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Medical images synthesis of diabetic retinopathy using GANS

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Abstract
The scarcity of annotated medical images is a significant challenge in training effective machine learning models for diagnosing diabetic retinopathy, a leading cause of blindness. Acquiring high-quality retinal images is costly and time-consuming, and a lack of diversity in existing datasets raises the challenge even further. Such limitations make it challenging to come up with reliable diagnostic tools that depend on comprehensive and varied data for effective training. In order to generate real images for the different diabetic retinopathy stages, this work uses GANs. Therefore, such an issue could be addressed by just incorporating those realistic images into current datasets that increase both size and variability as well as enhance diagnostic models. Furthermore, the generated data serves as a valuable asset for exploring disease patterns that are typically underrepresented in existing datasets, offering a promising approach to advance diabetic retinopathy diagnosis.
Keywords: *Diabetic Retinopathy, Generative Adversarial Networks (GANs), Retinal Fundus Images, Medical Imaging, Image Synthesis*

INTRODUCTION

Diabetic retinopathy (DR) is a significant global cause of vision impairment, affecting millions of diabetic patients. Considering the increasing incidence of diabetes, it is crucial to identify diabetic retinopathy at its early stages, to manage it effectively and minimize loss of sight. Present diagnostic measures are based on the subjective assessment of retinal fundus photography, which is time-consuming and requires specialist skills. Moreover, the interpretation of these procedures is often inconsistent and heavily relies on the availability of strong datasets. The lack of annotated and varied datasets remains a key limitation in building reliable diagnostic models to distinguish different stages of DR.

The present study addresses the problem of dataset scarcity by using Generative Adversarial Networks (GANs) to generate realistic synthetic retinal images depicting different stages of diabetic retinopathy. The process of incorporating these synthetic images will not only augment existing datasets but also introduce greater heterogeneity and increase dataset volume. This will help ensure the development of more robust and generalized diagnostic models. Such an approach addresses existing challenges related to insufficient data while also promoting the creation of superior DR detection systems, thereby enhancing clinical outcomes and advancing medical imaging research.

Literature Survey

S. Pavithra et al. [1] presented the approach to optical imaging with ensemble machine learning models for diagnosing diabetic retinopathy. The paper mainly concentrated on the advanced techniques of capturing features of the retina through optical imaging and the ensemble technique to produce a better accuracy by combining the outputs of various models. The authors insisted on early diagnosis since severe complications can result in loss of vision. These findings indicate the considerable improvement in terms of sensitivity and specificity over individual models, so it became important to have ensemble-type approaches for medical diagnostics. It also pointed out that this model was capable of minimizing error while enhancing the reliability for detection of diabetic retinopathy, but computational intensity as well as dependency on better quality imaging systems limited such models.

Neetha Merin Thomas and S. Albert Jerome [2] proposed a detection approach of diabetic retinopathy based on the enhanced adaptive dual-band stochastic classifier combined with an improved dilated ensemble Convolutional Neural Network (CNN) model. The technique advances to increase the detection accuracy based upon the utilization of dilations of convolutions in its extraction process without a great burden in computational cost. This brought reduced false positives and increased adaptability for different datasets. All stages of diabetic retinopathy were found with a good classification performance and robust detection. Nonetheless, this work contributes toward better automation of diabetic retinopathy detection, aiding in heightened classification performance and reliability.

Sowmyashree Bhoopal et al. [3] designed a sophisticated algorithm for automatic detection and classification of diabetic retinopathy in fundus images using ResNet50 in conjunction with CLAHE-GAN.This combination provided better accuracy in the recognition of different stages of the disease. Authors have shown that the CLAHE-GAN preprocessing process reduces noise and brought forth features of the retina that had improved the classification results. Even though the results were fairly promising, the study points out that the dependency for training requires high computational power, and the method with dependency on large data may limit its applications in a resource-limited setup. Nevertheless, the approach has much promise toward computer-assisted diabetic retinopathy diagnosis.

