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Collaborative Deep Learning for Diabetic Retinopathy Diagnosis: A Federated Learning Approach

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***Abstract*—Early detection of diabetic retinopathy is necessary because it is the leading cause of blindness. For diagnosing diabetic retinopathy deep learning plays a significant role but there is challenge of privacy of patients data and various transactions. To address these issues, we propose a collaborative deep learning approach based on Federated Learning, where multiple clients can work in collaboration while training on data takes place at client side. In our system, deep learning model forwarded to clients and updations are forwarded back to global model. This ensures data privacy while benefiting from a diverse, multicenter dataset, which is crucial for enhancing model generalization across different demographics. We evaluate the performance of our federated learning approach in comparison to traditional centralized deep learning models, demonstrating its ability to achieve competitive accuracy levels without compromising data security. Furthermore, the system allows for scalable and continuous learning, where new data can be incorporated incrementally. Our results suggest that federated learning can be a promising framework for advancing DR diagnosis, making it feasible to build a robust, privacy-preserving diagnostic tool that can be deployed across various healthcare settings. This approach has the potential to revolutionize the detection and management of diabetic retinopathy globally while addressing critical challenges in healthcare data privacy.**

***Index Terms*— diabetic retinopathy, deep learning, federated learning, classification.**

I. INTRODUCTION

Untreated diabetes for longer duration starts to have a severe impact on the health of the retina. Severe impact can lead to loss of vision. As per previous analysis, unawareness about diabetic retinopathy is a major concern. Patients take it lightly and avoid visiting hospitals for regular eye checkup. Diabetic retinopathy can cause from premature newborn to old age person. Symptoms of diabetic retinopathy can be seen on the retina like abnormal blood vessels, cotton white spots, blurred vision etc. Now a days, ophthalmologists are using developed automatic technologies and various advance techniques like Artificial Intelligence, Machine Learning, Deep Learning and Federated Learning for various reasons like accuracy, privacy of data, effectiveness etc[1]. On the other hand, if any patient visits a doctor for regular eye checkup and it is found that the retina is affected by diabetic retinopathy then there is a possibility that an ophthalmologist can help to avoid further complications. In the existing system, for diagnosis of diabetic retinopathy doctors were using ultra wide field retinal photography, Optical coherence tomography angiography etc. Fundus images are useful in deciding severity of diabetic retinopathy. Manual diagnosis is very time consuming and may lead to human errors. Till 2045,number of patients affected by DR may increase to 700 million[2].
In Fig 1.Classification of Diabetic Retinopathy is shown in five classes. According to the International Clinical

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Diabetic Macular Edema Severity Scale (ICDMEESS) Diabetic retinopathy can be classified into five severity levels that is, No DR, mild NPDR, moderate NPDR, severe NPDR, and PDR.
To provide solutions using machine learning based algorithms there are challenges in terms of security and privacy. Federated learning is a solution to address this challenge. Existing system uses machine learning and deep learning algorithms for classification of diabetic retinopathy using retinal datasets. Datasets were shared to server for processing using machine learning and deep learning models. So privacy is the main concern.

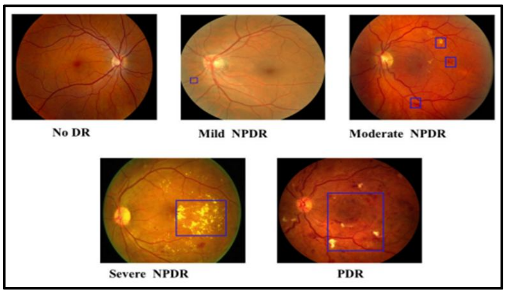

Figure 1. Classification of Diabetic Retinopathy [3]

A. Issue with existing system:

Data Privacy Concerns: Centralized data storage on the server increases the risk of data breaches and unauthorized access.
Communication Overhead: Frequent data transfer between clients and the server can be bandwidth-intensive and slow, especially with large datasets.
Single Point of Failure: The server is a critical component, and its failure can disrupt the entire system.
Scalability Challenges: Handling a large number of clients and massive datasets can be computationally expensive and resource-intensive for the server.
Federated learning helps by using decentralized approach so that clients data remains private. Motivation behind research is sensitivity of medical data is high so federated learning helps to work collaboratively on multiple datasets with sharing patients data. Using federated learning accuracy can be achieved without compromising on data privacy. It is less time consuming and easy to scale with growing number of participating institutions and datasets[3].

