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# Computer Vision-Based Deep Learning Techniques for Diabetic Retinopathy Assessment from Fundus Images

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**Abstract**

Long-term diabetes can damage the blood vessels in the retina, resulting in diabetic retinopathy (DR), a form of vision impairment. It affects around 191 million people worldwide and is the most prevalent cause of blindness. Although earlier studies have focused on DR categorization by retinalfundus pictures, current techniques typically concentrate on identifying certain tumors without providing a thorough basis for concurrently detecting each lesion. Prior research focused on earlystage Features such as blood vessels, hemorrhages, aneurysms, and exudates highlight lesions at the severe stage.such as exceedingly severe intraretinal microvascular abnormalities (IRMA), venous beading, and cotton wool patches,Retinal pigment, capillary degeneration, diffuse intraretinal hemorrhages, and extremely active microglia impairment of RPE. This work suggests that deep learning can be used to classify DR fundus images.different degrees of severity, using adaptive particle swarm optimizer-based GoogleNet and ResNet models (APSO) to improve feature extraction. After then, the hybrid model's features are put to use.employing a range of machine learning methods, such as decision trees, random forests, support vector machines, and models of linear regression. According to experimental results, the suggested hybrid framework performed better than sophisticated methods that achieved an astounding 94% accuracy rate on the benchmark dataset. This approach illustrates possible improvements in F1 score, recall, accuracy, and precision for varying degrees of DR severity.

Keywords: Diabetic retinopathy gradingFundus imagesDeep learningAttention mechanismExplainable artificial intelligence

## 1. INTRODUCTION

One microvascular effect of diabetes mellitus that might impair eyesight is diabetic retinopathy. It affects about one-third of the 463 million individuals with diabetes globally [1]. According to the International Diabetes Federation (IDF), the number of people with diabetes is expected to rise significantly from the 552 million estimated in 2035 to 642 million by 2040 [2], [3]. By 2030, there will be over 191 million persons with diabetic retinopathy, up from the present total of over 158.2 million [4], [5].Diabetic retinopathy is one of the main causes of blindness in the modern world. Those with poorly managed blood sugar levels are more likely to suffer from this condition. Normal, non-proliferative diabetic retinopathy (NPDR), and proliferative diabetic retinopathy (PDR) are the three main categories into which diabetic retinopathy is typically divided [6].The slowdown of retinal blood vessel creation and the increasing deterioration of the vessel walls are the primary characteristics of non-proliferative diabetic retinopathy (NPDR).NPDR is then separated into three groups: mild, moderate, and severe, depending on how serious the problem is. However, the formation of new blood vessels in the retina, which prevents the retina's normal blood flow, is a feature of proliferative diabetic retinopathy (PDR) [7], [8].

## 2. PROPOSED SYSTEM

GoogleNet uses the Inception module to efficiently reduce the arithmetic resources of the while gaining critical roomand local features. ResNet-16 includes a skip connectionto reduce the disposal of issues and minimize training errors. Combining the features from both models create a hybrid feature vector with 2000 features. This hybrid vectorserves as an input for different classifiers, allowing for a comparative evaluation of performance in classifying diabetic retinopathy.Search photos are divided into four groups for classification. There is no evidence of diabetic retinopathy (NDR). This represents levels 0 and level 0 of ICDR-scherskala at several stages of diabetic retinopathy. Multiclas classification divides the photo into three classes of three thick levels: ICDR : NDR (level 0), MDR (level 1 and 2), PDR (level 3 and).The methodology proposed in Figure 1 described the hybrid property extraction and classification process of the basic image. According to temporary preprocessing level images such as Google and Reset-16 are input into the transfer learning model that performs the functions independently. The resulting properties are used as the input for various classifiers, such as: The results are compared with existing literature and provide a progress in diabetic retinal classification technology.

