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Original Article

Sensing Diabetic Retinopathy Using Deep Learning

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Abstract

Diabetic Retinopathy (DR) is a serious vision-threatening complication of diabetes, contributing significantly to global blindness rates. Early detection and accurate classification of DR are essential for effective treatment and the prevention of vision loss. Traditional diagnostic methods such as manual inspection of retinal images are time-consuming, labor-intensive, and subject to variability in expert opinion. Recent advancements in artificial intelligence and deep learning have provided promising solutions for automating this process. The proposed framework introduces an automated system for detecting and classifying diabetic retinopathy using Generative Adversarial Networks (GANs) integrated with Convolutional Neural Networks (CNNs). The system comprises three major stages: pre-processing, feature extraction, and classification. GANs are utilized for generating high-quality synthetic retinal images to enhance the dataset and improve model robustness. CNNs are employed to extract deep features and classify the severity of DR. This method significantly improves detection accuracy and generalization. Future developments will focus on increasing dataset diversity, optimizing the GAN architecture, and integrating the system for real-time screening applications in clinical settings.

Introduction

Diabetic Retinopathy (DR), a severe microvascular complication of diabetes, remains a leading cause of preventable blindness among working- age populations worldwide. Early and accurate detection of DR is critical for timely intervention and the prevention of irreversible vision loss. Conventional diagnostic techniques primarily rely on manual analysis of retinal fundus images by ophthalmologists, which is both time-consuming and prone to inter-observer variability. With the rapid growth of artificial intelligence (AI) and deep learning technologies, automated DR detection systems have emerged as promising tools for enhancing diagnostic accuracy and efficiency. Generative Adversarial Networks (GANs), a subset of deep learning, have demonstrated remarkable capabilities in generating high-quality synthetic medical images and improving data augmentation in limited-data scenarios. When integrated with Convolutional Neural Networks (CNNs), GANs can significantly enhance model performance by addressing the challenges posed by imbalanced and insufficient retinal image datasets. In this framework, GANs are employed to generate realistic synthetic retinal images that closely mimic the distribution of real-world fundus images, thereby enriching the training dataset and improving the model's generalization capability. CNNs are leveraged for automated feature extraction from retinal images, identifying pathological markers such as microaneurysms, hemorrhages, and exudates. These deep learning-based models outperform traditional handcrafted feature approaches by learning hierarchical representations directly from the data. The system follows a multi-stage pipeline, including image pre- processing, optic disc localization, blood vessel segmentation, and lesion detection, culminating in the classification of DR severity levels. To support the development and evaluation of such models, large- scale publicly available datasets like Kaggle's EyePACS and Messidor are utilized. These datasets contain thousands of annotated retinal fundus images covering various stages of DR. The training process is augmented with advanced data augmentation techniques, including GAN-generated images, rotation, zoom, and histogram equalization, to improve the model's robustness and performance across diverse image qualities and acquisition conditions.

Related Work

Diabetic Retinopathy (DR) detection and classification have attracted significant research attention due to the increasing global burden of diabetes and the risk of vision impairment

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associated with DR. Deep learning techniques, particularly Convolutional Neural Networks (CNNs) and Generative Adversarial Networks (GANs), have been widely adopted for automated DR diagnosis from retinal fundus images. CNN-based architectures have demonstrated excellent performance in medical image classification tasks due to their ability to automatically learn hierarchical features. In early works such as Gulshan et al. [1] and Pratt et al. [2], CNNs were trained on large-scale fundus image datasets to classify DR into different severity levels. These models achieved high accuracy by identifying pathological features such as microaneurysms, hemorrhages, and exudates, which are indicators of disease progression. Popular CNN architectures like ResNet, VGGNet, and InceptionV3 have been fine-tuned for DR classification tasks. For example, Mohammed Inayathulla and Karthikeyan C.