II. LITERATURE SURVEY

Federated Learning (FL), as described by S. Vucinich et al. [4], is a decentralized machine learning approach that addresses critical concerns in AI, namely fairness and privacy. By training models on data distributed across multiple devices, FL minimizes the need to centralize sensitive information, thereby enhancing privacy. This decentralized nature also helps mitigate biases that can arise from training on a single, potentially skewed, dataset, promoting fairer outcomes. However, FL faces challenges such as limited scalability, particularly when dealing with a vast number of devices. Furthermore, achieving fairness can sometimes come at the cost of reduced model accuracy, requiring careful consideration of the trade-off. Finally, the implementation of effective FL systems can be complex, demanding significant technical expertise and careful design to ensure efficient and secure communication and aggregation of model updates.
N.J. Mohan et al. [5] discuss the technology used in Federated Learning, particularly focusing on Deep Learning techniques such as Convolutional Neural Networks (CNN). The advantages of this approach include improved accuracy in diabetic retinopathy (DR) grading, privacy preservation, and the elimination of the need for central data storage. However, there are some disadvantages, including issues related to data heterogeneity, communication overhead, and the limitations imposed by the quality of local data.
Q. Hou et al. [6] explore the technology used in Image Quality Assessment, focusing on Collaborative Learning and Deep Learning techniques. The advantages of this approach include enhanced image quality, which leads to better classification results, as well as the benefits of a collaborative approach. However, there are some drawbacks, such as the computational complexity involved and the dependency on the quality of the input images.
M. Gencturk et al. [7] discuss the technology used in Federated Learning, particularly focusing on Boosting and Random Forest techniques. The advantages of this approach include efficient handling of horizontally partitioned data and the use of boosting algorithms to enhance performance. However, there are some

disadvantages, such as the need for careful tuning and the potential for suboptimal performance when dealing with imbalanced datasets.

M. Zhang et al. [8] explore the technology used in Federated Learning, focusing on Deep Learning techniques such as Convolutional Neural Networks (CNN) and heterogeneity-aware methods. The advantages of this approach include its ability to acknowledge and handle data heterogeneity, which in turn improves medical imaging outcomes. However, the approach also has some disadvantages, such as increased communication costs and the requirement for advanced system architecture.

N. Z. Abidin et al. [9] examine the technology used in Federated Learning, specifically utilizing Deep Learning techniques such as Convolutional Neural Networks (CNN). The advantages of this approach include enabling decentralized diabetic retinopathy (DR) detection, preserving privacy, and facilitating low-risk data sharing. However, some disadvantages include challenges with data imbalance and the need for large amounts of data for effective training.

S. Gulati et al. [10] discuss the technology used in Federated Learning, focusing on privacy-preserving techniques and Deep Learning. The advantages of this approach include ensuring the privacy of medical data, fostering a collaborative approach, and improving retinal disease detection. However, there are some disadvantages, such as potential communication overhead and the possibility that privacy-preserving techniques may reduce the accuracy of the model.

F. Ullah et al. [11] explore the technology used in Federated Learning, particularly focusing on scalable systems, smart healthcare, and medical imaging. The advantages of this approach include its scalability for intermittent clients, real-time functionality in healthcare environments, and privacy-preserving capabilities. However, there are some challenges, such as issues with intermittent client availability, data imbalance, and high latency in certain cases.

M. Abaoud et al. [12] discuss the technology used in Federated Learning, with a focus on privacy-preserving mechanisms. The advantages of this approach include its emphasis on enhancing privacy preservation and providing better protection for healthcare data. However, there are several disadvantages, such as computational complexity, implementation challenges, and the potential difficulty in generalizing the approach across different applications.

X. Liu et al. [13] examine the technology used in Federated Learning, with a focus on the integration of Meta Learning and AI approaches. The advantages of this work include a comprehensive review of the integration between federated and meta-learning, along with a discussion of future directions in this field. However, the study's limitations include being primarily a survey, with no specific implementations or case studies discussed.

F. Zheng et al. [14] explore the technology used in Federated Learning, particularly focusing on Deep Reinforcement Learning and client selection. The advantages of this approach include optimized client selection and resource allocation, which enhance the efficiency of federated learning. However, the approach also presents challenges, such as the complexity of real-time resource allocation and high computational costs.