## 3. SYSTEM ARCHITECTURE

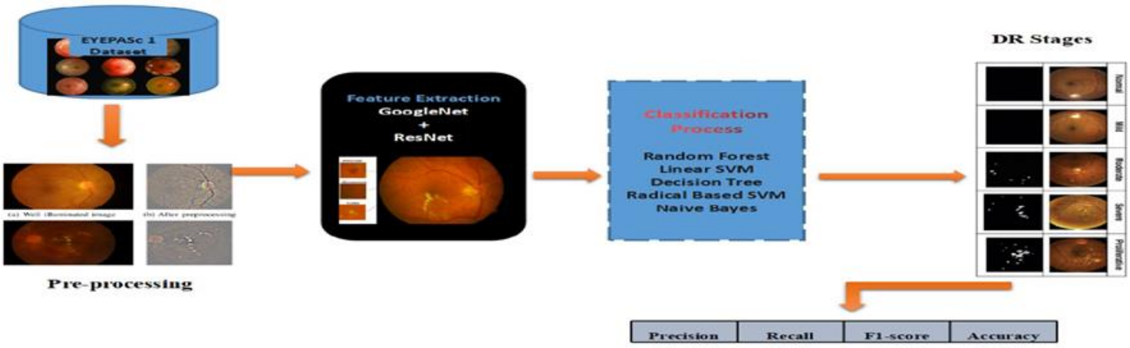



Fig 4.1 System Architecture

fig 4. 1: Architecture of the proposed methodology for diabetic retinopathy detection**.** Retinal images are preprocessed—resized, denoised, and normalized—then partitioned into training, validation, and test sets to ensure robust model development and evaluation

**4. Methodology**

. Data Preprocessing and Enhanced

Predicting diabetic retinopathy typically requires preprocessing of retinal images to improve model output and accuracy. Below you will find a pretreatment method:

1. TEMP: Harves up non-reticular parts of the image so that the model focuses only on areas of interest, increasing processing efficiency.

2. Try GausschenBlur's pre-processing method: The brightness and contrast of diabetic retinopathy are very different, so Gaußsche Blurs can be used to improve image improvements to improve image contrast and visualization.

3. Tripping and Gaussian Blur Color Version Pre-processing: While cutting Retina images, you can also use the Gaußsche Blur pre-processing method to improve the image and prevent corrupting the color information of the image.

4. Auto crop: The automatic cutting algorithm can automatically dig areas of interest according to the characteristics of the retinal image, improving the efficiency and accuracy of preprocessing.

5. Central Access: For large-scale retinal images, you can choose the center cultivation method. This means that the central portion of the image is preserved and other preprocessing methods can be used to improve image contrast and visualization.

Professor

. (a) The first row indicates that the original image was not processed by the image preprocessing algorithm. (b) Line 2 represents the results of the original image processed by the image preprocessing algorithm proposed in this article.

An architecture of a hybrid model with efficient Swin transformer

This study proposes a hybrid model combining efficient net and SWIN transformer for prediction of diabetic retinopathy. This model is divided into two branches, one of which is used as a backbone network and the other uses a SWIN transformer. The outputs of the two branches are chained and fused by fully connected layers.

Framework structure for a hybrid model with two branches. Using the benefits of Swin Transformer and efficient network models, accurately record global and local lesion features, and combine global and local features to connect classification layers to classify classification retinal images. In particular, efficient net branches are primarily used to extract local features of images, while SWIN trans branches are used to extract global properties of images. An efficient net branch consists of a basic network, feature extraction layer, global average pooling levels, and some head attention. The Swin Transformer Branch consists of Swin Transformer blocks, adaptive pooling layers, attention coordinates, and fully connected layers. A very small window size is used in Swin Transformer blocks to improve the ability to share images and recognize details. Diabetic retinal images are efficiently delivered. EfficientNet consists of several layers of multipurpose attention that achieves varying depths and widths, batch normalization levels, activation layers, pooling layers, and localized image characterization extraction.

## 5. RESULTS AND DISCUSSION

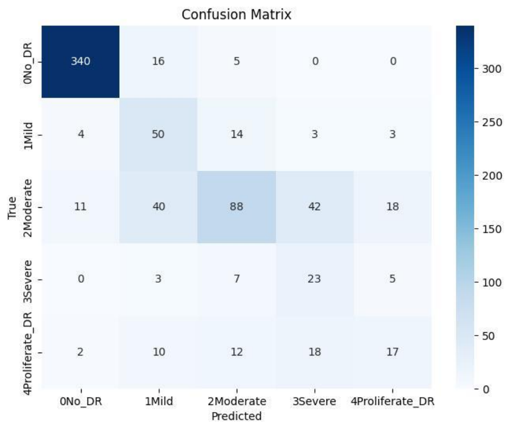
**Classification Report:**

CNN_MobileNet Classification Report

| | precision | recall | f1-score | support |
|---|---|---|---|---|
| 0No_DR | 0.95 | 0.94 | 0.95 | 361 |
| 1Mild | 0.42 | 0.68 | 0.52 | 74 |
| 2Moderate | 0.70 | 0.44 | 0.54 | 199 |
| 3Severe | 0.27 | 0.61 | 0.37 | 38 |
| 4Proliferate_DR | 0.40 | 0.29 | 0.33 | 59 |
| accuracy | | | 0.71 | 731 |
| macro avg | 0.55 | 0.59 | 0.54 | 731 |
| weighted avg | 0.75 | 0.71 | 0.71 | 731 |

