International Journal of Scientific Research & Engineering Trends
Volume 12, Issue 4, Jul-Aug-2026, ISSN (Online): 2395-566X

Neural Network based Medical Data Classification by Moth Flame Feature Optimization

Nand Kishor, Prof. Akrati Shrivastava
Department Computer of Science and Engineering
Vaishnavi Inst. of Tech. & Science,Bhopal, India

Abstract- Medical practioner have huge load with growing population after corona in 2020, most of researcher work in this medical field. This paper has proposed a model to classify the diabetic patient retinopathy disease image class detection. This work has processed the image input image quality and train the model. Proposed (Medical Data Classification by Moth Flame Optimization) MDCMFO optimized the input image by moth flame algorithm that cluster input image. Clustered image was used for the feature extraction spatial and frequency domain. Extracted features were used for the training of the neural network. Experiment was done on real image dataset and result shows that proposed work has improved the work efficiency of correct class detection.

Keywords- Image Classification, Feature Extraction, Diabetic Retinopathy, Image Processing.

I. INTRODUCTION

Diabetes mellitus is a long-term metabolic disorder characterized by insufficient insulin production, impaired insulin utilization, or both, resulting in elevated blood glucose levels [1]. It has emerged as a major global health challenge, affecting a large population across the world [1,2]. The increasing prevalence of diabetes places a considerable burden on healthcare systems and may result in various severe health complications when appropriate management is not provided. Diabetic Retinopathy (DR) is one of the major complications associated with prolonged diabetes, and it is estimated that nearly one-third of individuals with diabetes may develop this condition.

Diabetic retinopathy is a diabetes-related microvascular disorder that primarily affects the retinal tissues of the eye [3]. Persistent hyperglycemia can damage the small blood vessels supplying the retina, which is responsible for sensing light and transmitting visual information to the brain. Continued exposure to high glucose levels can weaken retinal blood vessels, resulting in microaneurysms, vascular leakage, and retinal edema [4]. With disease progression, the obstruction of retinal blood vessels reduces the supply of oxygen and essential nutrients. In response to this ischemic condition, abnormal new blood vessels may develop during advanced stages of the disease. These newly formed vessels are fragile and can rupture easily, causing retinal hemorrhages, fibrosis, and potentially retinal detachment. Consequently, progressive retinal damage can significantly impair visual function. If diagnosis and treatment are delayed, diabetic retinopathy may result in severe visual impairment and, ultimately, irreversible blindness [5].

The clinical manifestations of diabetic retinopathy vary according to disease severity and may include blurred or unstable vision, dark or blank regions within the visual field, reduced ability to see in low-light conditions, and the perception of spots or floaters [6]. In severe or untreated cases, progressive retinal damage can ultimately result in complete loss of vision. Important pathological features commonly associated with diabetic retinopathy include hard and soft exudates (EX), microaneurysms (MA), retinal hemorrhages (HM), and neovascularization [7].

Early screening of diabetic retinopathy (DR) is very important for preventing serious eye-related complications [8]. Early detection helps in identifying the disease before it reaches an advanced stage, where treatment becomes more difficult and may not provide effective results. In the initial stage of diabetic retinopathy, patients may have no symptoms or only minor vision-related problems. If the disease is identified at this stage, timely treatment can help to reduce the risk of severe vision loss by controlling the condition before permanent retinal damage occurs. Doctors can control or slow down the progression of diabetic retinopathy through proper management of blood glucose levels, regular monitoring, and treatments such as laser therapy.

Traditionally, the identification and classification of diabetic retinopathy have mainly depended on examinations performed by ophthalmologists. This process requires significant time and effort and may also be affected by differences in the observations and experience of different experts [8]. In recent years, researchers have started using artificial intelligence (AI) and deep learning techniques to make diabetic retinopathy screening and classification more automated and efficient [9]. Several deep learning methods, particularly Convolutional Neural Networks (CNNs), have been developed for analysing medical images and have shown promising results in retinal image analysis.

The application of deep learning in diabetic retinopathy offers several advantages in medical research, clinical diagnosis, and healthcare services. As a result, many studies have focused on developing reliable deep learning models for the automatic detection and classification of diabetic retinopathy [9]. These models analyse retinal fundus images to identify the severity or stage of DR and can also help in deciding whether a patient should be referred to an ophthalmologist for further examination and treatment.

