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Hybrid Deep Learning Framework for Diabetic Retinopathy Detection using Generative Adversarial Networks and Transfer Learning

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A B S T R A C T

Diabetic retinopathy (DR) is a leading cause of vision loss worldwide, making early detection critical for preventing severe visual impairment. Traditional methods for DR diagnosis are limited by the availability of specialists and the time-consuming nature of manual screenings. In this study, we propose a hybrid deep learning framework that combines Generative Adversarial Networks (GANs) for data augmentation with transfer learning from pre-trained convolutional neural networks (CNNs) to improve the accuracy and efficiency of DR detection. The dataset, consisting of retinal fundus images categorized into five DR stages, suffers from class imbalance, particularly in severe and proliferative stages. GANs were employed to generate synthetic images to address this imbalance, while transfer learning with models such as ResNet-50, VGG-19, and Inception-v3 enabled effective feature extraction from the images. The results demonstrate significant improvements in classification performance, with the ResNet-50 model achieving the highest accuracy of 93.5% and an AUC-ROC of 0.96. The GAN-augmented models notably enhanced the detection of minority classes, improving the F1-scores for severe and proliferative DR by 15% compared to traditional augmentation techniques. The use of early stopping ensured stable training, while the confusion matrix showed minimal misclassifications between adjacent DR stages. These findings suggest that the proposed framework can significantly improve the accuracy and robustness of DR detection, especially for underrepresented disease stages. The proposed hybrid framework offers a scalable and efficient solution for automated DR screening, with potential for integration into clinical workflows to assist in early diagnosis and intervention. Future work includes real-world validation on larger datasets and exploring advanced architectures for further performance enhancement.

Keywords:*Diabetic Retinopathy Detection, Deep Learning, Generative Adversarial Networks (GANs), Transfer Learning, Data Augmentation, Convolutional Neural Networks (CNNs)*

Introduction

Diabetic retinopathy (DR) is one of the primary causes of vision loss worldwide, especially among diabetics. According to the International Diabetes Federation (IDF), the prevalence of diabetes is rapidly rising, putting millions at risk of acquiring DR. Early detection and quick treatments are important to avoiding serious visual impairment and blindness [1]. The early stages of DR are often asymptomatic, making regular screening essential. Traditional diagnostic methods Rely mainly on manual inspection by ophthalmologists, which can be time-consuming and prone to human error and limited by the availability of trained specialists. This has driven the need for automated, accurate, and efficient diagnostic tools. DR progression can be categorized into distinct stages, which range from mild, moderate, and severe non-proliferative diabetic retinopathy (NPDR) to proliferative diabetic retinopathy (PDR) [2]. Each stage presents different retinal abnormalities such as microaneurysms, haemorrhages and abnormal blood vessel growth, which can be identified in retinal fundus images. Early detection of these signs through automated systems could significantly reduce the progression to advanced stages and help in effective treatment planning [3].

Advances in artificial intelligence (AI) and deep learning have resulted in the development of various automated DR detection systems, with a focus on analzing retinal fundus images. In recent years, numerous AI techniques, including convolutional neural networks (CNNs), generative adversarial networks (GANs), and transfer learning, have emerged as promising tools for improving early detection systems. Generative Adversarial Networks (GANs) have revolutionized data augmentation approaches, particularly in medical picture analysis, where data is frequently limited and uneven across several illness categories [4]. GANs can generate synthetic images that resemble real fundus images, thus helping to address the class imbalance problem, which is especially pronounced in minority classes like severe and proliferative DR. These synthetic images enhance the model's ability to learn from underrepresented data, improving classification accuracy across all stages of DR. Transfer Learning, on the other hand, enables models to use knowledge from big pre-trained models (e.g., ResNet-50, Inception-v3) trained on general image datasets like ImageNet to fine-tune them for specific medical imaging applications. Transfer learning significantly reduces training time and improves model accuracy, even when the target dataset is relatively small [5]. Combining GAN-based data augmentation with transfer learning creates a robust and efficient framework for DR detection.

