Comprehensive Analysis of Artificial Intelligence Techniques for Diabetic Retinopathy Disease Detection

AanchalMehta
Chitkara University Institute of Engineering and Technology,Chitkara University,Punjab,India
Aanchal.3944@chitkara.edu.in
Vandana Bajaj*
Chitkara University Institute of Engineering and Technology,Chitkara University,Punjab, India
Vandana.bajaj@chitkara.edu.in
Rattan Deep Aneja
Chitkara University Institute of Engineering and Technology, Chitkara University, Punjab, India
rattananeja@gmail.com

Abstract. Machine Learning (ML) and Deep Learning (DL) have emerged as powerful techniques in many fields, including speech recognition, cybersecurity, text generation, financial fraud detection and medical image analysis. There are numberless Image Processing (IP) techniques used for processing, analyzing and extracting information from images. The ML and DL models rely on a centralized system for disease prediction on medical imaging. Medical image processing exposes a non-invasive strategy for disease screening. However, to collect medical records at a centralized location, leading to data dependency, adversarial vulnerability, high computational resources and data storage concerns. Diabetic Retinopathy (DR) is a vision threatening disease in human beings. If DR is not identified in an early stage or not treated timely, the damage is irreversible. The diagnosis of DR disease is challenging, especially with limited resources, time-consuming and dependent on the ophthalmitis experiences. The research highlight has ML and DL models showing strong potential in DR disease detection, grading, segmentation, feature extraction, classification, diagnosis and even prediction in early stages on retinal images.

Keywords - Artificial Intelligence, Machine Learning, Deep Learning, Image Processing, Diabetic Retinopathy.

1. Introduction

ML is a branch of Explainable Artificial Intelligence (XAI) that develops algorithms, which focus on training machines to learn from data and make predictions based on that learning without human beings explicitly [1]. The XAI are evolving toward more scalable and multimodal systems. While the effectiveness of ML algorithms depends on the input data [2]. The link between AI, ML and DL is depicted as overlapping circles in Fig. 1. ML is classified into four categories based on their learning process. Supervised learning trains machines using labelled data to make predictions. In this learning, the machines already know the correct answers. Supervised learning work on classification problems [3]. Unsupervised learning trains machines using unlabelled data to achieve specific goals [4]. In this learning, the machines do not know the correct answers. Unsupervised learning work on clustering problems, dimensionality reduction, association rule learning problems [6]. Semi-supervised learning has both supervised and unsupervised learning, and work on image classification, text classification problems [4]. Reinforcement learning is a response-based method where machines learn from their environment and receive rewards or punishment based on their actions. Reinforcement learning focuses on strategy learning development and automated decision problems [5].

DL is a subpart of ML and XAI is influenced by the information-processing stages present in hierarchical structures [6]. DL is built using a number of layers called Artificial Neural Networks (ANNs), also known as Deep Neural Networks (DNNs). ANN is made by neurons [7]. Neurons are inspired by the biological cell like structure of the human brain [9]. All neurons are interconnected by each one in layers for processing, further these include hidden layers that learn different features and perform calculations from the raw data, with each node using an activation function to often handle non-linear relationship in data [11]. The input layer receives the raw data and output layers for the purpose of achieving the desired outcomes [8]. DL is also called representation learning to tackle complex problems [10]. Deep neural symbolic integration models are used to improve transparency and reasoning capabilities [12].

R. Vasanth Kumar Mehta et al. (eds.), *Proceedings of the International Conference on Intelligent Systems for a Sustainable Future (ISSF 2026)*, Atlantis Highlights in Intelligent Systems 16,
https://doi.org/10.2991/978-94-6239-693-7_27