Although considerable progress has been made in using deep learning for diabetic retinopathy screening, several challenges still need to be addressed. One of the major challenges is the availability of large and diverse datasets. A wide range of retinal images is required to train reliable and generalised deep learning models; however, collecting such datasets is difficult because of patient privacy, limited data availability, and differences in image acquisition methods [10]. In addition, ethical and regulatory issues are also important considerations. Healthcare applications must ensure patient confidentiality and data security while complying with different healthcare regulations and standards, which may vary between countries and regions.

II. RELATED WORK

M. Tavakoli et al. [11] presented a study focused on developing both unsupervised and supervised methods for effectively addressing the problem of Microaneurysm (MA) detection in retinal images. In the initial stage, preprocessing was applied to retinal images to reduce background variations and improve the accuracy of MA detection. In the next stage, important retinal structures, including the optic nerve head and blood vessels, were identified and masked using the Radon Transform (RT) and multi-overlapping window techniques. After removing these structures, Microaneurysms were detected and counted using a combination of the Radon Transform and a supervised Support Vector Machine (SVM) classifier. The proposed method was evaluated using three publicly available datasets along with a local dataset, containing a total of 749 retinal images.

D. Yi et al. [12] introduced a new compound scaling encoder-decoder network to improve both the accuracy and computational efficiency of microvascular lesion segmentation. In the encoder part, a lightweight network was designed to reduce the training time. The encoder was scaled in terms of network depth, width, and image resolution. In the decoder section, an attention mechanism was included to improve segmentation performance. In particular, Concurrent Spatial and Channel Squeeze and Channel Excitation (scSE) blocks were used to effectively utilise spatial and channel-level information. Further, a compound loss function combined with transfer learning was applied to address the class imbalance problem and improve the overall segmentation results.

M. S. B. Phridviraj et al. [13] investigated the use of deep learning techniques at different stages of the fundus image-based diagnostic process for diabetic retinopathy detection. Deep learning-based methods have already shown good performance in different medical image classification applications. In their work, a bidirectional extended short-term memory-based model was proposed for detecting diabetic retinopathy from retinal fundus images. Before performing the classification, Multiscale Retinex with Chromaticity Preservation (MSRCP) was applied to improve the quality of the retinal images. However, one of the major challenges of the Retinex method is selecting suitable parameter values, such as Gaussian scales, gain, and offset. Proper adjustment of these parameters is necessary to obtain better image enhancement results. Therefore, the main objective of the proposed method was to identify suitable parameter values for the MSRCP algorithm. The enhanced retinal images were then given to an EfficientNet-based deep learning feature extractor to generate useful feature vectors for further diabetic retinopathy analysis.

Fernando K. Malerbi et al. [14] conducted a study in which fundus images were captured from participants using a portable

International Journal of Scientific Research & Engineering Trends
Volume 12, Issue 4, Jul-Aug-2026, ISSN (Online): 2395-566X

retinal camera called Phelcom Eyer. The obtained retinal images were automatically analysed using two deep learning-based methods, namely Retinal Alteration Score (RAS) and Diabetic Retinopathy Alteration Score (DRAS). Both methods were based on Convolutional Neural Networks (CNNs), which were initially trained using the EyePACS dataset and later fine-tuned using fundus images collected from portable retinal imaging devices. To evaluate the performance of the proposed system, the ground-truth labels were obtained from expert assessments. The final DR classification was determined through the independent evaluation and agreement of three certified ophthalmologists.

Zeru Hai et al. [15] proposed a Diabetic Retinopathy Grading Convolutional Neural Network (DRGCNN) model for classifying the severity of diabetic retinopathy. The proposed model was designed to address the issue of imbalanced data distribution among different DR categories. To achieve a more balanced representation, the model assigns an equal number of channels to feature maps corresponding to different DR classes. In addition, a CAM-EfficientNetV2-M-based encoder was introduced to process retinal fundus images and generate meaningful feature vectors. These extracted features were then used for further classification of diabetic retinopathy grades.

D. R. Manjunath [16] investigated machine learning-based classification methods for diabetic retinopathy and diabetic nephropathy. For diabetic retinopathy classification, Voting and Stacking ensemble classifiers achieved very high performance across multiple datasets. These ensemble techniques combine the predictions of multiple individual models, which can improve the overall accuracy and reliability of the classification system. For diabetic nephropathy prediction, CatBoost and LightGBM models showed good performance on both original and class-balanced datasets. These methods are effective for handling complex nonlinear relationships and interactions commonly found in clinical datasets.