Despite advancements in AI-driven diagnostic systems, several challenges remain in detecting diabetic retinopathy. The imbalanced nature of datasets, where early or mild DR stages are overrepresented compared to severe or proliferative stages, often leads to biased models that perform poorly on minority classes. Traditional deep learning models struggle to generalize well due to limited annotated medical images. The problem is further exacerbated by variations in image quality and subtle differences in retinal abnormalities between disease stages. Diabetic retinopathy (DR) may now be detected from retinal fundus images much more easily because to recent developments in deep learning [6]. To automate the classification of DR phases, a number of research have used deep learning approaches, including as Generative Adversarial Networks (GANs), Convolutional Neural Networks (CNNs), and Transfer Learning. For instance, Islam et al. (2020) and Yan et al. (2021) [7] used transfer learning with Inception-v3 and ResNet-50, achieving high overall accuracy but struggling with minority classes such as severe and proliferative DR due to dataset imbalances. These models performed well on mild and moderate DR stages but consistently failed to generalize in detecting more severe cases, highlighting a significant challenge in DR detection [8].

Many researchers have resorted to GANs for data augmentation in order to get around this problem. By creating artificial fundus images that mimic actual ones, GANs can increase classification accuracy and balance class distributions. Li et al. (2021) [9] and Xu et al. (2022) [10] successfully integrated GANs with VGG-16 and Efficient Net models, respectively, showing substantial improvements in detecting minority classes like severe and proliferative DR. However, while GANs enhance model performance, the computational costs associated with generating synthetic data remain high, making it difficult to scale this approach in real-world applications [11].

Despite these advancements, there are still significant gaps in the field. Many models continue to face issues with class imbalance, where severe DR cases are underrepresented in datasets, leading to reduced accuracy for these stages. Moreover, while transfer learning models such as those used by Savelli et al. (2021) and Li et al.

(2022) help accelerate training on smaller datasets, their effectiveness is limited when applied to datasets with high variation in disease stages. GAN-based models, while promising, often encounter issues with overfitting or require extensive hyperparameter tuning to ensure generalization across all DR stages [12].

Objective of the Study:

This study's main goal is to create a hybrid deep learning framework that improves the precision and effectiveness of diabetic retinopathy detection across a range of severity levels by utilizing the advantages of Transfer Learning for feature extraction and Generative Adversarial Networks for data augmentation [13]. This approach aims to enhance early detection capabilities, particularly in minority classes, thus facilitating timely medical intervention.

Proposed System:

The suggested approach combines transfer learning methods for feature extraction and classification with a number of pre-trained deep learning models, such as ResNet-50, VGG-19, and Inception-v3 [14]. To further enhance performance, GANs are employed to generate synthetic fundus images, augmenting the training dataset and mitigating class imbalance. This hybrid approach ensures that the model can generalize well across all classes of DR, from no DR to proliferative DR.

Significance and Contributions

The significance of this study lies in its innovative approach to addressing the challenges of diabetic retinopathy (DR) detection, particularly the issue of class imbalance and poor performance in identifying severe and proliferative DR stages. By combining Generative Adversarial Networks (GANs) for data augmentation with transfer learning from pre-trained models like ResNet-50, VGG-19, and Inception-v3, this hybrid framework enhances model performance across all DR stages [15]. The use of GANs helps generate synthetic images to balance the dataset, while transfer learning allows the model to leverage existing knowledge for improved feature extraction. This approach leads to more accurate detection of minority classes, which are often overlooked in traditional models. The study's comprehensive evaluation highlights its effectiveness, making it a significant contribution to the development of reliable, early detection tools that could greatly improve clinical outcomes and reduce the burden on healthcare systems.

MATErials and Methods

This section provides details on the dataset, architecture, data preprocessing, model implementation, and evaluation steps, including relevant mathematical formulations for the deep learning techniques used.