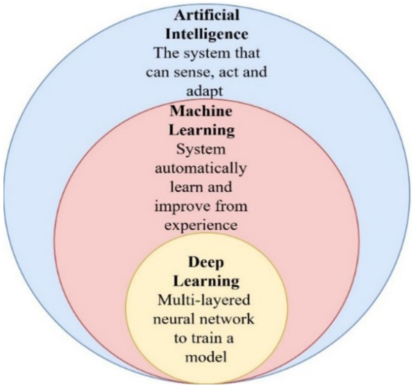

Fig. 1. DL Family

In the medical domain, the ML and DL techniques are used in blood tests to diagnose various diseases in the human body, such as dengue, typhoid and blood cancer [11]. The patient's health monitoring systems in hospitals use ML and DL models at the backend for maintaining records such as blood pressure, body temperature and pulse oximeter [12]. The ML and DL algorithms are capable of segmenting and penetrating the areas effected by the diseases using different image datasets including Magnetic Resonance Imaging (MRI) which is used to create views of organs inside the human body, such as the brain and heart [13]. Ultrasound uses high-frequency sound waves to create images of organs [15]. Fundus images are interior retinal structure images taken by the fundus camera, including the blood veins and fovea [16]. Electroencephalogram (EEG) displays brain waves on a computer screen [17]. Electrocardiogram (ECG) records heart rhythms, then translates them into a wavy line graph [18]. Position Emission Tomography (PET) scan shows how organs are functioning [19]. Mammography images are used to examine breast cancer [14]. Nuclear medicine imaging is tracing injected, swallowed or inhaled organs inside the human body [20]. Endoscopy is used to diagnose the digestive system and respiratory system [22]. Optical Coherence Tomography (OCT) is a high-resolution retinal image used to detect glaucoma and the thickness of the distinctive retinal layers can be measured [11]. Radiological imaging has been used in diagnosing respiratory conditions, including pneumonia and tuberculosis [23]. Commonly radiological imaging is called X-Rays [21]. Fluorescein angiography is an imaging technique used to see the blood veins in the retina and retinal abnormalities such as leakage, blockage and abnormal vein growth [18]. Demonstrated ML and DL algorithms for disease diagnosis include Decision Tree (DT), Random Forest (RF), Support Vector Machine (SVM), K-nearest neighbor, Multi-Layer Perceptron (MLP), Convolutional Neural Network (CNN), Recurrent Neural Network (RNN), AutoEncoder (AE), Generative Adversarial Network (GAN) and many more models that have shown remarkable accuracy [24].

2. Diabetic Retinopathy

DR is a neurovascular complication leading to vision impairment problems or blindness in eyes among all age groups across the world [12]. DR happens when blood glucose levels are too high in the human body, damaging the blood veins in the retina surface [18]. The retina is a part of the eye that detects light and sent signals to the brain to process the visual information [13]. The DR disease symptoms seen in the retina surface as shown in Fig 2, weaken the blood veins, appearing as tiny red dots called Microaneurysm (MA). Haemorrhage (HM) are leaks of blood from damaged blood veins. HM spot size is greater than 125µm [14]. Cotton Wool Spot (CWS) are fluffy patches that appear due to the lack of oxygen and Exudate (HE) develops in the outer layer and leaks a plasma-like substance [15]. In the advanced stage, neovascularization occurs, abnormally new veins start growing in the retina surface.

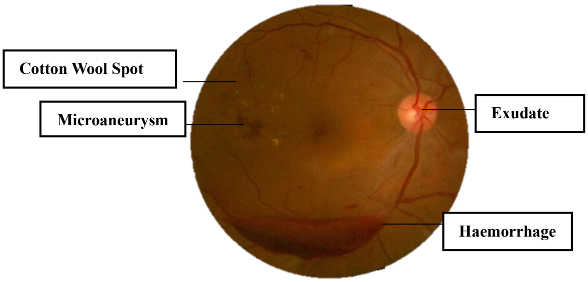

Fig. 2. Diabetic Retinopathy [16]

3. Comparative Analysis

The researchers have implemented various ML and DL based DR disease detection models with IP techniques on binary classification (DR and No DR) [12][15][22][30] and multi-class classification included 5-stage and 7-stage (No DR, Mild NDR, Moderate NDR, Severe NDR, Very Severe, Proliferative Diabetic Retinopathy (PDR), Advanced PDR) datasets [4][5][8][13][16][17], which can have domain specific knowledge and decision making[4]. In comparative analysis, despite different ML and DL models, such as ResNet50[2], DenseNet121[2], CNN [13][23][5][31], SVM [12] Visual Geometry Group 16 (VGG16) [8] [19], XGBoost [20], being proposed for image classification, image segmentation and deep feature extraction [12][28]. Although these models use different approaches, they are designed to predict and improve accuracy up to 97.54% [3][13][16]. Transfer learning models have been extensively used to improve model performance up to 96.95% [8]. Hybrid models have improved performance in both binary and multiclass classification on DR disease detection [15][17][24][4]. Ensemble models combining classifiers have improved the performance up to 86.53% on several benchmark retinal datasets and determine their robustness [16][28]. Data augmentation techniques are utilized to increase the retinal image datasets, which help in increasing the accuracy of models [5][6][8][15][16][19][32]. Size modification, cropping, horizontal and vertical scaling and rotation are some techniques of data augmentation [8][13][20]. However, reliance on traditional ML methods on manually extracted handcrafted features from images, which can be limited in performing complex tasks [13][20]. Traditional ML methods are logistic regression and naïve bayes [19][23].