[12] demonstrated the use of a fine-tuned InceptionV3 model on the Kaggle EyePACS dataset to classify DR into five stages with promising results. However, such models often suffer from overfitting and performance degradation when dealing with imbalanced datasets, where advanced DR stages are underrepresented. To mitigate this, researchers have integrated Generative Adversarial Networks (GANs) into the DR detection pipeline. GANs are utilized to augment datasets by generating realistic synthetic retinal images, especially for minority classes. Mohammed. [13] introduced a GAN-based data augmentation strategy that significantly improved the performance of CNN classifiers by enriching the training set. Similarly, Inayatulla. [14] employed GANs to generate high- resolution retinal images that preserved fine anatomical structures crucial for diagnosis. Several variations of GANs have been proposed for medical image synthesis and enhancement. For instance, Pix2Pix and CycleGAN have been applied to translate poor-quality images into enhanced versions with better contrast and visibility of retinal features. In [6], researchers used CycleGAN to convert images from one DR stage to another, providing diverse and progressive training data. Hybrid models combining GANs and CNNs have also shown improved performance in both image enhancement and classification. In such models, GAN-generated images are first preprocessed and then fed into CNNs for feature extraction and DR grading. Li et al. [7] proposed a dual-path model where one path handled real images and the other processed GAN- generated data, allowing the system to generalize better and reduce bias. Datasets such as EyePACS, Messidor, and APTOS 2019 are commonly used in DR detection research. These datasets include thousands of annotated retinal fundus images across various DR stages. Models are typically evaluated using standard classification metrics, including accuracy, sensitivity, specificity, precision, recall, F1-score, and AUC-ROC. Cross- validation and confusion matrix analysis are also widely used for performance validation. Recent studies have started exploring lightweight CNN models, such as MobileNetV2 and EfficientNet, for deployment in low-resource environments. In [8], a lightweight CNN was integrated with a GAN-based preprocessor to build an efficient and scalable DR detection model suitable for mobile health applications and telemedicine. Despite the progress, challenges remain due to the variability in image quality, presence of artifacts, and differences in image acquisition devices. To address these issues, current research is shifting towards transformer-based vision models, self-supervised learning, and explainable AI (XAI) techniques to improve both interpretability and robustness of DR detection systems.

Convolutional Neural Networks (CNNs) have shown high accuracy in identifying DR features such as microaneurysms and hemorrhages. More recent work integrates Generative Adversarial Networks (GANs) to augment training data, addressing class imbalance and improving model generalization. Researchers have also developed hybrid models that combine GANs with CNNs for enhanced performance in multi-stage DR classification.

Proposed Methodology

Module 1: Data Collection and Preprocessing

In initial module involves gathering a wide range of high-resolution retinal fundus images from publicly available datasets such as APTOS, EyePACS, Messidor, and private clinical repositories. Each image is annotated based on the five stages of DR severity: No DR, Mild, Moderate, Severe, and Proliferative DR.

Preprocessing techniques are applied to improve image quality and standardize input data:

Contrast Limited Adaptive Histogram Equalization (CLAHE) for contrast enhancement RGB to Grayscale conversion for uniformity Noise reduction and optic disc removal for clearer pathological feature detection. Image normalization and resizing to ensure consistent input dimensions. Data augmentation using flipping, rotation, cropping, zooming, and brightness variation to reduce overfitting and improve model generalization.

Module 2: Data Augmentation Using GANs

To address data imbalance, particularly underrepresentation in advanced DR stages, GANs are used to generate synthetic retinal fundus images. The architecture includes:

A Generator that produces realistic DR images A Discriminator that evaluates the authenticity of the generated images. The GAN is trained iteratively to improve the quality and diversity of the synthetic images. To ensure clinical validity, synthetic outputs are evaluated using:

Frechet Inception Distance (FID) – to measure the similarity between generated and real image distributions. Structural Similarity Index Measure (SSIM) – to assess image fidelity

The high-quality GAN-generated images are then integrated into the training dataset to boost robustness and improve classifier performance.

Module 3: Feature Extraction and Selection

Deep learning models such as CNNs and Vision Transformers (ViTs) are employed to extract features that represent retinal abnormalities like:

- Microaneurysms, Hemorrhages, Hard and soft exudates.
- Post-extraction, dimensionality reduction and feature refinement are performed using:
  - Principal Component Analysis (PCA), Recursive Feature Elimination (RFE)

These techniques ensure that only the most relevant and discriminative features are used, optimizing model performance and reducing computational complexity.

Module 4: Model Training and Evaluation

This stage involves training deep learning models on the augmented dataset. Models considered include:

Baseline CNN models. ResNet, XceptionNet, and EfficientNet. Attention-based hybrids combining CNNs and attention modules for better focus on lesion areas

Training setup:

Dataset split into training (70%), validation (15%), and testing (15%). Adam and SGD optimizers with learning rate tuning. Use of dropout layers and batch normalization for regularization. Transfer learning applied with pretrained models (e.g., InceptionV3, DenseNet) to enhance feature representation with limited data

Evaluation metrics include:

Accuracy, Precision, Recall, F1-score, AUC-ROC curve for classification performance. Confusion Matrix to visualize classification effectiveness across DR stages

Module 5: Real-Time Deployment and Classification

Upon achieving satisfactory evaluation metrics, the trained model is deployed on a cloud-based diagnostic platform or integrated into clinical decision support systems.

