Multi-Class Classification of Diabetic Retinopathy using GANs

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***Abstract*— Diabetic retinopathy (DR) is a conventional condition that leads to blindness in people with diabetes. The best approach to control the condition is through quick management and routine screening using fundus photography. Due to the large number of diabetic patients and the need for frequent screenings, there is growing interest in using computer-assisted, fully automated DR diagnosis. The idea is to explore the application of GANs in the context of Diabetic Retinopathy for multi-class classification. By harnessing the capabilities of GANs, we aim to enhance the quality of retina scans, thereby enabling more precise and reliable diagnosis of DR.**

Keywords*— Diabetic Retinopathy, Generative Adversarial Network (GAN), Multi-class classification, semi-supervised learning., CNN Introduction (Heading 1)

Diabetes Mellitus can directly lead to the development of Diabetic Retinopathy (DR), a diabetes-related complication characterized by the blockage of blood vessels supplying the eye, resulting in swelling and the leakage of blood or fluids, potentially causing severe eye damage. The significant vision impairment associated with DR typically occurs when there is swelling of the central area of the retina.[2]

One potential consequence of the disorder is the abnormal proliferation of blood vessels in retina, which can lead to blotching or bleeding in retina, ultimately leading to loss of vision. This might lead to a gradual loss of vision, potentially culminating in blindness in advanced stages. Globally, DR is responsible for causing 2.6% of cases of blindness.[3]

Generative Adversarial Networks, or GANs, have become a robust and innovative emerging machine-learning technique that has gained attention recently. GANs leverage deep learning algorithms to generate data, images in this context, that closely resemble real-world examples. They do so by employing a unique adversarial training process, where two neural networks, a generator, and a discriminator, compete, driving the model to produce increasingly accurate and realistic outputs.[10]

To diagnose and monitor the progression of Diabetic Retinopathy, obtaining clear and accurate retina scans is imperative. However, it is essential to prioritize the patient's well-being by minimizing exposure to harmful radiation during the scanning process. This dilemma calls for innovative solutions that can enhance the quality of these scans without compromising patient safety.

To diagnose DR retina scans are essential but we cannot expose the patient to strong radiation. Thus, GANs(Generative Adversarial Network) would be the best model to implement to obtain clear images of scans. GANs is a Machine Learning model which uses deep learning algorithms to become more accurate in its predictions.

I. Related Works

Generative Adversarial Networks (GANs) have been demonstrated to be an exceptionally powerful approach to machine learning. GANs leverage deep learning algorithms to generate images that closely resemble real-world examples with remarkable accuracy. This is achieved through a unique adversarial training process, where two neural networks, a generator, and a discriminator, compete, resulting in increasingly realistic outputs. It's an incredibly effective technique that has quickly become an essential tool in the field of machine learning.

A 2023 study at the Sindh Institute of Ophthalmology & Visual Sciences used a modified CNN to classify Diabetic Retinopathy images achieving 96.68% accuracy. The model utilized innovative techniques like Optimum Path Forest and Restricted Boltzmann Machine. Trained on a private dataset, the deep learning model offered promising prospects for efficient DR diagnosis and management.[4]

A new deep-learning architecture was developed in 2023 to detect and classify Diabetic Retinopathy (DR). The architecture combined VGG16 as the feature detector and XG Boost as the classifier, achieving an accuracy of 79.50%. The model's training as well as evaluation of retinal images was from the APTOS 2019 Blindness Detection Kaggle Dataset, showing promising results in automated DR diagnosis.[5]

In 2023, a paper introduced a revised ResNet-50 model for diabetic retinopathy (DR) detection The model incorporated visualization and preprocessing techniques, alongside structural modifications such as adaptive learning rates, regularization, and alterations to the ResNet-50 architecture. Trained on a DR dataset from Kaggle comprising 35,126 fundus images, with 9,321 exhibiting DR across four stages and 25,805 normal images, the model achieved a training accuracy of 83.95% and a test accuracy of 74.32%.[6]

Our research on diabetic retinopathy explores data augmentation and Generative Adversarial Networks (GANs) to improve model accuracy. In 2022, research achieved a 76% performance improvement on the APTOS dataset using under-sampling. This shows potential for enhancing diagnostic outcomes in detecting diabetic retinopathy with these techniques.[7]

In 2021, researchers used a DCGAN to generate synthetic medical images of eye diseases. They aimed to improve disease classification accuracy using the GMD model, achieving 80.45% and 83.74% accuracy with and without synthetic images, respectively. They used the Kaggle dataset and iChallenge-GON Comprehension for their research.[8]
Below is a comparative study of various ML models used for DR detection.