Various IP techniques are used in the detection of DR disease by enhancing retinal images for extracting meaningful features and identifying abnormalities, Such as Contrast-Limited Adaptive Histogram Equalization (CLAHE) [1][2][7], blob detection [7][26], image denoising [4][13][22], shape-based features [24], thresholding [1], template matching [24][26] median filtering [18][21][24][27] gaussian smoothing [20][23] and region-based segmentation [18]. The integration of OCTA imaging with DL models has also been explored for improved DR diagnosis [12]. Principal Component Analysis (PCA) has been used to improve retinal image quality, dimensionality reduction and for feature extraction. Lesion detection, classification of DR disease severity level using harris hawk optimization algorithm [9]. Segmentation detection techniques have been used to detect retinal lesions on fundus images [30]. They detect the severity level of DR disease by using the fluorescein angiography imaging technique [25]. Scanning Laser Ophthalmoscope (SLO) can be used for DR diagnosis [29]. Ultra-Wide Field (UWF) imaging Field Of View (FOV) is up to 200 degrees, which is the most significant technique for detecting DR disease [24].

The ML and DL approaches are extremely versatile and adaptive. Table1. shows the comparative analysis of the performance of DR disease detection, diagnosis, segmentation and classification using ML and DL techniques, with improved methodology and robust results. To identify outperforming ML and DL models as compared to traditional methods such as the Hybrid model (InceptionResNetV2+MobileNetV2) demonstrated by Intifa Aman Taifa et al [15]. achieved an accuracy rate of 98.36% in binary class and 95.50% in multi-class classification using the APTOS 2019 dataset. Samia Akhtar et al [22]. proposed Retinopathy Severity Grading Net (RSG-Net) model, which achieved the highest accuracy on both binary classification and multi-class classification, 99.37% and 99.36% respectively on Messidor-1 dataset. A Quantum Chip Optimization algorithm proposed by Anas Bilal et al. [21] achieved the highest accuracy 99.80%, in multi-class classification on Indian Diabetic Retinopathy Image Dataset (IDRiD).

