, VGG16, VGG19, DenseNet121, MobileNetV2 and EfficientNet2L were used as base models achieving an overall accuracy of 96.61% on the Kaggle's diabetic retinopathy detection dataset with split ratio of 80%, 10% and 10%. General pre-processing techniques like removal of noisy and redundant images, image resizing and augmentation and contrast enhancement were implemented onto the dataset. As it was trained for only one dataset there might be an issue of the model sensitivity towards diverse datasets. Over-fitting issue being another limitation of the model [35]. The below given Table 3 summarizes some of the top DL models reviewed and their features.

Table 3: Comparison of DL approaches for diabetic retinopathy diagnosis.

Ref	B/M	Preprocessing	Model	Dataset	Performance
[24]	B	Resizing, Denoising	RSG-Net	Messidor-I	A: 99.37%, P: 98.86%, F1: 99.42%, S: 100.00%
[25]		Normalizing, Augmenting	Custom DL (37-layer)	APTOS2019	A: 99.06%, S: 99.00%
[26]		SMOTE, Filtering	FedCNN	EyePACS	A: 98.00%, P: 98.20%, F1: 98.50%, S: 98.10%
[12]		Green Channel, Thresholding	CNN-RBF	STARE, HRF, FFA	A: 96.10%, P: 97.62%, F1: 96.47%, S: 95.35%
[35]		RGB Conversion, Cropping	Inception ResNetV2	KaggleDR	A: 96.61%, P: 100.00% F1: 100.00%, S: 100.00%
[36]		Rescaling, Augmenting	QuantumNet	APTOS2019	A: 94.11%, P: 96.90%, F1: 95.86%, S: 94.84%
[2]	M	Cropping, Resizing, Augmenting	MAFNet	DDR, APTOS2019, Messidor-2	A: 88.20% κ: 93.40% A: 87.40% κ: 93.60% A: 82.20% κ: 91.70%
[31]		Augmenting, Normalizing	DRdiag	Messidor-2, APTOS2019	A: 97.60%, F1: 96.10% A: 98.00%, F1: 96.30%
[32]		Augmenting, Normalizing	P-EDR (CNN)	KaggleDR	A: 93.00%, P: 92.00%, AUC: 97.00%, S: 92.00%
[33]		Subdivision, Normalizing, Augmenting	DenseNet121, InceptionV3, MobileNet	APTOS2019, IDRID, DDR, Messidor-2	A: 92.00%, P: 92.00%, F1: 92.00%, S: 92.00%
[34]		SMOTE, Augmenting	ResNet-18	APTOS2019	A: 91.65%

Source: Authors, (2026).

II.3 HYBRID - BASED TECHNIQUES FOR DR CLASSIFICATION

Hybrid techniques combine multiple models together to utilize the best of both models to achieve the highest accuracy for the model. Integrating the model with various preprocessing techniques can also generate significant change in accuracy.

II.3.1 Binary-Class Classification

A hybrid model called Diabetic Retinopathy Detection-Capsule Network-Deep Learning combining the UNet++ for semantic segmentation and Capsule Networks for feature classification was proposed by I. Govindharaj et al [37]. The images pre-processed by the technique of CLAHE and Histogram Equalization are fed to the UNet++ model for segmentation of two essential structures of the eye namely the Optic Disc and Optic Cup. The segmented images are carry forwarded to the CapsNet to understand the underlying patterns and details of the image. It analyzes the images the segmented features to classify if the eye is normal or glaucomatous. The same architectural model is used for DR detection. Kerem Gencer et al. proposed a hybrid framework combining the Generative Adversarial Networks, Denoising Autoencoders and a fine tuned EfficientNetB0. GAN was used to generate synthetic retinal images to solve the issue of class imbalance and enrich the training dataset. The Denoising Autoencoders were responsible for enhancing the image quality by reducing the noise level and other factors like speckle noise, motion blur, and illumination inconsistencies present in both the original and GAN-generated images. The EfficientNetB0 was used for classification of the pre-processed images. The model used a custom created Optical Coherence Tomography image dataset consisting of 4274 images [38]. Govindharaj et al. proposed a hybrid model combining UNet++ for segmenting parts of eye indicating glaucoma and Capsule Network for finding intrinsic patterns and details hidden in the segmented image. Model was trained and tested on combined dataset consisting of RIM-ONE Database, DRIONS-DB and ORIGA-Light. Techniques like Histogram Equalization and CLAHE were used for pre-processing the retinal images to enhance their quality by improving the contrast and clarity of the image. The limitation of the model being highly computational and sensitive to image quality giving more importance to the pre-processing techniques [39]. K.V.

Naveen et al. proposed a hybrid model EffNet-SVM which combined the EfficientNetV2-Small 15 as a feature extractor and RBF kernel SVM as a classifier for the disease. Instead of soft-max layer generally used with CNNs, SVM was used as a classifier as it proves to be better at separating class. The model converted the multi-class APTOS 2019 dataset into a binary dataset and achieved an accuracy of 97.26%. The limitation being that the model was trained only for binary datasets and limited experiment only on two datasets namely, APTOS and HRF [13]. Ghulam Ali et al. combined ResNet-50 and Inception-v3 to study the features leading to DR. The extracted features are combined and fed to IR-CNN (Inception-ResNet CNN) and trained on Messidor and IDRiD datasets with the Messidor giving the maximum accuracy of 90.89%. The model aimed to solve the issue while detecting the lesions in early-stages [40]. Amar Shukla et al. [41] developed an integrated model of Self-Attention Network used for in detail analysis of retina features and Vision Transformer (ViT) being responsible for combining their results for DR detection. The model is named as HybridFusionNet and tested on Kaggle DR dataset achieving an accuracy of 99% for binary and 91% for multi-class classification. But the model had high computational requirements due to integration of transformer models and was sensitive to variations in quality of fundus images. Butt et al. combined transfer-learning models like GoogLeNet and ResNet-18 then the resized images are given as input to each of these model responsible to extract the deep hidden features which are further combined to create a 2000-dimensional hybrid feature set. Then for the DR identification and severity grading several ML classifiers like SVM, Random Forest, Naive Bayes, RBF, etc. are used on the APTOS 2019 dataset achieving an accuracy of 97.8% for binary classification and 89.29% multi-class classification [42].