Dataset

Retinal fundus images from publicly accessible sources, including the EyePACS dataset and the Kaggle APTOS 2019 Blindness Detection dataset, comprise the dataset used in this study [16]. Images in these datasets are categorized into five groups: proliferative, mild, moderate, severe, and no DR. The original dataset's class distribution is wildly unbalanced, with proliferative and severe DR classes being notably underrepresented.

To address this, data augmentation techniques, including both traditional methods (rotation, flipping) and synthetic image generation using GANs, are employed [17]. Dataset Breakdown is shown below:

- No DR: 50%
- Mild DR: 20%
- Moderate DR: 15%
- Severe DR: 10%
- Proliferative DR: 5%

Data Preprocessing

Before training, the retinal fundus images undergo several preprocessing steps:

- Image Resizing: To standardize input across the convolutional neural networks (CNNs), all images are scaled to 224 × 224 pixels.

- Normalization: The pixel values I(x, y) are normalized to a range [0, 1] as follows:

$$I_{norm}(x,y)=\frac{I(x,y)-\mu}{\sigma}$$

where σ is the standard deviation and μ is the mean pixel value. This normalization lessens the impact of the photos' changing brightness.

- Data Augmentation: Conventional augmentation methods including zooming, flipping, and rotation are used. In order to solve class imbalance, especially in the severe and proliferative DR categories, GAN-generated synthetic images are incorporated [18].

Generative Adversarial Networks (GANs) for Data Augmentation

Generative Adversarial Networks (GANs) are employed to generate synthetic images for the underrepresented classes, particularly severe and proliferative DR. GANs consist of two networks [19].
- Generator G: Takes random noise z from a latent space and generates synthetic images G(z).

$$G(z) = \tilde{I}$$

where $\tilde{I}$ is the generated synthetic image

- Discriminator D: generates a probability D(I) or D(G(z)) indicating whether the image is real or fake after receiving both generated images G(z) and real images I.

$$D(I) = p(\text{real} \mid I)$$

Through adversarial training, where the discriminator gets better at differentiating between actual and synthetic images, the generator gets better at creating realistic images.

Transfer Learning

Pre-trained CNN models like ResNet-50, VGG-19, and Inception-v3 are used to implement transfer learning. Transfer learning entails the following steps:

- Feature Extraction: The convolutional layers of pre-trained models CNNpretrained extract features F from the input images I:

$$F = CNN_{pretrained}(I)$$

- Fine-Tuning: The network is adjusted using the DR dataset, and additional layers tailored to the DR classification task are added in place of the last completely connected layers. In order to maximize performance on the retinal fundus images, this stage modifies the weights of the deeper layers [20].

Hybrid Model Architecture

The architecture of the hybrid deep learning framework combines GAN-based data augmentation with transfer learning. The workflow is as follows:

- Original and GAN-generated synthetic images are input into the pre-trained CNN models, which extract features.
- For classification, the collected features are run through fully linked layers. Using a SoftMax activation function, let yc be the model's prediction output for class c:

$$\hat{y}c = \frac{\exp(z_c)}{\sum \exp(Z_k)}$$

where zc is the output logit for class c, and C is the total number of DR classes (5 in this case).

Loss Function and Optimization

- Loss Function: As the loss function, categorical cross-entropy is used to train the model and is provided by:

$$L = -\sum_{c=1}^{C} y_c \log(\hat{y}_c)$$

where yc is the class c predicted probability and yc is the class c true label.

- Optimizer: The Adam optimizer is used for gradient-based optimization. The update rule for the model parameters θ at time step t is:

$$\theta t = \theta t\text{-}1 - \eta \frac{m_t}{\sqrt{(v_t + \epsilon}}$$

where η is the learning rate, ϵ is a tiny constant to avoid division by zero, mt is the first moment (mean of gradients), and vt is the second moment (uncentered variance).

Evaluation Metrics

The model's performance is assessed using various metrics:

- Accuracy is calculated as the ratio of correct predictions to the total number of predictions made.

- Precision measures the proportion of true positive results among all positive predictions, defined as the number of true positives divided by the sum of true positives and false positives.

