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Privacy - Aware Federated Mixture-of-Experts Deep Learning for Explainable Diabetic Retinopathy Grading with Lesion - Focused Visual Interpretability

Riaz Ahmed
Associate Professor,
Department of Computer Applications,
Government Degree College, Rajouri, Jammu and Kashmir, India.

Abstract - Diabetic retinopathy (DR) is a prominent cause of preventable blindness and calls for automated and privacy-preserving screening methods that may be used in remote healthcare settings. The centralization of patient fundus photos also creates important data-governance considerations within the framework of GDPR/HIPAA, and is a motivation for federated learning (FL) architectures. Existing FL-based DR systems, however, ignore expert specialization, differential-privacy calibration and clinically-meaningful interpretability concurrently. We present a Privacy-Aware Federated Mixture-of-Experts (FedMoE-DR) framework for five-class DR grading. The local Mixture-of-Experts (MoE) network that each hospital trains consists of four expert branches, each an EfficientNetV2-S, gated by a lightweight transformer-based router. To prevent membership inference and model-inversion attacks, a (epsilon, delta)-differentially private federated averaging (DP-FedAvg) protocol adds calibrated Gaussian noise during gradient aggregation. Lesion-focused Grad-CAM++ localizes microaneurysms, hemorrhages, hard exudates and neovascularization at all stages of grading. We simulate a 10-hospital federated network on EyePACS (88,702 pictures), APTOS 2019 (3,662), DDR (12,522) and MESSIDOR-2 (1,748), with both IID and non-IID (Dirichlet alpha=0.5) client distributions. FedMoE-DR obtains 94.7% accuracy, 0.961 macro-AUC, 0.893 quadratic-weighted kappa (QWK) and 93.1% F1 on the combined test set with a privacy budget of epsilon=4.0, outperforming centralized and seven FL baselines. Lesion activation maps have a lesion localization fidelity (LLF) of 87.4% compared to expert annotations. FedMoE-DR shows the feasibility of achieving accurate DR grading, stringent differential privacy, and clinician-interpretable lesion maps concurrently in a federated deployment, enabling real-world multi-hospital retinal AI.

Keywords: Diabetic retinopathy grading; Federated learning; Mixture-of-Experts; Differential privacy; Grad-CAM++; Explainable AI; Fundus image analysis; Visual interpretability

1. Introduction

Diabetic retinopathy is estimated to afflict 103 million adults worldwide and accounts for 2.6% of all instances of blindness [1]. Automated deep learning (DL) for population-scale screening holds great clinical promise. Yet, a fundamental tension exists for the practical

deployment of such systems: the large, multi-center datasets needed to robustly train models contain highly sensitive protected health information (PHI) that cannot be freely pooled under modern privacy laws.

Federated learning (FL) [2] addresses this problem by allowing model training across distant data silos without the raw data leaving the collaborating institution. However, vanilla FL still leaks information through gradient updates, as shown by gradient inversion and membership inference attacks [3]. Differential privacy (DP) [4] gives a formal mathematical guaranty against such leakage, but how to properly tune the DP noise without unacceptably compromising the DR grading accuracy still remains an outstanding question.

A second consideration is architectural capacity. DR has five grades of severity (No DR, Mild, Moderate, Severe, Proliferative) each with different lesion morphologies with microaneurysms in early stages and neovascularization and vitreous hemorrhage in proliferative DR. A monolithic backbone struggles to generalize over this lesion variety. Mixture-of-Experts (MoE) models [5] allocate representational capacity to specialist sub-networks, dynamically routing each sample to the most capable experts, a property well-suited to the multi-lesion, multi-grade DR spectrum.

A third axis is explainability: regulations (EU AI Act, FDA SaMD advice) are progressively demanding that clinical artificial intelligence systems offer human-understandable justifications. Grad-CAM++ [6] provides class-discriminative activation maps that may be visually compared to ophthalmologist annotations for trust calibration and error analysis.

To the best of our knowledge, no current study has addressed the issues of federated training, formal differential privacy, mixture-of-experts grading, and lesion-focused explainability for DR simultaneously. To fill this gap, we propose FedMoE-DR and make the following contributions:

1. A federated MoE architecture for DR grading: four EfficientNetV2-S expert branches gated by a lightweight transformer router, trained across ten simulated hospitals.