II.3.2 Multi-Class Classification

A.S. Sabeena et al. followed a hybrid approach and combined Xception, MoNet and PolyNet models. They used APTOS 2019 dataset with split of 80% and 20%. The pre-processing steps included Median filtering, SwinUNet for segmentation based on Gradient Descent-Sea Turtle Foraging Algorithm. The model MoNetPolyNetXception achieved an accuracy 98.9%. But the model requires high computational powers and can be dataset bias [43]. Sukran Yaman Atci combined pretrained CNN models, CAD (Computer-aided diagnosis) system and SHAP explainability on three datasets including Kaggle DR fundus dataset for predicting DR severity grades. The CNN models are used to extract the lesion in retina then hybrid ensemble classifiers predicts DR stages and SHAP is responsible for highlighting the affected regions but the model suffers with imbalanced class and comparatively lower performance in moderate/severe DR stages [44]. Kazi Ahnaf Alavee et al. proposed a model which integrated explainable AI(Grad-CAM) with DL models (DL-XAI) 16 for their better interpretability b generating heatmaps for the fundus images. The model was experimented on multiple datasets like APTOS 2019 Kaggle dataset, Messidor-2 and IDRiD. Multiple existing CNN models were used to extract lesions from the fundal images and custom CNN was trained to do the classification task with an accuracy of 95.27% [45]. Ayesha Jabbar et al. used GoogLeNet and ResNet for feature extraction and optimized it with Adaptive Particle Swarm Optimization (APSO) responsible for selecting only the most apt features extracted making the classification task more efficient with accuracy of 94%.

These features were then used to train the classical ML classifiers - SVM, RF, DT, LR. The model was used to detect not only the early stage lesions but cotton wool spots, IRMA, capillary degeneration. The model was trained on Kaggle EyePACS1 dataset [46]. Yasashvini R. et al. developed multiple models using CNN and hybrid transfer-learning model for DR diagnosis and severity grading - Simple CNN, CNN + ResNet and CNN + DenseNet with an accuracy of 96.22%, 93.18% and 75.61% respectively using Kaggle DR dataset. But the models faced limitations of small dataset size and class imbalance [47]. Md Nahiduzzaman et al. applied SVD(Singular Value Decomposition) on the features extracted to reduce dimensionality and select the unique and most prominent features. ELM(Extreme Learning Machine) classifier was used to classify DR into severity grades with an accuracy of 98.09% for Aptos-2019 and 96.26% for Messidor-2 dataset and 99.73% accuracy for Binary classification. For the preprocessing stage Ben Graham and CLAHE techniques were used on the fundus images (9605633). Anas Bilal et al. developed a hybrid CNN-SVD model integrated with several transfer learning models like Inception-V3, GoogLeNet, AlexNet, and ResNet. Furthermore, two different U-Net models were used for Optic Disc and Blood Vessel segmentation in order to remove unwanted features. A basic CNN model was used to extract 256 features reduced to 100 using SVD with Inception-V3 performing the best with an accuracy of EyePACS-1 - 97.92%, Messidor-2 - 94.59% and DIARETDB0 - 93.52% [48]. The below given Table 4 summarizes some of the top HL models reviewed and their features.

Table 4: Comparison of HL approaches for diabetic retinopathy diagnosis.

Ref	B/M	Preprocessing	Model	Dataset	Performance
[38]	B	Augmentation, Denoising	GAN + EffNetB0	Private OCT	A: 99.00%, P: 99.00%, F1: 95.00%, S: 99.00%
[39]		CLAHE, HE	DRD-CN-DL	RIM-ONE, Drions, ORIGA	A: 97.77%, P: 97.00%, F1: 95.40%, S: 96.80%
[13]		Augmentation, CLAHE	EffNet-SVM	APTOS2019	A: 97.26%, P: 96.98%,
[47]	M	Rescaling, Enhancing	HDCNN	APTOS2019	A: 98.97%, P: 98.97%, F1: 98.97%, S: 98.97%
[43]		Median Filtering	MoNet + PolyNet + Xception	APTOS2019	A: 98.90%, P: 98.40%, F1: 98.73%, S: 99.00%
[40]		Normalization	IR-CNN	Messidor, IDRiD	A: 96.85%, P: 96.46%, F1: 98.65%, S: 99.28%
[48]		Augmentation, Normalization	HDCNN	IDRiD	A: 96.34%, P: 97.58%, F1: 97.58%, S: 97.58%
[49]		Segmentation, Grayscale	HCSELM	IDRiD	A: 95.20%, P: 96.00%, F1: 96.00%, S: 97.00%
[45]	Both	Image Flipping, Augmentation	CNN + Grad CAM + XAI	APTOS2019	B: A: 100.00%, P: 97.55% M: A: 95.27%, P: 96.12%
[41]		Cropping, SMOTE, Filtering	FusionNet (SAN + ViT)	KaggleDR	B: A: 99.00%, P: 99.00% M: A: 91.00%, P: 91.00%

Source: Authors, (2026).

II.4 SYMPTOM - BASED TECHNIQUES FOR DR CLASSIFICATION

The main symptoms of DR include Microaneurysms, Exudates and Hemorrhages. Each symptom indicates different levels of severity of the disease. So it becomes essential to be able to detect each of these accurately and efficiently from the concerned image datasets. Figure 3 broadly visualized the major stages and symptoms of the disease.

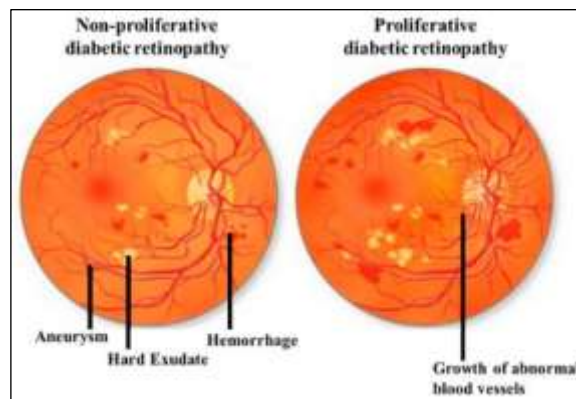


Figure 3: DR stages and symptoms

Source: [1]

II.4.1 Microaneurysms

Nianjia Wang et. al. developed an improved OCTA based image processing method to efficiently detect the Microaneurysms. It uses the OCTA blood flow signals along with Structural OCT hyper-reflective MA signals and 3D reconstruction to create a 3D-MA map known as the DVC-MA map to detect and visualize more Microaneurysms [50]. Abbas Rehman et. al. introduced FISM (Fundus Images Segmentation Model) based on Segment Anything Model (SAM) combining DL and reinforcement learning on the DDR dataset for the precise detection and segmentation of Microaneurysms (MAs). The model received AUC of 96.32% . But the model suffered from the limitation of using only one dataset [51]. Luís Mendes et. al. developed an automatic system - RetmarkerDR for the evaluation of Microaneurysms count and turnover using the fundus images at the hyperperfusion stage of non-proliferative diabetic retinopathy (NPDR). The dataset was collected from EUROCONDOR clinical trial helping us to keep track of DR progression. But the model only used fundus images and was highly dependent on the image quality [52]. Norah Asiri et. al. developed a DL-Based model using Dilated Residual Network (DRN) a better and modified ResNet-50 with dilation and techniques like ROI pooling and Patch-based detection. The model was trained and tested on several datasets like e-ophtha-MA, DiaretDB1-MA, ROCh, IDRiD (MA masks) and DDR. The model was able to detect even the smallest lesions present in the retina [53]. Aditya Sharma et. al. developed a deep learning-based model along with the approach of transfer learning on the E-Ophtha (MA) dataset. The model helps in early detection of Microaneurysms and classifying the images into MA and non-MA. But the model is focused only on Binary classification rather than on DR grading [54]. Pedro Romero-Aroca et. al. used modified ETDRS grid to find the count and exact count of Microaneurysms and found that these dots are not randomly distributed across the retina, rather majority of them are found in temporal and inferior quadrants of the modified ETDRS grid. Higher the concentration, higher is the severity of DR. The study was conducted for Miradataset and Messidor dataset [55]. The below given Figure 4 shows comparison of the Microaneurysms across various image.