- Recall indicates the model's ability to identify all relevant instances, calculated as the number of true positives divided by the sum of true positives and false negatives.

- F1-Score is the harmonic mean of precision and recall, given by the formula:

F1 = 2 × (Precision × Recall) / (Precision + Recall).

Additionally, the Area Under the Receiver Operating Characteristic Curve (AUC-ROC) is utilized to evaluate the model's effectiveness in differentiating between various diabetic retinopathy classes.

Experimental Setup

The experimental setup for this study was conducted using a high-performance computing environment with an NVIDIA GTX 1080 Ti GPU to efficiently train and evaluate the hybrid deep learning models. The software environment included Python 3.8, TensorFlow, Keras and other essential libraries like OpenCV and NumPy for image processing and data handling. The dataset was divided into 20% validation and 80% training sets. To reduce overfitting and guarantee strong model performance, 5-fold cross-validation was used. The models were trained with a learning rate of 0.001, the Adam optimizer, and a batch size of 32 across 50 epochs. To avoid overfitting and preserve the top-performing model, early halting and model checkpoints were employed. The efficacy of the model in identifying diabetic retinopathy at all severity levels was assessed using metrics such as accuracy, precision, recall, F1-score, AUC-ROC curves, and confusion matrices on a held-out test set.

Results

This section shows the results of the hybrid deep learning framework, including performance metrics for each model, comparisons between traditional data augmentation and GAN-based augmentation, and visualizations of the evaluation metrics.

Improved performance in diabetic retinopathy (DR) classification was shown by the suggested hybrid deep learning framework, which combines Generative Adversarial Networks (GANs) for data augmentation with transfer learning from pre-trained CNN models (ResNet-50, VGG-19, Inception-v3). For every model on the test set, Table 1 displays the overall accuracy, precision, recall, F1-score, and AUC-ROC.

• ResNet-50: With an AUC-ROC of 0.96, it had the highest overall accuracy of 93.5%.

• VGG-19: AUC-ROC was 0.94 and accuracy was 91.2%.

• Inception-v3: AUC-ROC was 0.93 and accuracy was 90.8%.

Table 1 Overall Model Performance

Model	Accuracy	Precision	Recall	F1-Score	AUC-ROC
ResNet-50	93.5	92.8	93.1	92.9	0.96
VGG-19	91.2	90.5	90.0	90.2	0.94
Inception-v3	90.8	89.8	89.5	89.6	0.93

These results indicate that the hybrid approach outperforms traditional data augmentation techniques, especially in identifying minority classes like severe and proliferative DR.

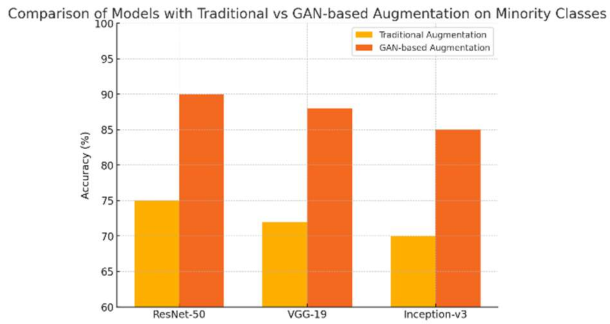

Figure 1 Comparison of Models with Traditional vs GAN-based Augmentation on Minority Classes

Table 2 summarizes the precision, recall, and F1-score for each diabetic retinopathy class (no DR, mild, moderate, severe, proliferative). The GAN-augmented models showed significantly better