Table1. Comparative Analysis on DR disease

Authors /Ref	Severity Classification	Dataset	Tools	Techniques	Models	Results	Research Gap	Limitation
Brahami Menaouer et al[4].	Multi-Class Classification	APTOS 2019	Python	Image Denoising, Normalization	Hybrid Model	Accuracy:90.60% Recall:95% Precision:94.66% Specificity:94.66 %	Dataset imbalanced	Computational Power
Aswin Shriram Thiagarajan et al[5].	Multi-Class Classification	IDRiD	Open CV Keras Library	Image resizing, Data Augmentation	CNN	Accuracy:80%	Minimize false +ve and false -ve cases	Single Dataset
Mahesh S Patil et al[6].	Multi-Class Classification	APTOS EyePACS	Tensor Flow Fast.ai	Data Augmentation	ResNet 50	Accuracy:97%	EyePACS dataset is imbalanced	Used only pretrained model
Abdul Qadir Khan et al[8].	7-Stage classification	Dataset Collect from Hospital	Not Mention	Image Normalization, Data Augmentation	Vgg16-TL	Accuracy:96.95% Sensitivity:98.94 % Specificity:94.12 %	Expanding the Model Capabilities	7-stage Single Dataset
Nagaraja Gundluru et al[9].	Classification on NPDR and PDR	DR Debrecen Dataset	Python	PCA	Harris Hawks Optimization	Accuracy:97%	Model overfitting	Low - dimensional dataset
Abdul Muiz Fayyaz et al [10].	DR1, DR2, DR3, Normal	DR Detection Dataset	Not Mention	Data Augmentation	Ant Colony System	Accuracy:93%	Lack of Severity Stages	Single Dataset
Zhiping Lu et al[12].	Binary Classification	OCTA Images	MATLAB	2D Discreate Wavelet Transform (DWT)	SVM, LR-EN Algorithms	Accuracy:0.82	Work on multi-class classification	OCTA single-centre dataset used
Nidhi Kamothi et al[13].	Multi-Class classification	EyePACS	Google Colab	Image Denoising, Size Normalization.	CNN	Accuracy:85% Kappa Score:0.72	Improve Kappa Score	Computational Power
Intifa Aman Taifa et al [15].	Binary Classification Multi-Class Classification	APTOS 2019	Python 3.7	Image Resizing, Data Augmentation	Hybrid Model	Binary Class Accuracy:98.36% Multi-class Accuracy:95.50%	Lack of robustness in hybrid Model	Imbalance dataset after augmentation
Lakshay Arora et al[16].	Multi-class Classification	DR Detection Dataset	Tensor Flow	Data Augmentation	EfficientNetB 0	Accuracy:86.53%	Class Imbalance	Single Dataset
Ayesha Jabbar et al [17].	Multi-class Classification	EyePACS	Google Collab	Data Augmentation	Hybrid Model	Accuracy:94%	Improve preprocessing techniques	Biases in Dataset
Posham Uppama et al [18].	Multi-class Classification	IDRiD	Python	Median Filtering, Lesion Segmentation	Tylora Avoa Algorithms	Accuracy:94.2% Sensitivity:94.8% Specificity:93.4%	Scalability issue	Computational Complexity
Kachi Anvesh et al[19].	Multi-class Classification	Fundus Images Mendeley Dataset	Google Colab	Data Augmentation	VGG16	Accuracy:93.42%	Overfitting problem in Model	Small Dataset Size
Cheena Mohanty et al [20].	Mult-class Classification	APTOS 2019	Python	Image Resize, Gaussian Blur, Ben Graham Approach	VGG+ XGBoost Classifier	Accuracy:79.50%	Enhance performance of proposed model	Dataset Imbalance
Anas Bilal et al [21].	Multi-class Classification	IDRiD	MATLAB	Contrast Stretching, Median Filtering	Quantum chimp optimization algorithm	Accuracy:99.80% Sensitivity:99.90 % Specificity:100%	Difficultly in detection lesion size and shape	Single Dataset
Samia Akhtar et al[22].	Binary Classification Multi-class Classification	Messidor -1	Python	Image cropping, Image Denoising	RSG-Net Model	Binary class Accuracy: 99.37% Mult-class Accuracy:99.36%	Overfitting due to high accuracy in trained model	Single dataset
Laxmi Math et al [23].	Multi-class Classification	DIARET-DBI	MATLAB 2016B	Scaling, Gaussian Smoothing	CNN	AUC:0.963 Sensitivity:96.37 % Specificity:96.37 %	Variability in retinal images	Computational power

Nisha Wankhade et al [24].	Multi-class Classification	DR Detection dataset	MATLAB, Python	Median Filtering, Texture Formation	Hybrid Framework	Accuracy:96.7%	Class Imbalance	Clinical Validation
Gigi Tabacaru et al [25].	Multi-class Classification	IDRiD	Pycaret 3.0.4 version	Histogram Equalization, Feature Extraction	Gradient Boosting Classifier	Accuracy:0.929 AUC:0.941 F1 score:0.902	Images are not segmented into region of interest	Single Dataset
Paresh Chandra Sau et al [27].	Multi-class Classification	IDRiD	Python	Median Filtering	Grasshopper Optimization Algorithm	Accuracy:0.95 Sensitivity:0.97 Specificity:0.46 Precison:0.97 F1-score:0.97	Improve small lesion detection	Dataset Bias
P.Saranya et al [28].	Exudates detection	Messidor, E-optha ex public dataset	Scikit learn	Data Augmentation	CNN	Messidor Accuracy:97.54% E-optha ex public Accuracy:96.32%	Detection on all severity classes	The model is designed to detect only exudates
Muhammad Mohsin Butt et al [30].	Binary class classification Multi-class Classification	APTOS Dataset	MATLAB	Image resizes, Image Normalization	Hybrid Model	Binary class Accuracy:97.80% Multi-class Accuracy:89.29%	Imbalance Dataset	Single Dataset
Akwasi Asare [32].	Multi-class Classification	EYEPACS	Tensor Flow	Data Augmentation, Normalization	MobileNet	Accuracy:96.45%	Enhance model robustness	Single Dataset

A comparative analysis graph in Fig.3.This graph compares the accuracy of the models in different research studies conducted by various authors on DR disease classification. Each bar represents the accuracy achieved by a specific model.