Aryan Rapti Chaudhuri and Suman Deb [4] proposed a methodology for diabetes retinopathy detection. The methodology includes lesion analysis with accurate approach of Generative Adversarial Networks (GAN) and Mask-RCNN. The approach will be on the segmentation of lesions from the fundus images, which is primarily crucial in diabetic retinopathy diagnosis. GAN allows for the production of high-quality synthetic images, which augment a training dataset due to limited data that is annotated. Some experiments that were carried concluded that the integration of GAN with Mask-RCNN in the lesion detection enhanced the accuracy in the detection while reducing false positives. The authors also concluded that the model was expensive to run in computation and had required a good quality of annotated datasets

Dr. Sasikala et al. [5] proposed a method to identify diabetic retinopathy using Bidirectional Gated Recurrent Units (BiGRUs) and Generative Adver-sarial Networks (GANs). This work had made use of preprocessing methods such as Water-shed-based segmentation and histogram equalization on a dataset of more than 80,000 retinal images on Kaggle. The model scored a high accuracy of 98.5% and outperformed traditional methods such as Random Forest and AlexNet in precision, recall, and F1-score. With the use of state-of-the-art deep learning algorithms and bio-inspired optimization techniques, this system offers a very scalable and efficient way of automating the diagnosis of diabetic retinopathy, which would improve clinical outcomes and accessibility to healthcare.

Zubair Khani et al. [6] introduced a new diabetic retinopathy (DR) detection method through a deep model, VGG-NiN. This new method uses the VGG16 architecture, Spatial Pyramid Pooling (SPP) layer, and Network-in-Network (NiN) layers to gain improved feature extraction and classification efficiency. This re-search used the Kaggle EyePACS dataset, consisting of 88,702 fundus images. The point of interest here is that the ability of the model to classify early-stage DR correctly renders it distinct from traditional methods such as ResNet50 and DenseNet121, which fail under such challenging conditions. The objective is to enhance the classification accuracy, especially for challenging early-stage DR cases.

Dr. Jimmy S. Chen et al. [7] created GAN application in ophthalmology. They trained GANs on a multicenter ROP screening program dataset of more than 4,000 fundus image pairs using the Pix2Pix HD model. Results were stunning: synthetic images were so realistic that only experienced ophthalmologists could correctly classify them as real images 59% of the time. While there are still problems to be solved, such as how to ensure synthetic images capture clinical diversity and how to keep ethical considerations in mind, this work is a huge step in bringing AI into healthcare with promises towards safer, more accurate, and accessible diagnostic solutions.

Dr. Wejdan L et al. [8] published a detailed review on detection and classification methods for DR using deep learning. In their paper, they explain how CNNs become the focal point of the analysis of fundus images of retinal as they are utilized efficiently to highlight some key DR features such as microaneurysms, hemorrhages, and exudates. Limitations found in the review were imbalanced datasets, lack of lesion detection, and underutilization of multi-stage classification, hence the need for models that are capable of detecting DR stages and lesions simultaneously with high reliability. The study points to the potential of DL in transforming DR diagnosis, with the need for improved datasets and sophisticated models to enhance early detection and clinical outcomes.

Y. Sravani Devi et al. [9] proposed a strategy adopting DC-GANs that could make synthetic diabetic retinopathy images. Synthesis of such retinal images, in turn, makes this work highly useful in the enhancement of the classification model also like ResNet50. Using elaborate data augmentation experiments toward a figure of accuracy 98.66% toward a perfect detectable model are identified in the APTOS Blindness datasets. This method seems promising for increased precision of diagnosis but still faces problems concerning computational intensity and scalability, which need to be optimized for wider clinical applications.

Huma Naz et al. [10] presented an ensemble approach using the Deep Convolutional Generative Adversarial Network (DC-GAN) in order to manage the data imbalance in the grading of diabetic retinopathy. Their methodology synthesizes some realistic retinal images to achieve better diagnostic accuracy while keeping intra-class variance in a dataset. Such an ensemble model showed an improved capability to identify diabetic retinopathy stages more than any traditional method. Although effective, problems in this scheme, such as computational intensity, suggest the necessity for further optimization for this model to become clinically applicable.

Saif Hameed et al. [11] designed the DR-LL GAN model for synthesizing high quality fundus images with rich detailed diabetic retinopathy lesion information. Generative Adversarial Networks has been applied to overcome ordinary issues that happen with the applications of ophthalmology-based deep learning: there is limited and usually imbalanced annotated datasets. On account of synthesizing photorealistic synthetic images, synthesis image enhances the DR grading and segmentation tasks. The promising segmentation accuracy and reduced loss values by the experiments conducted with the datasets IDRiD and MESSIDOR indicate potential applicability in clinical diagnosis through automated diagnostic tools and ease of accessibility in medical imaging.