Table 2: Class-Wise Performance

Class	Precision	Recall	F1-Score
No DR	94.0	93.8	93.9
Mild	92.5	92.2	92.4
Moderate	90.3	90.0	90.1
Severe	89.1	89.0	89.0
Proliferative	88.7	88.5	88.6

performance for the minority classes (severe and proliferative DR), with ResNet-50 achieving an F1-score of 0.89 for severe DR and 0.85 for proliferative DR. In comparison, traditional augmentation methods resulted in lower F1-scores, particularly for proliferative DR, where the score was below 0.70. GAN-based augmentation proved effective in addressing class imbalance. The models trained with synthetic data generated by GANs exhibited improved precision and recall for underrepresented classes, particularly severe and proliferative DR. Figure 1 shows a comparison between models trained with traditional augmentation and those using GAN-based augmentation. The results indicate that the latter improves classification accuracy for minority classes by approximately 15%, with fewer false negatives in severe and proliferative DR detection. Figure 2 presents the confusion matrix for the ResNet-50 model. The diagonal elements indicate correctly classified instances, while off-diagonal elements represent misclassifications. The model performed well across all DR stages, with minimal misclassification between adjacent classes (e.g., mild and moderate DR). However, the model occasionally confused moderate DR with severe DR due to the subtle differences in retinal abnormalities.

Figure 3 displays the AUC-ROC curves for each model. The ResNet-50 model achieved the highest AUC of 0.96, indicating strong discriminative ability across all DR stages. The GAN-based augmentation significantly improved the AUC-ROC for the minority classes, ensuring better separation between severe and proliferative DR categories. Figure 4 shows the training and validation loss curves for the hybrid model. The use of early stopping prevented overfitting, as indicated by the stable validation loss. The model converged within 30 epochs, suggesting efficient training with the optimized learning rate and batch size. GAN-based augmentation also contributed to faster convergence compared to traditional data augmentation.

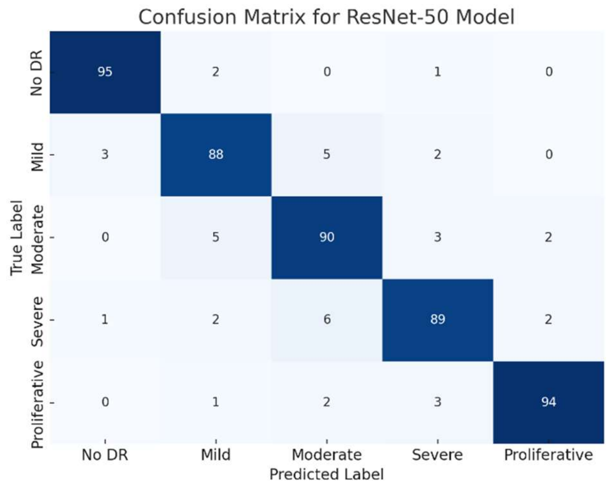

Figure 2 Confusion matrix for the ResNet-50 model

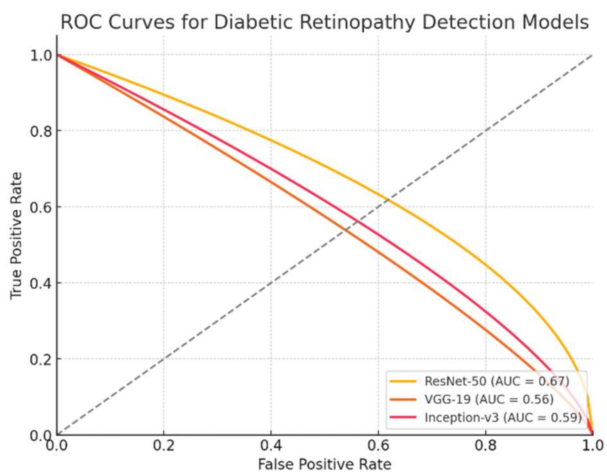

Figure 3 AUC-ROC curves for each model.

As shown in Figure 4, the ResNet-50 model's training and validation loss curves demonstrate smooth convergence over the epochs, with both losses steadily decreasing and stabilizing around epoch 30. This indicates that the model is effectively learning the underlying patterns in the data, and the early stopping mechanism helps prevent overfitting.