III. PROPOSED METHODOLOGY

The proposed (Medical Data Classification by Moth Flame Optimization) MDCMFO consists of four major stages: image preprocessing, feature optimization using the Moth-Flame Optimization (MFO) algorithm, feature extraction, and classification. Whole steps of model is shown in fig. 1. The objective of this framework is to identify the most informative image features for training while eliminating irrelevant or redundant features. The optimized features are subsequently transformed into discriminative feature vectors using Discrete Cosine Transform (DCT) and histogram-based features for diabetic retinopathy classification.

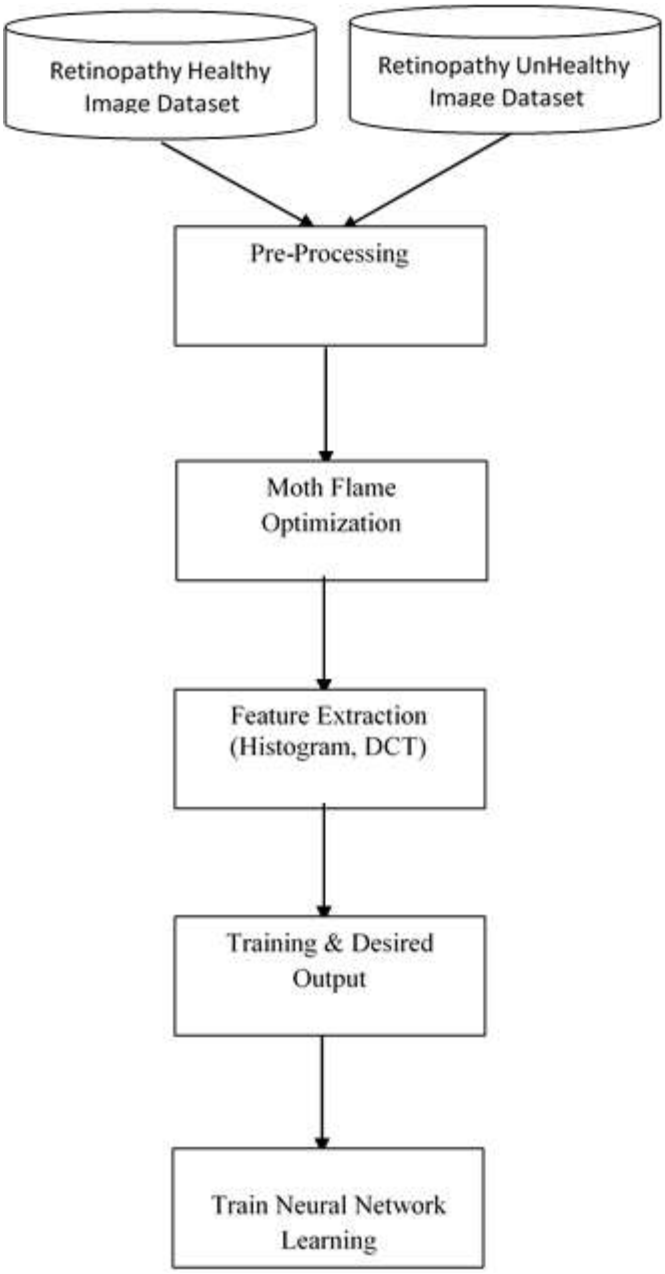

Fig. 1 Block diagram of proposed MDCMFO model.

Preprocessing
A retinal image is represented as a matrix of pixels, where each pixel contains an intensity value. For a grayscale image, the

intensity value generally ranges from 0 to 255. During preprocessing, the input diabetic retinal image is read and converted into a matrix corresponding to its pixel intensity values.

PI←Pre_Process(DRID[i])

Since the images in the DRID (Diabetic Retinopathy Image Dataset) dataset may have different spatial dimensions, all input images are resized to a predefined fixed dimension [17]. This standardization ensures that every image generates a consistent number of input values for subsequent processing. The resulting normalized image matrix is then provided to the feature optimization stage. Dataset have class of image as well term as IC, Image Class.