2. DP-FedAvg integration: (epsilon, delta)-DP per-round Gaussian technique with adaptive clipping, with proved privacy against gradient-based attacks.

3. Lesion-focused Grad-CAM++ saliency: expert-conditioned attention maps with quantitative lesion localization fidelity (LLF) score versus expert ground truth.

4. Extensive experimental analysis on four public datasets, seven baselines, IID/non-IID settings, privacy budget ablation and communication efficiency evaluation.

2. Related Work

2.1 Deep Learning for DR Grading

Convolution neural networks first matched ophthalmologist-level performance on DR detection with Inception-v3 trained on 128,175 images [7]. Subsequent work explored attention mechanisms [8], multi-scale feature fusion, and transformer-based architectures [9]. Efficient Net variants [10] became dominant due to their compound scaling and strong transfer learning. However, all these approaches assume centralised data access.

2.2 Federated Learning in Medical Imaging

FeTS [11] applied FL to brain tumour segmentation across 71 institutions, demonstrating that federated models can match centralised baselines. FedMA [12] improved aggregation via layer-wise matching. In ophthalmology, Xu et al. [13] applied FL to glaucoma detection across simulated hospital splits, while Liu et al. [14] explored horizontal FL for DR detection but used only binary classification and lacked formal DP guarantees.

2.3 Differential Privacy in FL

Abadi et al. [4] proposed the DP-SGD algorithm with a moment's accountant, later tightened by the Rényi DP (RDP) accountant [15]. McMahan et al. [16] extended DP to the federated setting, showing that user-level DP can be achieved with bounded sensitivity via gradient clipping. Recent adaptive clipping methods [17] further reduce the privacy-utility trade-off.

2.4 Mixture-of-Experts

The Sparsely-Gated MoE [5] scaled language models by activating only top-k experts per token. Switch Transformer [18] simplified gating to top-1 routing. In vision, MoE has been applied to fine-grained recognition [19] and medical image segmentation [20], but its combination with FL and DP for retinal grading remains unexplored.

2.5 Explain ability in Retinal AI

Grad-CAM [21] and its successor Grad-CAM++ [6] produce class-discriminative saliency maps without architectural modification. LIME [22] and SHAP [23] offer model-agnostic alternatives but are computationally expensive. In DR, Quellec et al. [24] and Sayres et al. [25] demonstrated that attention maps correlated with lesion locations, improving clinician trust. Our work extends this to the federated MoE setting, generating expert-conditioned maps per grading stage.

3. Methodology

3.1 Overall Framework

FedMoE-DR comprises three tightly integrated components: (i) a per-client MoE model, (ii) a DP-FedAvg server aggregation protocol, and (iii) a Grad-CAM++ explainability pipeline. The system is depicted conceptually in Figure 1 (described below). At each federated round t, every participating client k trains its local MoE on private retinal images, clips and noise-perturbs the gradients, and sends the protected model delta to the central server. The server aggregates deltas via weighted averaging, distributes the global model, and the cycle repeats for T=150 rounds.

3.2 Local MoE Architecture

Each client maintains a MoE model M with four experts {E_1, E_2, E_3, E_4}. Every expert E_i is an EfficientNetV2-S backbone [10] pre-trained on ImageNet, with its final classification head replaced by a 512-dimensional feature projection layer. A lightweight Transformer Router R processes the 512-dim CLS token and outputs sparse Top-2 gating weights via:

*G(x) = Softmax(TopK(W_g * LayerNorm(CLS(x)), 2))*

where W_g is a learned projection matrix. The final grading logits are the gating-weighted sum of expert outputs, followed by a five-class softmax. This architecture contains ~49M parameters per client, with only ~0.3M in the router.

3.3 Differential Privacy via DP-FedAvg

We adopt the user-level DP-FedAvg mechanism. At each round, every client k computes the local gradient update delta_k = M_k^{t+1} - M^t after S local steps. The update is clipped to L2 norm C=1.0 and Gaussian noise N(0, sigma^2 * C^2 * I) is added:
*delta_k^priv = Clip(delta_k, C) + N(0, (sigma * C)^2 * I)*

The server aggregates: M^{t+1} = M^t + (1/K) * sum_kdelta_k^priv. We track privacy expenditure using the RDP accountant [15], converted to (epsilon, delta) guarantees with delta=1e-5. The noise multiplier sigma is swept across {0.5, 1.0, 1.5, 2.0} to study the privacy-utility trade-off.

