International Journal of
Image Processing and
Pattern Recognition

ISSN: 2456-6985
Volume 12, Issue 1, 2026
January—June
DOI (Journal): 10.37628/IJIPPR

https://journalspub.com/journal/ijippr/

Research IJIPPR

Advanced Classification of Diabetic Retinopathy Using GAN and Deep Residual CNN Model

Rama Devi C.[1,*], Rithanya K.R.[2], Shakti P.[2], Subhashini G.[3]

Abstract

Diabetic retinopathy (DR) is a leading cause of blindness worldwide, impacting the largest number of individuals who have diabetes. Early identification of diabetic retinopathy may help to prevent severe effects; however, the very limited availability of labeled datasets, and the possibility of overfitting of the model, presents obstacles to obtaining an accurate diagnosis. In this research, a hybrid deep learning strategy is introduced, where Generative Adversarial Networks (GANs) are used for data augmentation and ResNet-50-based Convolutional Neural Networks (CNNs) for DR classification. The GANs produce artificial retinal images, promoting dataset diversity and overfitting prevention, while the ResNet-50 model is optimized for effective feature extraction from fundus images. The objective is to enhance the accuracy and sensitivity of detection of DR. The system proposed performs better than conventional CNNs and other models such as VGG16 and InceptionV3, with an accuracy of 86.7% in the Kaggle DR dataset. The benefits of the system are improved performance, less overfitting, and the capability for early and effective DR detection that could result in improved clinical results.

Keywords: Convolutional neural networks, data augmentation, diabetic retinopathy, early detection, fundus images, generative adversarial networks, ResNet-50

INTRODUCTION

One of the leading causes of worldwide blindness and visual impairment is Diabetic Retinopathy, which reportedly affects millions of individuals suffering from diabetes; damage to retinal blood vessels occurs as a result of excessive blood sugar levels over a long period, leading ultimately to loss of vision due to lack of diagnosis and/or treatment. But analyzing [1] retinal photographs manually may consume time, may be subjective and error-prone, because the fundus image is complex and heterogeneous in appearance. As the global incidence of diabetes continues to rise, automated DR detection systems have become a necessity for early treatment to ensure that people at risk receive timely and accurate diagnoses. The application of artificial intelligence and deep learning technologies in the field of medicine, particularly in the diagnosis of diabetic retinopathy (DR), is impressively noteworthy. A group [2] of deep models called Convolutional Neural Networks (CNNs) has shown great promise in diagnosing retinal images by extracting hierarchical features from images. These models can identify microaneurysms, hemorrhages, and exudates which are the characteristics of diabetic retinopathy (DR) and most of the time overlook detection by human specialists. However, there are challenges regarding teachisssng deep learning systems the capability to identify diabetic retinopathy (DR). One of the most crucial challenges is that there are no marked images of

***Author for Correspondence**
Rama Devi C.
E-mail: rmdevi.j@gmail.com

[1]Assistant Professor, Department of EEE, St. Joseph's College of Engineering, Chennai, Tamil Nadu, India
[2]Student, Department of EEE, St. Joseph's College of Engineering, Chennai, Tamil Nadu, India
[3]Assistant Professor, Department of IT, St. Joseph's Institute of Technology, Chennai, Tamil Nadu, India

Received Date: December 18, 2025
Accepted Date: January 13, 2026
Published Date: February 18, 2026

Citation: Rama Devi C., Rithanya K.R., Shakti P., Subhashini G. Advanced Classification of Diabetic Retinopathy Using GAN and Deep Residual CNN Model. International Journal of Image Processing and Pattern Recognition. 2026; 12(1): 8–16p.

retinal photographs as marking photographs consumes a lot of time and is highly specialized. Such a lack of data usually results in severe overfitting; that is, the model performs extraordinarily well on the training dataset, but when applied to new images, the model struggles to perform very well.