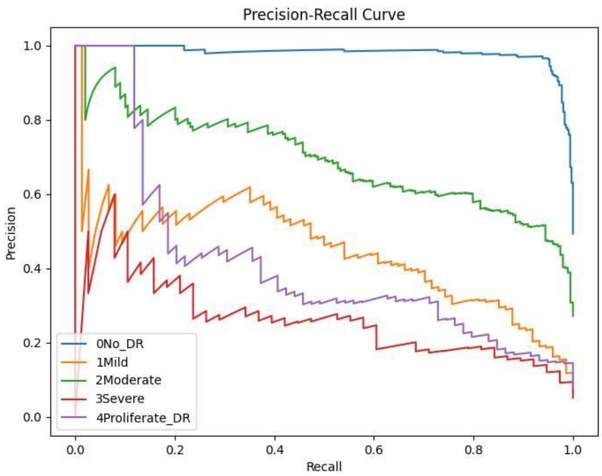
The classification report evaluates a CNN-MobileNet model for diabetic retinopathy detection across five stages. The model performs exceptionally for No_DR with a precision, recall, and F1-score of 0.95, reflecting strong identification of healthy cases. However, performance drops significantly for advanced stages like Proliferate_DR (F1-score: 0.33) and Severe (F1-score: 0.37), indicating challenges in correctly classifying critical disease stages. The macro average F1-score is 0.54, revealing imbalanced performance across classes. Despite an overall accuracy of 71%, the model demonstrates a tendency to favor the majority class (No_DR), highlighting the need for better class balance and feature discrimination, especially for minority severe categories.

**Confusion matrix:**




The confusion matrix highlights the performance of a CNN-MobileNet model in detecting diabetic retinopathy stages. The model classifies No_DR cases very accurately with 340 out of 361 correct predictions, indicating high sensitivity to healthy retinas. However, performance on other classes, especially Moderate, Severe, and Proliferate_DR, shows significant confusion. For example, only 88 out of 199 Moderate cases were correctly identified, with many misclassified as Mild or Severe. Severe and Proliferate_DR stages suffer from high misclassification, often confused with Moderate or Mild, suggesting poor class separation. These results underline the need for data balancing and enhanced feature learning for minority and advanced disease stages.

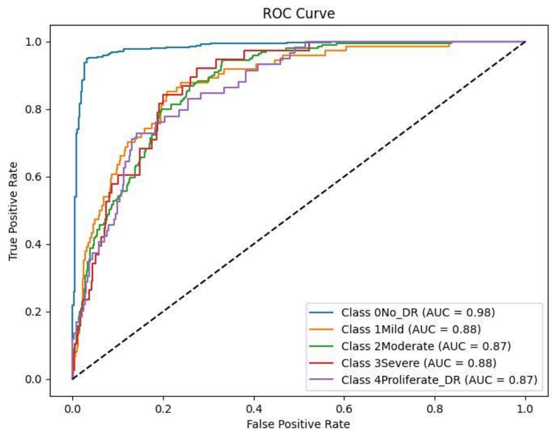
**Precision-Recall (PR) curve:**




The Precision-Recall (PR) curve visualizes the classification performance of the CNN-MobileNet model for different diabetic retinopathy stages. The No_DR class (blue curve) achieves consistently high precision and recall, indicating excellent classification reliability for healthy cases. In contrast, classes like Proliferate_DR (red) and Severe (purple) exhibit low and unstable precision across all recall levels, reflecting weak model performance for advanced

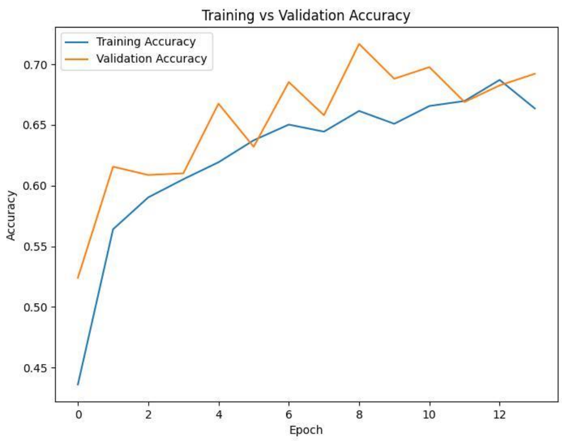
DR stages. The Moderate and Mild stages show moderate PR balance but still suffer from gradual precision decline as recall increases. This imbalance highlights the model's difficulty in discriminating between pathological stages and emphasizes the need for further training refinement and class balancing.