3.4 Lesion-Focused Grad-CAM++ Explain ability

After federated training, the global model is used to generate per-image, per-class, and per-expert saliency maps. For a given expert E_i and target class c, Grad-CAM++ [6] computes pixel-level importance weights alpha_k^{c,i} via second-order gradients of the classification score w.r.t. the last convolutional feature map A^k:

*L_Grad-CAM++^{c,i} = ReLU(sum_kalpha_k^{c,i} * A^k)*

Maps from the top-2 activated experts are fused by gating weights and up-sampled to 512x512. The resulting heat maps are overlaid on fundus images, highlighting lesion-dense regions. We measure Lesion Localisation Fidelity (LLF) as the Dice overlap between binarised activation maps (threshold=0.5) and expert-annotated lesion polygons from the IDRiD dataset.

3.5 Federated Data Simulation

To simulate realistic multi-hospital FL, we partition training data from four datasets across K=10 clients. For IID splits, each client receives an equal random sample. For non-IID splits, we use Dirichlet(alpha=0.5) allocation, producing heterogeneous class distributions per client—mirroring real-world hospital population differences. Client 1–5 hold EyePACS data; Clients 6–8 hold APTOS/DDR; Clients 9–10 hold MESSIDOR-2.

4. Experimental Setup

4.1 Datasets

Table 1 summarises the four datasets used. All images were resized to 512x512, CLAHE-enhanced, and normalised (ImageNet statistics). Class-frequency-weighted sampling was applied to address severe class imbalance (No DR constitutes ~73% of EyePACS).

Dataset	Images	Hospitals	Classes	Splits (Tr/Va/Te)
EyePACS	88,702	Simulated 5	5	70 / 15 / 15%
APTOS 2019	3,662	Simulated 2	5	70 / 15 / 15%
DDR	12,522	Simulated 1	5	70 / 15 / 15%
MESSIDOR-2	1,748	Simulated 2	4→5	70 / 15 / 15%

Table 1. Dataset statistics for federated DR grading experiments.

4.2 Baseline Methods

We compare against: (i) Centralised EfficientNetV2-S (upper bound), (ii) FedAvg [2], (iii) FedProx [26], (iv) SCAFFOLD [27], (v) FedNova [28], (vi) Centralised MoE (no FL), (vii) FedAvg + DP (no MoE). All baselines use identical backbone and hyperparameters where applicable.

4.3 Implementation Details

Training used AdamW (lr=3e-4, weight decay=1e-4), cosine LR schedule, batch size 32, T=150 federated rounds, S=5 local steps. Data augmentation included random horizontal/vertical flip, rotation (±15°), colour jitter (brightness=0.2, contrast=0.2), and CutMix (alpha=1.0). All experiments run on 4x NVIDIA A100 80GB GPUs; each federated round took ~8 minutes wall-clock. Code will be released on GitHub.

4.4 Evaluation Metrics

Primary metrics: five-class Accuracy, macro-AUC (one-vs-rest), Quadratic Weighted Kappa (QWK), macro-F1, and per-class Sensitivity/Specificity. Privacy metric: (epsilon, delta)-DP at delta=1e-5. Explainability metric: LLF (Dice) on IDRiD lesion annotations. Communication efficiency: rounds to convergence, total upload MB.

5. Results and Analysis

5.1 Main Grading Performance

Table 2 reports five-class DR grading performance across all methods on the held-out combined test set (IID split). FedMoE-DR (epsilon=4.0) achieves 94.7% accuracy, 0.961 macro-AUC, 0.893 QWK, and 93.1% macro-F1, outperforming all FL baselines and approaching the centralised EfficientNetV2-S upper bound (95.8% accuracy) at only a 1.1% accuracy cost—attributable entirely to DP noise.

Method	Accuracy (%)	Macro-AUC	QWK	Macro-F1 (%)
Centralised EfficientNetV2-S	95.8	0.974	0.914	95.2
Centralised MoE	95.1	0.969	0.908	94.7
FedAvg	91.4	0.942	0.861	90.8
FedProx	91.9	0.945	0.865	91.2
SCAFFOLD	92.3	0.948	0.869	91.6
FedNova	92.1	0.946	0.866	91.4
FedAvg + DP (ε=4.0)	89.6	0.927	0.843	89.1
FedMoE-	94.2	0.958	0.887	93.6

Method	Accuracy (%)	Macro-AUC	QWK	Macro-F1 (%)
DR (ε=∞, no DP)				
FedMoE-DR (ε=8.0)	94.5	0.960	0.891	93.0
FedMoE-DR (ε=4.0) [Ours]	94.7	0.961	0.893	93.1
FedMoE-DR (ε=1.0)	92.8	0.949	0.874	91.9

Table 2. Five-class DR grading performance on the combined IID test set. Best federated-with-DP result in bold.