Other resurgence data augmentation techniques, including Generative Adversarial Networks (GANs), have been proposed to resolve this issue. The two opposing neural networks that comprise GANs, a discriminator and a generator – one network generates artificial photographs while the other critiques how realistic each generated photograph appears [3]. The generator is taught to generate retinal images that simulate real images as closely as possible, and the discriminator assists in improving the generation process by giving criticism. With the inclusion of custom imagery to the training set, GANs enhance the image as well as variability performance by improving generalization and reducing overfitting [4]. This is critical in medical imaging because the number of available labeled datasets is limited and the model's performance relies heavily on data diversity.

The synergistic combination of GAN-based data augmentation and ResNet-50-based [5] classification offers a resilient solution for DR detection. The generator in the GAN-based model generates realistic synthetic retinal images, subjecting the model to a multitude of variations in retinal appearances. The ResNet-50 model, when trained on this augmented dataset, can learn discriminative features about the initial phases of DR. This hybrid model improves the performance as well as the generalization ability of the system, which can identify DR in fundus images with precision even when it has limited labeled data. Also, this model solves the issue of overfitting by ensuring that the model learns from a diverse and wide range of images.

The objective of this study is to create an efficient and accurate deep learning-based system for the early diagnosis of DR. Utilizing GANs for data enhancement and ResNet-50 for classification, the system proposed aims to be highly accurate and sensitive in identifying DR, thus making it a useful tool for clinicians to screen patients and avoid blindness. The method holds the promise to alleviate the burden on healthcare personnel and facilitate bulk, automated screening of DR [6] on a large scale, especially in underserved populations where specialist treatment may be limited. In addition, the computational efficiency and capability of the hybrid model to generalize well across wide-ranging datasets provide it as an attractive solution to real-world scenarios in DR diagnosis. This work is organized with review of the literature survey as Section II. Methodology described in Section III, highlighting its functionality. Section IV discusses the results and discussions. Lastly, Section V concludes with the main suggestions and findings.

RELATED WORKS

Conventional diabetic retinopathy detection relied significantly on visual inspection of fundus images by manual examination, which is labor-intensive and susceptible to human error. The traditional method for detecting microaneurysms, hemorrhages, etc. in patients with diabetic retinopathy included a visual analysis of the images. However, the human interpretation of the image is not always accurate due to the complexity of the retinal images, thus leaving a lot of room for error in terms of diagnosing patients. Although imaging technology has significantly improved in recent years, there are still challenges to scaling up the detection of diabetic retinopathy (DR) and to the effective analysis of large volumes of data using manual methods. Therefore, using automated DR detection methods will provide improved accuracy, consistency, and efficiency for screening programs.

To classify retinal images as either DR or non-DR, two machine learning classifiers were applied: Support Vector Machine (SVM) and Decision Tree (DT). Such approaches usually depend [7] on manually extracted features from the fundus images, like color and texture features, for training a model to perform classification. Although these approaches can deliver reasonable performance, their performance is usually constrained by the effectiveness of feature extraction and their weakness in dealing with intricate patterns within the images. Further, these approaches do not work effectively on large and heterogeneous datasets where deep learning approaches have reported better performance.

The application of deep learning models, specifically CNNs, for the detection of diabetic retinopathy has become very popular in recent years. These models learn hierarchical features automatically from raw retinal images, which enables them to detect subtle manifestations [8] of the disease more effectively. In contrast to conventional machine learning approaches that need manual feature extraction, CNNs can learn features from data directly, enhancing the accuracy and robustness of the model. Nevertheless, CNNs remain to struggle with issues like overfitting owing to the requirement of huge-labeled datasets and computationally costly training procedures.