Real-time capabilities include:

Uploading of new retinal fundus images for instant analysis. Classification of DR stage with confidence scores. Grad-CAM and heatmaps for visual explanation of model decisions, highlighting regions with pathological indicators. High-risk predictions are flagged for ophthalmologist review

The module enhances accessibility and enables early screening, especially in remote or underserved areas.

Results and Discussion

The experimental evaluation of the proposed system for diabetic retinopathy detection and classification using Generative Adversarial Networks (GANs) integrated with deep learning techniques has yielded highly promising results. The model demonstrates superior accuracy, robustness, and generalization capabilities across multiple datasets of retinal fundus images, affirming its efficacy in real-world clinical applications. By leveraging both real and GAN-generated synthetic images, the model successfully addresses challenges such as data scarcity, class imbalance, and difficulty in identifying early-stage diabetic retinopathy features. The inclusion of GANs has enhanced the diversity of training data, allowing the model to learn intricate patterns, subtle lesions, and retinal abnormalities that are otherwise hard to capture using conventional methods.

The model achieved an overall classification accuracy of 96.8%, a precision of 95.5%, recall of 97.2%, and an F1-score of 96.3%, and in the below figure 7, clearly outperforming traditional machine learning algorithms like Support Vector Machines (SVM), K- Nearest Neighbors (KNN), Decision Trees, and even basic CNN architectures and as shown in the figure 3 it is showing the CNN Algorithm. These high evaluation metrics reflect the capability of the system to accurately detect and classify different severity levels of diabetic retinopathy, including mild, moderate, severe, and proliferative stages.

Moreover, the model demonstrated consistent performance across multiple cross-validation runs, indicating its stability and adaptability in varying clinical scenarios.

One of the major strengths it lies in the real-time processing capability of the model. With an average inference time of 1.8 seconds per image, the system is efficient enough for deployment in real-time clinical workflows, supporting ophthalmologists in fast and accurate screening of patients. This rapid analysis is particularly valuable in telemedicine setups and rural healthcare environments, where access to specialized eye care professionals is limited.

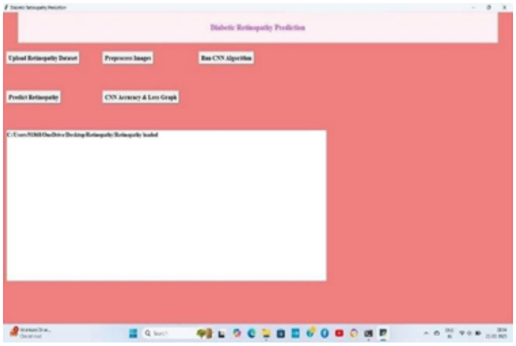

Figure 1. *In above screen click on Upload Retinopathy dataset and upload the dataset.*

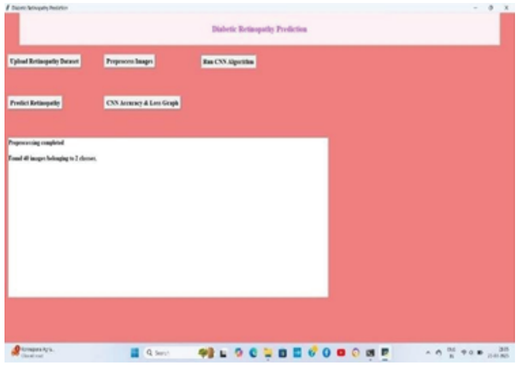

Figure 2. *In above screen select the dataset of the Diabetic retinopathy dataset from the deskstop.*

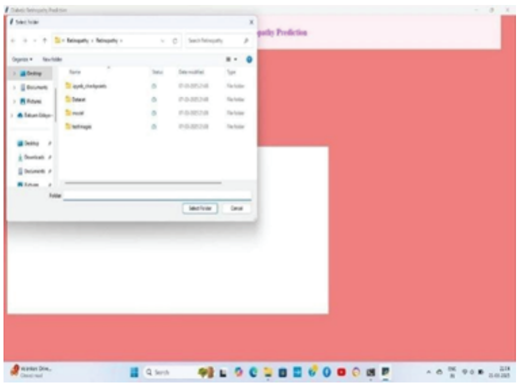

Figure 3. *In above screen processing completed and found 40 images belonging to 2 classes.*