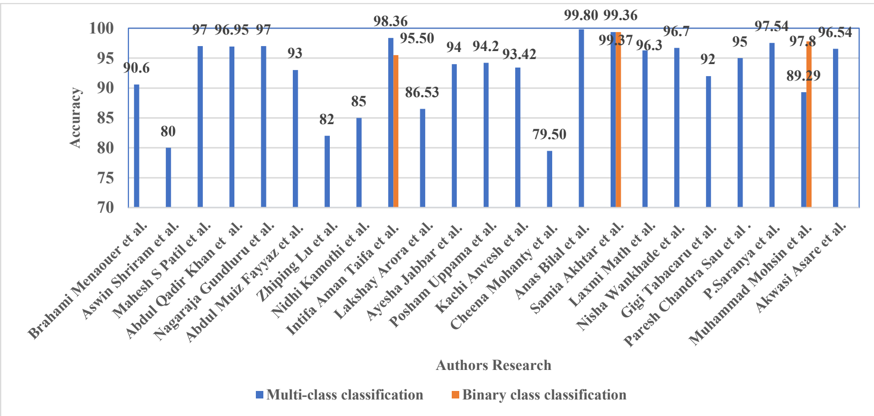

Fig. 3. Comparative analysis graph on DR disease

4. Challenges in Diabetic Retinopathy Detection

In research analysis of DR disease detection has identified a few key challenges, which are outlined below.

- Identifying of small - sized lesions such as tiny haemorrhages and early exudates in retinal images is a critical task due to image quality, differences in resolution, the presence of noise and brightness [21][25][27].
- Classification is difficult at severity stages because of the similarity in exudates, minor microaneurysms and optical disc appear in the retinal images, which led to inaccurate classification results [12] [17] [23] [28].
- The medical validation on real-time implementation of ML and DL algorithms in clinical practice remains

challenging due to issues including interpretability and generalizability [24] [26][28][29].

- All publicly available retinal image datasets are imbalanced, containing an unequal number of images for all severity stages of DR disease, which effects models accuracy [4][16][22][24][27][30].

5. Conclusion and Future Work

DR is a retinal disorder disease. The Computer Aided Diagnosis (CAD) health care systems use ML and DL techniques at the backend. This study covered a comparative analysis of DR disease detection that uses several preprocessing techniques performed on retinal image datasets in severity classification tasks. The ML and DL models have achieved outcomes on accuracy, F1-score, recall, precision, specificity and sensitivity on the DR disease domain. This analysis also highlighted challenges in the automated DR disease detection systems. However, the ML and DL models have a limitation, as they require a huge volume of data for accurate predictions. The future research should focus on real-world validations and expand datasets. It should implement privacy based advanced techniques for DR disease detection to achieve high accuracy while improving the time complexity of models. Feature fusion will be used in the enhancement techniques for improved DR disease prediction and detection. Integration of Electronic Health Records (EHR) systems with real time systems for expand clinical records. Distributed computing platforms can be used for better visualization for lesion detection in retinal images. The researcher should also explore different hybrid architectures for identifying and classifying retinal images and further enhance the methodology used for early DR detection.

References

[1] A. Chakraborty, G. Wilson, and C. Luca, "A lightweight classification system for the early detection of diabetic retinopathy," *Informatics Med. Unlocked*, vol. 57, pp. 655–666, 2025, doi: https://doi.org/10.1016/j.imu.2025.101655.

[2] M. Youldash *et al.*, "Deep learning empowered diagnosis of diabetic retinopathy," *Intell. Autom. Soft Comput.*, vol. 40, no. 1, pp. 125–143, 2025, doi: https:// 10.32604/iasc.2025.058509.