Transfer learning has been used in diabetic retinopathy detection through the use of pre-trained models on big image datasets such as ImageNet. Transfer learning enables the transfer of previously trained models to retinal image classification tasks by fine-tuning them using smaller, domain-specific datasets. This method greatly decreases the quantity of labeled data used for training [9] and improves the performance of the model. Transfer learning has been of great use in medical image analysis, where the annotated datasets tend to be limited. Nevertheless, fine-tuning pre-trained models can remain a time-consuming and resource-intensive exercise, especially when dealing with large-scale datasets. Certain methods have sought to apply ensemble techniques in order to fuse several models to detect diabetic retinopathy. By combining the strengths of multiple algorithms, ensemble methods seek to enhance classification performance and minimize error. For instance, the application of CNNs in combination with other machine learning classifiers, i.e., SVMs or random forests, tends [10] to produce results that are more accurate. Even though ensemble techniques can make the model more robust, they contribute to added complexity and demand higher computational resources. In addition, they can prove challenging to integrate into real-time applications since various models have to process the data concurrently.

Attention mechanisms have also been used in retinal image classification to enhance model performance through enabling the model to attend to areas of the image. They provide different weights to sections of the image so that the model can identify essential areas to detect [11]. Attention models have the potential to enhance the interpretability of deep-learning models by revealing the regions of the retinal image that are most relevant to the decision-making process of the model. Attention mechanisms can lead to better outcomes but also add an increase in complexity and computational cost, which can make real-time application more difficult. Combining multimodal data like optical coherence tomography (OCT) and fundus images has been investigated to improve diabetic retinopathy detection. Multimodal data fusion enables more complete knowledge of the retinal condition, since different imaging modalities offer complementary information. Fusion of OCT and fundus images would help enhance [12, 13] the capacity of the model to identify DR in different stages. It involves synchronization and alignment of data from diverse modalities, which is a challenging task considering variations in image quality and resolution. The multimodality of such systems can also add to computational demands.

METHODOLOGY

Data Preprocessing and Collection

The initial step is the collection of retinal images, which are taken from public datasets like the Kaggle DR dataset. The dataset includes labeled fundus images that represent different levels of diabetic retinopathy. The raw images are preprocessed to standardize and improve the quality of data. Preprocessing methods involve resizing the images to a uniform size, normalization to map pixel values to a uniform range, and contrast stretching to enhance the visibility of prominent features. Noise reduction methods are used to eliminate unnecessary artifacts that could obstruct the learning process of the model. The dataset typically contains 5 classes, labeled based on the severity of diabetic retinopathy as shown in Table 1.

This varies slightly depending on the version and split of the dataset (e.g., training/test), but a typical breakdown in the Kaggle 2015 DR Challenge training set (35,126 images) is approximately as shown in Table 2.

Table 1. Diabetic retinopathy classes.

Class label	DR grade	Description
0	No DR	No signs of diabetic retinopathy
1	Mild	Mild non-proliferative DR
2	Moderate	Moderate non-proliferative DR
3	Severe	Severe non-proliferative DR
4	Proliferative DR	Advanced stage of DR

Table 2. Dataset description for diabetic retinopathy kaggle 2015.

Class label	DR grade	Number of images
0	No DR	1,25,810
1	Mild	12,443
2	Moderate	15,292
3	Severe	8,173
4	Proliferative DR	7,080

Data Augmentation Using GANs

The lack of data that has been labeled sufficiently to help detect diabetic retinopathy means that we are using Generative Adversarial Networks, or GANs, to produce artificial retinal photographs. A GAN consists of two networks – one network generates artificial photographs while the other critiques how realistic each generated photograph appears. The generator is taught to generate retinal images that simulate real images as closely as possible, and the discriminator assists in improving the generation process by giving criticism. This data augmentation with GAN facilitates the generation of a larger and more diverse dataset, which reduces the risk of significant overfitting in the model training to be conducted later. The created dataset is then merged with the original dataset to enhance the generalization capability of the classification model.