Table.1 Comparison table of existing ML models for DR detection

Name	Description	Model Used	Accuracy	Dataset
Application of data-efficient generative techniques for Multi-Class Diabetic Retinopathy Classification	A major challenge in medical imaging classification is the lack of class-specific data, especially for rare diseases, leading to suboptimal model performance. In this study, we used a data-efficient generative technique to create synthetic DR images.	StyleGAN2-ADA	76%	Kaggle dataset, GAN-supplemented dataset
Investigating on Data Augmentation and Generative Adversarial Networks (GANs) for Diabetic Retinopathy	Using data augmentation and GANs to address class imbalance and the shortage of labelled images. Applied to the APTOS dataset after undersampling	GAN	75%	Kaggle dataset
A hybrid neural network approach for classifying diabetic retinopathy subtypes	This study aims to enhance the prediction accuracy of diabetic retinopathy by utilizing the hybrid neural network model EfficientNet and Swin Transformer	hybrid neural network, EfficientNet, Swin Transformer,	75.5% and 96%	Kaggle EyePACS, DR1 and MESSIDOR, MESSIDOR
Development of revised ResNet-50 for diabetic retinopathy detection	This paper aims to improve the ResNet-50 model's calibration using visualization and preprocessing for accurate DR prediction. The DR grading system is implemented on a website for user-accessible fundus image checks.	ResNet-50	Train accuracy: 83.95% Test accuracy: 74.32%	The DR dataset from Kaggle includes 35,126 fundus images, of which 25,805 are normal (without disease). Only 9,321 fundus images exhibit DR, which is divided into four stages

A. Gap Analysis

1. **Performance:**
We want to obtain the correct mean using ML models like SVM and CNN. The stages of diabetic retinopathy are classified into different levels.

Future state:
Improved accuracy and increased robustness by integrating GAN for image processing with multiclassification ML model.

Bridging the gap:
- Collect more information for the training dataset.
- Try various machine learning algorithms such as Random Forest or Gradient Boosting to find which gives the best results.
- The methods are combined with SVM implementation to combine CNN and other classifiers.

2. **Data Availability:**
For research purposes, the data availability from health sectors is limited. Diversity and knowledge regarding the training of good models are lacking.

Future situation:
- Working with hospitals and specialists to collect images from a variety of sources.
- Explore synthetic data generation techniques to improve training data.
- Take advantage of pre-trained models used to transfer learning from other domains.

3. **Computational resources:**
Educational models and theories require computational power as well as resources that are accurate for medical data.

Future state:
To increase the efficiency of these data models with relatively less computational power

Bridging the gap:
- Optimize existing machine learning models to improve performance.
- Explore cloud computing options for scalable and cost-effective model training.

4. **Model Robustness:**
The model may not be robust in practical situations when the dataset is relatively big. There are power differences due to limitations that are not very different from the real world.

Future state:
Improving model robustness through GAN-based data augmentation and adversarial training techniques.

Bridging the gap:
- Using various support methods to develop training materials to simulate the real-world.
- Conduct feedback training to improve the capital structure of the model to prevent attacks.
- Performs rigorous assessment and evaluation in different situations to identify and resolve security vulnerabilities.

B. Optimizing CNN Model for Classification

- **Model Architecture:**
Input: Images resized to 224x224 pixels.
Layers: Convolutional: 32, 64, 128 filters (3x3), ReLU activation.
Max-Pooling: 2x2 following each convolutional layer.

- **Training**:
  Optimizer: Adam or RMSprop, initial learning rate: 0.001 with decay.
  Loss Function: Categorical Cross-Entropy.
  Batch Size: 32 or 64.
  Epochs: 50-100, with early stopping based on validation performance.

- **Data Augmentation:** Techniques such as horizontal/vertical flips, rotations, zoom, and brightness changes.

- **Optimization Techniques:**
  Pruning: Eliminate unnecessary neurons/weights to reduce model size.
  Quantization: Convert weights to 8-bit integers to save memory and boost inference speed.

C. Optimizing GANs for Data Augmentation

- **Model Architecture:**
  Generator:
  Input: 100-dimensional random noise vector.
  Up-sampling: Transposed convolutions, Batch Normalization, ReLU activation, Tanh output to generate images.
  Discriminator:
  Convolutional: 64, 128, 256 filters, Leaky ReLU activation, Dropout layers, Sigmoid output for real/fake classification.