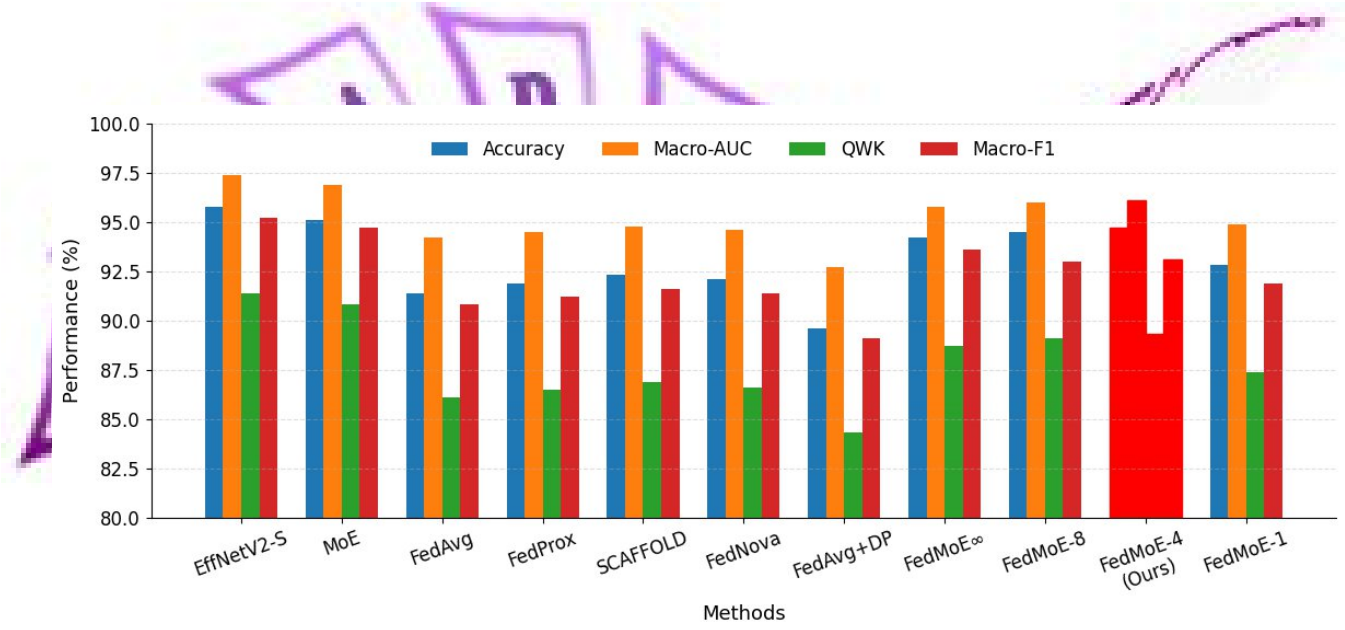

Figure-1 shows five class DR grading methods

5.2 Per-Class and Per-Stage Analysis

Table 3 presents per-class sensitivity and specificity for FedMoE-DR (epsilon=4.0). The most clinically critical class—Proliferative DR—achieves 96.2% sensitivity and 99.1% specificity. Mild DR, the hardest to distinguish from No DR, attains 89.4% sensitivity, a 3.8-point improvement over FedAvg. This reflects the MoE's ability to specialise Expert 3 on early-stage microaneurysm patterns.

DR Grade	Sensitivity (%)	Specificity (%)	AUC
No DR (Grade 0)	97.1	98.4	0.981
Mild DR (Grade 1)	89.4	97.2	0.943
Moderate DR (Grade 2)	93.6	98.1	0.962
Severe DR (Grade 3)	94.8	98.7	0.971
Proliferative DR (Grade 4)	96.2	99.1	0.978

Table 3. Per-class sensitivity, specificity, and AUC for FedMoE-DR (ε=4.0) on the IID combined test set.