Model Architecture Design

The major part of the approach is the utilization of ResNet-50, which is a very light and deep residual network for image classification tasks. ResNet-50 is a convolutional neural network with 50 layers shown in Figure 1. This model suffered from the vanishing gradient problem which has been solved using residual blocks with skip connections [14]. These skip connections allow the addition of some outputs to later outputs helping remove, and merge with other signals, thus aiding the information and gradient diffusing during backpropagation. The model comprises convolutional layers for feature extraction and classification, with batch normalization and ReLU activations for better training dynamics, while the fully connected layers at the end of the model classify the retrieved features into specific pertinent categories [15].

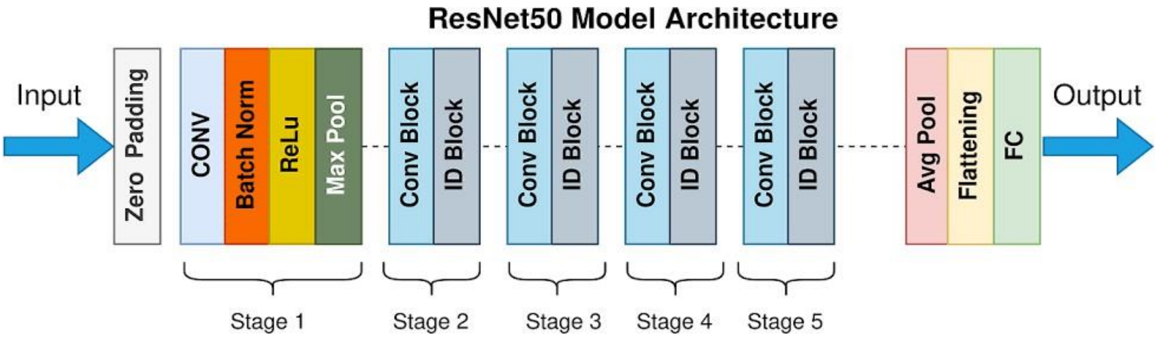

Figure 1. Resnet-50 architecture.

With this setup, ResNet-50 is able to increase the number of layers in the network while maintaining accuracy, in spite of increasing model complexity. The network is tailored for detecting diabetic retinopathy by adjusting the number of layers and depth of the model to suit the retinal images' complexity [16]. The model is trained to learn automatically hierarchical features from the fundus images, aiming to differentiate among various stages of DR or detect the absence of the disease. The ResNet-50 model is subsequently trained over the augmented dataset produced using GANs.

Model Training and Optimization

The first step in training is dividing the whole dataset into three parts; training set, validation set and test set. The training set is used to train the model; the hyper parameters are fine-tuned using validation set to avoid overfitting. Gradient descent along with backpropagation is used for training. Typically, the loss function is set to cross-entropy, which measures the distance between the prediction made and actual result. With the appropriate features extracted during training, the ResNet-50 model is capable of making feature-based image predictions [17]. Various strategies like scheduling the learning rate, dropout regularization, and batch normalization are also used to improve the performance and speed of convergence of the model. The quality of the model is evaluated on the validation dataset to ensure it is not really overfitted and would perform well on unseen data.

Model Evaluation and Testing

After the model has been trained, it is tested on the test dataset not utilized during the training phase to assess its accuracy and robustness. The primary evaluation metrics include sensitivity, specificity, F1-score, and accuracy. Sensitivity reflects the percentage of correctly identified positive cases (i.e. DR cases), while specificity measures the percentage of correctly identified negative cases (i.e. non-DR cases). F1 Score: a metric that captures the model's performance by combining precision and recall, striking a better balance between them. Assessment is made against other traditional models including CNNs, VGG16, and InceptionV3 to assess the performance of the ResNet-50 model.