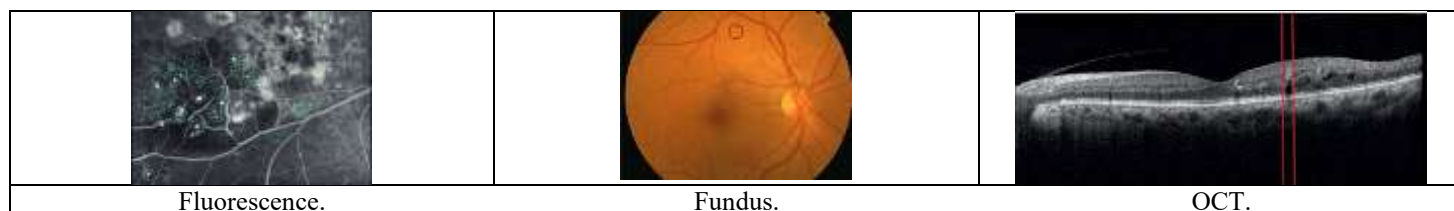


Figure 4: Microaneurysm detection across imaging modalities.

Source: [56] [57] [58].

II.4.2 Hemorrhages

Gang-Min Park et. al. conducted two approaches - Severity-Based Approach using APTOS dataset and Lesion-Based Approach using NMC dataset for the binary and multi-class classification and multi-label classification. NMC dataset has various types of hemorrhages such as Retinal hemorrhages, Vitreous hemorrhages, and Preretinal hemorrhages. The study also used Cross dataset for fine tuning. It concluded that integrating both the approaches can result in more precise accuracy and interpretability of the model. EfficientNet was found to be the best performing model [59]. Saurabh Chavanke et. al. 20 proposed an automated system called the Rule-Based Hemorrhage Detection Architecture to automatically detect hemorrhages using DIARETDB0 and DIARETDB1 datasets. The focus is on pre-processing the fundus images in such a way as to highlight the hemorrhages spots by using techniques like extracting green channel of the image then enhancing it to make the dark hemorrhages more visible. Techniques like Top-Hat Transform and thresholding are used to highlight possible blobs. At last Rule based filtering based on size, shape and color is adopted for further classification [60]. Instead of using traditional methods for lesion identification for DR detection Ronsong Sun et. al. proposed an AI model called EVision AI system to calculate two efficient indicators - ratio of haemorrhagic area to the total retinal area and ratio of the haemorrhagic area to the microaneurysm count for accurate detection of DR in type-2 diabetes patients.

The system uses non-mydriatic fundus images to detect hemorrhages. The EVision system used DL semantic segmentation algorithms integrated with CNN models [61]. Patsaphon Chandhakanond et. al. proposed a modified version of Iterative NICK Thresholding Region Growing (INRG) to effectively identify and segment Hemorrhages and Exudates. Watershed Separation technique for accurate segmenting of overlapped or poorly defined areas and χ^2 Feature Ranking (χ^2) for accurate selection of features so as to efficiently classifying the segmented region were combined with INRG. DR2019 Mobile Dataset and JSIEC dataset were used for the study. INRG was used along with SVM classifier [62]. Sujuan Tang et. al. developed SAM-ada-Res tool to understand the overall context of the fundus images using the Segment Anything Model (SAM2) model integrated with an Adapter and ResNet101 Encoder for studying the tiny details and textures of the focused area for accurate detection of the complicated and irregularly shaped hemorrhage lesions. The information received from the Adapter and the Encoder is fused together and forwarded to U-Net decoder generating the final segmentation mask. The model was trained on OIA-DDR, IDRID and JYFY-HE datasets. Model performance was evaluated using two key metrics: normalized Intersection over Union (nIoU) and normalized Dice coefficient (nDice) [63]. The below given Figure 5 shows comparison of the Hemorrhages across various image.

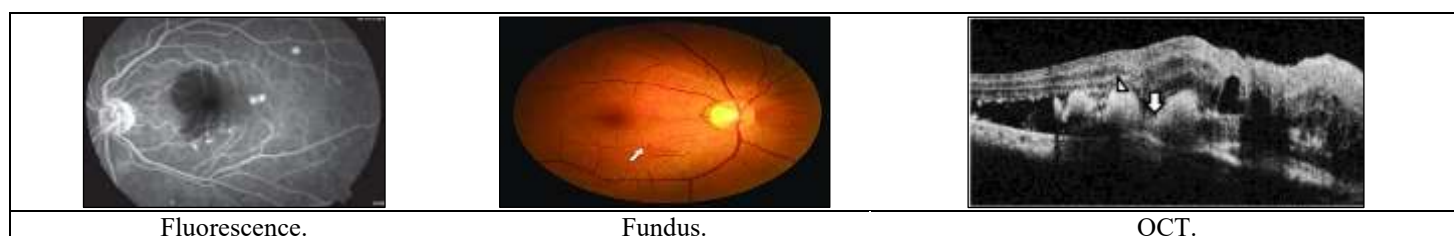


Figure 5: Hemorrhages detection across imaging modalities.

Source: [64] [65] [66].

II.4.3 Exudates

Esmat Ramezanzadeh et al. proposed a method to differentiate exudates from other bright structures like the optic disc, blood vessels, reflections and background noise using the textural difference between them and thus modified Radon transform technique into capturing textural changes and directional intensity patterns. Kirsch edge detection was used to highlight exudates by identifying its rough sharp borders differentiating it from vessels and bright noise. Further morphological reconstruction was applied to filter out the unwanted structures and smooth the image retaining only the true exudate regions. At last Otsu threshold was implemented to separate the bright lesions - exudates and the background. The technique was tested on DIARETDB1 and a local MUMS-DB dataset [67]. Chang Ki Yoon et al. used the OCT (Optical Coherence Tomography) scans instead of traditional fundus images to detect and segment HE which have 3D features at 3D-level by evaluating the volume of HE in the retina to better understand the presence and severity of HE. DUCK-Net - a modified version of U-Net was developed to segment HE which look like bright, hyper-reflective foci in OCT B-scans. Hard exudates are detected and segmented for each OCT slice then all the slices are combined to evaluate the 3D volume of the HE. The 3D OCT data is then projected to create a 2D fundus like image. The model achieved an excellent accuracy of 99.9% [68]. Rajesh et al. focused on grading the severity of diabetic maculopathy based on the closeness of the lesion to macula. Initially the retinal image is preprocessed to improve its quality by removing noise and applying contrast enhancement. Further various morphological operations were applied to eliminate the structures that look like exudate to retain only the 22 true exudates. Extended minima transform algorithm was used to isolate the exudate from rest of the image area by taking brightness, shape, and texture as a base.