**ROC curve:**



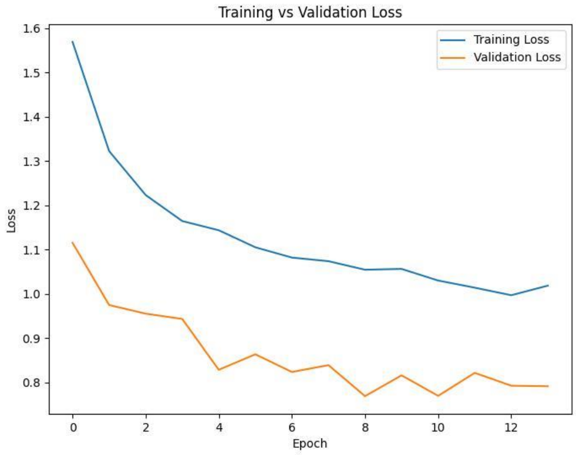

The ROC curve illustrates the discriminative ability of the CNN-MobileNet model across all diabetic retinopathy classes. The No_DR class demonstrates superior performance with an AUC of 0.98, indicating excellent separation between healthy and diseased cases. The remaining stages—Mild (0.88), Moderate (0.87), Severe (0.88), and Proliferate_DR (0.87)—show strong but slightly lower AUCs, suggesting competent yet imperfect class separation. The proximity of these AUC values indicates the model is fairly consistent across stages, though it performs best in detecting the absence of disease. This performance highlights the model’s robustness but also suggests a need for improvement in distinguishing between more advanced DR stages.

**Training vs Validation Accuracy Analysis**



The plot demonstrates the progression of training and validation accuracy across 14 epochs for the CNN-MobileNet model. Initially, both accuracies rise rapidly, indicating effective learning. The validation accuracy consistently outperforms the training accuracy until around epoch 11, suggesting that the model generalizes well and does not suffer from early overfitting. Post epoch 11, the curves converge, and training accuracy slightly dips at the final epoch, while validation accuracy stabilizes around 0.69, showing relatively consistent model behavior. Overall, the model exhibits a steady learning trajectory, with minor fluctuations and no significant overfitting, reflecting good training stability and generalization capability.

**Training vs Validation Loss Analysis:**




This plot illustrates the comparison between training and validation loss over 14 epochs. The training loss shows a steady downward trend, indicating that the model is learning and optimizing effectively on the training data. The validation loss also decreases and stabilizes around 0.78, reflecting improved generalization and reduced error on unseen data. Interestingly, the validation loss remains consistently lower than the training loss, which may suggest regularization effectiveness or early stopping techniques. The lack of divergence between the two curves indicates minimal overfitting, and the model appears well-balanced in learning from both training and validation sets.

## 6. CONCLUSIONS AND FUTURE WORK

This study illustrates a hybrid approach to recognize early diabetes retinopathy by extracting features from Fundus Images by sending reset 16 and Google models based on adaptive particle swarm optimization. These functions are entered into Ipax records of various classifiers for classification of diabetic patients from retinopathy with several classes The combination of characteristics of the Modelsignificantly increases the power metrics for classifying diabetes disorders and improves overall system effectiveness.The proposed technique is promised with the help of an ophthalmologist as knowledge of early diabetic retinopathy. Results highlights the effectiveness of the combination of CNN feature extraction and classifiers for machine learning, providing quick and incredible results. Surprisingly, the hybrid model with SVM current and multiclass diabetic retinopathy exceeds the detection technique of at 9 % with an astonishing average accuracy. The results show the efficiency of the combination of CNN feature extraction for machine learning, classification using This gives you quick and highly accurate results. Surprisingly, the average accuracy of the SVM hybrid model is I look forward to testing algorithms for diagnosis at and To successfully remove noise and artifacts, we need to focus on improving strategies, such as data expansion and other processing approaches. This field is also important to improve and achieve the with continuous efforts to improve and achieve the accuracy of the and the continued efforts to achieve the effectiveness of the DR recognition system. The possibility that may change the early detection and treatment of diabetes retinopathy is working together, especially when technology progresses. Future studies should treat these possible distortions in of the data record to improve the robustness of the proposed model and generalizability of numerous patient groups. can be used using methods such as sample layer, data extension, careful assessment of demographic parameters, facilities, and fair and clinically useful models for the detection of diabetic retinopathy. is also a disclosure of dataset distortions and distortion openness for a more comprehensive understandingand analysis of research findings.