Moth-Flame Optimization-Based Feature Selection

The preprocessed retinal image matrix is further processed using the Moth-Flame Optimization (MFO) algorithm to select the most relevant features for diabetic retinopathy classification [18]. The primary objective of MFO is to reduce the dimensionality of the training vector while retaining the features that contribute most effectively to classification accuracy.

Generate Moth Flames

In the proposed method, a Moth represents a candidate cluster-center solution. Each Moth contains a fixed number of pixel values randomly selected from the input retinal image. These selected pixel values act as the initial cluster centers.

For example, if a Moth contains (k) pixel values, it can be represented as:

M←Generate_Moth Flame(k, w, I)

Multiple Moths are randomly generated to form the initial Moth population. Each Moth therefore represents one possible clustering solution for partitioning the pixel values of the diabetic retinal image.

Fitness Function

Each Moth Flame were rank as per distance. So evaluation of distance done by fitness value. Moth Flame feature vector pass training vector to the neural network for training and measure the detection accuracy of the work [11]. This detection accuracy value is distance parameter in the work.

Input: M, m,n

Output: Wf

1. Loop w=1:W // for w Moth Flames
2. For p=1:mxn // m,n are image dimension
3. F←Min(Dist(w, p))
4. EndLoop
5. Wf[w]←F
6. Endloop

Update Moth Flame position

Once F value obtain by fitness function then sort f in deseding order and find best Moth Flame out of all chromosomes available in the population.

Crossover: Genetic algorithm success depends on change of chromosomes, hence as per changing parameter X, number of random position value of Moth Flames were modified. This operation was not done in best local Moth Flame. In this step each Moth Flame X number of positions were modified randomly from zero to one or one to zero as per best local Moth Flame feature set. These Moth Flame were further test for path distance and compared its fitness value with parent Moth Flame if child Moth Flame has better values then remove parent otherwise parent will continue. After this step if maximum iteration steps occur then jump to filter feature block otherwise evaluate fitness value of each Moth Flame Moth Flame.

Population Update: Accept new possible solution or resultant chromosome after crossover if it gives a better fitness function value. Once this phase is over then check for the maximum iteration for the genetic algorithm if iteration not reach to the maximum value then GOTO step of selection phase else stop learning. So the best solution from the available population is consider as the final best chromosome of the work.

Filter Feature Once iteration get complete then find best Moth Flame from the last updated population.

CI←Cluster_Image(I, M, Wf)

Extract Feature

Two feature set were extract from the clustered image first is histogram and other is discrete cosine transformed [17].

Histogram Feature: In this step image vector obtained after pre-processing is used where histogram of the image is find at one bins. This can be understand as let scale of color is 1 to 10, than count of each pixel value is done in the image. So as per above vector Hi=[0, 0, 0, 4, 3, 5, 2, 1 2, 0] where H represent the color pixel value count and i represent the position in the H matrix with color value.

Training of Neural Network

Neural network consider takes input training vector and desired output during training [19]. For each set of training vector neuron weight value adjust for e number of epochs. Trained neural network was directly used for predicting the session class as attack or normal.

MICNN←Train_Neural_Network(H,DCT,IC)

Proposed MDCMFO Algorithm

Input: DRID, IC // IC: Image Class
Output: MICNN

1. Loop i=1: N
2. PI←Pre_Process(DRID[i])
3. EndLoop
4. M←Generate_Moth_Flame(k, w, I)
5. Loop 1:itr // itr: Number of Iteration
6. Wf←Fitness_Function(M,m,n)
7. M←Moth_Flame_Position(M,Wf)
8. M←Update_Population(M)
9. EndLoop
10. Wf←Fitness_Function(M,m,n)
11. CI←Cluster_Image(I,M,Wf)
12. [H, DCT]←Extract_Feature(CI)
13. EndLoop
14. MICNN←Train_Neural_Network(H,DCT,IC)

IV. EXPERIMENTAL RESULTS

Experiment Setup

The tests were performed on an 2.27 GHz Intel Core i3 machine, equipped with 4 GB of RAM, and running under Windows 7 Professional. MATLAB 2016a is the tool use for the implementation of this work. Experimental dataset have two image class for training and testing [20].

