

To Develop a Federated Learning-based Model for Detection and Classification of Diabetic Retinopathy

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Abstract—Diabetic retinopathy (DR) is a serious public health issue that frequently causes diabetic people to lose their eyesight. Early detection is significant for effective management and treatment of patients; however, the traditional centralized approach to medical data analysis poses significant challenges related to patient privacy and data security. This project addresses these challenges by leveraging federated learning. Several healthcare organizations can work together to jointly build a model using this decentralized machine learning technique without disclosing private patient information.

The proposed solution involves developing a neural network model that processes retinal images to accurately classify the severity of diabetic retinopathy. The model uses local datasets from many institutions through the use of federated learning, guaranteeing data privacy while preserving excellent performance. The incorporation of cutting-edge strategies like differential privacy further improves the security of patient data. In addition to increasing diagnostic precision, this strategy encourages healthcare providers to work together on research projects.

Index Terms—Diabetic Retinopathy, Federated Learning, Fundus Image, Augmentation, GAN.

I. INTRODUCTION

Artificial Intelligence, is transforming modern healthcare by offering innovative solutions to some of the biggest medical challenges. Complex data in the form of patient symptoms, medical images, health records, and vital signs is now analyzed through AI, transforming the way doctors make decisions [1]. Diabetes is a chronic condition caused due to inadequate production of insulin in a human body. Diabetic Retinopathy is one of the condition of Diabetes [2]. Symptoms of diabetes are blurred visions, watery eyes and itchy retina. These symptoms if not encountered early may result into vision loss [3] Automating the way diabetic retinopathy is found and categorised in retinal pictures has shown encouraging results thanks to recent advancements in deep learning. [4] Models trained with machine learning and deep learning can identify the features that prove diabetic retinopathy and its grades. Convolution Neural Network is the technique in deep learning that recognizes the parameters like textures, edges and patterns [4] Despite such advancements, a lot of barriers exist in healthcare for the total application of AI. This study will fill the gaps by introducing a privacy-protecting method called Federated Learning (FL). FL can enhance disease detection and classification accuracy without compromising data security [6]. While previous works have used deep learning for the detection of diabetic retinopathy (DR), they have not explored how Federated Learning can improve model accuracy while maintaining privacy. This work proposes a solution that improves detection accuracy and addresses privacy concerns. [6] Today, with the

advanced digital world, it is quite challenging for healthcare systems to protect the sensitive data of patients. Most hospitals and medical institutions are very hesitant to share raw data as there are lots of privacy regulations and ethical issues involved. Fragmented data are not suitable to develop strong AI models that require diversified data from various sources. FL solves this problem by enabling hospitals to train the model without sharing raw data. [7] This paper proposes a deep learning model designed specifically to classify the stages of DR accurately, using Federated Learning.

II. METHODOLOGY

The suggested system architecture illustrates how the complete system functions as a whole. Deep Convolutional GAN (DCGAN) is used to preprocess and enhance the input image. The image is submitted to the model for disease diagnosis and categorization after augmentation. A convolutional neural network (CNN) is used by the model to do this. Following delivery of the result to the local computer, the result is transmitted to the central server, also referred to as the central model, which combines the results and provides the user with the most suitable and optimized result along with an updated model.

A. Data Collection

Dataset Collection and Preprocessing: The designed methods are tested on three different kinds of Data, namely- APTOS Kaggle, MESSIDOOR and EYEPACS. These datasets are publicly available [5] **Resizing:** All images were resized to a specific size to standardize the input. images that are too large for their container must be shrunk down by the system to which they're uploaded. The opposite problem can also occur: sometimes an image is too small for its container. [24].

B. Augmentation Using GANs

Augmentation: Augmentation is a kind of pre-processing technique used to provide a wide variety of data to the model [11]. There are several methods to perform augmentation on image datasets. Geometric Transformation, hue saturation are some traditional augmentation techniques that gives us the result [12]. GAN also known as Generative Adversarial Network does the work of augmentation easy, efficiently and quickly. GAN is the last type of neural network and is operated in two steps generator and discriminator[18]. The Generator generates images similar to the input image fed to the model. The discriminator discriminates the original image and the generated image [19]. Only the images that the discriminator cannot identify as duplicate are selected for further processing.