Yuhao Niu, Lin Gu, Yitian Zhao, and Feng Lu [12] came up with a novel interpretability-based approach to the detection of diabetic retinopathy. In this paper, he proposed Patho-GAN: A Generative Adversarial Network for Synthesizing Realistic Retinal Images and Lesions for Explainable Medical Diagnosis. He defined pathological descriptors by encoding spatial and visual lesion information in the form of activated neuron patterns. Such descriptors allowed controlled generation, for instance lesion type and location. The image-quality and generation-time were further superior compared to existing techniques through this model. Such characteristics open data augmentation in general and application of image-based clinical diagnostics in particular.

Shuqiang Wang et al. [13] proposed a semisupervised multichannel Generative Adversarial Network for diabetic retinopathy diagnosis. It addressed limited labeled data and the nature of the retina, generating sub-fundus images related to some diabetic retinopathy features. Semisupervised models with both labeled and unlabeled data improved grading accuracy and feature detection significantly. It is evaluated on the Messidor dataset; sensitivity, specificity, and area under the ROC curve values are obtained using MGAN, indicating that the model may be useful in assisting clinical diagnostics.

Shalini Agarwal et al. [14] performed a comprehensive review of the recent advances in diabetic retinopathy detection by deep learning methods. The paper includes works on applications of CNNs, ViTs, and hybrids on lesion detection, grading, and segmentation tasks. The survey considers the evolution from classical machine learning to advanced deep learning approaches, with an emphasis on data augmentation and self-supervised learning to overcome the issue of scarcity in data. This research points out the possibility of improving the accuracy and scalability of these technologies for clinical use applications.

METHODOLOGY

The proposed methodology tries to address the scarcity of annotated and diverse datasets for the diagnosis of diabetic retinopathy using Deep Convolutional GANs. This paper uses Kaggle Aptos dataset for retinal fundus images, normalizes them, and applies basic augmentation techniques to make sure that the images are always consistent. The DCGAN architecture includes the generator to create realistic images, and the discriminator evaluates the authenticity of those images. Hence, the iterative training will produce high-quality outputs.

The quality of the generated images is measured using a performance metric such as Fréchet Inception Distance (FID). Finally, the synthetic images are integrated into existing datasets for creating an augmented dataset for training machine learning models towards diabetic retinopathy detection. VGG-16, ResNet models are fine-tuned by making use of the enriched dataset and improvements in performance are measured through accuracy, precision, recall, and F1-score. The diversity of the dataset makes it more accurate and further research into less-represented disease patterns can also be supported

Dataset Description (APTOS 2019):

The APTOS 2019 Diabetic Retinopathy Dataset was utilized. It has 5593 files, occupying almost 10GB of storage. The dataset contains retinal fundus images of DR severity grades as follows:

- Class 0: No DR (Healthy Retina)
- Class 1: Mild DR (Few microaneurysms, minimum effect)
- Class 2: Moderate DR (More widely spread hemorrhages and exudates)
- Class 3: Severe DR (Large hemorrhages, venous beading, extensive damage)
- Class 4: Proliferative DR (Neovascularization, risk of vision loss)

The work of classification is to classify the stage of the provided retina image, employing ResNet-50 and VGG-16 classifiers.

Preprocessing:

The preprocessing operations involved:

- Resizing the image to a standard shape (e.g., 128x128 pixels for GAN training, 224x224 pixels for classifier training).
- Normalization: Scaling pixel values between 0 and 1.
- Data Augmentation: Rotation, flipping, and contrast adjustments.

GAN-based Data Augmentation

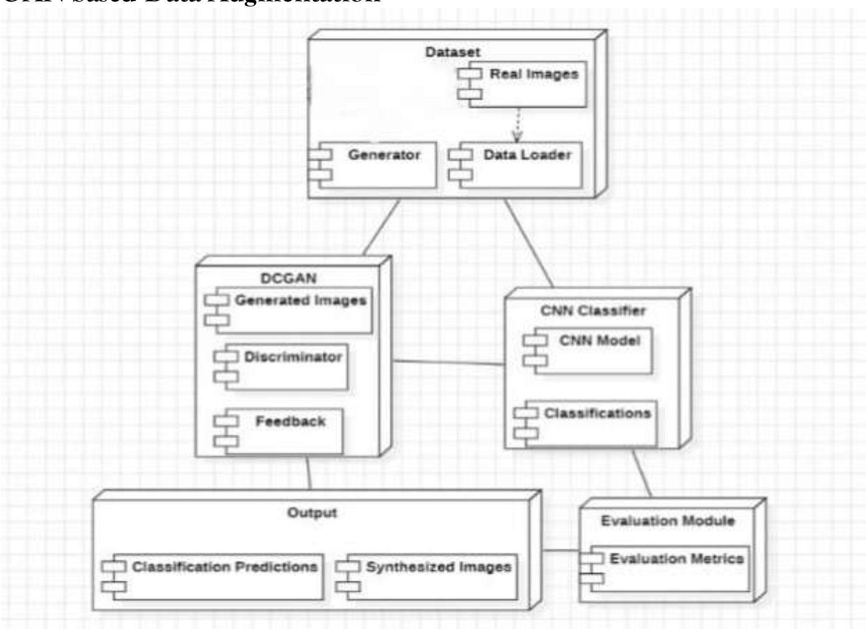

Figure 1: The System Architecture

A Deep Convolutional GAN (DCGAN) architecture was employed for generating synthetic retinal images.