[3] M. Bader Alazzam, F. Alassery, and A. Almulihi, "Identification of Diabetic Retinopathy through Machine Learning," *Mob. Inf. Syst.*, vol. 2021, no. 1, pp. 116–127, 2021, doi: https://doi.org/10.1155/2021/1155116.

[4] B. Menaouer, Z. Dermane, N. El Houda Kebir, and N. Matta, "Diabetic retinopathy classification using hybrid deep learning approach," *SN Comput. Sci.*, vol. 3, no. 5, pp. 357–373, 2022, doi: https://doi.org/10.1007/s42979-022-01240-8.

[5] A. S. Thiagarajan, J. Adikesavan, S. Balachandran, and B. G. Ramamoorthy, "Diabetic retinopathy detection using deep learning techniques," *J. Comput. Sci*, vol. 16, no. 3, pp. 305–313, 2020, doi: DOI: 10.3844/jcssp.2020.305.313.

[6] M. S. Patil, S. Chickerur, C. Abhimalya, A. Naik, N. Kumari, and S. Maurya, "Effective deep learning data augmentation techniques for diabetic retinopathy classification," *Procedia Comput. Sci.*, vol. 218, pp. 1156–1165, 2023, doi: 10.1016/j.procs.2023.01.094.

[7] M. R. Islam *et al.*, "Applying supervised contrastive learning for the detection of diabetic retinopathy and its severity levels from fundus images," *Comput. Biol. Med.*, vol. 146, pp. 602–620, 2022, doi: https://doi.org/10.1016/j.compbiomed.2022.105602.

[8] A. Q. Khan, G. Sun, M. Khalid, M. Farrash, and A. Bilal, "Multi-Deep Learning Approach With Transfer Learning for 7-Stages Diabetic Retinopathy Classification," *Int. J. Imaging Syst. Technol.*, vol. 34, no. 6, pp. 213–230, 2024, doi: https://doi.org/10.1002/ima.23213.

[9] N. Gundluru *et al.*, "Enhancement of detection of diabetic retinopathy using Harris hawks optimization with deep learning model," *Comput. Intell. Neurosci.*, vol. 2022, no. 1, pp. 469–482, 2022, doi: https://doi.org/10.1155/2022/8512469.

[10] 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*, vol. 14, no. 1, pp. 30–44, 2023, doi: https://doi.org/10.3390/info14010030.

[11] M. A. A. Albadr, M. Ayob, S. Tiun, F. T. Al-Dhief, and M. K. Hasan, "Gray wolf optimization-extreme learning machine approach for diabetic retinopathy detection," *Front. Public Heal.*, vol. 10, pp. 901–917, 2022, doi: https://doi.org/10.3389/fpubh.2022.925901.

[12] Z. Liu, C. Wang, X. Cai, H. Jiang, and J. Wang, "Discrimination of diabetic retinopathy from optical coherence tomography angiography images using machine learning methods," *IEEE access*, vol. 9, pp. 51689–51694, 2021, doi: http://10.1109/ACCESS.2021.3056430.

[13] N. Kamothi and R. Thakur, "Automatic Detection of Diabetic Retinopathy Using Convolution Neural Network," *IRJET*, vol. 7, pp. 810–816, 2020, doi: e-ISSN: 2395-0056 p-ISSN: 2395-0072.

[14] 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. 79–96, 2025, doi: https://doi.org/10.1007/s13369-024-09137-9.

[15] I. A. Taifa, D. M. Setu, T. Islam, S. K. Dey, and T. Rahman, "A hybrid approach with customized machine learning classifiers and multiple feature extractors for enhancing diabetic retinopathy detection," *Healthc. Anal.*, vol. 5, pp. 346–363, 2024, doi: https:/https/doi.org/10.1016/j.health.2024.100346.

[16] L. Arora ., "Ensemble deep learning and EfficientNet for accurate diagnosis of diabetic retinopathy," *Sci. Rep.*, vol. 14, no. 1, pp. 554–570, 2024, doi: https://doi.org/10.1038/s41598-024-81132-4.

[17] A. Jabbar., "A lesion-based diabetic retinopathy detection through hybrid deep learning model," *IEEE Access*, vol. 12, pp. 40019–40036, 2024, doi: doi:http://10.1109/ACCESS.2024.3373467.