And lastly Optic disc location and Relative distance is used to find the locate the macula and hence evaluating the closeness of exudate from the region. Based on the distance macula region is divided into three concentric circles - C1 (closest), C2 and C3 with the grading being severe if lesion is in C1 circle , moderate or mild if lesion in C2 or C3 and normal if no exudate found. The study was carried out on the Messidor dataset. The performance of system being 90% sensitivity for HE detection and 92% accuracy for Maculopathy detection [69]. S. Preetha developed a model using CNN classifier - ResNet100 to detect HE hence detecting DR. The model was tested on several datasets like Kaggle EyePACS, APTOS 2019 and IDRiD achieving an accuracy of 76% for DR classification. Their paper also included a survey on various DL models used for DR detection and concluded that CNN based models can generate high accuracy results if trained on large, good quality datasets [70]. The below given Figure 6 shows comparison of the Exudates across various image.

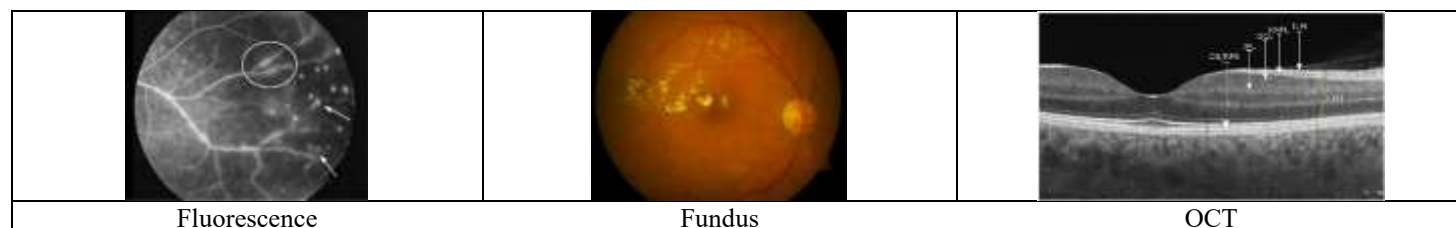


Figure 6: Exudates detection across imaging modalities.
Source: [71] [72] [73].

Table 5 summarize the state-of-the-art work on symptom based approaches of DR.

Table 5: Symptom Based Comparison Table.

Ref	Symptom	Preprocessing	Model	Dataset	Performance
[54]	Micro	CLAHE, Denoise	DNN IDRiD	Private OCT	A: 97.90%, P: 98.50%, F1: 97.20%
[51]		Convert Color Space	FISM - RLDN + AEFFN	IDRiD	A: 97.68%, P: 98.11%, F1: 97.77%, S: 97.44%
[59]	Hemo	Resizing	EfficientNet B4	APTOS2019	A: 84.00%, S: 83.80%, P: 81.11%, F1: 82.40%
[61]		CLAHE, Extraction, Normalize	EVision AI system	Cross-sectional	S: 86.14%, AUC: 91.70%
[69]	Exudates	CLAHE, BV and OD Removal	SVM + Morphology	Messidor	A: 98.71%, S: 98.71%, P: 98.71%, F1: 98.71%
[68]		Augmenting, Resizing	DUCK-Net	1,811 OCT B-scans	B: A: 99.00%, P: 99.00% M: A: 91.00%, P: 91.00%

Source: Authors, (2026).

III. DATASETS

Datasets used for DR detection include retinal images taken from different angles to capture lesions that show presence of DR. A dataset with diverse demography helps us with accurate detection of the disease and a generalized model. Some of the commonly used types of retinal images are: 1 - Fundus image: 2D images used for capturing Retinal Surface, Microaneurysms, Hemorrhages, Hard exudates and blood vessels. It helps in early stage detection of DR. 2 - OCT (Optical Coherence Tomography): 3D images used to study retinal structure layer-wise. It shows thickness of macula and exudate volume, usually used for detecting Diabetic Macular Edema. 3 - OCTA (Optical Coherence Tomography Angiography): used for capturing Microaneurysms and non-perfusion areas, helps in detecting proliferative DR(PDR) [1]. 4 - FA (Fluorescein Angiography): mostly used to study where blood is flowing abnormally or leaking. Helps in early detection of fluid leakage and Microaneurysms (fluoro). Table 6 categorizes the various retinal datasets into broader categories of public and private based on their availability.

Table 6: Public and Private Diabetic Retinopathy Dataset Comparison.

Category	Type	B / M	Dataset Name	No. of Images	Resolution
Public	Fundus	B	STARE	90	700×605
			DIARETDB1	89	Various
			HRF	30	3504×2336
		M	Messidor-1	1200	1400×960
			Kaggle DR	88702	227×227
			APTOS2019	3662	584×565
			DDR	12522	227×227
	Fundus/OCT	M	FairVision	6000	227×227
	Fluorescence	B	FFA	70	700×605
Private	Fundus		SN-DREAM	Not Known	2896×1944

		M	Aravind DR	Not Known	1500×1500
	Fundus / OCT	M	SNEC/SERI	Not Known	2048×1536
			Moorfields 005	Not Known	1536×1536

Source: Authors, (2026).

Figure 7 demonstrates the images form different classes from two prominent datasets i.e. APTOS and Messidor.

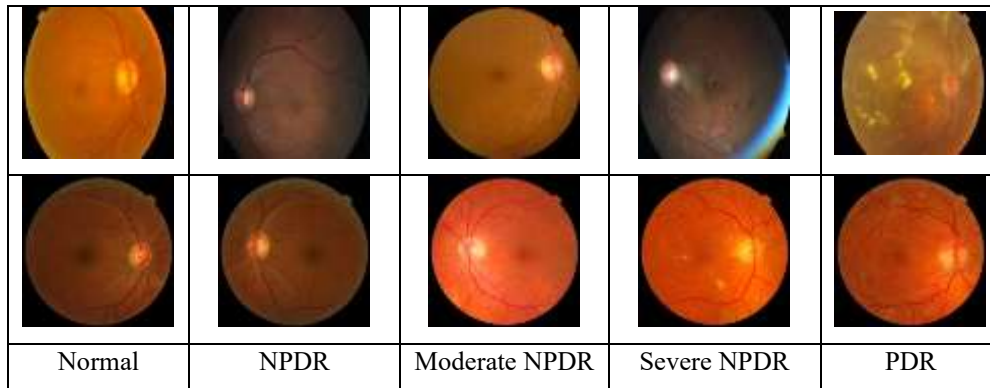


Figure 7: Class-Wise Comparison of APTOS2019 (Top Row) and Messidor Dataset (Bottom Row).

Source: Authors, (2026).