M. Chen et al. [15] discuss the technology used in Federated Learning, focusing on Ensemble Learning and Generative Adversarial Networks (GANs). The advantages of this approach include privacy preservation through the use of GANs and improved performance achieved through ensemble learning. However, the method also has some drawbacks, such as the potential increase in model complexity due to GANs, the need for large datasets, and the risk of overfitting.

After studying the above papers, the existing system is having some research gap which need to be overcome. The timely identification and management of diabetic retinopathy can significantly reduce the likelihood of vision impairment. In contrast to automated diagnostic techniques, ophthalmologists are required to assess DR through the manual examination of retinal fundus images, a process that is time-consuming, labor-intensive, and costly, while also being susceptible to inaccuracies. Transferring data to other entities will have issue of privacy.

III. SYSTEM ARCHITECTURE

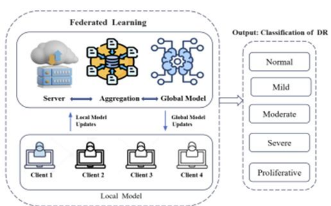

Figure 2. Proposed system architecture

In figure 2. Federated learning framework is a distributed machine learning environment consisting of a combination of server and clients. Private data is sourced from clients. Hub of the framework is the central server that helps in training and updating hyper parameters for every client. Another important task of the central server is to redistribute weights of clients after collecting updates from clients in the previous round. Once the central server receives weights then performs averaging and aggregation and the result is forwarded to all clients again. A Local client has a local server to maintain its own data. Client data is private and third parties do not have access to it. Data transfer between client and server was handled by self hosted file synchronization which is open sourced. Client creates its own folder inaccessible to other clients. Training cycle consists of all weights related updates and configuration file of clients. Configuration file have current epoch information and learning rate of every epoch. There is backup of data for client as well as server. If connections get disturbed between client and server then there is provision to reconnect both again.

To understand this system, first we will discuss horizontal and vertical federated learning those are the types of federated learning. Both these types have different clients but horizontal federated learning consists of same feature space with different data instances. Whereas vertical federated learning consists of same data instances with different feature space. In our proposed system we are considering horizontal federated learning approach.

In the proposed system architecture, four clients are shown and consider those clients like Hospital A, Hospital B, Hospital C and Hospital D respectively. Every hospital will have its own retinal dataset securely stored on their local machines. Main aim of using federated learning is to achieve privacy of data. Server will have global model which is shared machine learning model. After initializing the global model it is shared to all hospital clients. Every client updates gradients to global model and forwarded back to central server. Servers task is to collect this updates and aggregate weights values to improve global model. Again global model is shared to all clients and repeatedly this process takes place. Basically, output is classification of diabetic retinopathy in multiple classes like Normal, Mild, Moderate, Severe and Proliferate etc. If changes in the global model are negligible then updates can be stopped.

Advantages of proposed system architecture –

1. Protecting data from third parties,
2. Scalability is improved,
3. Promotes data diversity,
4. Improves privacy of clients data.

IV. Proposed Algorithm

Proposed algorithm consists of 9 steps i.e. Data collection, Preprocessing, Local model initialization, Local model training, Federated aggregation, Global model update, Iterative training, Evaluation and Deployment etc. Basically data is stored on local clients. Preprocessing of images takes place using various functions like normalization and standardization etc. Local model does not forward data to global model, it initializes and starts training of data. Once weight get updated, get forwarded to server and aggregation of weights takes place. This process takes place iteratively until weight updation gets stop.

A. Data Collection

- Let Dk = {(xi, yi)}i=1..nk represent the local dataset at client k, where:
- xi ∈ℝ^d is the input image (represented as a d-dimensional vector).
- yi∈ Y is the corresponding label (where Y is the set of possible labels).

B. Preprocessing

- Preprocess each image xi in Dk as:
- xi' = f(xi) where f(.) is the preprocessing function (e.g., normalization, standardization).

C. Local Model Initialization

- Initialize the local model parameters at client k, denoted as θk(0), as:
- θk(0) ~ N(0, I) where N(0, I) represents a multivariate normal distribution with zero mean and identity covariance matrix.