- **Training:**
  Optimizer: Adam with a learning rate of 0.0002 and beta_1 of 0.5.
  Loss Function: Binary Cross-Entropy for both generator and discriminator.
  Batch Size: 32.
  Epochs: Train until the generator produces high-quality images (typically several thousand epochs).

- **Training Strategy:**
  Alternate between training the discriminator and generator to maintain balance.
  Use transfer learning to initialize the discriminator with weights from a pre-trained classification model for stability.

By implementing these strategies, we aim to optimize our models for practical deployment in resource-limited settings,

ensuring they are both effective and efficient. This comprehensive approach addresses the computational

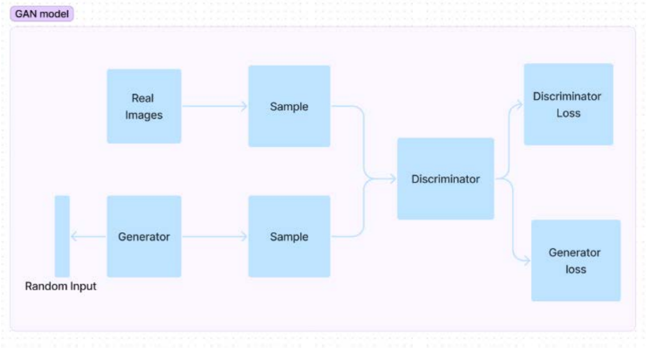
resource constraints highlighted in the paper and facilitates the broader application of our proposed system.

II. PROPOSED METHOD

To diagnose and monitor the progression of Diabetic Retinopathy, obtaining clear and accurate retina scans is imperative. However, it is essential to prioritize the patient's well-being by minimizing exposure to harmful radiation during the scanning process. This dilemma calls for innovative solutions that can enhance the quality of these scans without compromising patient safety.

GANs leverage deep learning algorithms to generate data, images in this context, that closely resemble real-world examples. They do so by employing a unique adversarial training process, where two neural networks, a generator, and a discriminator, compete with each other, driving the model to produce increasingly accurate and realistic outputs.

Figure.1 Flowchart of GAN model



It revolves around improving the classification of Diabetic Retinopathy (DR) using a novel approach that incorporates Generative Adversarial Networks (GANs). Currently, existing classification models for DR typically focus on a binary classification, determining whether DR is present or not. However, our goal is to develop a more sophisticated multi-class classification model that can differentiate between five distinct levels of DR, ranging from "No DR" to "Proliferative DR."

Additionally, GANs, we suggest adopting a semi-supervised learning approach to achieve more accurate multi-class classification. In this technique, our model will be trained labeled as well as unlabeled data.

Initially, a random input is provided, which includes a collection of retina scan images. This random input is first directed to the Generator, and subsequently, the generated images are passed on to the Discriminator.

In this process, the fake images are discarded, leaving only the genuine retina images for further pre-processing steps.

These authentic images are then subjected to feature extraction, wherein the system identifies and isolates specific attributes and features that indicate symptoms related to Diabetic Retinopathy. These features and attributes are aggregated into a distinct set of images, creating what we refer to as a feature set.

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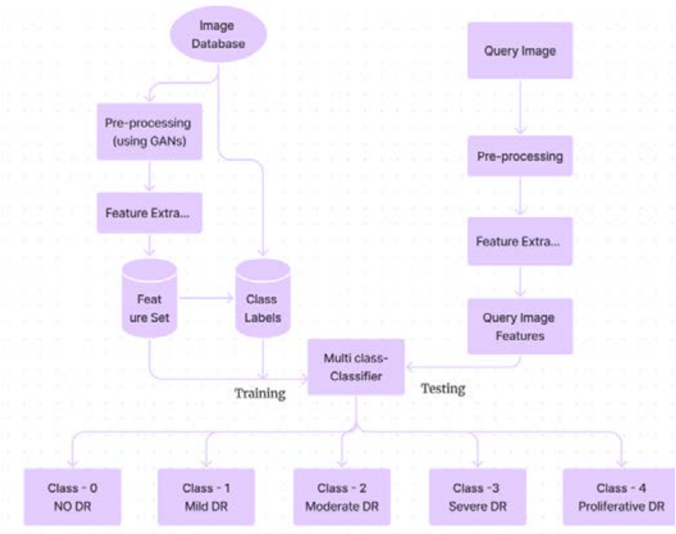
Our model employs semi-supervised learning, which means it leverages a training dataset containing labeled images. These labeled images are categorized into five distinct classes, ranging from Class 0 to Class 4, representing different levels of Diabetic Retinopathy severity. Class 0 signifies the absence of DR, while Class 1, Class 2, Class 3, and Class 4 correspond to Mild DR, Moderate DR, Severe DR, and Proliferative DR, respectively.