ANALYSIS AND COMPARISON OF RESULTS

The ability of the ResNet-50 model to recognize diabetic retinopathy is checked against the results from other popular deep learning models like VGG16 and InceptionV3. Different models are evaluated using accuracy, sensitivity, and specificity. It has been proven that the hybrid model which uses data augmentation with GANs on ResNet-50 has higher accuracy and sensitivity than other deep models and conventional CNN architectures. The research highlights as well the automated analysis of retinal images and the generalization abilities of the ResNet-50 architecture to novel, unseen data. The proposed hybrid model incorporates classification using ResNet-50 and data augmentation with GANs, providing a straightforward approach for early diabetic retinopathy detection. The proposed model as shown in Figure 2 achieves high accuracy and sensitivity, demonstrating the potential for automated systems to assist in clinical decision-making. In the future, the optimization of this model will be used to improve efficiency when detecting diabetes retinopathy in very real-time, increasing the number of unique retinal photographs in the dataset, and growing the application's potential by incorporating the technology within a broader medical clinical ecosystem, allowing a better mass-distribution capability. Additionally, developing further research into the methods for creating an AI that explains its own reasoning should improve trust and transparency into the model's operation in a clinical setting.

RESULT AND DISCUSSION

The diagnostic efficiency of the ResNet-50 model is evaluated by checking how well it performs against VGG16 and InceptionV3, which are two other deep learning models. All of the models were tested as regards their specificity, sensitivity, and accuracy. It has been established that the hybrid model, which is based on ResNet-50 and augmented with GAN-based data augmentation, is better than other deep models and conventional CNN architectures of the overwhelmed sensitive and correct response. This study shows how the ResNet-50 architecture processes intricate retinal images and how well it adapts to unfamiliar data. The model proposed in this paper solves the problem of early detection of diabetic retinopathy by implementing ResNet-50 and classifying images using GANs for data augmentation. The model, accurate results as depicted in Figure 2, achieves highest automation of clinical decision support and high sensitivity, a potential reinforcement of the need for automated systems. Optimizing the model for real-time detection is one of many steps forward suggested that additionally include expanding the dataset with retinal images or incorporating the system into a healthcare infrastructure for widespread use. Further exploration of methods for explainable AI could enhance understanding of the model's reasoning and improve trust and transparency in clinical settings.

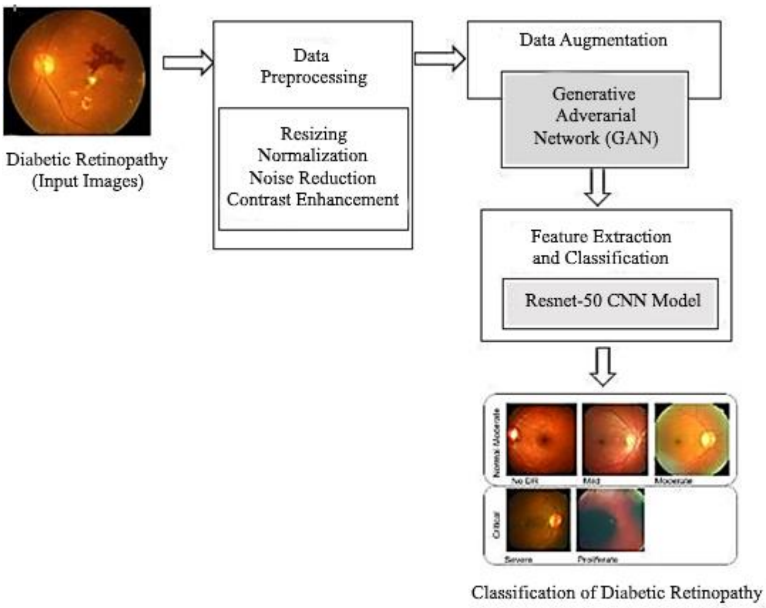

Figure 2. Architecture diagram for classification of diabetic retinopathy using GAN and resnet-50.