Evaluation Parameters

$$Precision = \frac{True\_Positive}{True\_Positive + False\_Positive}$$

This recall rate is the ratio of the number true class identified by an algorithm to the number of sources actually class present in the system.

$$Recall = \frac{True\_Positive}{True\_Positive + False\_Negative}$$

F-measure is an inverse average of precision and recall values.

$$F\_Score = \frac{2 * Precision * Recall}{Precision + Recall}$$

Accuracy its an ratio of total number of correct prediction for all class set to the total number of prediction sets.

$$Accuracy = \frac{Correct\_Classification}{Correct\_Classification + Incorrect\_Classification}$$

Results:

Table 1 Medical image classification models precision value based comparison.

Testing Images	Base Model [16]	MDCMFO
30	0.8824	0.9333
60	0.871	0.8629
90	0.8367	0.8888
120	0.8769	0.916
150	0.878	0.9205

Table 1 shows precision value of retinopathy image classification models. It was shown that use of moth flame optimization algorithm proposed work will improved the precision value 3.903% as compared to existing model.

Table 2 Medical image classification models recall value based comparison.

Testing Images	Base Model [16]	MDCMFO
30	0.75	0.875
60	0.7297	0.896
90	0.7455	0.911
120	0.7308	0.8883
150	0.7579	0.897

Recall values of comparing retinopathy image classification models shown in table 2. It was found that use of neural network for learning of optimized image extracted features has improved the work recall value 16.86%, as compared to existing model.

Table 3 Medical image classification models f-measure value based comparison.

Testing Images	Base Model [16]	MDCMFO
30	0.8108	0.9032
60	0.7941	0.8792
90	0.7885	0.8998
120	0.7972	0.902
150	0.8136	0.9086

F-measure values of comparing retinopathy image classification models shown in table 3. It was found that use of neural network for learning of optimized image extracted features has improved the work F-measure value 10.87%, as compared to existing model.

Table 4 Medical image classification models accuracy value based comparison.

Testing Images	Base Model [16]	MDCMFO
30	77.419	89.2827
60	76.2712	88.1430
90	75.8242	90.0977
120	76.6129	90.0416
150	78	90.74

Table 4 shows accuracy value of retinopathy image classification models. It was shown that use of moth flame optimization algorithm proposed work will improved the accuracy value 14.31% as compared to existing model.

V. CONCLUSION

This study presented the proposed Medical Data Classification by Moth Flame Optimization (MDCMFO) framework for diabetic retinopathy image classification. The proposed approach integrates image preprocessing, Moth-Flame Optimization-based feature selection, image clustering, DCT and histogram-based feature extraction, and neural network classification. MFO effectively identifies relevant pixel-based features and reduces redundant information, enabling the classifier to learn more discriminative representations. Experimental results demonstrate that MDCMFO consistently outperforms the base model across the evaluated testing sets. The proposed method achieved improvements of approximately 3.90% in precision, 16.86% in recall, 10.87% in F-measure, and 14.31% in accuracy compared with the existing model. These findings indicate that optimized feature selection combined with DCT and histogram features can significantly improve diabetic retinopathy classification performance.

REFERENCES

1. Chilukoti, S. V., Maida, A. S. & Hei, X. Diabetic retinopathy detection using transfer learning from pre-trained convolutional neural network models. IEEE J. Biomed. Heal Inf. 20, 1–10 (2022).
2. Al-Smadi, M., Hammad, M., Baker, Q. B. & Sa'ad, A. A transfer learning with deep neural network approach for diabetic retinopathy classification. Int. J. Electr. Comput. Eng. 11 (4), 3492 (2021).
3. Akhtar, S., Aftab, S., Ahmad, M. & Ihnaini, B. A transfer learning based framework for diabetic retinopathy detection using data fusion. In 2024 2nd International Conference on Cyber Resilience (ICCR). 1–5. (IEEE, 2024).
4. Akhtar, S. & Aftab, S. A framework for diabetic retinopathy detection using transfer learning and data fusion. Int. J. Inform. Technol. Comput. Sci. (IJITCS). 16 (6), 61–73 (2024).
5. Sebti, R., Zroug, S., Kahloul, L. & Benharzallah, S. A deep learning approach for the diabetic retinopathy detection. In The Proceedings of the International Conference on Smart City Applications. 459–469. (Springer, 2021).
6. Gangwar, A. K. & Ravi, V. Diabetic retinopathy detection using transfer learning and deep learning. In Evolution in Computational Intelligence: Frontiers in Intelligent Computing: Theory and Applications (FICTA 2020). Vol. 1. 679–689. (Springer, 2021).
7. Jabbar, M. K., Yan, J., Xu, H., Ur Rehman, Z. & Jabbar, A. Transfer learning-based model for diabetic retinopathy diagnosis using retinal images. Brain Sci. 12 (5), 535 (2022).
8. Ghosh, S. & Chatterjee, A. Transfer-Ensemble Learning based Deep Convolutional Neural Networks for Diabetic Retinopathy Classification. arXiv preprint: arXiv:2308.00525 (2023).
9. M. Kropp et al., "Diabetic retinopathy as the leading cause of blindness and early predictor of cascading complications—risks and mitigation," EPMA Journal, vol. 14, no. 1, pp. 21–42, 2023.