The GAN model is trained using key hyperparameters such as a batch size of 32 and an image size of 128×128 pixels. The training runs for 10,000 epochs, allowing the generator and discriminator to progressively improve through adversarial learning. The latent space input to the generator is a 100-dimensional noise vector sampled from a normal distribution. For optimization, both the generator and discriminator use the Adam optimizer with a learning rate of 1e-4, which ensures stable convergence while handling sparse gradients effectively. The loss functions are based on binary cross-entropy, with the generator aiming to fool the discriminator and the discriminator striving to distinguish real from synthetic images.

.DR Classification Models

The CNN models VGG16 and ResNet-50 were utilized as classifiers for DR classification.

The models were enhanced with training based on a bigger dataset with synthetic images generated by the GAN..

Evaluation Metrics

Image Quality Measure:

The image quality produced by the GAN was measured using the appropriate metrics such as Fréchet Inception Distance (FID) score.

FID score calculates to what extent the two distributions of real and generated image feature vectors are apart, with lower values indicating high quality and high similarity of the two distributions.

Classification Performance Metrics:

The performance of DR classification models was evaluated based on metrics such as accuracy, sensitivity, specificity, and F1-score.

- Accuracy**:** (TP + TN) / (TP + TN + FP + FN)
- Sensitivity / Recall (True Positive Rate): TP / (TP + FN)
- Specificity (True Negative Rate): TN / (TN + FP)
- Precision: TP / (TP + FP)
- F1-Score: (2 * Precision * Recall) / (Precision + Recall)

where TP, TN, FP, and FN are True Positives, True Negatives, False Positives, and False Negatives, respectively.

RESULTS

This section presents the results of the experiments performed to test the proposed system for diabetic retinopathy (DR) detection. The results include the evaluation of synthetic image quality generated by GAN and DR classification model performance trained with and without GAN-based data augmentation.

Figure 2: GAN-Generated Images

FID Score: 75.84

DR Classification Performance

The performance of the VGG16 and ResNet50 models trained on the original APTOS 2019 dataset (without GAN augmentation) is compared with the performance of the VGG16 and ResNet50 models trained on the augmented dataset (original APTOS 2019 data combined with GAN-generated synthetic images).

Before GAN Augmentation:

Performance of VGG-16:

Classification Report:

	precision	recall	f1-score	support
0	0.92	0.98	0.95	361
1	0.47	0.20	0.28	74
2	0.56	0.90	0.69	200
3	0.50	0.03	0.05	39
4	0.00	0.00	0.00	59
accuracy			0.75	733
macro avg	0.49	0.42	0.39	733
weighted avg	0.68	0.75	0.69	733

Figure 3: Classification Report

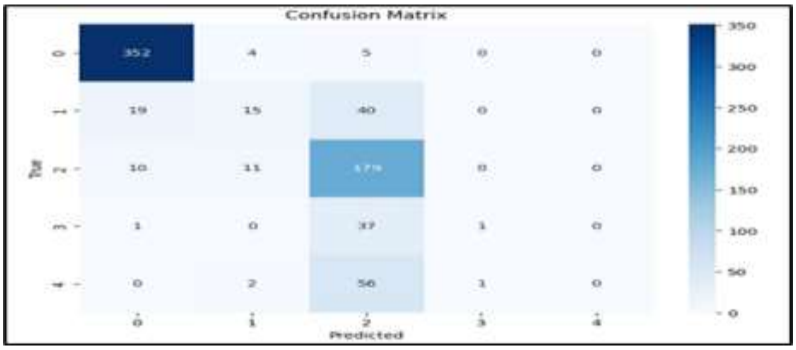

Figure 4: Confusion Matrix

Performance of ResNet-50:

Classification Report:

	precision	recall	f1-score	support
0	0.96	0.98	0.97	361
1	0.53	0.53	0.53	74
2	0.71	0.82	0.76	200
3	0.42	0.26	0.32	39
4	0.66	0.42	0.52	59
accuracy			0.81	733
macro avg	0.66	0.60	0.62	733
weighted avg	0.80	0.81	0.80	733

Figure 5: Classification Report

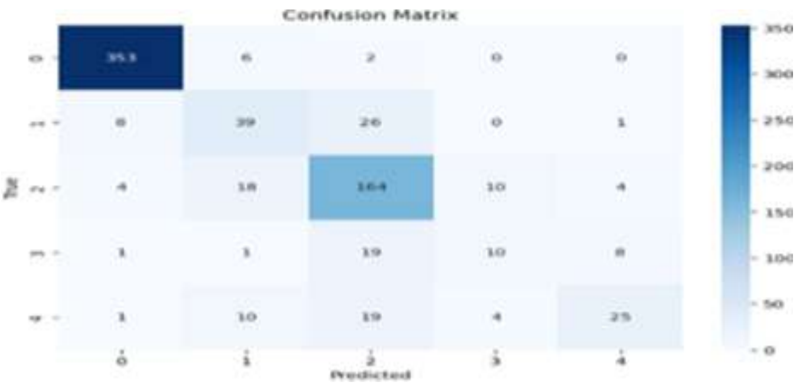

Figure 6: Confusion Matrix

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After combined with GAN-generated synthetic images:

Performance of VGG-16:

Classification Report:

	precision	recall	f1-score	support
0	0.94	0.88	0.91	589
1	0.52	0.66	0.58	74
2	0.68	0.78	0.73	214
3	0.38	0.25	0.30	40
4	0.86	0.86	0.86	414
accuracy			0.83	1331
macro avg	0.68	0.69	0.68	1331
weighted avg	0.83	0.83	0.83	1331

Figure 7: Classification Report

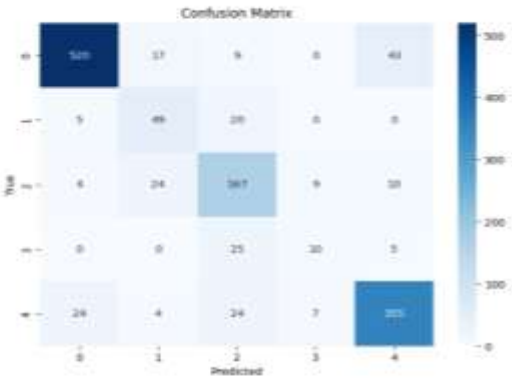

Figure 8: Confusion Matrix

Performance of ResNet-50:

Classification Report:

	precision	recall	f1-score	support
0	0.94	0.98	0.96	361
1	0.51	0.46	0.48	74
2	0.65	0.81	0.72	201
3	0.58	0.14	0.22	79
4	0.92	0.92	0.92	616
accuracy			0.85	1331
macro avg	0.72	0.66	0.66	1331
weighted avg	0.84	0.85	0.84	1331

Figure 9: Classification Report

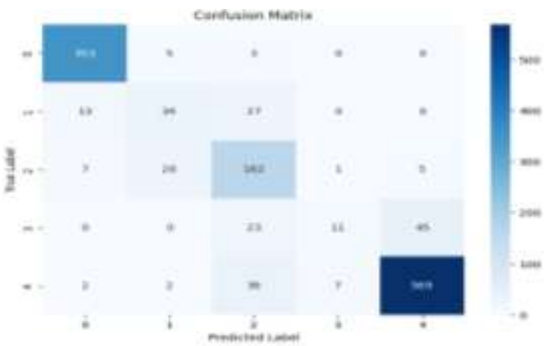

Figure 10: Confusion Matrix

Model	DataSet	Accuracy
VGG16	Before GAN Augmentation	75%
VGG16	After GAN Augmentation	83%
ResNet50	Before GAN Augmentation	81%
ResNet50	After GAN Augmentation	85%

Table 1: Table summarizing "Before" and "After" GAN augmentation.

DISCUSSION

This paper outlines the technique developed to improve the diagnosis of diabetic retinopathy by tackling two major pitfalls in traditional methods like lack of annotated data and diversity in datasets. Realistic synthetic retinal images produced by Deep Convolutional GANs (DCGANs) are augmented into existing datasets, making the machine learning model more robust for the detection. This methodology improves dataset diversity and accuracy in diagnosing while laying the foundation for further research on underrepresented disease patterns. Therefore, further work should thus take place in clinical validation and scaling of application in other problems of medical image challenge towards wide-scale improvements in healthcare delivery.

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