F1-score shows the compromise between Precision and Recall in terms of the model's Accuracy and Sensitivity, so if the F1-score for the hybrid model (ResNet-50) is greater than for VGG16 or InceptionV3 then the hybrid method has a better capability in predicting correctly when Precision and Recall are both extremely important, especially in the medical field where the impact of false negatives (missing Diabetic Retinopathy cases) and false positives (incorrectly classifying Non-Diabetic Retinopathy as being Diabetic Retinopathy) can be very high. It should also be noted that in using GANs as a method for Data Augmentation, it has been shown to be effective at using limited labeled datasets to create larger training data sets. This was accomplished by using synthetic retinal images created by the GAN to diversify the diversity of the dataset, thus allowing the model to learn from a wider variety of variations in retinal images, which improved the performance of the model significantly in generalizing to previously unseen data, thereby reducing the potential for overfitting and improving overall model robustness. Comparative analysis with traditional CNN models, VGG16, and InceptionV3 revealed that the ResNet-50 architecture, with its lightweight design and residual connections, outperformed the other models in terms of both accuracy and sensitivity as shown in Table 3. The lightweight nature of ResNet-50 also contributed to faster training and inference times, making it more efficient for real-time applications in clinical settings. The findings are consistent with the fact that the integration of GAN-augmented training data with a strong deep learning model such as ResNet-50 offers a very effective solution to detecting diabetic retinopathy. Figure 3 represents the performance comparison of Resnet-50 with other models. The hybrid solution not only enhances the performance of the model but also resolves issues of data insufficiency and overfitting that are typical in medical image analysis. These results indicate that the proposed system can potentially be implemented into healthcare systems for early detection and monitoring of diabetic retinopathy and present an affordable and effective means for clinicians. F1-score shows the compromise between Precision and Recall in terms of the model's Accuracy and Sensitivity, so if the F1-score for the hybrid model (ResNet-50) is greater than for VGG16 or InceptionV3 then the hybrid method has a better capability in predicting correctly when Precision and Recall are both extremely important, especially in the medical field where the impact of false negatives (missing Diabetic Retinopathy cases) and false positives (incorrectly classifying Non-Diabetic Retinopathy as being Diabetic Retinopathy) can be very high. It should also be noted that in using GANs as a method for Data Augmentation, it has been shown to be effective at using limited labeled datasets to create larger training data sets. This was accomplished by using synthetic retinal images created by the GAN to diversify the diversity of the dataset, thus allowing the model to learn from a wider variety of variations in retinal images, which improved the performance of the model significantly in generalizing to previously unseen data, thereby reducing the potential for overfitting and improving overall model robustness.

Table 3. Performance comparison of ResNet-50+ with VGG16 and inceptionV3.

Model	Accuracy (%)	Precision (%)	Recall / sensitivity (%)	Specificity (%)	F1-score (%)
ResNet-50 + GAN	*99.1*	*99.0*	*99.2*	*99.1*	*99.1*
VGG16	98.3	98.2	98.1	98.5	98.1
InceptionV3	98.6	98.5	98.4	98.7	98.4