Figure.2 Flowchart of GAN model imposed on CNN model



When it comes to testing the model, we input unlabeled retina images, which then undergo a similar series of steps as seen during the training phase.

This process ultimately leads to the feature extraction of the testing dataset, enabling the model to classify these images into one of the five aforementioned classes.

This multi-class classification approach goes beyond the binary classification often used to determine the presence or absence of Diabetic Retinopathy, allowing for a more detailed and informative assessment of the condition's severity.

The outcome of this implementation will be to eventually combine the proposed GAN model with the pre-existing

CNN model, already implemented for the DR dataset. Thus, resulting in higher accuracy of predictions.

III. RESULT

We utilized some methods to understand the performance of our classification model.

When our model correctly determines positive class, True positive (TP) is outcome. A true negative (TN) is result when our model determines the negative class. While if our model substantiates the positive class wrongly, the outcome is a false positive (FP), if the prediction of the negative class is done incorrectly, it is deemed to be a false negative (FN).

We have evaluated a few measures to assess our model's performance.

ACCURACY (all correct / all):

$$\frac{TP + TN}{TP + TN + FP + FN}$$

PRECISION (true positives / predicted positives):

$$\frac{TP}{TP + FP}$$

SENSITIVITY/RECALL (true positives / all actual positives) :

$$\frac{TP}{TP + FN}$$

SPECIFICITY (true negatives / all actual negatives):

$$\frac{TN}{TN + FP}$$

For the implementation of CNN model, we used 900 images from the DR Kaggle dataset. For each level of severity, we used 900 images so we had a total of 4500 total images of our dataset. After training and testing the model we acquired the confusion matrix.

It represents that, of 900 images used for testing for "NO DR" we get 881 images with high resolution and accuracy. Similarly, for "Mild" level of DR, we get 674 images. For "Moderate" we get 648 images. For "Sever" we get 393 images and for "Proliferative DR" we get 369 images.

It shows that as the severity of DR increases it becomes difficult and complex to achieve proper high-resolution images. Thus, our proposed system method can be a meaningful contribution towards solving this problem.

Figure.3 Confusion Matrix of CNN model for DR dataset

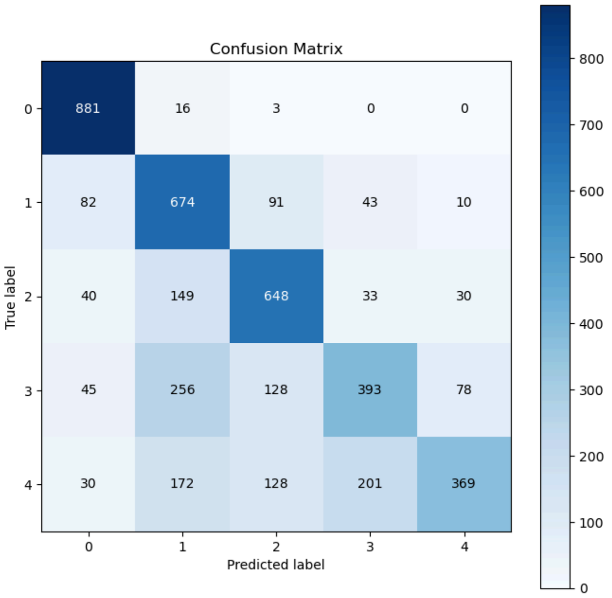


Table 2. Accuracy table for CNN model

	Precision	Recall	F1-score	Support
No DR	0.79	0.98	0.88	93
Mild DR	0.52	0.78	0.62	94
Moderate DR	0.66	0.73	0.69	77
Severe DR	0.64	0.46	0.54	93
Proliferate DR	0.86	0.40	0.54	93
Accuracy			0.67	450
Macro avg	0.69	0.67	0.65	450
Weighted avg	0.70	0.67	0.65	450

The accuracy of 67% was achieved by implementing hybrid CNN incorporated with DenseNet.

The accuracy of the CNN with DenseNet model trained on the original balanced Kaggle dataset was 0.67. We believe that this accuracy will increase when the dataset is supplemented with GAN-generated images. Our hypothesis is that models trained on diabetic retinopathy (DR) datasets supplemented with GAN-generated images will perform significantly better on classification tasks, based on preliminary research.