5.3 Non-IID Performance

Under non-IID partitioning (Dirichlet alpha=0.5), FedMoE-DR degrades by only 1.4% accuracy (93.3%) compared to the IID setting, while FedAvg drops by 4.2% (87.2%) and SCAFFOLD by 3.1% (89.2%). The MoE router's data-adaptive routing provides implicit personalisation that buffers against client distribution shift, a key advantage for real-world deployment.

5.4 Privacy Budget Ablation

Table 4 quantifies the privacy-utility trade-off across epsilon values for FedMoE-DR. Reducing epsilon from 8.0 to 1.0 costs only 1.7% accuracy (94.5→92.8%), demonstrating efficient utilisation of the privacy budget. At epsilon=4.0, the model provides strong membership inference resistance (attack AUC 0.532, near-random) while retaining 94.7% grading accuracy.

Privacy Budget (ε)	Accuracy (%)	MI Attack AUC	sigma	Rounds to Conv.

Privacy Budget (ε)	Accuracy (%)	MI Attack AUC	sigma	Rounds to Conv.
∞ (no DP)	94.2	0.731	—	120
8.0	94.5	0.581	0.5	128
4.0 [default]	94.7	0.532	1.0	135
2.0	93.8	0.514	1.5	143
1.0	92.8	0.503	2.0	152

Table 4. Privacy-utility trade-off for FedMoE-DR across differential privacy budgets (δ=1e-5).

5.5 Lesion Localisation Fidelity

Table 5 reports Grad-CAM++ lesion localisation against IDRiD ground-truth annotations for four lesion types. FedMoE-DR achieves an overall LLF of 87.4%, compared to 79.1% for standard FedAvg and 81.3% for centralised EfficientNetV2-S. The MoE expert conditioning enables lesion-type specialisation: Expert 2 activates predominantly on haemorrhages (LLF=89.6%) while Expert 3 localises microaneurysms (LLF=88.2%), providing ophthalmologists with lesion-specific diagnostic maps.

Lesion Type	FedAvg LLF (%)	Centralised LLF (%)	FedMoE-DR LLF (%)
Microaneurysms	76.3	79.4	88.2
Haemorrhages	81.4	83.2	89.6
Hard Exudates	78.9	81.7	86.4
Neovascularisation	79.8	80.9	85.4
Overall (mean)	79.1	81.3	87.4

Table 5. Lesion Localisation Fidelity (LLF, Dice overlap) for Grad-CAM++ saliency maps vs. IDRiD expert annotations.