## REFERENCES

[1] W. L. Alyoubi,W. M. Shalash, and M. F. Abulkhair, "Diabetic retinopathydetection through deep learning techniques: A review," Informatics in Medicine Unlocked, vol. 20, p. 100377, 2020.

[2] R. Rajalakshmi, R. Subashini, R. M. Anjana, and V. Mohan, "Automateddiabetic retinopathy detection in smartphone-based fundus photography using artificial intelligence," Eye, vol. 32, no. 6, pp. 1138–1144, 2018.

[3] World Health Organization, "Diabetes." https://www.who.int/health-topics/diabetes#tab=tab_1, 2022.

[4] S. Bhandari, S. Pathak, and S. A. Jain, "A literature review of early-stagediabetic retinopathy detection using deep learning and evolutionary computing techniques," Archives of Computational Methods in Engineering,vol. 30, no. 2, pp. 799–810, 2023.

[5] A. K. Gangwar and V. Ravi, "Diabetic retinopathy detection using transfer learning and deep learning," in Evolution in Computational Intelligence: Frontiers in Intelligent Computing: Theory and Applications (FICTA 2020), Volume 1, pp. 679–689, Springer, 2021.

[6] Z. Khan, F. G. Khan, A. Khan, Z. U. Rehman, S. Shah, S. Qummar, F. Ali, and S. Pack, "Diabetic retinopathy detection using vgg-nin a deep learning architecture," IEEE Access, vol. 9, pp. 61408–61416, 2021.

[7] E. Özbay, "An active deep learning method for diabetic retinopathy detection in segmented fundus images using artificial bee colony algorithm,"Artificial Intelligence Review, vol. 56, no. 4, pp. 3291–3318, 2023.

[8] A. Panwar, G. Semwal, S. Goel, and S. Gupta, "Stratification of the lesions in color fundus images of diabetic retinopathy patients using deep learning models and machine learning

classifiers," in Edge Analytics: Select Proceedings of 26th International Conference—ADCOM 2020, pp. 653–666, Springer, 2022.

[9] G. Parthasharathi, R. Premnivas, K. Jasmine, et al., "Diabetic retinopathy detection using machine learning," Journal of Innovative Image Processing,
vol. 4, no. 1, pp. 26–33, 2022.

[10] N. Tsiknakis, D. Theodoropoulos, G. Manikis, E. Ktistakis, O. Boutsora,A. Berto, F. Scarpa, A. Scarpa, D. I. Fotiadis, and K. Marias, "Deep learning for diabetic retinopathy detection and classification based on fundus images: A review," Computers in biology and medicine, vol. 135,p. 104599, 2021.

[11] R. Pires, S. Avila, J. Wainer, E. Valle, M. D. Abramoff, and A. Rocha, "A data-driven approach to referable diabetic retinopathy detection," Artificial intelligence in medicine, vol. 96, pp. 93–106, 2019.

[12] Y. Yang, T. Li, W. Li, H. Wu, W. Fan, and W. Zhang, "Lesion detection and grading of diabetic retinopathy via two-stages deep convolutional neural networks," in Medical Image Computing and Computer Assisted Intervention- MICCAI 2017: 20th International Conference, Quebec City, QC, Canada, September 11-13, 2017, Proceedings, Part III 20, pp. 533– 540, Springer, 2017.

[13] P. Saranya and S. Prabakaran, "Automatic detection of non-proliferative diabetic retinopathy in retinal fundus images using convolution neural network," Journal of Ambient Intelligence and Humanized Computing, pp. 1–10, 2020.

[14] T. M. Usman, Y. K. Saheed, D. Ignace, and A. Nsang, "Diabetic retinopathy detection using principal component analysis multi-label feature extraction and classification," International Journal of Cognitive Computing in Engineering, vol. 4, pp. 78–88, 2023.

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