The below images display the gradual improvement in generating clearer images through the generator.

The generator starts with the first image as complete noise and eventually generates more clear and accurate images. These images are then further pre-processed for classification. With the use of our proposed system, ophthalmologists will be able to define preventive measures at an earlier stage, helping patients to avoid the devastating impact of losing their vision.

Figure.4 Output of GAN model on DR dataset

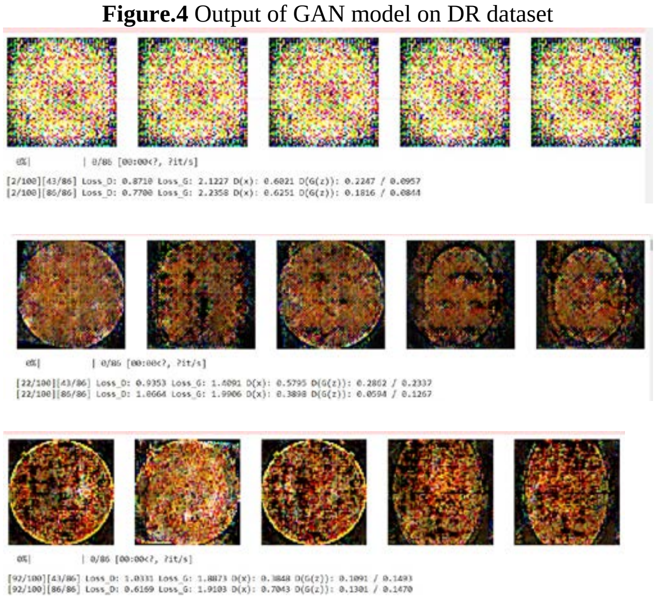
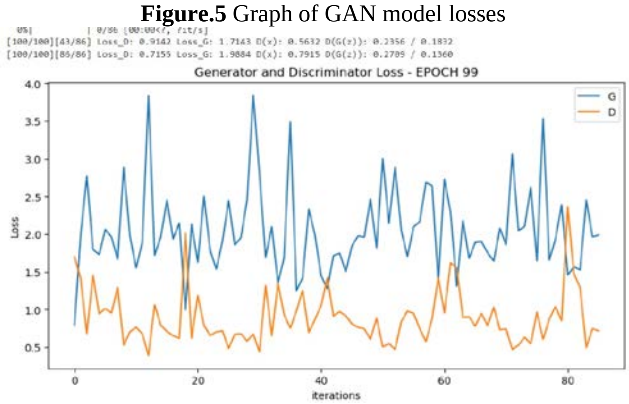


Figure.5 Graph of GAN model losses



The above graph shows the loss function between the generator and discriminator. As the loss for the discriminator gradually decreases, the loss of the generator increases. GAN is a type of min-max function. The generator incorporates the noise which arises while training through multiple epochs. Using this noise, the generator generates more clearer and accurate images.

Since our problem statement is healthcare-related, it can be difficult to obtain actual datasets or retinal records from different hospitals. As a result, we are restricted to using the existing web databases. This limitation underscores the importance of generating supplementary data through GANs to enhance the available datasets and improve the robustness of our models.

IV. Conclusion

The objective of our study is to identify diabetic retinopathy and its severity through the implementation of machine learning and deep learning algorithms. Through extensive image processing, we successfully highlighted key features such as cotton wool patches, blood vessels, and exudates. By leveraging these advanced technologies, we aim to provide an accurate and efficient detection system for diabetic retinopathy, which can contribute to the enhancement of clinical practice and improve patient outcomes.

Based on the research and evaluation of various methodologies, it can be concluded that deep learning algorithms, when coupled with transfer learning, have a vast potential for predicting diabetic retinopathy. Conventional machine learning classifiers are not able to classify images.

Generative Adversarial Networks (GANs) have achieved impressive growth in recent years, particularly in the domain of generating retinal images. This has sparked our growing interest in the generation of high-quality synthetic fundus images that depict various retinal disorders. These synthetic images hold great potential for integration into deep-learning models.

Thus our proposed GAN model when integrated with the existing ML models such as CNN has great potential to resolve the problem. On implementing the CNN model on the of the Kaggle DR dataset, we have seen an accuracy of 67%. Further on integration with the GAN model we aim at achieving a higher accuracy.

This approach not only addresses the need for improved diagnostic accuracy but also aligns with the imperative of minimizing patient exposure to radiation, ultimately contributing to more effective healthcare practices in the management of Diabetic Retinopathy.

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