IV. CHALLENGES

Detecting and classifying DR is a crucial task to avoid total blindness. Integrating AI into traditional methods can fasten the detection process and make the prediction task accurate. It also ensures earlier response-time hence avoiding the risk of disease getting severe. Employing hybrid technologies like RSG-Net, CNN-RBF model the accuracy of model can be increased significantly. Along with the model and techniques used diversity and size of dataset also plays a significant role in the performance of model. It is essential to use a balanced and diverse dataset so as to develop a generalized model. The fundus images are usually characterized by noise and taken in dark so using an appropriate preprocessing technique like image augmentation through GAN and denoising autoencoders is also a crucial part of model development. Medical images are required to be employed with sophisticated feature extraction techniques to highlight the affected areas so as to focus on regions having lesions. Employing hybrid architectures to increase the efficiency can lead to higher computational cost and complexity of the model hence it is required for the researchers to develop a light-weight, feasible architecture to be easily integrated into local clinics. Along with this binary classification usually enjoys a higher accuracy rate as compared to multi-class classification for severity grading. So there is a need to develop a model which is light-weight, feasible and can be easily integrated to medical institutions for diverse range of patients making the model more generalized.

- **Traditional time-consuming methods:** The traditional methods used for detecting diabetic retinopathy include manual analysis of the fundus images by Ophthalmologists which can be inaccurate and time-consuming [13]. Delay in detecting the disease can lead to it getting severe, which can ultimately lead to blindness. Concerns may also increase the accuracy of the results generated through manual work. Therefore, there is a need for an automated system which can detect the disease faster and give more accurate results.
- **Imbalanced Dataset:** Datasets play an important role in the diagnosis of any disease. As it can help us to understand the common traits and symptoms which can be used while predicting the presence of the disease while diagnosing. But usually, the medical images suffer from the issue of noisy or blur images, or they can be taken in a dark background making it unclear for diagnosis. The publicly available and commonly used datasets like Messidor and APTOS2019 are highly imbalanced and biased towards more images for the No-DR, Mild and Moderate classes. This can generate biased results and does not provide equal representation to all the severity classes [3].
- **Diverse Image qualities:** A dataset consists of multiple images with a wide variety of differing features like size, resolution, color, illumination, and noise which can influence the model's generalizability[39]. If the images are not normalized to similar levels, it can lead to inaccurate results. Along with that the dataset should be having samples from a diverse range of patients which can make the model more included for all kinds of cases. The various demographics include samples from all age and gender groups and from various ethnicities and races.
- **Model Complexity:** Although ML-DL models can significantly increase their performance, it can become difficult for normal people to understand their working and integration with local cameras and in local hospitals [45]. If the models are not designed to be lightweight and portable, it can become difficult to integrate them with local clinics and be accessible to everyone [25]. Thus, the model should be made easier to understand and implement. The experts should be able to understand its work and know how to handle the machine.
- **Transparency:** The models developed generally follow a black-box approach that means inner logic and data is not visible to clinical doctors. But being in the medical sector the transparency with patient data is very much required while keeping their data secure [45]. There should be logical reasoning for justifying the results so that patients can trust the system.
- **Computationally Heavy and Costly:** Although using DL can increase the time and efficiency of the detection model, integrating complex models and techniques can increase its complexity and make it costly to maintain it [45]. The main intention behind developing such systems is that they are accessible to everyone and feasible to be integrated into real life.

V. CONCLUSION

Detecting and classifying DR is a crucial task to avoid total blindness. Integrating AI into traditional methods can fasten the detection process and make the prediction task accurate. It also ensures earlier response-time hence avoiding the risk of disease getting severe. Employing hybrid technologies like the RSG-Net, CNN-RBF model the accuracy of the model can be increased significantly. Along with the model and techniques used, diversity and size of the dataset also plays a significant role in the performance of the model. It is essential to use a balanced and diverse dataset so as to develop a generalized model. vThe fundus images are usually characterized by noise and taken in dark so using an appropriate preprocessing technique like image augmentation through GAN and denoising autoencoders is also a crucial part of model development. Medical images are required to be employed with sophisticated feature extraction techniques to highlight the affected areas so as to focus on regions having lesions. Employing hybrid architectures to increase the efficiency can lead to higher computational cost and complexity of the model hence it is required for the researchers to develop a light-weight, feasible architecture to be easily integrated into local clinics. Along with this binary classification usually enjoys a higher accuracy rate as compared to multi-class classification for severity grading. So there is a need to develop a model which is light-weight, feasible and can be easily integrated to medical institutions for a diverse range of patients making the model more generalized.

VI. AUTHOR'S CONTRIBUTION

Conceptualization: Shreya Dubey, Mahesh Goyani, Pinal Patel, Safwan Vahora, Uttam Chauhan, Mahendra Patel.

Methodology: Shreya Dubey, Mahesh Goyani, Pinal Patel, Safwan Vahora, Uttam Chauhan, Mahendra Patel.

Investigation: Shreya Dubey, Mahesh Goyani, Pinal Patel, Safwan Vahora, Uttam Chauhan, Mahendra Patel.

Discussion of results: Shreya Dubey, Mahesh Goyani, Pinal Patel, Safwan Vahora, Uttam Chauhan, Mahendra Patel.

Writing – Original Draft: Shreya Dubey, Mahesh Goyani, Pinal Patel, Safwan Vahora, Uttam Chauhan, Mahendra Patel.

Writing – Review and Editing: Shreya Dubey, Mahesh Goyani, Pinal Patel, Safwan Vahora, Uttam Chauhan, Mahendra Patel.

Resources: Shreya Dubey, Mahesh Goyani, Pinal Patel, Safwan Vahora, Uttam Chauhan, Mahendra Patel.

Supervision: Shreya Dubey, Mahesh Goyani, Pinal Patel, Safwan Vahora, Uttam Chauhan, Mahendra Patel.

Approval of the final text: Shreya Dubey, Mahesh Goyani, Pinal Patel, Safwan Vahora, Uttam Chauhan, Mahendra Patel.