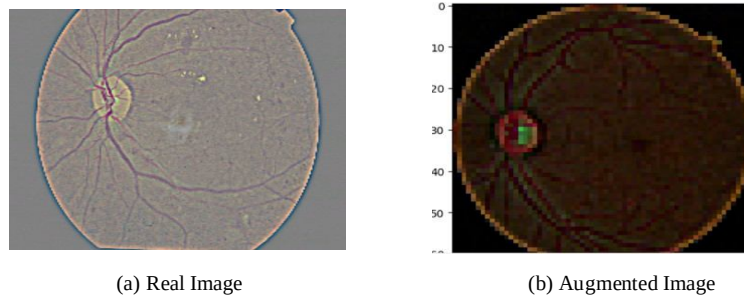


Figure 1: Comparison of real and augmented images

C. Federated Learning

Federated Learning: Federated Learning is used for the detection and classification of diabetic retinopathy using the Flower framework with three clients, each simulating separate datasets. A CNN model was trained locally on each client's data for five epochs per round, followed by aggregation at a central server using Federated Averaging (FedAvg) over ten rounds. The global model achieved an accuracy of 85 percent, demonstrating effective generalization. FL enabled privacy-preserving training, leveraging diverse datasets to enhance classification accuracy and scalability.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (16)$$

$$Precision = \frac{TP}{FP+TP} \quad (16)$$

$$Recall = \frac{TP}{TP+FN} \quad (16)$$

$$F1 = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \quad (16)$$

The following illustrates the class-wise performance of the CNN-based classification model across the five grades of diabetic retinopathy (DR) based on the above equations:

- NO DR: Precision: 0.97, Recall: 0.99, F1-score: 0.98. The model successfully identifies almost all cases classified as No DR, with minimal false negatives.
- MILD: Precision: 0.61, Recall: 0.55, F1-score: 0.58. The model shows good performance for Mild DR. The lower recall indicates difficulty in detecting all true Mild DR cases.
- Moderate: Precision: 0.67, Recall: 0.76, F1-score: 0.71. The model performs better, but slightly lower precision suggests some false positives.
- Severe: Precision: 0.38, Recall: 0.27, F1-score: 0.32. The model's performance significantly declines here. The low recall indicates many missed true positive samples, affecting the F1 Score.
- Proliferative DR (P-DR): Precision: 0.55, Recall: 0.39, F1-score: 0.36. The model struggles in identifying P-DR classes, as reflected by lower precision and recall.