D. Local Model Training

- At each communication round t:
- Client k updates its local model parameters using gradient descent (or a variant):

- $\theta k(t+1) = \theta k(t) - \eta \nabla L(\theta k(t); Dk)$ where:
- η is the learning rate.
- $L(\theta k(t); Dk)$ is the loss function (e.g., cross-entropy) evaluated on the local dataset Dk using the current model parameters $\theta k(t)$.

E. Federated Aggregation

- The server collects the updated local model parameters $\{\theta k(t+1)\}$ from all clients.
- The server computes the global model parameters at round t+1 as a weighted average:
- $\theta G(t+1) = \sum k=1K\ wk\theta k(t+1)$ where:
- K is the total number of clients.
- wk is the weight assigned to client k (e.g., based on the number of samples in Dk).

F. Global Model Update

- The server broadcasts the updated global model parameters $\theta G(t+1)$ to all clients.

G. Iterative Training

- Repeat steps 4 to 6 for T communication rounds.

H. Evaluation

- Evaluate the performance of the final global model $\theta G(T)$ on a held-out test set Dtest:
- Accuracy = $(1/|Dtest|) \sum(xi,yi)\in Dtest\ I(\hat{y}i = yi)$ where:
- $\hat{y}i = argmax\_yp(y|xi; \theta G(T))$ is the predicted label for input xi.
- I(.) is the indicator function.

I. Deployment

- Deploy the trained global model $\theta G(T)$ for inference.

V. Implementation and Result

In implementation, we have shown model status by considering input as retinal images. Retinal image is uploaded and model will classify based on severity of diabetic retinopathy. Output is consists of multiple classes like No DR, Mild, Moderate, Proliferative and Severe DR etc.
Figure 3 shows classification of diabetic retinopathy, in this case it is Moderate with confidence of 57.24%.In aggregation and updation of weights in federated learning needs total 12 rounds.
In the case of figure 4, the classified image contributes to the training of the model with round 13.

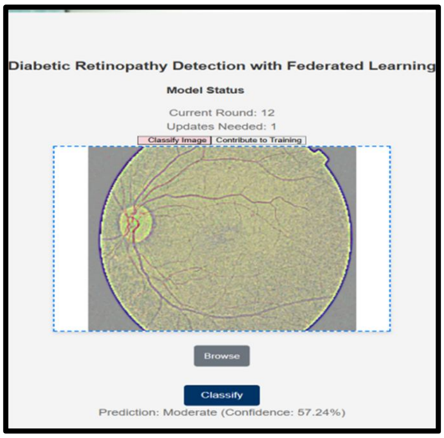

Figure 3. Classification of DR

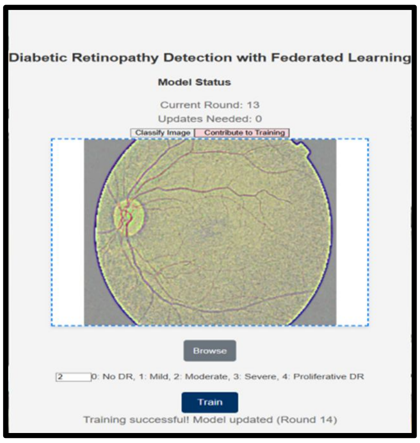

Figure 4. Training of Model

In figure 5 the proposed algorithm demonstrates a significant improvement in performance compared to both Fed Prox and Fed Fold, achieving the highest accuracy (0.78), precision (0.83), recall (0.81), and F1-score (0.79). This suggests that the proposed algorithm is more effective at learning from distributed data while maintaining high predictive accuracy and capturing a good balance between precision and recall.

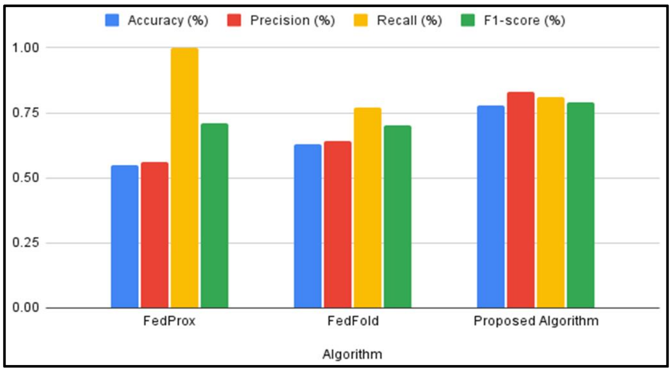

Figure 5. Comparisons of algorithm

VI. CONCLUSION

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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