VII. REFERENCES

- [1] D. Nagpal, S. N. Panda, M. Malarvel, P. A. Pattanaik, and M. Zubair Khan, "A review of diabetic retinopathy: Datasets, approaches, evaluation metrics and future trends," Oct. 01, 2022, *King Saud bin Abdulaziz University*. doi: 10.1016/j.jksuci.2021.06.006.
- [2] L. Sun *et al.*, "MAFNet: A novel adaptive multi-scale model for fine-grained grading of diabetic retinopathy," *Sci. Rep.*, vol. 15, no. 1, Dec. 2025, doi: 10.1038/s41598-025-17158-z.
- [3] M. Sushith, A. Sathiya, V. Kalaipoonguzhali, and V. Sathya, "A hybrid deep learning framework for early detection of diabetic retinopathy using retinal fundus images," *Sci. Rep.*, vol. 15, no. 1, Dec. 2025, doi: 10.1038/s41598-025-99309-w.
- [4] X. Wang, W. Wang, H. Ren, X. Li, and Y. Wen, "Prediction and analysis of risk factors for diabetic retinopathy based on machine learning and interpretable models," *Heliyon*, vol. 10, no. 9, May 2024, doi: 10.1016/j.heliyon.2024.e29497.
- [5] N. M. A. Tajudin *et al.*, "Deep learning in the grading of diabetic retinopathy: A review," Dec. 01, 2022, *John Wiley and Sons Inc.* doi: 10.1049/cvi2.12116.
- [6] E. Bakker *et al.*, "Adaptive optics ophthalmoscopy: a systematic review of vascular biomarkers," Mar. 01, 2022, *Elsevier Inc.* doi: 10.1016/j.survophthal.2021.05.012.
- [7] M. Kale, S. Manmath, and P. R. Patil, "DETECTION OF HEMMOREGES OF DIABETIC RETINOPATHY USING MACHINE LEARNING ALGORITHMS".
- [8] B. Haj Najeeb, B. S. Gerendas, A. Montuoro, C. Simader, G. G. Deák, and U. M. Schmidt-Erfurth, "A Novel Effect of Microaneurysms and Retinal Cysts on Capillary Perfusion in Diabetic Macular Edema: A Multimodal Imaging Study," *J. Clin. Med.*, vol. 14, no. 9, May 2025, doi: 10.3390/jcm14092985.
- [9] Y. Shen, H. Wang, J. Fang, K. Liu, and X. Xu, "Novel insights into the mechanisms of hard exudate in diabetic retinopathy: Findings of serum lipidomic and metabolomics profiling," *Heliyon*, vol. 9, no. 4, Apr. 2023, doi: 10.1016/j.heliyon.2023.e15123.
- [10] A. Ikram *et al.*, "A Systematic Review on Fundus Image-Based Diabetic Retinopathy Detection and Grading: Current Status and Future Directions," 2024, *Institute of Electrical and Electronics Engineers Inc.* doi: 10.1109/ACCESS.2024.3427394.
- [11] K. Nazir, J. Kim, and Y. C. Byun, "Enhancing Early-Stage Diabetic Retinopathy Detection Using a Weighted Ensemble of Deep Neural Networks," *IEEE Access*, vol. 12, pp. 113565–113579, 2024, doi: 10.1109/ACCESS.2024.3432867.
- [12] A. M. Mutawa, G. R. Hemalakshmi, N. B. Prakash, and M. Murugappan, "Randomization-Driven Hybrid Deep Learning for Diabetic Retinopathy Detection," *IEEE Access*, vol. 13, pp. 38901–38913, 2025, doi: 10.1109/ACCESS.2025.3546359.
- [13] K. V. Naveen, B. N. Anoop, K. S. Siju, M. K. Kar, and V. Venugopal, "EffNet-SVM: A Hybrid Model for Diabetic Retinopathy Classification Using Retinal Fundus Images," *IEEE Access*, vol. 13, pp. 79793–79804, 2025, doi: 10.1109/ACCESS.2025.3566073.
- [14] A. Chakraborty, G. Wilson, and C. Luca, "A lightweight classification system for the early detection of diabetic retinopathy," *Inform. Med. Unlocked*, vol. 57, Jan. 2025, doi: 10.1016/j.imu.2025.101655.
- [15] K. Barik and A. Kumar, "Identification of diagnostic biomarkers in diabetic retinopathy using machine learning and RNA sequencing data," *In Silico Research in Biomedicine*, vol. 1, p. 100069, 2025, doi: 10.1016/j.insr.2025.100069.
- [16] M. Hassaballah and M. A. Hameed, "NOVEL METAHEURISTIC ALGORITHMS AND THEIR APPLICATIONS TO EFFICIENT DETECTION OF DIABETIC RETINOPATHY," *Journal of Artificial Intelligence and Soft Computing Research*, vol. 15, no. 2, pp. 167–195, Dec. 2024, doi: 10.2478/jaiscr-2025-0009.