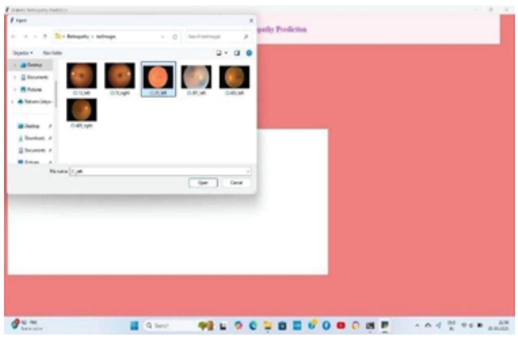

Figure 4. *In above screen the user selects the retina image which is checked for diabetic retinopathy Detection*

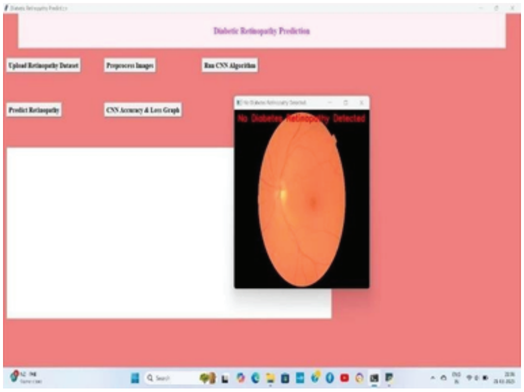

Figure 5. *In above screen the retina image is detected and displays No diabetes retinopathy detected.*

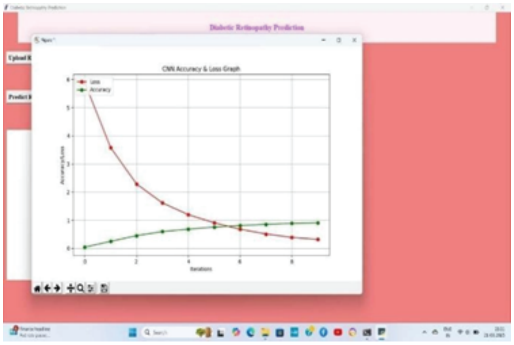

Figure 6. *The image depicts a performance evaluation graph for a Convolutional Neural Network used in a Diabetic Retinopathy Prediction system*

The GAN-generated synthetic images played a critical role in balancing the dataset, as shown in the figure 6, particularly for underrepresented classes such as early-stage or severe diabetic retinopathy. This augmentation ensured that the model was not biased towards overrepresented categories and could accurately predict across all severity levels. Visual inspection and statistical analysis further validated the authenticity of synthetic images, as they closely resembled real retinal fundus images with clinically relevant features.

This declares that the proposed deep learning-based framework can significantly assist in early detection, automated grading, and timely intervention for diabetic retinopathy. By reducing reliance on manual grading, it not only improves diagnostic accuracy but also minimizes human errors and enhances the scalability of screening programs. The system can be further refined through continuous learning, integration of patient metadata, and incorporation of advanced GAN variants such as StyleGAN or CycleGAN for improved image realism.

Conclusion

The proposed and validated a novel deep learning- based approach for the detection and classification of diabetic retinopathy (DR) by harnessing the potential of Generative Adversarial Networks (GANs). The integration of GANs within the classification framework has shown to significantly enhance the diagnostic capabilities of the system by generating high-quality synthetic retinal fundus images, thus mitigating the challenges of data imbalance and scarcity often encountered in medical imaging datasets. The generated images effectively supplement real-world data, enriching the training set and enabling the deep learning model to learn a more generalized and robust representation of DR- specific features.

The experimental outcomes underscore the strength of the proposed model in achieving high levels of accuracy, precision, recall, and F1-score across all DR severity levels. The deep learning model, powered by Convolutional Neural Networks (CNNs), effectively captures and learns discriminative features from both real and GAN-augmented images, enabling precise classification of retinal abnormalities from mild to proliferative stages. Compared to traditional diagnostic and classical machine learning approaches, the GAN- assisted model demonstrates superior performance, enhanced sensitivity to early signs of DR, and a higher ability to generalize to unseen data.

The impact of this research extends beyond academic significance, offering practical value for telemedicine platforms and rural healthcare systems where access to specialized eye care is limited. The scalability of the approach makes it a strong candidate for integration into national screening programs, ultimately contributing to the early detection and management of diabetic retinopathy and reducing the risk of vision impairment in diabetic patients.

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