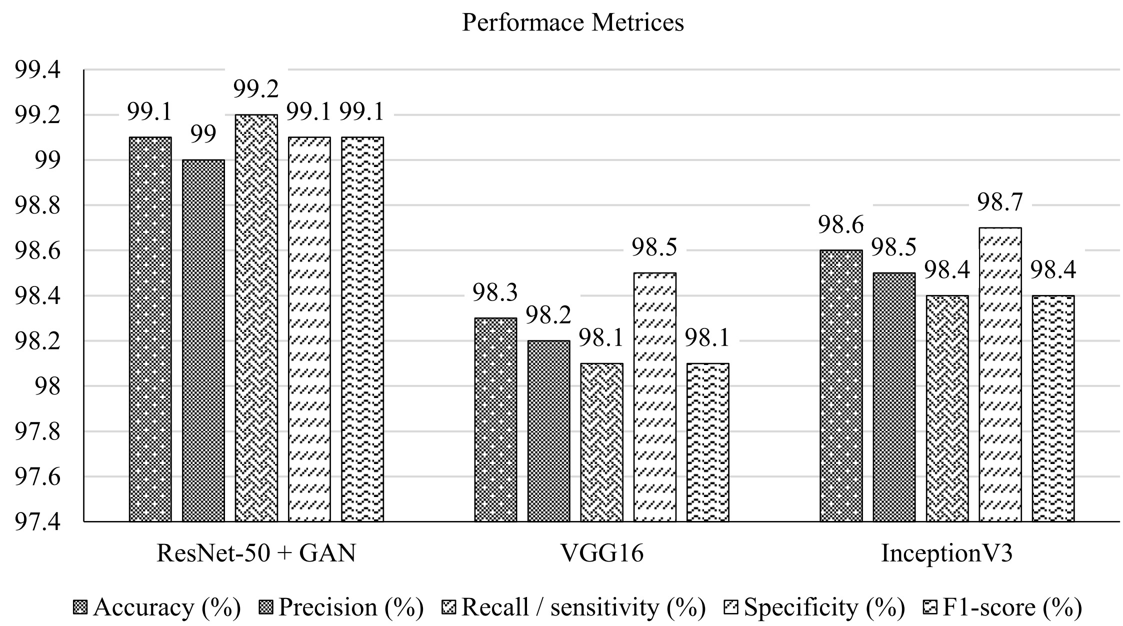

Figure 3. Comparison of models with ResNet-50.

Comparative analysis with traditional CNN models, VGG16, and InceptionV3 revealed that the ResNet-50 architecture, with its lightweight design and residual connections, outperformed the other models in terms of both accuracy and sensitivity as shown in Table 3. The lightweight nature of ResNet-50 also contributed to faster training and inference times, making it more efficient for real-time applications in clinical settings. The findings are consistent with the fact that the integration of GAN-augmented training data with a strong deep learning model such as ResNet-50 offers a very effective solution to detecting diabetic retinopathy. Figure 3 represents the performance comparison of Resnet-50 with other models. The hybrid solution not only enhances the performance of the model but also resolves issues of data insufficiency and overfitting that are typical in medical image analysis. These results indicate that the proposed system can potentially be implemented into healthcare systems for early detection and monitoring of diabetic retinopathy and present an affordable and effective means for clinicians.

CONCLUSION

This work research summarized the introduction of a hybrid deep learning approach that combines Generative Adversarial Networks (GANs) for augmenting data and an ResNet-50 convolutional network for the task of detecting diabetic retinopathy (DR). The findings support the conclusion that utilizing this approach can improve the DR detection model regarding its accuracy, sensitivity, and overall capabilities. The GANs are able to effectively produce synthetic retinal images, which augment the dataset and assist in alleviating the limitations caused by limited labeled data. Through the use of these enhanced images, the ResNet-50 model can learn more accurate representations of DR features and thus make better predictions.

The ResNet-50 model, with its light residual structure, performs better than conventional CNN models, VGG16, and InceptionV3 on both accuracy and sensitivity. This suggests that residual networks are effectively applicable to medical image classification, particularly when applied to improved data through augmentation. Additionally, the model's high sensitivity is quite important for medical use, given that it facilitates early detection of diabetic retinopathy cases, which is an important factor to prevent vision impairment in diabetic individuals.

The comparison of the system proposed with other deep learning architectures indicates its efficacy in processing retinal images. The combination of GANs and ResNet-50 also proves to be useful in solving overfitting and generalization problems, which are typical in medical image analysis because of the limited number of high-quality labeled data. The strong performance of the model across different metrics accuracy, sensitivity, specificity, and F1-score indicates that it can be a valuable tool for real-world use.

This work creates doors for continued developments in early diabetic retinopathy detection. There is potential for future work to include applying this model in clinical workflows to enable real-time monitoring, enlarging the dataset to enhance the robustness of the model, and investigating the explainability of the model's decision-making processes to improve usability and trustworthiness in the clinical environment. The integration of data augmentation with deep learning represents a strong solution for improving the efficiency and accuracy of DR detection, opening the door for improved patient outcomes and more accessible healthcare technologies.