- [17] M. Gandor *et al.*, “Diagnostics of diabetic retinopathy based on fundus photos using machine learning methods with advanced feature engineering algorithms,” *Sci. Rep.*, vol. 15, no. 1, p. 34486, Dec. 2025, doi: 10.1038/s41598-025-06973-z.
- [18] P. Pragathi and A. Nagaraja Rao, “An effective integrated machine learning approach for detecting diabetic retinopathy,” *Open Computer Science*, vol. 12, no. 1, pp. 83–91, Jan. 2022, doi: 10.1515/comp-2020-0222.
- [19] M. Bernardini, L. Romeo, A. Mancini, and E. Frontoni, “A Clinical Decision Support System to Stratify the Temporal Risk of Diabetic Retinopathy,” *IEEE Access*, vol. 9, pp. 151864–151872, 2021, doi: 10.1109/ACCESS.2021.3127274.
- [20] X. Li *et al.*, “Identification of diabetic retinopathy classification using machine learning algorithms on clinical data and optical coherence tomography angiography,” *Eye (Basingstoke)*, vol. 38, no. 14, pp. 2813–2821, Oct. 2024, doi: 10.1038/s41433-024-03173-3.
- [21] G. Tăbăcaru, S. Moldovanu, E. Răducan, and M. Barbu, “A Robust Machine Learning Model for Diabetic Retinopathy Classification,” *J. Imaging*, vol. 10, no. 1, Jan. 2024, doi: 10.3390/jimaging10010008.
- [22] E. Abdelmaksoud, S. El-Sappagh, S. Barakat, T. Abuhmed, and M. Elmogy, “Automatic Diabetic Retinopathy Grading System Based on Detecting Multiple Retinal Lesions,” *IEEE Access*, vol. 9, pp. 15939–15960, 2021, doi: 10.1109/ACCESS.2021.3052870.
- [23] A. Ali *et al.*, “Machine learning based automated segmentation and hybrid feature analysis for diabetic retinopathy classification using fundus image,” *Entropy*, vol. 22, no. 5, May 2020, doi: 10.3390/E22050567.
- [24] S. Akhtar *et al.*, “A deep learning based model for diabetic retinopathy grading,” *Sci. Rep.*, vol. 15, no. 1, Dec. 2025, doi: 10.1038/s41598-025-87171-9.
- [25] A. Zafar, K. S. Kim, M. U. Ali, J. H. Byun, and S. H. Kim, “A lightweight multi-deep learning framework for accurate diabetic retinopathy detection and multi-level severity identification,” *Front. Med. (Lausanne)*, vol. 12, 2025, doi: 10.3389/fmed.2025.1551315.
- [26] S. Alanazi and R. Alanazi, “Enhancing diabetic retinopathy detection through federated convolutional neural networks: Exploring different stages of progression,” *Alexandria Engineering Journal*, vol. 120, pp. 215–228, May 2025, doi: 10.1016/j.aej.2025.02.026.
- [27] Y. Li *et al.*, “Enhancing diabetic retinopathy diagnosis: automatic segmentation of hyperreflective foci in OCT via deep learning,” *Int. Ophthalmol.*, vol. 45, no. 1, Dec. 2025, doi: 10.1007/s10792-025-03439-z.
- [28] K. K. Mujeeb Rahman, M. Nasor, and A. Imran, “Automatic Screening of Diabetic Retinopathy Using Fundus Images and Machine Learning Algorithms,” *Diagnostics*, vol. 12, no. 9, Sep. 2022, doi: 10.3390/diagnostics12092262.
- [29] M. Shi *et al.*, “Equitable Deep Learning for Diabetic Retinopathy Detection Using Multidimensional Retinal Imaging With Fair Adaptive Scaling,” *Transl. Vis. Sci. Technol.*, vol. 14, no. 7, Jul. 2025, doi: 10.1167/tvst.14.7.1.
- [30] A. M. Fayyaz, M. I. Sharif, S. Azam, A. Karim, and J. El-Den, “Analysis of Diabetic Retinopathy (DR) Based on the Deep Learning,” *Information (Switzerland)*, vol. 14, no. 1, Jan. 2023, doi: 10.3390/info14010030.
- [31] A. Zedadra, O. Zedadra, M. Yassine Salah-Salah, and A. Guerrieri, “Graph-Aware Multimodal Deep Learning for Classification of Diabetic Retinopathy Images,” *IEEE Access*, vol. 13, pp. 74795–74806, 2025, doi: 10.1109/ACCESS.2025.3564529.
- [32] M. Hussain *et al.*, “An Enhanced Convolutional Neural Network (CNN) based P-EDR Mechanism for Diagnosis of Diabetic Retinopathy (DR) using Machine Learning,” *Engineering, Technology and Applied Science Research*, vol. 15, no. 1, pp. 19062–19067, Feb. 2025, doi: 10.48084/etasr.8854.
- [33] S. J. SIDIQ and T. BENIL, “A lightweight transfer learning based ensemble approach for diabetic retinopathy detection,” *International Journal of Information Management Data Insights*, vol. 5, no. 2, Dec. 2025, doi: 10.1016/j.jjimei.2025.100372.
- [34] O. Dib, “A decentralized privacy-preserving framework for diabetic retinopathy detection using federated learning and blockchain,” *Results in Engineering*, vol. 26, Jun. 2025, doi: 10.1016/j.rineng.2025.105456.
- [35] S. Guefrachi, A. Echtioui, and H. Hamam, “Diabetic Retinopathy Detection Using Deep Learning Multistage Training Method,” *Arab. J. Sci. Eng.*, vol. 50, no. 2, pp. 1079–1096, Jan. 2025, doi: 10.1007/s13369-024-09137-9.
- [36] A. M. Fayyaz, M. I. Sharif, S. Azam, A. Karim, and J. El-Den, “Analysis of Diabetic Retinopathy (DR) Based on the Deep Learning,” *Information (Switzerland)*, vol. 14, no. 1, Jan. 2023, doi: 10.3390/info14010030.
- [37] I. Govindharaj, R. Rampriya, G. Michael, S. Yazhinian, K. Dinesh Kumar, and R. Anandh, “Capsule network-based deep learning for early and accurate diabetic retinopathy detection,” *Int. Ophthalmol.*, vol. 45, no. 1, Dec. 2025, doi: 10.1007/s10792-024-03391-4.
- [38] K. GENCER, G. GENCER, T. H. CERAN, A. E. BİLİR, and M. DOĞAN, “Photodiagnosis with deep learning: A GAN and autoencoder-based approach for diabetic retinopathy detection,” *Photodiagnosis Photodyn. Ther.*, vol. 53, Jun. 2025, doi: 10.1016/j.pdpdt.2025.104552.
- [39] G. I *et al.*, “Enhanced diabetic retinopathy detection using U-shaped network and capsule network-driven deep learning,” *MethodsX*, vol. 14, Jun. 2025, doi: 10.1016/j.mex.2024.103052.
- [40] G. Ali, A. Dastgir, M. W. Iqbal, M. Anwar, and M. Faheem, “A Hybrid Convolutional Neural Network Model for Automatic Diabetic Retinopathy Classification From Fundus Images,” *IEEE J. Transl. Eng. Health Med.*, vol. 11, pp. 341–350, 2023, doi: 10.1109/JTEHM.2023.3282104.
- [41] A. Shukla, S. Tiwari, and A. Jain, “HybridFusionNet: Deep Learning for Multi-Stage Diabetic Retinopathy Detection,” *Technologies (Basel)*, vol. 12, no. 12, Dec. 2024, doi: 10.3390/technologies12120256.
- [42] M. M. Butt, D. N. F. A. Iskandar, S. E. Abdelhamid, G. Latif, and R. Alghazo, “Diabetic Retinopathy Detection from Fundus Images of the Eye Using Hybrid Deep Learning Features,” *Diagnostics*, vol. 12, no. 7, Jul. 2022, doi: 10.3390/diagnostics12071607.