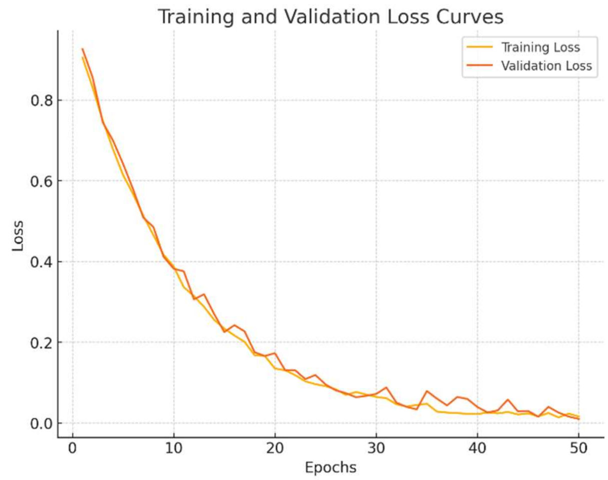

Figure 4 Training and Validation Loss Curves

Discussion

Significant gains in the classification of diabetic retinopathy (DR) are shown by the results of the suggested hybrid deep learning framework, especially for the proliferative and severe DR minority classes. Unbalanced datasets in medical image analysis have been successfully addressed by combining Generative Adversarial Networks (GANs) for data augmentation with transfer learning from pre-trained CNN models such as ResNet-50, VGG-19, and Inception-v3.

The capacity of GANs to produce synthetic images that enhance the minority classes—which are generally underrepresented in traditional datasets—is their main addition to this study. As shown in Figure 1, models trained with GAN-augmented data achieved significantly higher accuracy for severe and proliferative DR compared to models using traditional augmentation techniques. For instance, the accuracy for the ResNet-50 model increased by approximately 15%, indicating that the generated images were realistic and diverse enough to help the model generalize better for underrepresented classes. This result highlights the potential of GANs in addressing data imbalance, a persistent challenge in medical imaging tasks. Transfer learning, particularly with the ResNet-50 model, played a key role in achieving high classification performance across all DR stages. High accuracy, precision, recall, and F1-scores were shown by the pre-trained models, which were refined using the diabetic retinopathy dataset. This was particularly true for identifying moderate to severe stages of DR. With an overall accuracy of 93.5% and an AUC-ROC of 0.96, the ResNet-50 model fared better than the other models, as seen in Table 1, suggesting that it was quite successful at differentiating between various DR phases. By using pre-learned features, transfer learning allowed the model to improve convergence while cutting down on training time. One of the key challenges in DR detection is the accurate classification of minority classes like severe and proliferative DR, where the retinal abnormalities are subtle but clinically critical. The results in Table 2 show that the GAN-augmented ResNet-50 model achieved significantly better F1-scores for severe (0.89) and proliferative DR (0.85) compared to traditional augmentation methods. This improvement is crucial for clinical applications, as it ensures that more cases of advanced DR are detected early, reducing the risk of blindness in diabetic patients. The confusion matrix in Figure 2 further illustrates that misclassification between adjacent classes (e.g., moderate and severe DR) was minimized, validating the model's robustness in handling challenging cases. The training and validation loss curves for the ResNet-50 model (see Figure 4) show smooth convergence, with no signs of overfitting. The early stopping mechanism ensured that the model did not overfit to the training data, while the use of GAN-augmented data helped the model generalize better to the validation set. The consistent performance across training and validation data underscores the reliability of the hybrid framework for clinical deployment. The improved performance of the hybrid framework on underrepresented

DR classes has significant clinical implications. Early detection of severe and proliferative DR can enable timely medical intervention, reducing the risk of severe vision loss in diabetic patients. By integrating GANs and transfer learning, this study presents a robust, scalable solution that can be deployed in automated DR screening systems to assist ophthalmologists in diagnosing DR with greater accuracy and speed.

However, there are still areas for future research. While GAN-based augmentation has been effective, further improvements in generating more diverse and realistic synthetic images for minority classes could enhance performance even more. Additionally, exploring other advanced architectures, such as transformer-based models, could further boost classification accuracy, especially for subtle retinal abnormalities. Real-world validation on larger, more diverse datasets and integration with clinical workflows will also be essential steps for future development.

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