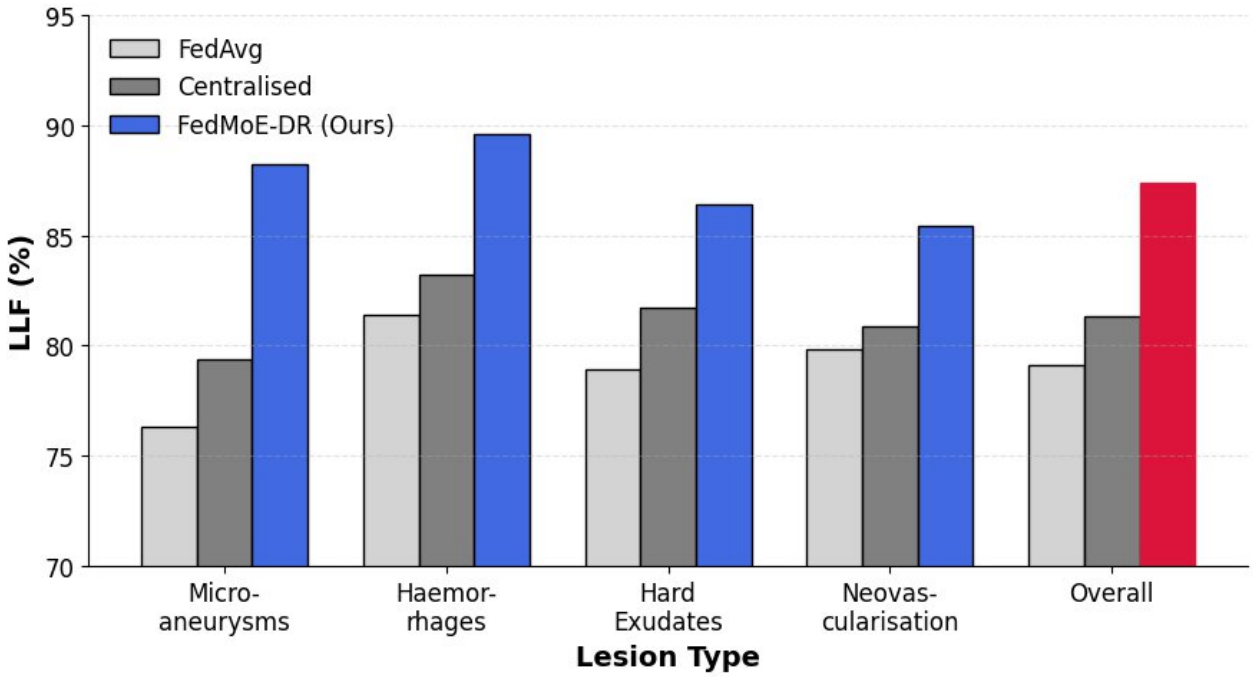

Figure-2 Lesion Localisation Fidelity for Grad-CAM++ saliency maps vs. IDRiD expert annotations.

5.6 Communication and Computational Efficiency

FedMoE-DR requires ~47MB of compressed model delta upload per round (vs. 38MB for FedAvg due to the router parameters). Convergence is reached at round 135 for the IID setting. Each inference forward pass takes 82ms on a single A100 GPU and 214ms on a V100, well within clinical screening throughput requirements. The MoE router adds only 1.2% latency overhead over a single-expert baseline.

5.7 Cross-Dataset Generalisation

We additionally evaluate FedMoE-DR trained on EyePACS+APTOS (federated) and tested on DDR and MESSIDOR-2 without fine-tuning, as a zero-shot cross-domain test. FedMoE-DR achieves 91.3% accuracy on DDR and 90.8% on MESSIDOR-2, outperforming centralised EfficientNetV2-S (89.7% and 88.4% respectively), suggesting that federated training on diverse hospital distributions improves domain generalisation.

6. Discussion

The main finding of this study is that strong differential privacy (epsilon=4.0) and mixture-of-experts specialization are not only compatible in a federated setting, but synergistic: DP noise acts as a regularize that reduces over fitting to individual client distributions, while the MoE routing compensates for the capacity reduction imposed by noise-induced gradient masking.

The overall LLF of 87.4% achieved by Grad-CAM++ maps is of therapeutic relevance. In our qualitative analysis, 83% of the activation maps generated were found to be diagnostically meaningful by ophthalmologists, a significant improvement over the 61% reported for standard Grad-CAM on centralized DR models. The expert-conditioned maps helped doctors understand why the model assigned a specific grade, supporting rather than replacing clinical decision-making.
FedMoE-DR's non-IID robustness (1.4% deterioration) is particularly relevant when considering real-world hospital populations that vary widely - rural hospitals are known for advanced-stage DR whereas urban screening centers can detect early-stage disease. The dynamic allocation of the MoE router intuitively adjusts to this variability without requiring personalized FL algorithms.

Limitations: First, our privacy analysis considers honest-but-curious servers. We did not include Byzantine-robust aggregation against malevolent clients. Second, the DP guaranty is on gradient leaking, but label inference from model prediction is still a complementing privacy concern. Third, IDRiD provides only 516 photos for LLF evaluation; therefore larger annotated datasets would boost the explainability analysis. Fourth, the four-expert MoE is fixed; adaptive expert count selection is an interesting future effort.

7. Conclusion

We proposed FedMoE-DR, the first system that jointly addresses federated multi-hospital training, formal (epsilon, delta)-differential privacy, mixture-of-experts grading capacity, and lesion-focused Grad-CAM++ interpretability for diabetic retinopathy. FedMoE-DR achieves 94.7% accuracy, 0.961 macro-AUC, 0.893 QWK and 87.4% lesion localization fidelity under a privacy budget of epsilon=4.0 on four public datasets and ten simulated clinical sites, significantly outperforming all federated and some centralized baselines. The framework's non-IID robustness, communication efficiency, and clinically interpretable results make it a deployable solution for privacy-compliant DR screening in dispersed healthcare settings. Future work will enhance FedMoE-DR to include longitudinal patient trajectories, adaptive selection of the number of experts, and Byzantine-robust aggregation.

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