[18] P. Uppamma and S. Bhattacharya, "Diabetic retinopathy detection: A blockchain and African vulture optimization algorithm-based deep learning framework," *Electronics*, vol. 12, no. 3, pp. 42–61, 2023, doi: https://doi.org/10.3390/electronics12030742.

[19] K. Anvesh., "A Novel Approach Deep Learning Framework for Automatic Detection of Diseases in Retinal Fundus Images.," *Comput. Model. Eng. Sci.*, vol. 143, no. 2, pp. 1–33, 2025, doi: http://dx.doi.org/10.32604/cmes.2025.063239.

[20] C. Mohanty *l.*, "Using deep learning architectures for detection and classification of diabetic retinopathy," *Sensors*, vol. 23, no. 12, pp. 26–44, 2023, doi: https://doi.org/10.3390/s23125726.

[21] A. Bilal, M. Shafiq, W. J. Obidallah, Y. A. Alduraywish, A. Tahir, and H. Long, "Quantum chimp-enanced SqueezeNet for precise diabetic retinopathy classification," *Sci. Rep.*, vol. 15, no. 1, pp. 90–102, 2025, doi: https://doi.org/10.1038/s41598-025-97686-w.

[22] S. Akhtar*l.*, "A deep learning based model for diabetic retinopathy grading," *Sci. Rep.*, vol. 15, no. 1, pp. 63–83, 2025, doi:

https://doi.org/10.1038/s41598-025-87171-9.
[23] L. Math and R. Fatima, "Adaptive machine learning classification for diabetic retinopathy," *Multimed. Tools Appl.*, vol. 80, no. 4, pp. 5173–5186, 2021, doi: https://doi.org/10.1007/s11042-020-09793-7.
[24] Wankhade, N., Jadhav, A., Patil, D. H., More, V., Gokhale, A., & Dahigaonkar, D. J. (2025). Diabetic Retinopathy Abnormality Classification and Identification Using Mathematical Morphological and Machine Learning Approach. International Journal of Environmental Sciences, 11(6s), 1167–1182. https://doi.org/10.1109/ACCESS.2025.3566073.
[25] G. Tăbăcaru, S. Moldovanu, E. Răducan, and M. Barbu, "A robust machine learning model for diabetic retinopathy classification," *J. Imaging*, vol. 10, no. 1, p. 8, 2024. http:// doi: 10.3390/jimaging10010008.
[26] T.R. Gakekallu et al., "Early Detection of Diabetic Retinopathy Using PCA-Firefly Based Deep Learning Model," Electronics, vol.9, no.2, pp. 274-284, Feb .2020.http://doi:10.3390/electronics9020274.
[27] P. C. Sau and A. Bansal, "A novel diabetic retinopathy grading using modified deep neural network with segmentation of blood vessels and retinal abnormalities," Multimedia Tools and Applications, vol. 81, no. 28, pp. 39605–39633, Apr. 2022,http://doi: 10.1007/s11042-022-13056-y.
[28] P. Saranya and K. M. Umamaheswari, "Detection ofexudates from retinal images for non-proliferative diabetic retinopathy detection using deep learning model," *Multimedia Tools and Applications*, vol. 83, pp. 52253–52273, Nov. 2023,http:// doi: 10.1007/s11042-023-17462-8.
[29] P. Macsik, J. Pavlovicova, S. Kajan, J. Goga, and V. Kurilova,"Image preprocessing-based ensemble deep learning classification of diabetic retinopathy," IET Image Processing, vol. 18, no. 3, pp. 807–828, 2024, http://doi: 10.1049/ipr2.12987.
[30] 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, p. 1607, Jul. 2022,http:// doi: 10.3390/diagnostics12071607.
[31] K. Singh, R.Kumar, A. Aggarwal, P.Soni, and R.D. Aneja, ""Deep Learning Models for Software Defect Classification," 2024 2nd International Conference on Device Intelligence, Computing and Communication Technologies, pp.1-6 http://doi:10.1109/DICCT61038.2024.10532830.
[32] A. Asare, D. A. N. Gookyi, D. Boateng, and F. A. Wulnye, "Deploying and Evaluating Multiple Deep Learning Models on Edge Devices for Diabetic Retinopathy Detection http://,doi: 10.1155/2022/7969389.