- [43] A. S. Sabeena and M. K. Jeyakumar, "An Ensemble Learning Approach Using Deep Learning Models For Diabetic Retinopathy Severity Classification," *Biomedical Materials and Devices*, 2025, doi: 10.1007/s44174-025-00418-x.
- [44] L. Learning, sükran, Y. Atci, A. Güne, sgüne, s, M. Zontul, and Z. Arslan, "Identifying Diabetic Retinopathy in the Human Eye: A Hybrid Approach Based on a Computer-Aided Diagnosis System Combined with Deep Learning, Sükran," vol. 10, pp. 215–230, 2024, doi: 10.3390/tomography.
- [45] K. Ahnaf Alavee *et al.*, "Enhancing Early Detection of Diabetic Retinopathy Through the Integration of Deep Learning Models and Explainable Artificial Intelligence," *IEEE Access*, vol. 12, pp. 73950–73969, 2024, doi: 10.1109/ACCESS.2024.3405570.
- [46] A. Jabbar *et al.*, "A Lesion-Based Diabetic Retinopathy Detection Through Hybrid Deep Learning Model," *IEEE Access*, vol. 12, pp. 40019–40036, 2024, doi: 10.1109/ACCESS.2024.3373467.
- [47] R. Yasashvini, V. Raja Sarobin M, R. Panjanathan, S. Graceline Jasmine, and L. Jani Anbarasi, "Diabetic Retinopathy Classification Using CNN and Hybrid Deep Convolutional Neural Networks," *Symmetry (Basel)*, vol. 14, no. 9, Sep. 2022, doi: 10.3390/sym14091932.
- [48] A. Bilal, L. Zhu, A. Deng, H. Lu, and N. Wu, "AI-Based Automatic Detection and Classification of Diabetic Retinopathy Using U-Net and Deep Learning," *Symmetry (Basel)*, vol. 14, no. 7, Jul. 2022, doi: 10.3390/sym14071427.
- [49] M. Nahiduzzaman, M. R. Islam, S. M. R. Islam, M. O. F. Goni, M. S. Anower, and K. S. Kwak, "Hybrid CNN-SVD Based Prominent Feature Extraction and Selection for Grading Diabetic Retinopathy Using Extreme Learning Machine Algorithm," *IEEE Access*, vol. 9, pp. 152261–152274, 2021, doi: 10.1109/ACCESS.2021.3125791.
- [50] N. Wang, X. Liu, J. Wu, X. Xiang, Y. Gao, and L. Yao, "A novel OCTA-based image processing method for enhanced microaneurysm detection and 3D visualization in diabetic retinopathy," *Photodiagnosis Photodyn. Ther.*, vol. 56, p. 105258, Dec. 2025, doi: 10.1016/j.pdpdt.2025.105258.
- [51] A. Rehman *et al.*, "FISM: harnessing deep learning and reinforcement learning for precision detection of microaneurysms and retinal exudates for early diabetic retinopathy diagnosis," *BioData Min.*, vol. 18, no. 1, Dec. 2025, doi: 10.1186/s13040-025-00485-2.
- [52] L. Mendes *et al.*, "Microaneurysm Counting as a Biomarker for the Hyperperfusion Stage of Nonproliferative Diabetic Retinopathy," *Ophthalmol. Ther.*, vol. 14, no. 8, pp. 1905–1915, Aug. 2025, doi: 10.1007/s40123-025-01179-y.
- [53] N. Asiri, A. M. Artoli, M. Al-Razgan, and T. Alfakih, "Dilated Neural Networks for Improving Microaneurysm Detection in Fundus Images," *IEEE Access*, vol. 13, pp. 104037–104046, 2025, doi: 10.1109/ACCESS.2025.3579342.
- [54] A. Sharma and V. Pawar, "INDIAN JOURNAL OF SCIENCE AND TECHNOLOGY Early Assessment of Diabetic Retinopathy by Detecting Microaneurysm with Deep Neural Network," *Indian J. Sci. Technol.*, vol. 17, no. 17, pp. 1786–1790, 2024, doi: 10.17485/IJST/v17i17.732.
- [55] P. Romero-Aroca, E. Garcia-Curto, J. Pascual-Fontanilles, A. Valls, A. Moreno, and M. Baget-Bernaldiz, "Distribution of Microaneurysms and Hemorrhages in Accordance with the Grading of Diabetic Retinopathy in Type Diabetes Patients," *Diagnostics*, vol. 14, no. 14, Jul. 2024, doi: 10.3390/diagnostics14141547.
- [56] D. Brown, I. Kozak, S. I. R. Lampen, and J. Chhablani, "Management of Coats Disease Microaneurysms With Fundus Fluorescein Angiography-Guided Navigated Laser," *J. Vitreoretin. Dis.*, vol. 3, no. 1, pp. 36–41, Jan. 2019, doi: 10.1177/2474126418810134.
- [57] I. Lazar and A. Hajdu, "MICROANEURYSM DETECTION IN RETINAL IMAGES USING A ROTATING CROSS-SECTION BASED MODEL."
- [58] E. S. Kazeminasab, R. Almasi, B. Shoushtarian, E. Golkar, and H. Rabbani, "Automatic Detection of Microaneurysms in OCT Images Using Bag of Features," *Comput. Math. Methods Med.*, vol. 2022, 2022, doi: 10.1155/2022/1233068.
- [59] G. M. Park, J. H. Moon, and H. G. Jung, "A Comparative Study of Lesion-Centered and Severity-Based Approaches to Diabetic Retinopathy Classification: Improving Interpretability and Performance," *Biomedicines*, vol. 13, no. 6, Jun. 2025, doi: 10.3390/biomedicines13061446.
- [60] S. Chavanke, S. Avhad, K. Aher, U. Shinde, and S. M. Kale, "Detection of Hemorrhage in fundus Images."
- [61] R. Sun *et al.*, "Ratio of haemorrhagic area to retinal area as a novel indicator for AI-based screening of diabetic retinopathy in type 2 diabetes: a community-based cross-sectional study," *BMJ Open*, vol. 15, no. 9, Sep. 2025, doi: 10.1136/bmjopen-2025-099062.
- [62] P. Chandhakanond and P. Aimmanee, "Diabetic retinopathy detection via exudates and hemorrhages segmentation using iterative NICK thresholding, watershed, and Chi2 feature ranking," *Sci. Rep.*, vol. 15, no. 1, Dec. 2025, doi: 10.1038/s41598-025-90048-6.
- [63] S. Tang and Q. Wu, "Research on recognition of diabetic retinopathy hemorrhage lesions based on fine tuning of segment anything model," *Sci. Rep.*, vol. 15, no. 1, Dec. 2025, doi: 10.1038/s41598-025-92665-7.
- [64] P. Baskaran and M. D. Sindal, "Acute angle closure glaucoma secondary to polypoidal choroidal vasculopathy-a devastating complication."
- [65] E.-C. Chang, J.-S. Huang, Y.-C. Hou, C.-H. Huang, and I.-H. Wang, "Optical coherence tomography as a useful adjunct in the early detection of meningioma with optic nerve compression," *Taiwan J. Ophthalmol.*, vol. 12, no. 3, pp. 354–359, Jul. 2022, doi: 10.4103/tjo.tjo_54_21.
- [66] R. Shenoy and A. Bialasiewicz, "The Effect of Photodynamic Therapy in the Management of Polypoidal Choroidal Vasculopathy in a 28-year-old."
- [67] E. Ramezanzadeh, N. Shoeibi, A. Feizabadi, T. Banace, M. H. B. Tussi, and M. Tavakoli, "Automated detection of hard exudates in retinal fundus images for diabetic retinopathy screening using textural-based radon transform and morphology reconstruction," *Biomedical Engineering Advances*, vol. 9, p. 100180, Jun. 2025, doi: 10.1016/j.bea.2025.100180.
- [68] C. K. Yoon, H. W. Lee, H. W. Kim, and J. L. Kim, "Deep learning based retinal hard exudates quantification of optical coherence tomography," *Int. J. Retina Vitreous*, vol. 11, no. 1, Dec. 2025, doi: 10.1186/s40942-025-00715-z.
- [69] I. S. Rajesh, B. M. Reshmi, B. Malakreddy A, and S. Bilakeri, "Automatic Detection of Hard Exudate in Color Retinal Fundus Image and Diabetic Maculopathy Grading," *IEEE Access*, vol. 13, pp. 6618–6631, 2025, doi: 10.1109/ACCESS.2025.3525499.

[70] S. Chaudhari, R. Gadakh, S. Mali, S. Govardhane, and S. Kale, “|| Issue 3 || 2025 || ISO,” vol. 8, 2007.

[71] A. Patil and C. Chakravorty, “Detection of hard exudate using retinal optical coherence tomography (OCT) images,” *Global Transitions Proceedings*, vol. 2, no. 2, pp. 566–570, Nov. 2021, doi: 10.1016/j.gltp.2021.08.067.

[72] M. Monemian and H. Rabbani, “Exudate identification in retinal fundus images using precise textural verifications,” *Sci. Rep.*, vol. 13, no. 1, Dec. 2023, doi: 10.1038/s41598-023-29916-y.

[73] A. Domagała, L. Domagała, N. Kopiś-Posiej, M. Harciarek, and P. Krukow, “Differentiation of the retinal morphology aging trajectories in schizophrenia and their associations with cognitive dysfunctions,” *Front. Psychiatry*, vol. 14, 2023, doi: 10.3389/fpsyt.2023.1207608.