10. Venkateswara Rao Naramala, B. Anjanee Kumar, Vuda Sreenivasa Rao, Annapurna Mishra, Shaikh Abdul Hannan, Yousef A.Baker El-Ebiary, and R. Manikandan. Enhancing diabetic retinopathy detection through machine learning with restricted boltzmann machines. International Journal of Advanced Computer Science and Applications, 14(9), 2023. ISSN 2158107X.
11. M. Tavakoli, A. Mehdizadeh, A. Aghayan, R. P. Shahri, T. Ellis and J. Dehmeshki, "Automated Microaneurysms Detection in Retinal Images Using Radon Transform and Supervised Learning: Application to Mass Screening of Diabetic Retinopathy," in IEEE Access, vol. 9, pp. 67302-67314, 2021.
12. D. Yi, P. Baltov, Y. Hua, S. Philip and P. K. Sharma, "Compound Scaling Encoder-Decoder (CoSED) Network for Diabetic Retinopathy Related Bio-Marker Detection," in IEEE Journal of Biomedical and Health Informatics, vol. 28, no. 4, pp. 1959-1970, April 2024.
13. M.S.B. Phridviraj, Raghuram Bhukya, Sujatha Madugula, Aakunuri Manjula, Swathy Vodithala, Mohammed Sharfuddin Waseem, A bi-directional Long Short-Term Memory-based Diabetic Retinopathy detection model using retinal fundus images, Healthcare Analytics, Volume 3, 2023.
14. Fernando K. Malerbi, Luis Filipe Nakayama, Gustavo Barreto Melo, José A. Stuchi, Diego Lencione, Paulo V. Prado, Lucas Z. Ribeiro, Sergio A. Dib, Caio V. Regatieri. "Automated identification of different severity levels of diabetic retinopathy using a handheld fundus camera and single-image protocol", Ophthalmology Science, 2024.
15. Zeru Hai, Beiji Zou, Xiaoxia Xiao, Qinghua Peng, Junfeng Yan, Wensheng Zhang, Kejuan Yue, A novel approach for intelligent diagnosis and grading of diabetic retinopathy, Computers in Biology and Medicine, Volume 172, 2024.
16. D. R. Manjunath, J. J. Lohith, S. Selva Kumar and A. Das, "Predicting Diabetic Retinopathy and Nephropathy Complications Using Machine Learning Techniques," in IEEE Access, vol. 13, pp. 70228-70253, 2025.
17. Bai, C., Kpalma, K., Ronsin, J. (2011). Analysis of Histogram Descriptor for Image Retrieval in DCT Domain. In: Tsihrintzis, G.A., Virvou, M., Jain, L.C., Howlett, R.J. (eds) Intelligent Interactive Multimedia Systems and Services. Smart Innovation, Systems and Technologies, vol 11. Springer, Berlin, Heidelberg.
18. Wang, B., Ma, C., Zhang, T. (2026). Learning Context Enhanced Features for Image Classification. In: Kountcheva, R., Patnaik, S., Liu, Y. (eds) DL-based Multidimensional Signals Analysis and Processing. 3DIT 2025. Smart Innovation, Systems and Technologies, vol 499. Springer, Cham.
19. Keerthanarani, U., Selvakumar, V., Singaravelan, S. et al. Moth flame optimization algorithm for efficient feature selection and hybrid classification technique for intrusion detection system. Multimed Tools Appl 84, 44405–44425 (2025).
20. https://www.kaggle.com/datasets/sachinkumar413/diabetic-retinopathy-dataset