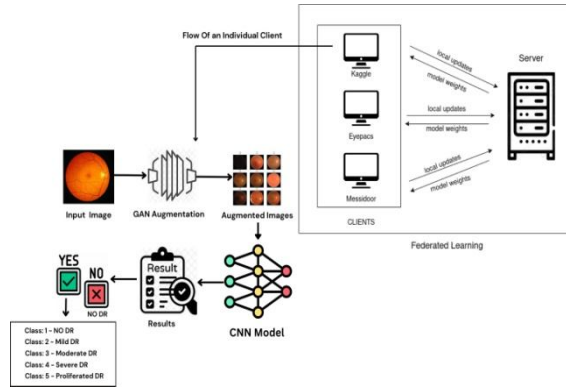


Figure2: System Architecture

Our proposed system leverages AI-driven health decisions to improve human health. The system architecture enables efficient data acquisition, processing, and analysis while ensuring security and communication between client and server. Data Pre-processing and augmentation: The classification model is fed with images as inputs. The images are fundus images or precisely retinal images. These images and their features are enough to classify diabetic retinopathy. GAN also known as Generative Adversarial Network is used to augment the data for training the model. Augmentation is specifically used to increase the size of the data and expose the model to a broader variety of data. GAN executes two of its operators - a generator and a discriminator. The generator generates images similar to the data it has. The discriminator discriminates generated images from the original pictures, essentially playing an adversarial game where the generator aims to fool the discriminator by producing increasingly realistic data, and the discriminator tries to become better at identifying fake data. There are a total of 5 classes of Diabetic Retinopathy:- 1. No DR, 2. Mild DR, 3. Moderate DR, 4. Severe DR, 5. Proliferated DR. Convolution neural network (CNN) is the only name heard when dealing with images as a dataset. Relu is the activation function used to activate the nodes in the neural networks. Federated Learning is an advanced type of Machine Learning. Federated Learning is implemented using Flower Framework. Our system is trained on three different clients. These clients consist of three different types of data. The datasets namely are: APTOS, EYEPACS, and MESSIDOOR. The clients are trained locally. The results (weights) of the clients are sent to the server. The server aggregates the weights and is transferred to the clients. These weights are considered, and the updated or aggregated results are provided to the end user. The outcomes of training each client separately and collectively with the server are shown in this section. Every client makes use of a separate database that is allotted to it. The outcomes of each conversation round with three clients utilizing the DRFL paradigm. The below table depicts the accuracy scores of individual models:

TABLE I: PERFORMANCE METRICS FOR CLIENTS

Client	Accuracy	Precision	Recall	F1Score
Client1	80%	79.2%	67%	79.8%
Client2	75%	65.8%	60%	63.5%
Client3	82%	81.2%	79%	83%

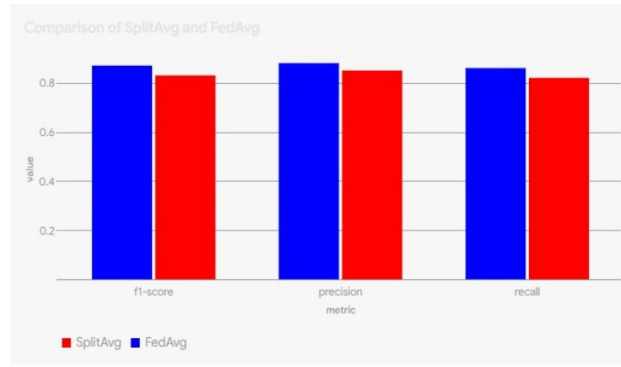


Figure 3: Comparison of SplitAvg and FedAvg

The comparison is made between two FL algorithms namely FedAvg and SplitAvg. SplitAVG algorithm requires local institutions to send data labels to a central server, which could lead to privacy issues, especially with high-dimensional labels. But these issues are resolved using FedAvg. SplitAvg is an algorithm that requires frequent communication, leading to higher communication costs. To overcome this, FedAvg is used to exchange the model weights only, making it more efficient. FedAvg is more scalable as the central server manages the model only unlike SplitAvg which is less scalable as it needs to manage the intermediate data [7].

TABLE II: PERFORMANCE COMPARISON OF SPLITAVG AND FEDAVG ALGORITHMS ACROSS CLIENTS

Client	Algorithm	Accuracy(%)	Precision(%)	F1-score(%)
1	SplitAvg	80	75	78
1	FedAvg	85	82	83
2	SplitAvg	78	72	75
2	FedAvg	83	80	81
3	SplitAvg	82	76	79
3	FedAvg	86	83	84

III. CONCLUSIONS

Recent advancements indicate that federated learning offers a transformative solution for detecting and classifying diabetic retinopathy while addressing significant concerns surrounding patient privacy and data security inherent in centralized machine learning systems. Our findings provide strong evidence that leveraging decentralized datasets from multiple healthcare institutions enables the development of a robust neural network capable of accurately diagnosing the severity of diabetic retinopathy from retinal scans without compromising sensitive patient information. The integration of advanced techniques, such as differential privacy, further substantiates the model's ability to maintain data confidentiality while delivering high diagnostic accuracy. This innovative framework fosters collaboration among healthcare providers and underscores the potential of machine learning to revolutionize clinical practice, ultimately contributing to better patient outcomes. Future directions will focus on broadening the model's applicability to diverse populations and evaluating its feasibility for deployment in real-time clinical settings.

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