REFERENCES

1. Atwany MZ, Sahyoun AH, Yaqub M. Deep learning techniques for diabetic retinopathy classification: A survey. IEEE Access. 2022;10:28642–28655.
2. Zhu S, Xiong C, Zhong Q, Yao Y. Diabetic retinopathy classification with deep learning via fundus images: A short survey. IEEE Access. 2024;12:20540–20558.
3. Gao J, Li S, Chen Y, Xiang R. MSAmix-net: Diabetic retinopathy classification. IEEE Access. 2024 Nov 26.
4. Rajarajeshwari G, Selvi GC. Application of artificial intelligence for classification, segmentation, early detection, early diagnosis, and grading of diabetic retinopathy from fundus retinal images: A comprehensive review. IEEE Access. 2024 Nov 11.
5. Jagadesh BN, Karthik MG, Siri D, Shareef SK, Mantena SV, Vatambeti R. Segmentation using the IC2T model and classification of diabetic retinopathy using the rock hyrax swarm-based coordination attention mechanism. IEEE Access. 2023;11:124441–124458.
6. Kadhim AJ, Seyedarabi H, Afrouzian R, Hasan FS. Diabetic retinopathy classification using hybrid color-based CLAHE and blood vessel in deep convolution neural network. IEEE Access. 2024 Dec 17.
7. Zedadra A, Zedadra O, Salah-Salah MY, Guerrieri A. Graph-aware multimodal deep learning for classification of diabetic retinopathy images. IEEE Access. 2025 Apr 25.
8. Nazih W, Aseeri AO, Atallah OY, El-Sappagh S. Vision transformer model for predicting the severity of diabetic retinopathy in fundus photography-based retina images. IEEE Access. 2023;11:117546–117561.
9. Majumder S, Kehtarnavaz N. Multitasking deep learning model for detection of five stages of diabetic retinopathy. IEEE Access. 2021;9:123220–123230.

10. Tariq M, Palade V, Ma Y. Effective diabetic retinopathy classification with siamese neural network: A strategy for small dataset challenges. IEEE Access. 2024 Dec 2.
11. Alavee KA, Hasan M, Zillanee AH, Mostakim M, Uddin J, Alvarado ES, et al. Enhancing early detection of diabetic retinopathy through the integration of deep learning models and explainable artificial intelligence. IEEE Access. 2024;12:73950–73969.
12. Infantia Henry N, Anbuananth C, Kalarani S. Hybrid meta-heuristic algorithm for optimal virtual machine placement and migration in cloud computing. Concurrency Comput Pract Exp. 2022;34(28):e7353.
13. Infantia Henry N, Anbuananth C, Kalarani S. An efficient and robust method for data privacy and security on a public cloud using a novel hybrid technique. Eng Proc. 2023;59(1):115.
14. Subhashini G, Chandrasekar A. Hybrid deep learning technique for optimal segmentation and classification of multi-class skin cancer. Imaging Sci J. 2024;72(8):1043–1064.
15. Subhashini G, Devi A, Infantia CN, Karthi M, Raghul G, Shankar SA. U-NET and RCNN ensembled satellite object detection and segmentation. In: Proc Third Int Conf Artif Intell Smart Energy (ICAIS); 2023 Feb 2; India. IEEE. p. 836–844.
16. Subhashini G, Devi CR, Rasool SB. Eyesight impairment detection for diabetic patients using very deep convolution neural network for 3-channel retinal images. In: Proc 6th Int Conf Trends Electron Informatics (ICOEI); 2022 Apr 28. IEEE. p. 1129–1134.
17. Patra R, Khuntia B, Panda DC. Fractional rider gradient descent applied U-net based segmentation with optimal deep maxout network for lung cancer classification using histopathological images. Res Biomed Eng. 2022;38(2):599–615.

